**A Web-Based Perinatal Decision Support System Framework Using a Knowledge-Based-Approach to Estimate Clinical Outcomes: Neonatal Mortality and Preterm Birth in Twins Pregnancies**

by

Marry Gunaratnam, B.Eng (Biomedical and Electrical Engineering),

Carleton University (Ottawa, Ontario)

A thesis submitted to the Faculty of Graduate Studies and Research

In partial fulfillment of the requirements for the degree of

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Department of Systems and Computer Engineering

Carleton University

Ottawa, Ontario, Canada, K1S 5B6

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The undersigned recommend to

The Faculty of Graduate Studies and Research

acceptance of the thesis

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Chair, Department of Systems and Computer Engineering

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Dr. Monique Frize, Thesis Supervisor

Carleton University

April 2013

**Abstract**

There are two main contributions to knowledge presented in this thesis: (1) improved method for predicting neonatal mortality and preterm birth in twin pregnancies, and (2) a framework to build a web-based perinatal decision support system (PEDSS) using a knowledge based approach.

Earlier identification of clinical outcomes may lead to more efficient allocation of resources. Thus, two novel prediction models using decision trees (DT) and hybrid ANN were evaluated. The DT prediction model had the highest performance outcome for predicting neonatal mortality (sensitivity=62.24%, specificity=99.95%, PPV=72.34%, NPV=99.92%) using information available within 10 minutes from birth, and preterm birth in twin pregnancies (sensitivity=80.00%, specificity=91.55%, PPV=67.35%, NPV=95.79%) before 22 weeks gestation.

The PEDSS includes three main components: the knowledge-base, a workflow engine, and a mechanism to communicate results. This tool provides the clinician prediction results within seconds. Clinicians may use the outputted information to inform families and initiate preventative care.

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**List of Acronyms**

|  |  |
| --- | --- |
| **ANN** | Artificial Neural Network |
| **AGPAR** | Activity, Pulse, Grimace, Appearance, and Respiration |
| **APACHE** | Acute Physiology and Chronic Health Evaluation |
| **AUC** | Area Under the Curve |
| **CBR** | Case Based Reasoning |
| **CDSS** | Clinical Decision Support System |
| **CMS** | Content Management System |
| **CL** | Cervical Length |
| **CRIB** | Clinical Risk Index for Babies |
| **DT** | Decision Tree |
| **ECMS** | Enterprise Content Management System |
| **EMR** | Electronic Medical Record |
| **fFN** | Fetal Fibronectin |
| **FN** | False Negative |
| **FP** | False Positive |
| **ICU** | Intensive Care Unit |
| **ID3** | Iteractive Dichotomiser |
| **LOS** | Length of Stay in ICU |
| **k-NN** | k-Nearest Neighbor |
| **MIRG** | Medical Information-technology Research Group |
| **MLP** | Multilayer Perceptron |
| **NICU** | Neonatal Intensive Care Unit |
| **NPV** | Negative Predicative Value |
| **PBNN** | Pruning Based Neural Network |
| **PPPSEO** | Perinatal Partnership Program of Eastern and Southern Ontario |
| **PPV** | Positive Predicative Value |
| **PTB** | Preterm Birth |
| **ROC** | Receiver Operating Curve |
| **SNAP** | Score for Neonatal Acute Physiology |
| **SQL** | Structured Query Language |
| **TBNN** | Tree Based Neural Network |
| **TN** | True Negative |
| **TP** | True Positive |
| **URL** | Uniform Resource Locator |

**CHAPTER 1 INTRODUCTION**

* 1. **MOTIVATION**

**1.1.1 HEALTHCARE PERSPECTIVE**

Healthcare in Canada has long been depicted as a source of national pride, yet clear opportunities exist to enhance patient outcomes and thus reduce the demands on our healthcare system. In particular, preventative interventions are considered to be an important element of a modern healthcare system. Many studies have demonstrated that preventative interventions during pregnancy have led to lower mortality and morbidity rates among newborns (Lim et al., 2009).

Earlier identification of newborns at risk of neonatal mortality or women at risk of preterm**[[1]](#footnote-1)** labour in a high risk population, would allow healthcare providers to be more efficient in the allocation of their resources and provide timely response to varying medical problems. Early diagnosis is required for effective treatment. Moving forward, leveraging the advances in technology and linking it with medical knowledge using advanced mathematical concepts would allow for the creation of sophisticated tools to generate more accurate predictions of complex outcomes in the medical field.

**1.1.2 TECHNOLOGY PERSPECTIVE**

The healthcare domain remains a paper-intensive and non-automated industry. A large amount of money is spent on administrative cost in healthcare, and in many cases, healthcare providers do not have a collaborative platform to share and exchange information. A collaborative platform would allow healthcare providers access to various clinical applications including prediction and assessment tools in order to determine appropriate care protocols and/or medication administration.

A web-based collaborative platform in a clinical setting would allow healthcare providers to collaborate in the form of sharing opinions and exchanging clinical data regardless of their geographic location (Chronaki, 1997). Further, the development of a high quality, low cost perinatal decision support system (PEDSS) to aid human decisions on a collaborative platform would improve the quality of care provided and reduce human errors.

**1.2 PROBLEM STATEMENT**

A number clinical problem exists specific to perinatal care. Early and accurate diagnosis of such outcome can initiate care early on and improve patient outcome. The goal of any prediction model is to successfully predict an outcome of choice while meeting clinical expectations. This thesis work includes prediction models for the identification of two perinatal problems: neonatal mortality and preterm labour in twin pregnancies. Most published risk estimation models attempt to meet clinically acceptable sensitivity and specificity, however in most cases successful identification of positive cases has been difficult. Further, irrelevant variables not only add noise and complexity to the problem, but it reduces the likelihood of identifying positive cases. The primary objective of this work was to incorporate the advantages of DTs to create a system that can predict the two perianal problems above at an earlier stage while maintaining high sensitivity, specificity, positive predicative and negative predicative values.

Once the fundamental objective was met, a framework for a perinatal decision support system (PEDSS) in order to allow healthcare providers access to the risk assessment tools and promote collaboration was presented. The PEDSS contains repositories for storing patient information and allows easy export of data for data mining and analysis. The combination of a decision support system with integrated assessment tool(s) to predict the risk of medical outcome(s), would initiate suitable care protocols early on and ensure effective treatment and thus improve patient care.

**1.3 NEED FOR PREDICTION MODELS IN PERINATAL CARE**

In order to mitigate complications associated with neonatal mortality or preterm birth in twin pregnancies, it is important to recognize important risk factors and initiate suitable care protocols in a timely manner to ensure effective treatment (Allen et al., 2002). In terms of neonatal mortality, correctly identifying a survivor from a non-survivor could lead to earlier development and execution of a treatment plan which may be in the form of more medical attention allocated to the newborn, or a more aggressive intervention (i.e assign palliative care instead of restorative care for terminally ill**[[2]](#footnote-2)** newborns) (Yu, 2009). Although it is a difficult topic to acknowledge, due to the high cost of resources required to keep a neonate within the ICU, the cost versus benefits should be analyzed, and thus the healthcare providers will require a prediction system that is clinically acceptable to aid their decisions.

Further, correctly identifying a high risk population (i.e. twin pregnancies) at risk of preterm birth early on would prevent the need for costly and invasive screening tests (i.e. cervical length (CL) and fetal fibronectin (fFN)). This may also avoid additional stress to the mothers, which is commonly encountered with invasive testing. The physicians may also initiate interventions, treatment and allocate necessary resources early on in an attempt to prevent preterm birth. Ultimately, a prediction model that correctly identifies the risk of preterm birth in twin pregnancies early on could lead to a decrease in the overall preterm birth rates.

* + 1. **INFANT MORTALITY RATES IN CANADA**

Infant mortality is an important indicator of the child’s health and the country’s well-being over time (The Conference Board of Canada, 2001). Infant mortality may be categorized into early neonatal mortality (death of newborn 0-7 days), neonatal mortality (death of newborn 8-27 days) and post neonatal mortality (death of infant 28-365 days) (The Daily Motion, 2008). Between 2004 and 2005, neonatal and post-neonatal mortality rates followed different paths, where neonatal mortality rate rose from 4.0 to 4.1 deaths per 1000 live birth, and no change was observed in the post-neonatal rate, it remained at 1.3 deaths per 1000 live birth (The Daily Motion, 2008). Although Canada’s overall infant mortality rate fell significantly since the 1960’s, it is still higher compared to its peer countries of similar socio-economic status including Sweden, Japan, Finland and France. Canada is now tied in 2nd place with United Kingdom with the highest infant mortality rate. United States has the leading highest infant mortality rate of the developed countries (The Conference Board of Canada, 2001).

* + 1. **PRETERM MORTALITY RATES IN CANADA**

Preterm birth is an important perinatal problem in Ontario, where about 8% of babies (1 in 12) are born before term (Allen et al., 2002). In 2006-2007, 1 in 7 babies born in Canada were considered to be either preterm or too small for their gestational age (Lim et al., 2009). Preterm births accounts for nearly 75% of all perinatal mortality and over 50% of long term morbidity (Alere’s Women’s & Children’s Health, 2008). Preterm birth results in a disproportionately high percentage of healthcare costs among newborns (Lim et al., 2009). The preterm birth rate in Canada has increased over the years (as with many other economically developed countries), from 6% in 1980 to 8.1% in 2006-2007. The rate varies across the provinces and territories, with the highest rate in Nunavut at 10.8%, followed by Alberta at 8.1% and the lowest rate in Prince Edward Island and New Brunswick at 7%.

* 1. **THESIS OBJECTIVE(S)**

**1.4.1 FIRST OBJECTIVE**

**Objective:** Improve the Prediction of Neonatal Mortality and Preterm Birth in Twin Pregnancies

The first objective of this thesis was to construct an improved classifier system for predicting: (1) neonatal mortality non-invasively using data available at 10 minutes from birth which yields a sensitivity of 60% and specificity of 85% or greater, and (2) preterm birth in twin pregnancies non-invasively at 22 weeks gestation which yields a sensitivity of 65% and specificity of 85% or greater. These threshold values are derived from previously completed thesis work of similar research and in collaboration with physicians. Perinatal data for this work will be obtained from the NIDAY and BORN (Better Outcomes Registry for Neonates) database.

The classifier system will be analyzed using two data mining techniques: decision trees (DTs) and hybrid ANN. The results of the DT and hybrid ANN approaches will be compared to past results using various performance measures to validate whether the new prediction model is superior.

**1.4.2 SECOND OBJECTIVE**

**Objective:** Design a Web- Based Content Management System Framework for Perinatal Decision Support

The second contribution of this thesis includes a conceptual framework, including the steps for the development and implementation of a web-based content management system for perinatal decision support. The system shall be low cost, easy to use and be designed to adapt to the clinician’s cognitive workflow.

The Perinatal Decision Support System (PEDSS) shall consist of a knowledge-base, a workflow engine, and a mechanism to communicate the results. The knowledge-base contains a set of rules or associations related to the desired predictions; the workflow engine combines the rules in the knowledge-base with the patient data; and the communication mechanism allows entry of the patient data into the system, and delivers the results in the form of notifications, alerts or emails to the end user. This system will help physicians to inform families and to initiate preventative care, monitoring, and treatment.

**1.5 THESIS OUTLINE**

This thesis is organized as follows:

**CHAPTER 1:** Provides motivation, problem statement, and the need for a prediction model to predict neonatal mortality and preterm birth in twin pregnancies in perinatal care. The objectives are presented.

**CHAPTER 2:** Provides an overview of relevant medical and technological concepts related to neonatal mortality and preterm birth. An overview of a web-based content management system (CMS), and criteria for the selection of a CMS is presented. Types of neonatal decision support system are presented

**CHAPTER 3:** Describes the methodology used to create the prediction model for neonatal mortality and preterm birth in twin pregnancies using: (1) decision trees (DT), and (2) hybrid ANN. An overview of the proposed perinatal decision support system (PEDSS) is also discussed.

**CHAPTER 4:** The results for predicting neonatal mortality and preterm birth in twin pregnancies are presented. A prototype of the PEDSS system is also provided.

**CHAPTER 5:** The concluding remarks, contributing knowledge and future work is presented.

**CHAPTER 2 LITERATURE REVIEW: OVERVIEW OF RELEVANT MEDICAL AND**

**TECHNOLOGICAL CONCEPTS**

**2.1 NEONATAL MORTALITY**

Neonatal mortality refers to death of infants aged 0-27 days. In 2007, the rate of neonatal mortality in Canada during the first month was 4.2 deaths per 1000 live birth, where 3.3 death per 1000 live birth occurred during the first week (Milan, 2011).

**2.1.1 CLASSIFICATION**

Neonatal mortality can be subdivided into early neonatal (< 7 days) and late neonatal (7-28 days) periods (Rowley et al., 2011). Neonatal mortality typically occurs as a result of surrounding events during the prenatal period and delivery.

**2.1.2 FACTORS CONTRIBUTING TO NEONATAL MORTALITY**

Neonatal mortality arises largely due to insufficient care during pregnancy, inappropriate management of complications during delivery, and poor hygiene during the critical hours of delivery (World Health Organization Press, 2006). During the perinatal period, factors that may lead to neonatal mortality include the presence of the following in the newborn: respiratory distress syndrome, short gestation, and low birth weight (Public Health Agency of Canada, 1996). Other risk factors associated with neonatal mortality include birth defects, disorders related to preterm birth, low birth weight, respiratory distress syndrome and congenital anomalies (Silins et al., 1985).

**2.1.2.1 BEHAVIORAL CHARACTERISTICS**

Modifiable risk factors associated with an increased risk of neonatal mortality include poor maternal diet, tobacco use and alcohol use (Silins et al., 1985). Interestingly, the neonatal death rate is not significantly higher in smokers; however it has been found that smoking during pregnancy results in a higher still birth rate. Further, the inhalations of smoke or second hand smoke are both risk factors of neonatal mortality (Rumeau-Rouquette, 1974).

**2.1.2.2 SOCIOECONOMIC CHARACTERISTICS**

The socio-professional characteristics of the parents contribute to the risk of neonatal mortality. In a study, the father’s occupation was used to estimate the social status of the family, and it was observed that the unskilled labour class resulted in the highest rate of neonatal mortality, whereas the intermediate class resulted in a lower rate of neonatal mortality and the executive class resulted in an even lower rate of neonatal mortality (Rumeau-Rouquette, 1974).

Furthermore, being unmarried, having a low socioeconomic status, or the use of tobacco and alcohol among adolescent mothers poses a significant risk of neonatal mortality (Silins et al., 1985). At highest risk of neonatal mortality are women under 20 years of age (Rowely et al., 2011). The neonatal mortality is significantly higher in rural areas compared to urban areas (Silins et al., 1985).

**2.1.2.3 LOW BIRTH WEIGHT**

Birth-weight is a good indicator of neonatal mortality. Birth weight is classified into Very Low Birth Weight (VLWB) (<1500g), Extremely Low Birth Weight (ELWB) (<1000g), and Low Birth Weight (LBW) (<2500g) (Rowely et al., 2011). In a study conducted to examine the relationship between neonatal mortality and birth weight, it was found that the leading cause of death for neonates weighing <1000g was respiratory distress syndrome, whereas the leading cause of death in neonates weighing 3000-4500g were intrauterine hypoxia or anoxia (Silins et al., 1985).

**2.1.2.4 MATERNAL HEALTH CHARACTERISTICS**

Maternal health characteristics related to neonatal death include uterine fibroids and tumors of the ovaries. Further, metrorrhagian during the first three months of pregnancy, or the presence of endocrine, severe cardiovascular, digestive or respiratory diseases lead to a higher rate of still births, and neonatal mortality (Rumeau-Rouquette, 1974).

**2.1.3 IMPACT OF NEW TECHNOLOGIES AND NEONATAL MORTALITY**

New technologies are not always advantageous, especially ones that allow for sex selection procedures and assisted reproduction to allow twins births. Twins births increase the risk of complications in both the mother and the fetus, where a large percentage of twins and nearly all triplets are born preterm. The neonatal mortality rates are higher among these groups compared to singleton pregnancy. Furthermore, gender preferences vary across the world, where most cultures prefer sons, and thus the neonatal mortality among girls is predicted to be about 1/3 higher than recorded (World Health Organization Press, 2006).

**2.1.4 ACCURACY OF STANDARD SCORING SYSTEMS FOR NEONATAL MORTALITY**

#### There are many scoring system available for neonatal mortality prediction. These scoring systems are typically used to identify newborns at risk of morbidity in order apply appropriate medical attention or intervention. Three of the most popular scoring systems used to date are: Clinical Risk Index for Babies (CRIB), Score for Neonatal Acute Physiology (SNAP) and AGPAR. The CRIB and SNAP models have gone through changes and have evolved into CRIB II, SNAP II and SNAP-PE.

**Table 2.1** Comparison between scoring systems used in neonatal care: (A) Scoring System; (B) Year the Model was Published; (C) # of Input Variables; (D) Time to Collect; (E) Gestational Requirement; and (F) Birth Weight Requirement (Mohkam, M. et al., 2010)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| (A) | (B) | (C) | (D) | (E) | (F) |
| AGPAR |  | 5 | 1 - 30 min |  |  |
| CRIB | 1993 | 6 | <12 hours | < 32 weeks | <1500g |
| CRIB II | 2003 | 6 | <12 hours | < 32 weeks | <1500g |
| SNAP | 1993 | 34 | <24 hours |  |  |
| SNAP II | 2001 | 6 | <12 Hours |  |  |
| SNAP – PE | 1993 | 38 | <12 hours |  |  |
| SNAP – PE II | 2001 | 6 | < 12 Hours |  |  |

In 2010, a cohort study was conducted to evaluate CRIB, CRIB II, SNAP, SNAP II and SNAP PE on 404 critically ill**[[3]](#footnote-3)** neonates, with detected mortality in 20% of neonates. The predicative accuracy was expressed as area under curve (AUC), sensitivity, specificity, PPV and NPV. The results for AUC in CRIB, CRIB II, SNAP, SNAP II and SNAP PE was 0.817, 0.698, 0.931, 0.901, 0.918, respectively, the sensitivity was 87.9, 69.6, 94.4, 84.8, 89.8, respectively, the specificity was 68.5, 63.0, 86.7, 62.8, 82.4, respectively, the PPV was 92.7, 76.2, 96.5, 90.8, 96.2, respectively, the NPV was 55.6, 54.8, 80, 54.4, 62.2, respectively, and the accuracy rate was 84.4, 67.1, 92.8, 82.7 and 88.6, respectively. The study concluded that the SNAP system had the highest AUC, sensitivity, specificity, PPV and NPV values and the lowest values were found using the CRIB II system (The Mothers Program, 2013).

In another study based on 295 newborns to assess the validity of SNAP, the resulting sensitivity, specificity, PPV, and NPV were 0.63, 0.95, 0.72 and 0.95, respectively. This study excluded neonates submitted <24 hours of admission to NICU and those shifted to NICU for observation as per specifications of SNAP (Maiya et al., 2001).

A case controlled study[[4]](#footnote-4) was conducted to evaluate the validity of CRIB II on 52 survivors and 52 non-survivors. The mean gestational age was 28.5 weeks and the mean weight was 865g. The results from this study indicated a sensitivity of 0.73 and a specificity of 0.60 (Fernandez-Carrocera et al., 2011).

In a study conducted to evaluate the validity of AGPAR scores and low birth weight in 3954 newborns with 3.8% mortality rate, the findings suggested a sensitivity of 0.84 and a specificity of 0.71, with a NPV value of 0.99; however the PPV was poor at 0.15. This estimation was based on 11 variables, where the AGPAR score at 1 min, birth weight and delivery mode were found to be variables that emerged as significant (Weirich et al., 2005).

In a similar study to evaluate the validity of low birth weight and 5-min AGPAR score, the sensitivity was lower at 0.722. This study was conducted on 875 newborns with 713 survivors and 163 non-survivors using 13 variables (Weirich et al., 2005).

**2.1.5 LIMITATIONS IN NEONATAL MORTALITY SCORING SYSTEMS**

One of the main disadvantages to these scoring systems is the time to collect the information, with the exception of the AGPAR scoring system. In addition, although these scoring systems have been in place for over three decades, the validity of the results varies (due to different prognostic variables, timing, quality of care etc.) and the ability to predict survival is poor. Most of these systems do not meet the clinical standards set by Dr. Bariciak, and even if these systems were to meet the clinical standards, it is accompanied by a poor PPV value, and in many cases these findings produced a high sensitivity followed by a low specificity. Further, these findings are all based on patient population of <900. Although the SNAP scoring system did meet the clinical standards, the data can only be obtained within 24 hours from admission NICU and required 34 variables. A data collection to include all 34 variables may be feasible for hospitals involved in R&D, but this is likely not be feasible for independent ICUs where it may not be part of their normal clinical routine. Further, the 24 hour period required for data collection is too long, especially in an environment where time is of the essence (Yu, 2009). Thus, there clearly exists the need for a scoring system that is able to predict neonatal mortality in a shorter time frame using fewer variables which meets clinical standards.

**2.2 PRETERM BIRTH**

Approximately 350 000 babies are born preterm in Canada each year. Despite significant advances in medical technologies, the rate of preterm birth has risen from 6.3% in 1981-1983 to 6.6% in 1991, and 7.6% in 2000. The rate of preterm births in Canada is currently ~7% (Goldenberg et al., 2008). Although advances in medical technologies has allowed for majority of the preterm babies in the current generation to survive, certain advances in medical technologies including IVF treatments or fertility drugs have been blamed for the increase in the number of preterm births.

Due to the direct correlation between preterm births and neonatal mortality, preventing preterm births is one of the main priorities within the healthcare domain. A common goal of perinatal care is to identify key factors contributing to preterm births. Previously many studies have attempted to predict women who are at risk of preterm birth, yet to date no scoring mechanism exists that has been proven to be superior to clinical judgment (Catley, 2007).

**2.2.1 CLASSIFICATION**

The World Health Organization (WHO) defines preterm births as births occurring before the completion of 37 week gestational period. An ideal term birth occurs between 37-41 weeks of gestation and post term birth occurs >41 weeks gestation. The gestational period is measured from the first day of the last normal menstrual period of the mother (Blackmore et al., 2011).

Preterm births can be further categorized according to gestational age and birth weight (Table 2.2). About 70% babies born preterm are categorized as low birth weight (<2500g) (Lim et al., 2009) (Allen et al. 2002). Low birth weight is an important variable for predicting health problems and disability of the newborn (Allen et al. 2002).

**Table 2.2 –**Preterm birth classified according to gestational period and birth weight. (A) Sub Groups; (B) Gestational Age; (C) Birth Weight; (D) Occurrence; (E) Survival; (F) Disability; (G) Cost; and (H) Length of Stay (LOS) (Goldenberg et al., 2008) (Lim et al., 2009)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| (A) | (B) | (C) | (D) | (E) | (F) | (G) | (H) |
| Extreme Prematurity  Severe Prematurity  Moderate Prematurity | 28 weeks  28-31 weeks  32-33 weeks  34-36 weeks | <1000g  <1500g  <2250g  <2500g | 5%  15%  20%  60-70% | >80%  >80%  >95%  99% | 15%  10%  5%  1% | 84 235  43 718  19 463  5 047 | 83.1  42.6  21.2  5.8 |

**2.2.2 FACTORS CONTRIBUTING TO PRE-TERM BIRTHS**

The pathogenesis associated with preterm birth is not clearly understood. However, certain factors may increase the risk of preterm birth (Alere’s Women’s & Children’s Health, 2008). Defining risk factors for preterm birth is favourable for many reasons including the fact that identifying an at-risk woman may allow for earlier treatment in order to prolong the gestational period. Moreover, defining an at-risk population may lead to further studies on the identification of vital risk factors that are linked to preterm birth (Goldenberg et al., 2008).

The root cause of preterm birth is a multi-factorial problem, with the risk factors varying from a combination of the maternal demographic, socioeconomic, health, genetic, biological, pregnancy, stress, and behavioural characteristics. Due to the large number of predictor variables associated with preterm births, prediction of preterm birth in an at-risk population remains a challenging problem. Please refer to Table F.1 for a complete list of risk factor variables associated with preterm delivery derived from the BORN and NIDAY databases. The following section provides a brief summary of the associated risk factors of preterm births.

**2.2.2.1 MATERNAL DEMOGRAPHIC & SOCIOECONOMIC CHARACTERISTICS**

It has been reported that African American women are at an increased risk of preterm birth, where Afro-Caribbean women are at nearly twice the risk of preterm birth compared to other races (Goldenberg et al., 2008). Several studies have identified that low socioeconomic and educational statuses, low or high maternal age and single maternal statuses are linked to preterm birth (Goldenberg et al., 2008).

East Asian and Hispanic women are at lower risk of preterm birth. Though women from South Asia have higher rates of low birth weight due to decreased fetal growth, they are not necessarily at risk of preterm birth (Goldenberg et al., 2008).

**2.2.2.2 GENETIC CHARACTERISTICS**

Women who previously delivered preterm are at higher risk of another preterm birth compared to women who previously delivered term. This may be due to the uterus not having had time to return to its normal state from the previous pregnancy, or due to maternal depletion (since pregnancy takes up maternal stores of vital vitamins, minerals and amino acids). Women with sister(s) who delivered preterm are at 80% risk of also delivering preterm. Underlying disorders that lead to preterm birth include diabetes, hypertension, and obesity (Goldenberg et al., 2008).

**2.2.2.3 MATERNAL HEALTH CHARACTERISTICS**

The mother’s health during pregnancy may be described by several indicators. It has been found that women with high or low body mass index (BMI) during pregnancy are at higher risk of adverse conditions during delivery. Women with high BMI are prone to adverse delivery outcomes including hypertensive complication and caesarean section, whereas women with low BMI are linked to preterm birth, low birth weight and increased rate of neonatal mortality (Yu, 2009). Women who have lower serum concentration of iron, folate or zinc are at higher risk of preterm birth.

Insufficient weight gain during pregnancy is also a risk factor associated with preterm birth. Thin women commonly intake lesser vitamins and minerals which may lead to decreased blood flow and increased infections. Obese women are more likely to have pre-eclampsia and diabetes or other medical conditions including glucose intolerance, hypoglycemia and gestational diabetes mellitus (GDM), which are all factors associated with preterm birth.

**2.2.2.4 BIOLOGICAL CHARACTERISTICS**

Several biological markers have been used to detect preterm birth, which includes amniotic fluid, urine, cervical mucus, vaginal secretions, serum or plasma, and saliva. The most powerful marker has been fetal fibronectin, which is a glycoprotein. Usually, it is absent from 24 weeks to near term, however if it is detected during routine screening in women between 24-32 weeks, this indicates that they are at increased risk of preterm birth (Goldenberg et al., 2008)

Intrauterine infection leads to 25-40% of all preterm birth due to the activation of innate immune system, although this may be an underestimation since it is difficult to detect using standard culture techniques. Bacterial vaginosis (disease that occurs due to the change in microbial ecosystem in the vagina) detected using a vaginal pH of greater than 4.5 leads to preterm birth. Although many genetic infections are related to preterm birth, there are also many non-genital tract infections associated with preterm birth, which include pyelonephritis and symptomatic bacteriuria, pneumonia and appendicitis. Further periodontal disease which leads to intrauterine infections is associated with preterm births. Viral infections including varicella or severe acute respiratory distress syndrome can also lead to preterm birth. Other maternal medical disorders that have led to preterm birth include thyroid disease, asthma, diabetes and hypertension (Goldenberg et al., 2008).

Decidual haemorrhage is also linked with preterm birth. This may cause bleeding in the placenta which causes thrombin formation and increased prostaglandin which leads to cervical change and rupture of the membrane (Allen et al. 2002). Uterine over distension causes the activation of the uterine muscles which may lead to preterm birth (Allen et al. 2002).

**2.2.2.5 PREGNANCY CHARACTERISTICS**

Women carrying twin fetuses are at higher risk of delivering prematurely. The presence of twin fetuses in the uterus limits the room available for fetal growth and development, which then leads to pregnancy related complications including uterine over distension and contractions leading to preterm birth (Goldenberg et al., 2008).

Other risk factors associated with preterm birth include vaginal bleeding caused by placental abruption or placenta previa, bleeding in the first and second trimester which is not related to placental abruption, high volume of amniotic fluid, and/or maternal abdominal fluid in second/third trimester (Goldenberg et al., 2008).

**2.2.2.6 STRESS**

Women experiencing high levels of psychological or social stress are at higher risk of delivering preterm. Although the underlying mechanism causing this is unknown, a hormone known as corticotrophin has been proposed (Goldenberg et al., 2008). Furthermore, women experiencing clinical depression are also at elevated risk of delivering preterm. Although the exact link is not clear, there is a relation in the fact that women experiencing depression are often correlated with an increased risk of smoking, drug abuse and alcohol. Depressed mood is also related to a natural killer cell activity and higher plasma concentration of inflammatory cytokines and their receptors, and therefore inflammation may relate depression to preterm birth (Goldenberg et al., 2008).

It has been observed that women who work long hours or are undertaking hard physical labour are at higher risk of delivering preterm. Although the level of physical activity is not related to preterm birth, the stress that is induced from over working is the underlying factor that leads to preterm birth (Goldenberg et al., 2008).

**2.2.2.7 BEHAVIORAL CHARACTERISTICS**

Tobacco, drugs (cocaine and heroin) and heavy alcohol use puts pregnant women at higher risk of delivering preterm. Smoking contains over 3000 chemicals, including nicotine and carbon monoxide which are both powerful vasoconstrictors, which lead to placental damage and decreased uteroplacental blood flow which may lead to preterm birth (Goldenberg et al., 2008).

**2.2.3 EARLIER DETECTION AND PREVENTION OF PRETERM BIRTH**

As much as 25% of all preterm births are associated with identifiable health problems in the mother, and thus recognizing the underlying pathway which leads to preterm births may lead to new preventative measures (Allen et al. 2002). There are certain measures which can be taken to reduce the chances of preterm birth, which include starting prenatal care early, eliminating and avoiding all modifiable risks associated with preterm birth (i.e. eliminating tobacco, drugs and alcohol use), following Canada’s guide to nutrition in order to maintain a healthy diet, seeking help when symptoms and signs are observed of preterm birth, and maintaining good communication with the respective doctor/midwife regularly (Ontario’s maternal newborn and early child development resource centre, 2004). Although it is not easy to tell if a women is at risk of preterm birth, a few vital signs and symptoms to look out for in pregnant women include persistent cramps, vaginal bleeding, lower back pain, a feeling of baby pushing down, contractions, and an increase in the amount of vaginal discharge (Ontario’s maternal newborn and early child development resource centre, 2004).

**2.2.4 ACCURACY OF STANDARD INAVSIVE TEST METHODS FOR PREDICTING PTB IN TWINS**

The ability to correctly identify and predict preterm birth in a high-risk population, such as women pregnant twins, could provide a better understanding of the risk factors leading to preterm birth. The gold standards for predicting preterm birth in women carrying twins are cervical length (CL) measurements and fetal fibronectin (fFN). Cervical length measurements are most useful between 16-32 weeks gestation. After 32 weeks, the cervix naturally shortens for women delivering term. Fetal fibronectin is a protein that is found between the maternal-fetal interface and in low levels in vaginal secretions. This protein is normally present before 24 weeks gestation, and again after 3 weeks prior to delivery, thus in term delivery it would be after 34 weeks gestation. This test is useful in gestational interval between 24-32 weeks, where levels above >= 50 mg/mL are marked as abnormal and are linked to spontaneous preterm births (Yu, 2009).

In a cohort study to evaluate cervical length measurement for the prediction of preterm birth <34 weeks gestation in 2757 women with twins pregnancies, the resulting sensitivity and specificity were different for varying for cut off points in cervical length. The summary estimates in terms of sensitivity and specificity were 0.78 and 0.66 for 35 mm, 0.41 and 0.87 for 30 mm, 0.36 and 0.94 for 25 mm, and 0.30 and 0.94 for 20 mm, respectively (Lim, A.C et al., 2011). In another cohort study with a total of 3523 women pregnant with twins to predict preterm birth before 32 and 34 weeks at 20-24 weeks gestation with cervical length <=20 mm, the pooled sensitivity were 39% and 29%, and specificity were 96% and 97%, respectively (Conde-Agudelo, Romero and Yeo, 2010). In a study to predict spontaneous preterm birth in twin pregnancies at 23 weeks gestation using cervical length measurement for cervical length up to 25 mm, the resulting sensitivity were 100%, 80%, 47%, and 35% for 28, 30, 32, and 34 weeks, respectively. The corresponding sensitivity values for cervical length up to 15 mm were 50%, 40%, 24% and 11% (Souka et al., 1999). In a study involving 147 women pregnant with twins to predict preterm birth before 35 weeks at 22-24 weeks resulted in a low sensitivity of 30% and high specificity of 88%, with PPV and NPV of 54% and 74%, respectively, for cervical length <=25 mm (Mella et al., 2009). In a study involving 252 women pregnant with twins to predict spontaneous preterm birth before 32 and 35 weeks, the results for cervical length <=30mm had a sensitivity of 46% and 27%, with a specificity of 89% and 90%, respectively. The results for cervical length <=25mm had a sensitivity of 100% and 54%, with a specificity of 84% and 54%, respectively (Vassiere et al., 2002). In a similar study to evaluate the validity of cervical length measurements in women carrying twins at 27 weeks gestation, the prediction for delivery <34 weeks had a sensitivity of 77%, specificity of 86%, with a poor PPV 0.34 for cervical length <=25 mm. These results were lower at 18 weeks with sensitivity of 14.3%. At 24 weeks gestation, for cervical length <=22 mm the results were poor with a sensitivity of 28.6%. Therefore a cervical length measurement alone is not a suitable predictor of preterm birth due to the poor sensitivity prior to 24 weeks gestation (Institute Advanced Medical Education, 2013).

In a study conducted on 52 pregnant women with twins to test the validity of fetal fibronectin to predict preterm birth before 37 weeks gestation, the following sensitivity, specificity, PPV, and NPV were found with respect to the following gestational age: 24-26 weeks – 0.667, 0.818, 0.778 and 0.72; 27-30 weeks – 0.857, 0.708, 0.774 and 0.809; 31-34 weeks – 0.846, 0.583, 0.688 and 0.778, respectively (Oliveira et al., 1999). In a cohort study involving 1221 women with twin pregnancies, the resulting sensitivity and specificity values for predicting preterm birth before 32, 34, and 37 weeks ranged from 0.33-0.45 and 0.80-0.94, respectively (Conde-Agudelo, A. and Romero, R., 2010). In a study to predict preterm birth before 35 weeks gestation with fFN present at 28 weeks resulted in sensitivity, specificity, NPV and PPV of 50.0%, 92.0%, 62.5% and 87.3%, respectively (Wennerholm et al., 1997). In another study to predict preterm birth before 32 and 35 weeks gestation with fFN present at 28 weeks gestation, resulted in sensitivity of 28.6% and 57.1%, and specificity of 96.1% and 26.5%, respectively. The presence of fFN at 30 weeks, resulted in sensitivity of 37.5% and 62.5%, and specificity of 98.9% and 72.7%, respectively (Blickstein and Keith, 2005). In a study containing 87 twin birth, the presence of fetal fibronectin after 24 weekstesting resulted in sensitivity, specificity, PPV and NPV values of 0.71, 0.74, 0.19 and 0.97 respectively (Singer, E. et al., 2007). In a similar study containing 48 twin births of primarily Hispanic ethnicity, the presence of fetal fibronectin between 22-24 weeks gestation to predict preterm birth before 35 weeks gestation, resulted in sensitivity, specificity, PPV and NPV values of 0.7683, 0.5833, 0.667 and 0.700, respectively (Ruiz, R.J. et al., 2004).

**2.2.5 LIMITATIONS IN INVASTIVE TESTING METHODS**

The standard clinical prediction methods (CL and fFN) commonly offered to high risk patients are costly and only effective >22 weeks gestation. Further, one of the biggest challenges in literature is trying to compare the performance outcomes with the varying cut off gestational ages for preterm including <32, <34, <35 and <37 weeks. For CL screenings, the CL cut off values and gestational timings have varying levels of risks associated. This heterogeneity makes it challenging to make a direct comparison between the various prediction accuracies in studies (Yu, 2009). A clear need exists for a non-invasive prediction tool that can predict preterm birth <22 weeks gestation in women carrying twins, with improved sensitivity while meeting clinical standards. Since preterm birth in women carrying twins is multifactorial problem, this thesis will explore non-linear techniques including decision trees and hybrid ANNs to predict this complex outcome.

**2.3 COLLABORATION PLATFORM FOR HEALTHCARE**

Collaboration is a term used to describe two or more people, or organizations interacting and working together. To date, many collaborative systems incorporate a virtual workspace feature for users to interact. Authorized users would have transparent access to shared virtual workspace regardless of their browser, network connection or geographic location (Intapong, 2010).

Hospitals, primary care physicians, specialists, and nurses are challenged to adhere to evidence based practises and are often pressured to execute the latest clinical technological advances in order to provide safer and enhanced patient care. Furthermore, patient information and clinical data may be scattered throughout the enterprise in the form of third party databases, electronic documents, diagnostic imaging, clinical trials etc.... In order to determine appropriate care protocols, medication administration, standard operating procedures and to improve patient care, healthcare providers (i.e. physicians, nurses, pharmacists, and other clinical staff) must have a means to easily collaborate.

The evolution of the web has transformed the internet into a strategic medium for many types of organizations including healthcare. Ideally, in a clinical environment, a web-based collaborative environment would allow healthcare providers to collaborate in the form of sharing opinions, exchange clinical data, and access clinical information, irrespective of their geographic location (Chronaki et al., 1997).

**2.3.1 OVERVIEW OF WEB-BASED CONTENT MANAGEMENT SYSTEMS**

A Content Management System (CMS) allows collaboration within organizations and is largely composed of content, process and software. The content portion of the system includes text, images and various media. The process, is the manner in which the system is developed, and the content is published. The software serves as a bridge to the CMS, which allow site administrators to control the site’s content without needing to learn extensive programming (Lurie, 2002).

In general, the site content of a CMS is stored in a database, and the content within the CMS is much easier to maintain compared to a standard web page. A CMS also supports easier management of security, allowing administrators to easily control their end users’ level of permissions. Many CMSs also supports workflow integration, and thus allow automation of business processes. In the long run, a content management system would lead to reduced operational costs and increased revenue. Since the non-technical staff are able to maintain the site; this eliminates the need to hire programmers, or a development team (Lurie, 2002).

An enterprise content management system (ECMS) is designed for enterprise usage, and allows forms processing, archival and retrieval of data (converting paper based patient data to electronic form), data warehousing (storing and analyzing information), and document distribution via internet. This in return eliminates many manual error prone processes in a corporate setting (i.e. the time and resources wasted in faxing referrals) (Fujitsu Computer Products of America Inc., 2010).

**2.3.2 CRITERIAS FOR SELECTING A CMS**

It is important to deliver targeted and useful content to clinical users upon entering into a site; this in turn will save the healthcare providers a lot of time within a clinical setting. Selecting the best content management system tailored towards the organizational need can be a difficult task. A few decisions need to be made prior to implementing a content management system. These include determining whether the organization would benefit from open source or commercial sources, or, an enterprise content management system (ECMS) or web specific. In a large healthcare setting, it is important to choose commercially available systems in order to upkeep the performance, security, reliability and commercial grade support. Although the initial cost of open source systems are lower, the development and maintenance costs over time are much higher compared to commercial grade products. Secondly, it is important to consider that in a clinical setting, it is likely that the public will not be given access to the system, due to the sensitive patient information which it may retain. An ECMS would be ideal in a clinical setting, and in addition, an ECM would result in a reduction in manual processes, increase productivity, and can be optimized to fit the needs of the organization (Sitecore, 2009). Furthermore, a CMS should support multi-platform compatibility. Especially for larger organizations such as healthcare, a CMS should be compatible with common platforms including Windows, Mac, Linux, Solaris etc. In the event that the organization is entirely a Windows based campus, a CMS designed for only one OS will limit the user’s functionality on the road or when working from home (Hannon Hill Corporation., 2010).

**2.4 OVERVIEW OF CLINICAL DECISION SUPPORT SYSTEMS**

Most Clinical Decision Support Systems (CDSS)s over the years were either designed to be a standalone system or part of a non-commercial computer-based patient record system. Recently vendors have started to include CDSS into computer based patient record systems (Berner, 2007). Studies have indicated that healthcare organizations utilizing a CDSS have led to enhanced outcome in the clinician’s performance as well as better patient outcomes (Child Health Research Project Special Report, 1999). Even though to date only 15-20% of doctor offices use electronic medical records (EMR), with the stimulus package introduced in 2009, this will soon change. As more doctors begin to use EMRs, the likelihood for CDSS integration within a healthcare setting will increase (Miller, 2010). EMRs are designed to improve both the accessibility and legibility of information (Berner, 2009). EMRs are considered to be the foundation for providing quality healthcare. A CDSS is essential to achieve the full potential of an EMR (Berner, 2009). With over 100 EMRs to choose from, it is important that data standardization protocols be enforced. Although humans may still make sense of information if the data were not standardized, computers will not be able to (Miller, 2010).

As society moves towards a service-oriented architecture, knowledge may be represented via web services. This allows EMRs to remotely subscribe to a publicly available web service and transfer data to the knowledge repository (Miller, 2010). CDSS are designed to intelligently filter information in order to aid the decision making process in a clinical setting (Berner, 2009). CDSSs may also be used to gather large sets of data and manage medication actions effectively. In turn, using a CDSS will reduce the occurrence of practice errors, and provide higher quality of care (Peleg & Tu, 2011).

**2.4.1 TARGET AREA OF CARE**

CDSSs may aid physicians in assessing varying clinical issues ranging from providing accurate diagnosis to ordering medication. The general target areas of care for CDSS are presented below (Berner, 2009).

* Preventative Care – screening and disease management
* Diagnosis – search for diagnosis based on patients signs and symptoms
* Follow up Management – reminders and alerts
* Hospital Provider Efficiency – records/management of hospital beds, length of stay etc..

**2.4.2 SYSTEM DESIGN**

A collaborative system design will include the following subsystems:

* Communication – to handle alerts and notifications
* Knowledge discovery – rules and conditions
* Knowledge repository – large sources of patient information
* Multi-participant presentation component (Frize, 2005)

**2.4.3 FACTORS LEADING TO SUCCESSFUL CDSS IMPLEMENTATION**

1. Simple, user friendly interface
2. Automated decision support
3. Workflow integration
4. Timely results
5. Continuous knowledge-base and user-interface update support ( Peleg & Tu, 2011)

**2.4.4 TYPES OF CLINICAL DECISION SUPPORT SYSTEMS**

CDSSs may be categorized into either a knowledge-based system or non-knowledge-based system. Most systems to date are classified as knowledge-based systems, and contain rules, guidelines or compiled knowledge (commonly derived from medical literature). CDSSs may be further be classified into active or passive systems, depending on whether the system responds actively or passively to physician input. The ultimate goal of decision support systems is to support and enhance human thinking (Berner, 2007).

**2.4.4.1 KNOWLEDGE-BASED SYSTEM**

There are three main parts to a knowledge-based system including the knowledge-base, inference engine (or reasoning engine) and a mechanism to communicate. The knowledge-base often contains rules in the form of IF-THEN. For example, a rule designed to prevent duplicate test ordering may be in the form of IF new order was placed for a particular blood test, AND IF blood test was ordered within 24 hours, THEN alert the physician. Other forms of knowledge-bases may also include probabilistic association between drug and food interactions, signs or symptoms and diagnosis. The inference engine consists of formulas to combine the rules (or associations) with the patient data in the knowledge-base. The communication mechanism is the method for transporting the patient data into the system, and the results out of the system, to be displayed to the user, who will then make the final decision. In a standalone system, the patient data will need to be entered into the system by the end user. However, CDSSs which integrate with EMRs will auto-populate the patient data into appropriate fields from the information available in the EMR. The output of the system may be in the form of notifications, alerts or emails (Berner, 2007).

In the past, systems were built to assist the clinicians’ with their decision making and were largely classified as diagnostic decision support systems. These were commonly standalone systems which would contain a large information repository, and would provide a list of potential diagnosis based on the patient’s signs and symptoms (entered by the clinician or extracted from the EMR). The users of these systems were expected to be active instead of being passive, and thus interact with the system to filter important information. The interaction between the user and the system is important in order to determine how the system will be used. There are also systems built to assist primary care providers with medication order known as computerized physician order entry (CPOE). A typical input to this type of system may be the patient’s lab result, and the knowledge-base may contain values and rules to output the list of potential medication as well as include various customized built-in features (i.e. an automatic alert to the physician if the toxic level of medication is too high). There are also types of CDSS that are part of CPOE, where the input of the system is the patient’s current medication and new medication, and the knowledge-base would include a drug database and output the drug interaction (Berner, 2007).

**2.4.4.2 NON-KNOWLEDGE-BASED SYSTEM**

Non-knowledge-based decision support systems use artificial intelligence in the form of machine learning, to allow the computer to learn from past experiences, or analyze and detect patterns in clinical data. Common type of non-knowledge-based systems includes artificial neural networks (Berner, 2007).

* + 1. **DESIGN CONSIDERATION AND GOALS**

There are several design elements that must be taken into consideration to produce an effective tool which provides high quality, safe and efficient patient care, which also encourages physician adoption. Successful implementation of a CDSS will be facilitated by a simple, intuitive and user-friendly interface, on an easily accessible and mobile-friendly platform. Furthermore, the system must be developed at low cost, provide timely results with automated decision support, as well as support a continuous knowledgebase and user interface updates (Peleg & Tu, 2011) (Frize & Weyand, 2010).

* + - 1. **CLINICIAN WORKFLOW PROCESS**

When designing a framework for a CDSS, a solid understanding of a typical clinician’s workflow process, including the performance of both routine and complex clinical tasks in a hospital setting is required. System builders often focus on a CDSS that produces good decisions, yet researchers have shown that the ability to produce a correct diagnosis is only one part of the formula for success. It is important to recognize that systems can fail if they require that the practitioner interrupts a normal work pattern (i.e. to shift to another station to start up a non-intuitive software program that contains time consuming start-up procedures) (Musen, Shahar & Shorliffe, 2006). Thus, a seamless integration of the CDSS into the clinician’s workflow routine would increase the likelihood of the CDSS being used.

One of the early steps in the system development phase would be to observe the clinicians’ typical routine and determine how the CDSS should be integrated. The clinicians’ workflow pattern is determined by observing their interactions with health information systems including the use of related tools and devices during their normal routine. The clinician’s may be required to incorporate minor changes in their normal routine either prior to the adoption of CDSS or during the adaption of CDSS to optimize care (Berner, 2009).

It is also important to realize the variability that exists among clinicians, and thus a single workflow design may not meet the needs of all clinicians, since each clinician may have developed his/her own particular work style. Therefore the business workflow component must be adaptable to accommodate the needs of the clinician (Berner, 2009). A solid understanding of the clinician’s workflow is required for system developers to design and implement effective workflows that encourage physician adoption.

* + 1. **OVERVIEW OF CURRENT CDSS**
       1. **HEART RATE OBSERVATION SYSTEM (HeRO)**

The HeRO project was led by J.Randall Moorman which focused on early detection of neonatal distress in very low birth weight (<1500g) infants using heart rate variability. Heart rate variability is commonly found in healthy patients, and thus a reduction in variability could signify illness. Earlier detection would allow for earlier treatment and interventions and improve patient outcome (Gilchrist, 2012). In a study conducted with over 3000 preterm infants using the HeRO monitoring system, a 20% reduction in mortality was observed. Where 1 neonate’s life was saved for every 48 hours monitored (The Journal of Pediatrics, 2011).

The HeRO system is non-invasive and generates a numeric score that quantifies the prevalence of abnormal patterns in each person’s heart rate. The HeRO system continuously acquires records and measurements to analyze heart rate patterns and provides a real-time display of the HeRO score. Further it supports secure remote monitoring capabilities and interfaces with any existing ECG systems (Medical Predictive Science Corporation, 2011).

* + - 1. **ARTEMIS**

The ARTEMIS is pilot collaboration between researchers from the University of Ontario Institute of Technology (UOIT), IBM and the Hospital of Sick Children in Toronto, Canada. The ARTEMIS platform supports acquisition and storage of neonatal data and other clinical information data in NICU for the purpose of online real-time analytics. A series of clinical rules are executed online and in real-time to detect medical conditions including IVH, nosocomical infection, periventricular leukomalacia and pneumothorax (Gilchrist, 2012).

The ARTEMIS system was first implemented at the Hospital of Sick Children in August 2006 and is still in use to date (Health Informatics Research, 2008). ARTEMIS utilizes IBM’s InfoSphere for the purpose of data processing. This middleware system supports real-time data processing and storage. The programming language used to support InfoSphere is IBM’s Stream Processing Application Declarative Engine (SPADE) (Health Informatics Research, 2008).

* + - 1. **Realtromis**

Realtromis (Real Time Risk of Mortality & Instability) is a software medical company which created an advanced predictive analytic for the purpose of continuously assessing the risk of neonatal mortality in critically ill infants in an attempt to identify high risk neonates (GlobalData, 2013). This system uses continuous physiological attributes including ECG, patient monitor data, laboratory results from organ functions, demographic, diagnosis related predictors, and other clinical parameters using the Health Level 7 (HL7) messaging standards (Gilchrist, 2012).

Their platform consists of an interface for physiological data collection, temporary data storage for analyzing the physiological data, and a mortality risk function which retrieves the data from the storage to calculate the mortality risk, and presents the outcome via a user interface. It is not clear how the mortality risk outcome is presented to the user (i.e numerical value, scoring system etc…). Further the performance result of the real-time neonatal medical system has not yet been disclosed to the public (Gilchrist, 2012).

* + - 1. **NEONATE**

The NEONATE project was officially launched in March 2001 by a team of computer scientists and cognitive psychologists at the University of Aberdeen and neonatal intensive care specialists at the Simpsons Maternity Hospital in Edinburgh (ESRC/EPSRC PACCIT Programme, 2003). The goal of the NEONATE initiative was to investigate decision support in NICU and appropriately develop and implement computerized aids to facilitate decision making.

The NEONATE team believes that by incorporating the results of their study and using artificial intelligence techniques, computers may be programmed to provide more useful outcome and provide useful information to clinicians. The finding of this study will be published in psychology, artificial intelligence and medical journals (ESRC/EPSRC PACCIT Programme, 2003).

* 1. **PATTERN CLASSIFICATION METHODS**

Pattern classification refers to theory and algorithms of assigning abstract objects (e.g. measurements on physical objects) into distinct categories, where these categories are typically known in advance. Methods of pattern classification have been applied for information retrieval, data mining, document image analysis and recognition, computational linguistics, forensics, biometrics and bioinformatics (Srihari, 2007). In this thesis work, we use two different pattern classification methods: Decision Trees (DTs) and Artificial Neural Networks (ANNs).

**2.5.1 DECISION TREES**

Decision trees are favoured in the data mining community due its highly interpretable structure, allowing business end users and analysts to understand the models, whereas neural networks are difficult to understand and interpret (Apte et al., 2002). A decision tree consists of a root node, branch nodes and leaf nodes. The tree starts with a root node, is further split into branch nodes (each of the nodes represent a choice of various alternatives), and terminates with a leaf node which are un-split nodes (represents a decision) (Peng, 2006).

Classification of decision trees are conducted in two phases, including the tree building (top down) and tree pruning (bottom-up). Tree building is computationally intensive, and requires the tree to be recursively partitioned until all data items belong to the same class. Tree pruning is conducted to improve the prediction and classification of the algorithm and to minimize the effects of over-fitting, which may lead to misclassification errors (Anyanwu and Shiva, 2009).

There are a number of decision tree algorithms that exist including Classification and Regression Trees (CART), Iterative Dichotomiser 3 (ID3), C4.5 and C5.0. This thesis work uses C5.0 based decision tree algorithm which is an improvement over C4.5, which itself is an improvements over the earlier ID3 method

**2.5.1.1 IMPROVEMENTS WITH C5.0**

Decision trees created using C5.0 are smaller, use less memory and are significantly faster compared to C4.5. C5.0 algorithm also supports boosting, variable misclassification cost and winnowing. Boosting is method of creating multiple decision trees and then combining it to improve the accuracy, where each tree votes for its predicted class and the final class is determined using a vote count. C5.0 will automatically generate 10 trees using its boosting feature and will aim to minimize the expected misclassification costs. C5.0 also has the ability to winnow attributes with high dimensionality prior to constructing the tree; this is done by removing the attributes which it predicts to have minimal relevance in an attempt to generate smaller trees with higher accuracy. C5.0 also supports additional data types including case labels, dates, time and ordered discrete attributes (Gilchrist, 2012).

**2.5.1.2 DECISION TREE ADVANTAGES AND DISADVANTAGES**

Decision algorithms are easy to interpret and comprehend. These algorithms are able to handle both metric (numerical, real values) and non-metric (categorical, descriptions) data, as well as handle missing values which are often encountered in clinical studies. The resulting Decision Trees (DTs) have comparable accuracy to other classification methods such as the ANNs. Further, little data preparation is required since the data does not need to be normalized or have missing data replaced with an imputed value. DTs can also handle large amounts of data in a short time frame compared to other pattern classification techniques and it can often be developed using common statistical techniques (Peng, 2006).

However, some drawbacks associated with decision trees is that it can over fit the data and create complex trees which may not generalize well. Further, a small change in the size of the dataset could result in a completely different tree.

**2.5.2 ARTIFICIAL NEURAL NETWORKS (ANN)**

Artificial Neural Networks (ANNs) are powerful non-linear mapping structures and are especially useful for modelling relationships which are unknown. ANNs function similar to the human brain and can solve problems involving data that is complex, non-linear, imprecise and/or noisy (Jha, 2011). The human brain is a collection of more than 10 billion interconnected neurons that is able to receive, process and transmit data. The human brain also consists of a highly parallel computing structure to support computationally demanding perceptual acts and control activities (Lisbboa, 2011).

Artificial neural networks were developed as generalized mathematical models to represent the biological nervous system (Lisbboa, 2011). The ANN is trained to detect a pattern between the inputted data and the related output value from a dataset. After training the set, the ANN can be used to predict the result of a newly inputted data (Jha, 2011). In a generalized mathematical model, the processing elements of neural networks is referred to as nodes, and the connection weights are used to represent synapses, where the non-linear characteristics exhibited by neurons are given by a transfer function. The weighted sum of the input signal, processed by the transfer function, is used to compute the impulse of the neuron. To improve the learning capability, the weights are adjusted according to the learning algorithm chosen (Lisbboa, 2011).

There are various types of ANNs including feed-forward, recurrent neural network and probabilistic network. The ANN structure used in this thesis is referred to as feed forward, back propagation multi-layer perceptron (Yu, 2009).

**2.5.2.1 DEVELOPMENT OF ANN MODEL**

ANNs are typically constructed using layers of units, and thus this is commonly referred to as multilayer ANNs. The first layer contains the input units, and the last layer contains the output units. The other units in the model are referred to as hidden units, and are referred to as hidden layers. Commonly there are two functions which govern the behaviours of a unit within each layer of the ANN, known as the input function and the output/activation function (Jha, 2011).

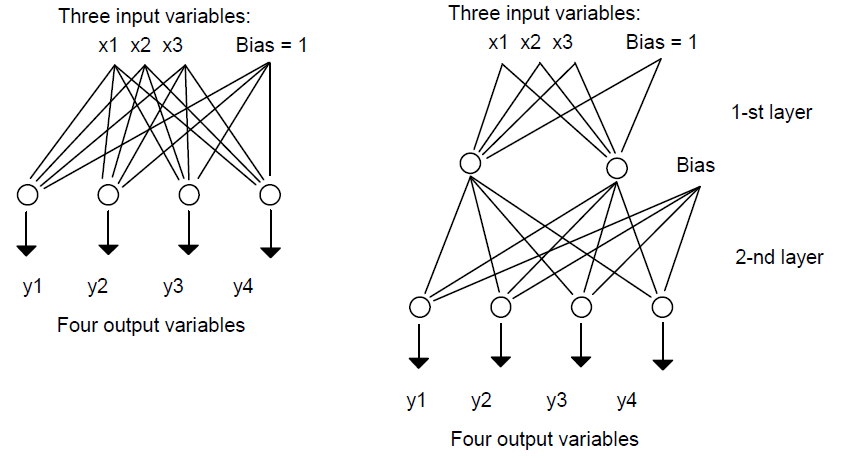
The input function is given by eq. 2.1, where the input to a node is the weighted sum of output from nodes connected to it (Jha, 2011).

Neti=∑jwijxj+µj (2.1)

* + Neti= result of the net inputs
  + wij= weights connecting neuron j
  + xj= output from unit j and
  + µj =threshold from neuron i

An activation function is then applied to each unit. The activation function is a mathematical formula that comes in many forms, and it has the largest impact on the ANN. The activation function is used to produce the output of a processing node. Activation functions typically use a non-linear function such as logistics, tanh etc… (Jha, 2011).

The ANN may be composed of various numbers of neurons, typically consisting one or two layer network, but may consist of more (Zupan, 1994). Figure 2.1 shows the difference between a one-layer and two-layer network, where the circles represent the neurons, and the lines connecting the circles represent the weights. A one layer network, has 4 neurons with each having 4 weights, thus totalling 16 weights. Each of the 4 neurons will accept an input signal and the signal coming from the bias. A two layer ANN has six neurons (2 in the first layer and 4 in the second layer), totalling 20 weights ((4x2)+ (3X4)=20).



**Figure 2.1** Left: One layer MLP Network, Right: Two Layer MLP Network

There are a few steps to be considered for developing a neural network as follows:

**2.5.2.1.1 VARIABLE SELECTION**

The input variables for modelling must be selected using an appropriate variable selection procedure (Jha, 2011). The input signals in this case are normalized between 0 and 1 (Zupan, 1994).

**2.5.2.1.2 TRAINING, TESTING AND VALIDATION SETS**

The dataset is divided into 3 distinct sets: training, testing and validation sets. The training set is used to learn patterns from the dataset; this is typically the largest set. The testing set is used to evaluate the generalized ability of the trained network. The validation set is used to check the performance of the trained network (Jha, 2011).

**2.5.2.2 NEURAL NETWORK ARCHITECTURE**

The neural network architecture consists of hidden layers, hidden nodes and output nodes as follows:

**Number of hidden layers** – the hidden layer(s) allows the network to generalize. A neural network with one hidden layer and various hidden neurons is sufficient for evaluating any continuous function. Ideally two hidden layers are used (Jha, 2011).

**Number of hidden nodes** – there is no formula for selecting the number of hidden nodes, however as a general rule of thumb, for a typical three layer network with *n* inputs and *m* output neurons, the hidden layer will have sqrt (*n*\**m*) nodes as proposed by the geometric pyramid rule (Jha, 2011). Further, a large number of hidden nodes will allow for correct learning. If too few hidden nodes are chosen, then the network may not be able to distinguish a relationship in the dataset and this may lead to poor results. Since the number of hidden nodes affects the performance of the network, choosing the correct number of hidden nodes is important (Lisbboa, 2011).

**Number of output nodes** – better results will be produced for neural networks with multiple outputs, compared to a network with a single output (Jha, 2011).

**2.5.2.2.1 CHOOSING INITIAL WEIGHTS**

There is no formula for choosing the weights. Several starting weights may be attempted to improve the network results. Typically the learning algorithm may choose the steepest descent technique, which rolls downhill in the weight space until the first valley is reached, and then this becomes the initial starting point (Oracle Data Mining Concepts, 2005).

**2.5.2.2.2 CHOOSING LEARNING RATE**

As each weight is modified, the learning rate controls the size of the step that is taken in the weight space. If the learning rate is too large, then the local minimum may be overstepped, and this may result in oscillations and slow convergence to lower the error rate. Conversely, if the learning rate is too low, the number of iterations required may be too large, and result in slow performance (Lisbboa, 2011).

**2.5.2.3 TYPES OF NETWORKS**

Two of the most widely used ANN architectures are feed forward networks and feedback/recurrent networks. The Medical Information Research Group (MIRG) has developed the ANN Research framework using MLP feed forward network with back propagation.

* + - * 1. **FEED FORWARD ANN**

Signal flows one way from the input to the output units in a strict feed-forward direction. Although data processing may extend over multiple layers, there is no feedback (Lisbboa, 2011).

* + - * 1. **FEEDBACK / RECURRENT NETWORKS**

Signal may travel in both directions using feedback. Feedback networks are dynamic and thus the state is continuously changing until the equilibrium is met (Jha, 2011).

**2.5.2.4 THE MULTI-LAYER PERCEPTRON (MLP)**

The multi-layer perceptron is a powerful system that is capable of modelling complex relationships between variables. It is the most popular neural network type due to its clear architecture and comparable simple learning algorithm (Eom, Kim, & Zhang, 2008). Multilayer feed forward neural network using back propagation algorithm architecture consists of a layered feed forward neural network, where non-linear elements are arranged in successive layers and the information flows uni-directionally from the input to output layers through the hidden layers. An MLP with one hidden layer has the ability to learn to approximate any function of high accuracy, and thus it is commonly used when little is known between the input and targets.

The weights or interconnections between the ANNs have a strength, which can be adjusted by a learning algorithm. There are three main types of learning algorithms used in neural networks known as (i) supervised learning (network constructs a model based on a known output), (ii) unsupervised learning (network constructs a model based on an unknown output), and (iii) reinforced learning (Jha, 2011).

**2.5.2.5 BACK PROPAGATION ALGORITHM**

The back propagation algorithm is used to train the MLP network. In order to minimize the error in its prediction on the training set, this algorithm uses the data to adjust the network weights and threshold. A unit in the output layer is used to determine the activity, by using a two-step procedure as follows:

First, the total weighted input xj is computed using the following formula:

Where

Xj=∑YiWij (2.2)

* + Yi – activity level of the jth unit in the previous layer
  + Wij – weight of the connection between the ith and jth layer

Then typically the sigmoid function is used:

Yj = [1 + e –xj]-1 (2.3)

Once the input units are determined, the error ‘E’ is computed as follows:

Where

E= ½ ∑ (yi-di)2 (2.4)

* + Yj – activity level of the jth unit in the top layer
  + Dj – desired output of the jth unit

**2.5.2.6 ANN ADVANTAGES AND DISADVANTAGES**

There are several advantages to ANNs. ANNs can generalize data even with noise, and does not require prior knowledge of the domain, and thus it requires less statistical training to develop. Further, ANN has the ability to implicitly detect complex relationships between dependent and independent variables and is able to detect all potential interactions with the predictor variable. This approach eliminates the tedious need to program IF-THEN rules and the need to obtain direct input from clinical experts. ANNs are also considered to be parallel networks (since the function of each neuron in each layer may be calculated in parallel). This allows the processing speed to be increased significantly by using computers with multiples processors. ANNs also have the advantage of applying different training algorithms to develop models based on the type of data to be analyzed or type of output required (Gilchrist, 2012). ANN will also improve the results every time it is trained due to its dynamic structure (Berner, 2007).

There are a few disadvantages to using ANNs. Firstly, the input data must be normalized for the ANN, and therefore the data has to be first analyzed and processed before feeding it into the ANN model. The maximum and minimum values must also be known prior to normalization. This is challenging when working in a real-time environment since the data is not known in advance, thus it will need to be calculated upon arrival (Gilchrist, 2012). The ANN does not handle missing data well, and any missing data will need to be replaced with an imputed value. Further, the training process is often time consuming. Although it is possible to determine the most contributing input, the resulting formulas and weights used are commonly not interpretable. Further, since this type of system uses a statistical pattern recognition method in order to derive formulas for weighting and combining the data, the reliability and accountability of these systems is a concern since the system cannot be justified as to why it works the way it does.

**CHAPTER 3 METHODOLOGY FOR PREDICTING**

**NEONATAL MORTALITY AND PTB IN TWIN PREGNANCIES**

* 1. **INTRODUCTION**

This chapter reinstates the problem in this thesis work, provides a description of the perinatal databases used, and an overview of performance measures. This chapter also discusses the methodology for the development of a prediction model for neonatal mortality and preterm birth in twin pregnancies. A framework to build a Perinatal Decision Support System (PEDSS) is also presented.

The first objective is presented and analyzed using two methods. First the development of a prediction model using the concept of knowledge discovery and decision trees is discussed, followed by a method using the hybrid ANN approach. Next, a section on achieving the second objective is presented where the development of the Perinatal Decision Support System (PEDSS) is discussed. The development of PEDSS is divided into four parts, including the following sections: platform consideration, overview of the system composition, system integration, and knowledge maintenance.

* 1. **RESTATING THE PROBLEM**

Fundamentally, there are two main problems of interest in this thesis work for the prediction of neonatal mortality, and preterm births in twin pregnancies which include:

1. Assess various data analysis methods to improve the prediction of neonatal mortality and preterm birth in twin pregnancies
2. Derive a conceptual framework for a Web-Based Content Management System Framework for Perinatal Decision Support.

Previous research on predicting neonatal mortality was obtained using knowledge-based method techniques. The DT model used only 3 attributes: lowest serum pH, lowest blood pressure, and lowest heart rate to produce good preliminary results where a sensitivity of 75% and specificity of 96% was achieved. However these results were obtained from a small database with a total of n=256 patient cases with 232 survivors and 24 neonatal death, thus an above normal mortality rate of 9%.When examining the DT model on a larger dataset with a total of n=17,364 newborn cases including 16677 survivors and 687 neonatal death and a 4% mortality rate using the same attributes. The DT model did not meet the clinical expectation, and achieved a low mean test sensitivity of 56% and a mean test specificity of 97%.

Previous research on PTB prediction models focused primarily on non-knowledge-based techniques, and in particular these models were only useful for predicting the risk of preterm labour in parous[[5]](#footnote-5) women. Previous studies focused on artificial intelligence based techniques using the Artificial Neural Network (ANN), and later a newer hybrid approach was introduced where it utilized a decision tree-artificial neural network model. One of the earlier model derived, utilized a hybrid method where the network parameters were extracted from a classification based ANN, and then a risk-stratification ANN was applied to estimate preterm birth. This method used only parous cases and US specific variables. The test data was processed in the system in three passes: first pass to maximize sensitivity, second pass to maximize specificity, and the third pass used a decision-tree voting algorithm to classify ambiguous cases. This achieved a sensitivity of 64%, a specificity of 84% and an AUC of 0.7795. Though these results are acceptable, the main drawback to this system is that it requires 48 variables to maintain this performance and this model is not applicable in the case of nulliparous[[6]](#footnote-6) women pregnant with twins (Catley, 2007).

The newer model used a hybrid approach integrating decision trees, classification ANN with weight elimination and risk stratification. The hybrid classifier used a decision-tree to eliminate variables with little impact on predicting the outcome of interest; the remaining variables were processed through an artificial neural network with weight elimination (ANN-we). This method achieved a sensitivity of 65.13%, a specificity of 84.07% and an AUC of 0.8195. This method used 19 variables and included parous cases. Though nulliparous cases were analysed separately, the prediction model did not meet clinical standards. Further, this model is not applicable to the cases of nulliparous women pregnant with twins.

Both the previous and newer approach focused on primarily non-knowledge-based systems, and thus knowledge-based systems were not considered. Yet many of the systems to date use knowledge-based approach with rules, guidelines or compiled knowledge which is commonly derived from medical literature (Miller, 2010). The main drawback to non-knowledge-based systems, and especially artificial neural networks, is that the results are derived from a ‘black box’ system, and thus, the reliability and accountability of these systems is a concern since the system cannot be justified as to why it works the way it does. Further, this type of system is best suited when supplied with a large amount of data with known results, and is typically focused on a single disease.

While the results obtained in both the older and newer models met the expectations set by their clinical advisor, there are a few enhancements to be performed: (1) explore methods using knowledge-based approach since it is more practical in an obstetrical environment, this allows the obstetrical outcome to be obtained at point of care, and since the results are derived from a rule based system, the outcome is intuitive and can be easily comprehended by the clinicians; (2) change the scope from predicting only preterm labour in parous women to include a high risk population of twin pregnancies and neonatal mortality in a heterogeneous population, and (3) derive a conceptual framework to build and implement the perinatal decision support system in a healthcare setting. These modifications should ideally maintain previous performance results or preferably exceed them.

* 1. **ETHICAL CLEARANCE**

The Carleton University Research Ethics approved this thesis work for the duration of September 2011- April 2013. The database used in this thesis work was the Niday Perinatal Database from the Perinatal Partnership Program of Eastern and Southeastern Ontario (PPPSEO) (2006-2007) and the BORN (Better Outcomes Registry & Network) database. An ethical clearance was signed prior to accessing the database due to the sensitive nature of the data.

* 1. **THE NIDAY DATABASE**

The Niday Perinatal Database (“Niday”) was created in 1997 under the direction of the Perinatal Partnership Program of Eastern and Southeastern Ontario (PPPSEO) and with collaboration of all hospitals across Eastern and Southeastern Ontario (Niday Perinatal Database Project, 2008). In January 1st, 2001, database systems which were originally housed within hospitals on standalone computers throughout Ontario were migrated into a web-based system known as CritiCall. This initiative was largely funded by the Ministry of Health and Long Term Care (MOHLTC) (Niday Perinatal Database Project, 2008).

The Niday database is a multidimensional data collection system for perinatal care providers, decision makers, educators and researchers (Dunn, Bottomley, Ali & Walker, 2011). The information available in the Niday database may be used for program management, benchmarking, quality improvement initiatives, planning, evaluation and research (Niday Perinatal Database Project, 2008). In Ontario, this is referred to as the source of data in order to evaluate outcomes, risk factors and interventions associated with perinatal care (Dunn, Bottomley, Ali & Walker, 2011).

This database has significantly evolved overtime and currently serves as a joint venture with over 100 healthcare organizations in Ontario. Each of the participating organizations contributes real-time perinatal data to this web-based system (Dunn, Bottomley, Ali & Walker, 2011). The participation of the hospitals in Ontario allows for inter-hospital comparisons. This is required in order benchmark and to facilitate change based on learning from partner hospital’s successes (Dunn, Bottomley, Ali & Walker, 2011).

In order to ensure the consistency of each of the variables found within the Niday database, a user guide is available which includes the variable definition and other information. Further each of the participating organization undergoes training in order to handle data entry and produce reports from the system (Niday Perinatal Database Project, 2008). The Niday database contains 90 defined patient elements. Of the total variables in the Niday database, 24 are mandatory and 66 are non-mandatory variables. The province has adopted the variables in the Niday database as the minimum dataset in 2001 (Dunn, Bottomley, Ali & Walker, 2011).

* 1. **THE BORN DATABASE**

The BORN (Better Outcomes Registry & Network) was created on January 25th 2010 under the direction of the Ministry of Health and Long Term Care (Born Ontario, 2010). The BORN database holds the most extensive maternal-child health data in the world including information about pregnancy, birth and early childhood. All of the birthing hospitals within Ontario have committed to contributing data to the BORN registry (The Mothers Program, 2013).

The BORN’s vision is to obtain the knowledge required to sustain lifelong health, and its mission is to facilitate and improve the care provided to maternal-fetal and child populations via linking the information and providers to recognize gaps in the care. The BORN database contains accurate, trusted and timely information in order to contribute to the high-performing healthcare system (The Mothers Program, 2013).

The data obtained in the BORN registry is mainly focused on maternal newborn outcomes/midwifery, congenital anomalies surveillance, newborn screening and prenatal screening. The data gathered from the BORN database may be used by health care providers and policy makers in order to improve the delivery of maternal-child care. The BORN data can also be used for research purposes, for tracking province-wide health trends, health effects and outcomes from early pregnancy and onwards (The Mothers Program, 2013).

The BORN database was streamlined from five existing maternal-fetal databases (The Mothers Program, 2013). To ensure consistency of each of the variables available in the BORN database, there is a guideline available which contains the variable and value types. The value(s) are then converted into a numeric code. The BORN database contains over 290 variables.

* 1. **OVERVIEW OF PERFORMANCE MEASURES**

Once a classification model has been developed, its predictive power must be evaluated using varying performance measures in order to determine how well the model will perform with new cases (Catley, 2007).

* + 1. **CONFUSION MATRIX (CONTINGENCY TABLE)**

A confusion matrix is used to present the # of correct and incorrect predictions resulting from a model, in comparison to the actual classification from the test data. A matrix is typically *n*-by-*n*, where *n* represents the # of classes (Oracle Data Mining Concepts, 2005). Table 3.1 represents a confusion matrix for a two-class problem.

**Table 3.1** Representation of a two-by-two confusion matrix

|  |  |  |  |
| --- | --- | --- | --- |
| Actual Value | | | |
| Predicted Value |  | Positive | Negative |
| Positive | True Positive (TP) | False Positive (FP) |
| Negative | False Negative (FN) | True Negative (TN) |

* + 1. **CORRECT CLASSIFICATION RATE**

Accuracy is a measure of correctly predicted results by the classifier (Catley, 2007).

Accuracy = = (3.1)

* + 1. **ERROR RATE**

Error rate is a measure of the incorrect predictions (Catley, 2007). The apparent error obtained by the prediction model using the training data is typically lower then the true error found using the validation (test) data (Yu, 2009).

Error Rate = = (3.2)

* + 1. **SENSITIVITY**

Sensitivity refers to the true positive rate (TPR) and its ability to correctly predict a patient with a type of disease. A test with 100% sensitivity will correctly predict all patients with the disease. A test resulting in 80% sensitivity results in correctly predicting 80% of patients with the disease (True Positive), where 20% are undetected (False Negative) (Lalkhem & McCluskey, 2008).

Sensitivity = TPR = (3.3)

* + 1. **SPECIFICITY**

Specificity refers to the true negative rate (TNR) and its ability to correctly identify patients without the disease. A test with 100% specificity would correctly predict all patients without the disease. A test resulting in 80% specificity would result in correctly predicting 80% of patients without the disease (True Negative), where 20% of patients incorrectly identified (False Positives) (Lalkhem & McCluskey, 2008).

Specificity = TNR= = 1 – FP (3.4)

* + 1. **LIKELIHOOD RATIO**

This is a measure of how much more likely a patient who tests positive has the disease compared to a patient who has tested negative (Lalkhem & McCluskey, 2008).

Likelihood ratio = (3.5)

* + 1. **PREVALENCE**

Prevalence is used to calculate the size of the population where the disease occurs. It is the # of occurrences of a disease within a specified period. The result is expressed as a percentage (Centre for Disease Control and Prevention, 2009).

Prevalence = x 100 (3.6)

* + 1. **POSITIVE PREDICTIVE VALUE (PPV)**

The positive predictive value (PPV) is the likelihood that that the positive prediction is correct, that is the probability of the actual disease given a positive prediction. The PPV is proportional to prevalence, and thus if prevalence is low, this will result in sharp decrease in PPV (Yu, 2009).

PPV = (3.7)

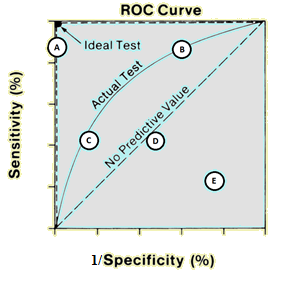
* + 1. **NEGATIVE PREDICTIVE VALUE (NPV)**

The negative predictive value (NPV) is the likelihood that the negative prediction is correct, that is the probability of a non-disease of the patient given a negative prediction. A low prevalence results in greater assurance that the patient with a negative prediction is correctly diagnosed (Yu, 2009).

NPV= (3.8)

* + 1. **RECEIVER OPRATING CHARACTERISTICS (ROC) CURVE**

Receiver operator characteristic curve is a plot of the false positive rate (FPR) (1/specificity) on the x-axis and the true positive rate (TPR) (sensitivity) on the y-axis. The dashed line *A*, represents an ideal scenario where all points are correctly classified. Point *B*, represents higher TPR then Point *A*, with a higher FPR compared to Point *C*. Point *C* has a low FPR with a TPR approaching 45% (Yu, 2009). The dashed line D*,* is when the TPR is equal to the FPR, which represents a zero discrimination with AUC at 0.5 (50/50 probability, which is no better the tossing a coin). At point *E* (below the dashed line *D)* it is worse than random guessing. If the classifier`s performance results in this area, this may indicate that although useful information may be contained in the classifier, the application is not correct (Yu, 2009).



**Figure 3.1** Receiver Operating Characteristic (ROC) Curve with Points of Significance Labelled

* + 1. **AREA UNDER THE CURVE**

The area under the curve is a measure of the classification model’s effectiveness in correctly predicting medical outcomes. The AUC values range between 0 and 1, where the dashed line *D*, in Figure 3.1 has a value of 0.5 and the dashed line *A*, has a value that is closer to 1. The AUC’s index and effectiveness for discrimination is given in Table 3.2 (Yu, 2009).

**Table 3.2** Area under the curve index and its effectiveness for discrimination

|  |  |  |
| --- | --- | --- |
| Min | Max | Effectiveness |
|  | <= 0.500 | No Discrimination (Random |
| 0.500 | <0.700 | Poor Discrimination |
| 0.700 | <0.800 | Acceptable Discrimination |
| 0.800 | <0.900 | Excellent Discrimination |
| 0.900 | 1.00 | Outstanding Discrimination |

**3.6.12 ENSURING CONFIDENCE IN THE MODEL**

The performance measures must be maximized or minimized for varying clinical outcomes, however determining which performance measures to maximize for predicting neonatal mortality or preterm birth in twin pregnancies is a challenge. To date no guaranteed treatment plan for the conditions described exists. Thus identifying a newborn at risk of mortality or preterm birth in a twin pregnancy does not necessarily imply that the negative outcome can be avoided. However, if a newborn or a mother has been diagnosed with a complication, then this tool may be useful in indicating whether further testing is necessary (Catley, 2007). Prompt recognition of these conditions may lead to more efficient allocation of resources and facilitate antenatal monitoring to ensure a timely response to medical problems.

**Table 3.3** The clinical implications of true and false positives vs. true and false negatives (Catley, 2007)

|  |  |  |
| --- | --- | --- |
|  | Benefits | Drawbacks |
| True Positives | Additional follow up such as invasive testing may be suggested to evaluate the mother’s risk. Pregnancy management strategy, including attending prenatal classes may be advised to mitigate the risk. | Some mothers may prefer not to know their elevated risk due to fear, or wish to avoid additional testing. Further, knowing this may contribute to additional maternal stress. |
| False Positives | Additional prenatal care may be beneficial if other potential maternal and infant implications were discovered and managed as a result. | Mothers may receive unneeded additional monitoring and testing which results in added cost to the healthcare system and stress on the mother. |
| True Negatives | Mothers may not require additional testing and visits, which reduces the costs of healthcare. Mothers also may experience less maternal stress knowing that they are at lower risk. | None identified. |
| False Negatives | None identified. | Mothers may not receive the additional prenatal care required, and the pregnancy management strategy may not be modified to reflect the mothers at high risk of pregnancy. |

From the analysis presented in table 3.3, it can be concluded that the greatest benefit with the least amount of negative impact is reached by maximizing the true positive rate (i.e sensitivity). However obtaining a reasonably high true negative rate (i.e specificity) is also important in order to avoid unnecessary prenatal care, testing and visits and thus decrease healthcare expenses (Catley, 2007).

* 1. **FIRST OBJECTIVE**

**Objective 1:** Improve the Classification of Neonatal Mortality and Preterm Birth in Twin Pregnancies

The first objective was to improve the classification of neonatal mortality and preterm birth in twin pregnancies. In order to address the first goal, a total 6 datasets were created as per table 3.4.

**Table 3.4:** Division of BORN and NIDAY database. (A) Dataset; (B) Parent Database; (C) Positive Cases; (D) Negative Cases; (E) # Grouped Attributes; (F) Total Cases

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| (A) | (B) | (C) | (D) | (E) | (F) |
| noMOD\_NEONATALMORT | Niday | 215 | 32 971 | 0 | 33186 |
| MOD\_NEONATALMORT | Niday | 215 | 32 971 | 1 | 33186 |
| noMOD\_TWINGEST | BORN | 323 | 1 591 | 0 | 1 914 |
| MOD\_TWINGEST | BORN | 323 | 1 591 | 5 | 1 914 |
| noMOD\_SINGLETON | BORN | 15 575 | 125 000 | 0 | 140 575 |
| MOD\_SINGLETON | BORN | 15 575 | 125 000 | 4 | 140 575 |

The noMOD dataset(s) contained raw data, and nominal attribute(s) were not grouped. In the MOD dataset(s), all nominal attribute(s) were grouped to prevent spurious splits (section 3.7.1.2.3). Then two classification methods were used: decision trees (DT) and hybrid ANN. First the datasets were split into 10 equal sized sets using 5x2 cross validation (section 3.7.1.4), then the C5.0 algorithm was run against the split dataset using the See5 application, and DTs were generated. The outputted results were in the form of a confusion matrix and included the attribute usage. Based on the attribute usage, the lowest contributing attribute was removed from the dataset to remove noise (section 3.7.1.6), and the C5.0 algorithm was re-run to determine whether the performance outcome improved. If the performance outcome didn’t improve, the attribute was re-inserted, and the next lowest contributing attribute was removed and the process described above was repeated until the optimal results were achieved.

The second method utilized a DT-ANN hybrid approach. First, any missing values in the dataset were imputed using a Case Based Reasoning (CBR) tool. The attributes that are best contributing (section 3.7.2.1) in a given dataset were extracted from the DT and was used to generate a table (section 3.7.2.4). This was then processed using the CBR tool to impute missing values. The results were stored in a .txt file. The .txt file was converted to a .csv file and 5x2 cross validation was applied to split the dataset into 10 equal sized sets. The training, verification and test sets were created in preparation for running the Artificial Neural Network (ANN) (section 3.7.2.7). The ANN was run using MATLAB (section 3.7.2.8), and the results were in the form of a confusion matrix. Results of both the DT and DT-ANN hybrid compared using various performance measures.

* + 1. **DEVELOPMENT OF A CLASSIFICATION MODEL USING THE CONCEPT OF KNOWLEDGE DISCOVERY AND DTs**

Accomplishing Objective 1 to predict neonatal mortality and preterm birth in twin pregnancies using Decision Trees (DTs):

Step 1: Partitioning the Original Dataset

Step 2: Data Pre-Processing

* Handle Missing Values
* Feature Selection & Importance
* Grouping Nominal Attributes

Step 3: Preparing the Dataset

Step 4: Training and Testing the Dataset

Step 5: Feature Selection

Step 6: Software Execution and Results

Step 7: Decision Tree Ensemble Classifiers

**3.7.1.1 STEP 1: PARTITIONING THE ORIGINAL DATASET**

The Niday database was divided into noMOD\_NEONATALMORT and MOD\_NEONATALMORT. The BORN database was divided into noMOD\_TWINGEST, MOD\_TWINGEST, noMOD\_SINGLETON and MOD\_SINGLETON (Table 3.4). The noMOD dataset contained raw attributes, and all nominal attributes were grouped in the MOD dataset. The BORN database did not contain neonatal death information; therefore it was not used for predicting neonatal death. Although the NIDAY database did contain preterm birth information and twin gestations, this database lacked maternal health information and thus it was not used for the prediction of preterm birth in twin pregnancies.

**3.7.1.2 STEP 2: DATA PRE-PROCESSING**

Data pre-processing is the first step in knowledge discovery, and it is typically executed before the creation of a pattern classification model (Yu, 2009). This step is used to clean the raw data. Different error types may exist in a database such as inconsistent data, missing values, outliers etc…and thus well-defined measures must be taken to correct these errors. This may be in the form of deletion, manipulation, or transformation of the data (Yu, 2009).

**3.7.1.2.1 HANDLING MISSING VALUES**

In the presences of missing data, the C5.0 algorithm is quite robust. A value that is missing or unknown was replaced with ‘?’ and a value that is not applicable to that particular case was be denoted as ‘N/A’. The C5.0 algorithm takes the weighted average of the predictions across all branches upon encountering missing data.

However, in the event of a large number of values missing per case or per attribute in the Niday or BORN database, for reasons such as human/technical error or participants not wishing to answer questions, the following techniques were applied to this thesis work in order to handle missing information (Yu, 2009).

**Eliminate Cases:** Discrete cases with more than 50% of variables missing may be deleted. The outcome of interest for neonatal mortality is neonatal death or not applicable, for preterm birth, it is term or preterm; if the outcome is missing, the case may be deleted.

**Eliminate Attributes:** If more than 50% of data is missing for a particular attribute and it is not a highly contributing attribute, then the attribute itself may be deleted.

**Imputation of Data**: If data is missing because the information does not apply to that particular variable, then it may be corrected. For example, if the question was “Did you previously have caesarian?” and the answer was ‘No’, and another question was “How many caesarians have you previously had?” and the answer was blank, this may be corrected to ‘0’.

**3.7.1.2.2 FEATURE SELECTION AND IMPORTANCE**

The preliminary task with the given dataset was to determine which attribute is likely to be predictive. Firstly any attribute that was not be available prior to 10 minutes from birth or could not be obtained non-invasively in the Niday database was eliminated. Similarly, any attribute that was not be available prior to 22 weeks gestation or could not be obtained non-invasively in the BORN database was eliminated.

The noMOD\_NEONATALMORT and MOD\_NEONATALMORT datasets originally contained 26 attributes from the NIDAY database which could be obtained before 10 minutes form birth non-invasively for the prediction of neonatal mortality. The list of attributes can be seen below in Table 3.5

**Table 3.5** List of attributes used for noMOD\_NEONATALMORT and MOD\_NEONATALMORT datasets

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Attribute List | | | | | | | |
| 1 | Baby Birth Date | 8 | Gestation | 15 | Birth Weight | 22 | Reproductive Assistance |
| 2 | Mothers Age | 9 | Labour Type | 16 | AGPAR1 | 23 | Aboriginal Status |
| 3 | Baby’s Sex | 10 | Presentation | 17 | AGPAR5 | 24 | First Trimester Visit |
| 4 | No. Previous Preterm Babies | 11 | Delivery Type | 18 | Intention to Breast Feed | 25 | AGPAR 10 |
| 5 | No. Previous Term Babies | 12 | Previous C/S | 19 | Neonatal Death/Stillbirth | 26 | Mother’s Primary Language |
| 6 | Twins Gestation | 13 | Forceps/Vacuum | 20 | Smoking |  |  |
| 7 | Prenatal Classes | 14 | Previous C/S Number | 21 | Maternal Province |  |  |

The noMOD\_TWINGEST and MOD\_TWINGEST datasets originally contained 21 attributes from the BORN database which could be obtained before 22 weeks gestation non-invasively for the prediction of preterm birth in twin pregnancies. The list of attributes can be seen below in Table 3.6

**Table 3.6** List of attributes used for noMOD\_TWINGEST and MOD\_TWINGEST datasets

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  | Attribute List |  |  |  |
| 1 | MULTGEST | 8 | INTBF | 15 | REPASS |  |
| 2 | MATAGE | 9 | SMOKING | 16 | FIRSTVIS |  |
| 3 | PPRETERM | 10 | MATHP0 | 17 | PRENCLAS |  |
| 4 | PTERM | 11 | MATHP3 | 18 | LANGUAGE\_up |  |
| 5 | PARITY | 12 | MATHP4 | 19 | MATHP\_sub |  |
| 6 | PREVCS | 13 | MATHP18 | 20 | MATHP\_ment |  |
| 7 | GENDER | 14 | MATHP27 | 21 | Diagnosis |  |

The noMOD\_SINGLETON and MOD\_SINGLETON datasets originally contained 21 attributes from the BORN database which could be obtained before 22 weeks gestation non-invasively for the prediction of preterm birth in twin pregnancies. The list of attributes can be seen in Table 3.7

**Table 3.7** List of attributes used for noMOD\_SINGLETON and MOD\_SINGLETON datasets

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  | Attribute List |  |  |  |
| 1 | MATAGE | 8 | SMOKING | 15 | FIRSTVIS |  |
| 2 | PPRETERM | 9 | MATHP0 | 16 | PRENCLAS |  |
| 3 | PTERM | 10 | MATHP3 | 17 | LANGUAGE\_up |  |
| 4 | PARITY | 11 | MATHP4 | 18 | MATHP\_sub |  |
| 5 | PREVCS | 12 | MATHP18 | 19 | MATHP\_ment |  |
| 6 | GENDER | 13 | MATHP27 | 20 | Diagnosis |  |
| 7 | INTBF | 14 | REPASS |  |  |  |

There are advantages and disadvantages of having too many or too few input attributes. Although having many attributes may lead to an improved classifier, this may also increase the complexity of the dataset and thus lead to added computational costs and noise. Further, having too many attributes may lead to spurious splits. These spurious splits will have almost no impact when evaluating the decision tree against a new dataset. Having fewer input attributes reduces the complexity of the database and improves the generalization of classifier; however it is important to not decrease the performance of the classifier. Therefore an ideal feature set must include only variables that are important (Yu, 2009).

**3.7.1.2.3 GROUPING NOMINAL ATTRIBUTES**

In order to achieve better results using decision trees, nominal inputs with many values was grouped. This is done to avoid spurious splits in the decision tree due to too many values. In extreme cases such as maternal age, where the input contains many values for each case, this was be grouped into high risk and low risk maternal age categories according to literature (i.e the world health organization considers women <18 and >40 to be high risk for preterm labour, therefore the maternal age was grouped into <18 (high risk), >=18 and <= 40 (low risk) and >40 (high risk)).

**3.7.1.3 STEP 3: PREPARING THE DATASET**

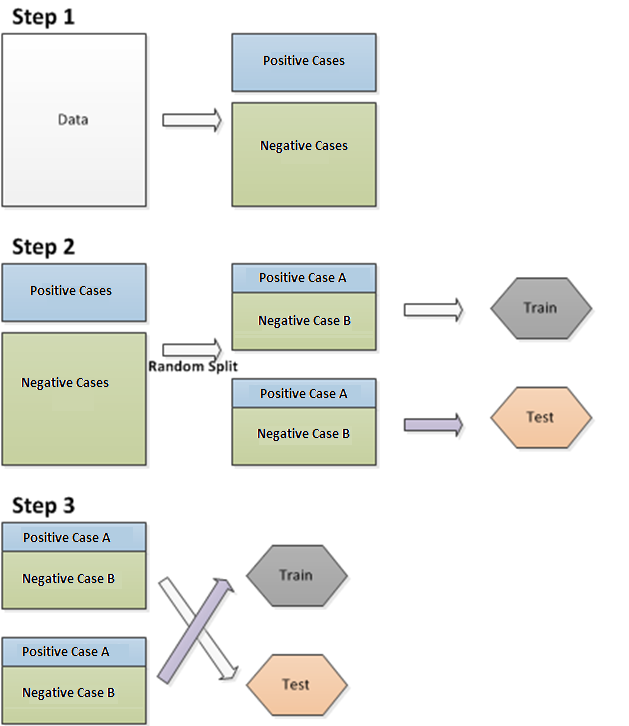
The See5 application requires the dataset to be divided into 3 distinct file types as follows: names, data and test. The names file contains the attributes and values. The attributes may be divided into explicitly-defined attribute such as discrete, continuous, date, time etc. or implicitly-defined attribute which may be specified by a formula. The values may be specified by separating each identified value by a comma (Rulequest Research, 2012).

The data file includes the dataset for training the algorithm. The values of all explicitly-defined attributes are entered as a new row of data for each case. The data file may consist of one or more lines, where each value is separated by a comma, and the case entry is terminated with a period. A ‘?’ may be used for missing values, and ‘N/A’ may be used when a value is not applicable for that particular case (Rulequest Research, 2012).

The test file is the same format as the data file. The test file contains unseen data for validation and is used to evaluate the classifier. (Rulequest Research, 2012).

**3.7.1.4 STEP 4: 5x2 CROSS VALIDATION (TRAINING AND TESTING)**

In order to reduce the bias on the dataset and randomize, a 5-by-2 cross validation method was used. The advantage of the 5-by-2 cross validation method is that all data points can be used for both training and testing the data; therefore important attributes that may lead to better estimations are not left out. In this method, the data was first split into positive and negative cases (step1). This set was then further randomly split into equal sized training and test sets where the first positive and negative sets were merged for training, and the second positive and negative sets were merged for testing (step 2). This allows there to be equal number of positive and negative cases in the training and testing sets. The first train and test set was labelled 1a, this was then reversed such that the test set is used for training and training set is used for testing, this was labelled 1b. This process is repeated 5 times to create 10 separate training and test sets (Gilchrist, 2012).



**Figure 3.2** Steps to randomize a dataset using 5-by-2 cross validation technique

**3.7.1.5 STEP 5: SOFTWARE EXECUTION AND RESULTS**

The results of the execution are stored in an .out text file. This file includes a list of important attributes to be used to construct the classifier, with the usage of the attributes represented by percentage and listed in order of highest importance. When there are more than 20 classes to be evaluated, this file also includes a decision tree and a confusion matrix. The confusion matrix provides additional details on the correct and incorrect classifications, and is used to evaluate various performance measures, see section 3.6.1 (Rulequest Research, 2012).

**3.7.1.6 STEP 6: REMOVE VARIABLE OF LEAST RELEVANCE**

Based on the results of the execution, variable(s) of poor usage as per the attribute usage list were removed and steps 6-8 were repeated to see if better performance outcomes could be achieved. If the overall prediction accuracy improved, these variable(s) were removed from the dataset, otherwise it was re-inserted.

* + 1. **DEVELOPMENT OF A CLASSIFICATION MODEL USING THE CONCEPT OF HYBRID ANN**

The hybrid ANN architecture includes both knowledge-based components (decision tree algorithm) and non-knowledge-based components (Case Based Reasoning (CBR) tool and the ANN component). In a hybrid system, a decision tree algorithm (C5.0) is used to extract important attributes. A database was then created, and the ANN weights are adjusted according to the importance of the attributes. Then the CBR tool is run against the database for the purpose of case matching, case retrieval and reasoning. The ANN was used to train the network to learn general domain knowledge, and thus the trained network may be used as a source of general knowledge (Chen & Burrel, 2011).

One of the hybrid structures under consideration was the decision tree combined with a neural network (TBNN). Although this method may improve the classification accuracy, it would be difficult to implement this on the ANN Research Framework (ANN-RFW) since it has one hidden layer, and thus direct mapping of this algorithm would be complex and computationally expensive.

The hybrid algorithm used in this thesis work was pruning based neural networks (PBNN). This method integrates well into the ANN-RFW and uses a slightly different approach, where instead of directly mapping variables and rules to the ANN, decision trees are used to construct binary patterns which are then fed into the ANN (Yu, 2009).

Accomplishing Objective 1 to predict neonatal mortality and preterm birth in twin pregnancies using hybrid Artificial Neural Network (ANN):

Step 1: ANN Feature Selection

Step 2: Normalization / Standardization

Step 3: Incorporating a KNN Case-Based Reasoning Tool to Impute Data

Step 4: Database Format Requirements

Step 5: Execution of the KNN Tool

Step 6: Configuring ANN

Step 7: Preparing the Dataset for ANN

Step 8: Running ANN & Result

**3.7.2.1 STEP 1: ANN FEATURE SELECTION**

In order to select variables of importance, section 3.1.7.1-6 were applied. The features that remained in the resulting DTs were then selected as the features to be used in the ANN classification model.

**3.7.2.2 STEP 2: NORMALIZATION/STANDARDIZATION**

In order to account for the large range differences that may occur between values, and to increase the efficiency of the ANN, the data inputs were normalized (Durai & Saro, 2006). Normalization is used to minimize the bias of one feature over another. Studies suggest that neural networks perform best when the values range between -1 and 1. Further, if the values were not normalized, the ANN may place importance on higher values (Durai & Saro, 2006). Normalization may speed up the training process by initiating the training process of each feature within the same range of values (Jayalakshmi & Dr. Santhakumaran, 2011). Various techniques can be used to normalize the data. In this study, for variables which were in two categorical format, the most frequent cases were set to -1, and for nominal cases the method used for normalizing the data was derived from the MIRG ANN Guide, which suggests a modified Z-score transformation equation as follows:

ẋin= (3.9)

where: ẋin = Normalized value

= Value

= Average

= Standard deviation

**3.7.2.3 STEP 3: INCORPORATING A KNN CASE-BASED REASONING TOOL TO IMPUTE DATA**

The MIRG has developed and validated a K-Nearest Neighbor (KNN) case-based reasoning (CBR) tool for a Neonatal Intensive Care Unit (NICU) (Catley, 2007). The CBR system is used to fill in missing data values from the knowledge retained from similar previously encountered cases (Cotea & Jiwani, 2003). The CBR methodology includes the following 4 steps (Cotea & Jiwani, 2003).

1. **Retrieve** – Retrieve similar past case(s) and the result(s)
2. **Reuse -** Based on previous cases, adapt a solution for the current case
3. **Revise** - Adjust any differences between the current case and retrieved case
4. **Retain** – Store the solution in the current case and re-use for future problems

**3.7.2.4 STEP 4: DATABASE FORMAT REQUIREMENTS**

The CBR tool runs on a Microsoft Access based database. The database must include four tables labelled: match, query, weights and index. The descriptions of these tables are given below (Cotea & Jiwani, 2003):

*Match* – contains the portion of the dataset with known values

*Query* – contains the remainder of the dataset with each row missing one or more value(s)

*Index* – contains the minimum and maximum value for each attribute

*Weights* – contains the weight associated with each attribute

The database also requires that an attribute labeled ‘Caselink’ to be set as the last column consisting of unique identifiers for each case (Cotea & Jiwani, 2003).

**3.7.2.5 STEP 5: EXECUTION OF KNN TOOL**

The CBR system can be used to fill in missing values and validate inconsistent predicted outcomes. The KNN algorithm is used to retrieve the closest matches for each missing value and to replace the missing value by accounting for the weights assigned to each input variable (Catley, 2007). This application was developed in Java 1.4.1, and the connection to the database is made available using Java Database Connectivity (JDC) interface. The Graphical User Interace (GUI) was designed using the Swing API (Cotea & Jiwani, 2003).

The following steps must be taken to run the KNN Tool:

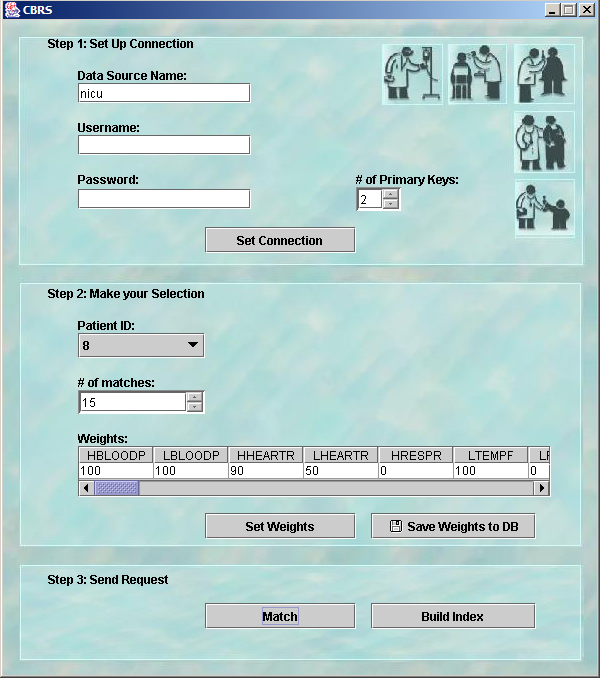
**Step 1**: Connect to the database via ODBC connection; enter a username and password if necessary.

**Step 2**: Set the ‘k’ value to the desired number of matches in the ‘# of matches’ field.

**Step 3**: Set the weights ranging from 0-100 in the ‘Weights’ table.

**Step 4**: Click on the ‘Build Index’ button.

**Step 5**: Click on the ‘Match’ Button.



**Figure 3.3** Screenshot of the CBR Interface

In a large dataset, this tool may require up to 3 days to process the information. The results of this tool are stored in a text (.txt) file.

**3.7.2.6 STEP 6: CONFIGURING ANN**

The ‘ANN\_Research\_Framework\_1.3.doc’ includes steps on setting up the MATLAB files. The following files were edited.

* main\_autoANN\_Sequential.m
* getData.m

**3.7.2.7 STEP 7: PREPARING THE DATASET FOR ANN**

The resulting dataset from the CBR tool was randomized using a 5-by-2 cross validation method to create .data and .test files. These files are used to produces 10 datasets, which are categorized into three distinct sets including: training, testing and validation. The train and test sets are used to generate the structure. The validation set containing unseen data is used for confirming the model. The validation set contains unseen data. If the classifier generalizes well on new cases using the validation set, then this indicates a satisfactory performance. However, if poor performance was observed, then this may indicate that the network has been over-trained (Yu, 2009).

**3.7.2.8 STEP 8: RUNNING ANN & RESULTS**

To run the ANN, the following steps were executed:

1. Load MATLAB 2010a

2. Double click on the folder to process

3. Run ANN code in MATLAB by dragging the file "main\_autoANN\_Sequential.m" to the command window.

The results are stored in a log file and the performance outcomes were calculated.

* 1. **SECOND OBJECTIVE**

The second objective of the thesis was to construct a framework for a Perinatal Decision Support System (PEDSS) using a web-based content management system. Once the fundamental components were established, the integration and extension onto a web-based collaborative platform was considered. A detailed description of a conceptual framework to build a PEDSS using a knowledge-based approach is to follow.

* + 1. **SYSTEM ARCHITECTURAL CONSIDERATION**

A PEDSS may be deployed onto varying platforms such as internet-based, local computer, networked with EMR or a handheld device. Further, varying techniques may be used as follows: (i) system may be integrated into an EMR, (ii) based on knowledge extracted from a central repository, or (iii) the entire system may be housed externally and accessed remotely, and thus not integrated to an EMR. Although the PEDSS may be built using any of the above described computational architecture, the final design will be based upon the clinical systems in place already, workflow, security, budget etc… (Berner, 2009).

For the purpose of this thesis, our PEDSS framework focuses on a web-based, mobile supported platform, where the entire system is housed externally and is accessed remotely. The PEDSS may be accessed via the internet by authenticated users on any computer or hand held device.

* + 1. **DEVELOPMENT OF PERINATAL DECISION SUPPORT SYSTEM**

The web-based PEDSS introduced in this thesis is to serve as diagnostic tool to predict neonatal mortality and preterm labour in twin pregnancies based on patient’s signs and symptoms. Ideally, a web-based collaborative system in a clinical environment would allow healthcare personnel to share opinions, exchange clinical data, and access clinical information regardless of their geographic location. Furthermore, the development of a high quality, low cost PEDSS to augment human decision-making on a collaborative platform will provide intelligently filtered information to the clinicians, staff and patients. This in turn will improve the quality of care provided and may reduce human errors.

The PEDSS is to include the following: a large knowledge-base of perinatal information extracted from the BORN database, a workflow to combine the knowledge with patient specific information, a communication mechanism to allow the clinicians to enter in patient information, and an interface to provide relevant results back to the clinician (Berner, 2009).

**3.8.2.1 STEP 1: PLATFORM CONSIDERATION**

The PEDSS shall be implemented on a user friendly, low cost platform that is mobile supported. The platform must adhere to confidentiality and privacy requirements as per national standards. An ideal platform shall support and meet the needs of two distinct groups of users, which include healthcare providers, and the MIRG research group. The healthcare providers’ require a system that is user-friendly, minimally disrupts their normal workflow and produces clinically satisfactory results (Catley, 2007). Importantly, healthcare providers will not use a system that does not guarantee protection and security of the data that is captured and recorded (Chakravarti, & Dr. Battacharyya, 2006). The MIRG research group will be more focused on a flexible framework design, with the ability to access and customize each system component to continuously improve the system performance and reliability over time.

* + - 1. **STEP 2: DEFINING SYSTEM COMPOSITION**
         1. **SYSTEM OVERVIEW**

The proposed PEDSS framework employs a web-based modular design that allows for extensibility and scalability; it is designed for the healthcare industry where retrieval and processing of real-time patient information is crucial. The solution architecture of this web-based system permits for ‘anytime and anywhere’ access utilizing an asynchronous data-driven design to allow for real-time information flow. Authenticated users may access the PEDSS from a laptop/desktop or a hand held device such as a mobile phone, PDA etc. This framework can be viewed as a 6-layer encapsulated system as presented in Figure 3.4.

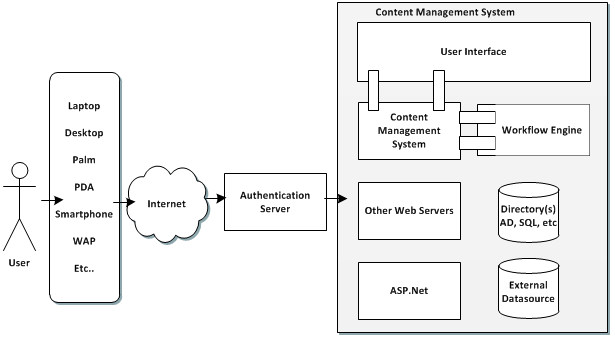
**Figure 3.4**: Integration of Technical and Clinical Processes

* + - * 1. **SYSTEM HARDWARE / SOFTWARE / COMMUNICATION ARCHITECTURE**

The web-based PEDSS architecture is highly scalable and can easily be extended to many new users at low cost (Frize, Yang, Walker, & O’Conner, 2005). The PEDSS system architecture consists of the components as outlined in table 3.8 and figure 3.5.

**Table 3.8** Components for a web-based PEDSS

|  |  |
| --- | --- |
| Components to Build a Web-based PEDSS | |
| Components | Description |
| Authentication Server | Authenticates users into the system |
| Content Management System | The heart of the system used to display, search, and process the data, based upon the user request |
| Workflow Engine | Required to automate alerts, warning and actions |
| External Data Source | A repository of the patient, or user information |
| Directories | A database of user information, etc. |
| Other Web Servers | Other servers required to operate the PEDSS |
| ASP.Net, XML, HTML | The interface presented to the user |



**Figure 3.5** System Architecture of Web-based PEDSS

Details of the main system components are further discussed as follows:

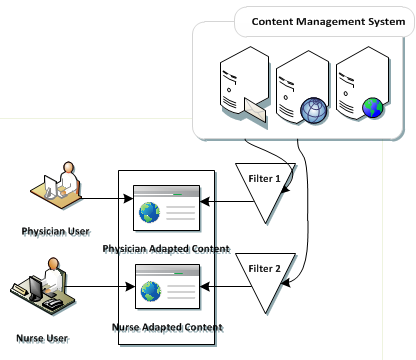
* Authentication Server

The authentication server is used to verify that the user accessing the PEDSS has the appropriate privileges to view content on the page. The end user typically will need to provide a username and password; this information is checked to see if it matches the credentials stored in the system directory. This step is required to comply with the data security and confidentiality requirements to ensure that the transmission of data is in keeping with current privacy legislation. This is especially important for medical applications.

* Content Management System (CMS)

The content management system is considered to be the heart of the PEDSS and it includes all of the engines and support modules. **A web-based content management system is required to host the PEDSS. The interface that is developed is published to the content management system. The CMS receives the inputted information from the clinician and auto starts the workflow engine for processing, the results are then displayed back to the clinician. The CMS is also composed of several databases which may be physically located over a large geographic area (Chakravarti, & Dr. Battacharyya, 2006).**

**The CMS supports advanced features including audience targeting, where filters can be set up based on the user logged in, so that varying levels of user-groups are presented with filtered views on what is relevant to them (Figure 3.6). The CMS also includes a search module which consists of an intelligent filter, thus only information applicable to the user will be displayed based on the search criteria.**



**Figure 3.6** Custom Views based on Audience Targeting

* Workflow Engine

A workflow engine is a new class of software which allows the translation of code into a graphical model. This is required to automate the knowledge-base (Rasmussen et al., 2011). The workflow can incorporate various actions including sending out timed alerts, warnings and recommendations. The workflow engine is used to process the inputted patient data, as well as send alerts, diagnostic results, and/or recommendation to the clinician depending upon the requirements (Chakravarti, & Dr. Battacharyya, 2006). The workflow alerts and warnings are typically rule based and predetermined, based on the decision tree results obtained using the See5 program (C5.0). The recommendations are derived from evidence based medicine outcome, as well as information compiled from historical data stored in a clinical data warehouse (Chakravarti & Dr. Battacharyya, 2006). The workflow is customizable to the users’ needs, as this will ultimately lead to increased efficiency, ease of use, and usefulness.

* External Data Source:

The external data sources will contain various SQL based databases, including a database containing the patient information extracted from an EMR or HER, and a database containing the users’ information. A connection from the content management system to the external data source will be established for authenticated users to store and retrieve patient information.

**3.8.2.3 STEP 3: SYSTEM INTEGRATION**

The Perinatal Decision Support System (PEDSS) is composed of many discrete subsystems and components including the knowledge-base, content management system and workflows, which must be integrated physically and functionally in order to serve as a coordinated system. The entire PEDSS can be separated into three layers: Layer 1: Knowledge Discovery and Data Mining, Layer 2: Perinatal Decision Support System (PEDSS) and Layer 3: Knowledge Integration: Semantic Web Services for Healthcare. The relationship and linkages between each of these systems is shown in Figure 3.7. Each of the layers are further discussed as follows:

**Layer 1:** Knowledge Discovery and Data Mining

In the first layer, a decision tree was derived using the concept of knowledge discovery and data mining. The knowledge discovery process is an interactive and iterative process where most of the steps are manually processed by the user. For our framework, the data used for predicting neonatal mortality was extracted from the Niday perinatal database and the data for predicting preterm birth in twin pregnancies was extracted from the BORN database. The algorithm used to produce the DTs was C5.0, using the commercial See5 program (available in the MIRG laboratory). Each of the derived trees was evaluated using varying performance measures outlined in section 3.6. Once satisfactory results were obtained, the resulting decision tree was presented to Dr.Bariciak. The practitioner’s tacit domain knowledge defines the PEDSS composition template.

**Layer 2:** Clinical Decision Support System

The second layer is where the PEDSS was developed and deployed. The system is to be hosted on a web-based content management system with the architecture set up as outlined in section 3.8.2. A workflow engine shall be used to convert the decision tree results into a graphical model in the form of logical statements (i.e. IF ‘Twins Gestation’ AND ‘Smoking THEN ‘Preterm’). The workflow can also incorporate various actions including sending out timed alerts, warnings and recommendations based on requirements set in CDS composition template. This workflow shall also enable data connections to retrieve information / send captured data to SQL based databases via web services. Once the workflow model has been built, it is published to the content management system.

The graphical user interface is developed using asp.net. This interface is then browser enabled, such that the content may be viewed using only an internet browser, and thus preventing the need of users having to install additional add-ons or software to run the PEDSS. The developed .asp form was then published to the content management system.

**Layer 3:** Knowledge Integration: Semantic Web Services for Healthcare

The last layer ensures that authenticated users only view content relevant to them. Once the PEDSS is developed and deployed, the system shall be filtered based on the various user groups which exist within the system. There are 5 user groups under consideration: physicians, nurses, MIRG Researchers, system administrators, and visitors/auditors. The physicians shall have the ability to fill out assessments electronically, retrieve/view patient information and results, as well as have access to any relevant announcements. The nurses shall have the ability to fill out assessments electronically, submit patient information, and have access to any relevant announcements. The MIRG research group shall have access to de-identified data, and view system components. The system administrator shall have full access to the system, including the ability to set roles, modify workflows and control the design privileges. Visitors/auditors shall have restricted read capability on the system. The system shall be set up and configured to present targeted views to the groups of users identified above, and thus only information relevant to the user shall be filtered and displayed.

Only authenticated users may access the system. The system shall include an authentication server in order to validate the user. The user would provide a username and password; this information is checked to see if it matches the credentials stored in the system directory. If the user’s credentials match, then filtered content shall be displayed to the user based on their role stored in the system directory.



**Figure 3.7** Conceptualization of the Perinatal Decision Support System

**3.8.2.4 STEP 4: KNOWLEDGE MAINTENANCE**

There are two main areas of knowledge maintenance that are challenging. The first challenge is to keep up to date the amount of the information within the perinatal database. As more information is recorded each year, it is important to update the system with the current information. As new medical devices emerge, if this affects the mortality rate on newborns or has an impact on delivering preterm for women pregnant with twins, then the new information must be captured, analyzed and incorporated into the system. For example, assisted pregnancy tools have resulted in twin pregnancies, where twins pregnancies often lead to preterm birth, and therefore this is a good indicator of preterm birth and must therefore be appropriately captured and recorded into the PEDSS (Berner, 2009).

Another other area of challenge that is partially related to the first problem, is maintaining the knowledge embedded within the PEDSS. As medical knowledge expands, it is important to take into account new drugs and diagnosis that are continually discovered. Therefore the PEDSS must be flexible and extensible in order to incorporate new updates without requiring significant resources and time (Berner, 2009).

There are a few potential solutions available for maintaining knowledge in a CMS. One solution would be an in-house knowledge management process; this however will require significant resources at each of the local sites. An alternate solution, and the solution developed for this thesis, was to develop a web-based repository using service oriented architecture (SOA). SOA allows for one central site to remotely maintain the knowledge. This approach is low cost, since only a few resources are required (Berner, 2009).

**CHAPTER 4 RESULTS AND DISCUSSION**

**4.1 DECISION TREE & HYBRID ANN RESULTS**

Two databases, Niday and BORN were evaluated using C5.0 algorithm. The Niday database was split into noMOD\_NEONATALMORT and MOD\_NEONATALMORT, the BORN database was split into noMOD\_TWINGEST, MOD\_TWINGEST, noMOD\_SINGLETON and MOD\_SINGLETON (Table 3.4). 5x2 cross validation method was used to generate ten equal sized datasets (Section 3.7.1.4). Each dataset was trialed 10 times, thus generating a DT at each trial. The sensitivity and specificity varied for each dataset. The average test sensitivity and specificity exceeded 60% and 85%, respectively, for the MOD\_NEONATALMORT set and exceeded 65% and 85%, respectively, for the MOD\_TWINGEST set.

**4.1.1 NEONATALMORT DATASET**

A total of 32 760 cases were evaluated using 13 attributes, where 32 695 cases were survivors and 65 resulted in neonatal death. The attributes used were Mother’s Age, Baby Gender, Gestation, Labour, Delivery, Previous Cesarian, Birth Weight, AGPAR 1, AGPAR 5, Intention to Breast Feed, Smoking, AGPAR 10 and Diagnosis. The prevalence of the dataset was 0.65%. This is very close to the prevalence of neonatal mortality rate of 0.40% in Canada in 2010 (UNICEF, 2010).

**4.1.1 .1 noMOD\_NEONATALMORT DT RESULTS**

Out of the 13 input attributes, the attribute that was common in all datasets was AGPAR 5. The resulting test sensitivity was 57.176.84% and the test specificity was 99.980.01%, where during training it was slightly higher with TR\_sensitvity at 61.67% and TR\_specificity at. 99.99%. The highest performing decision tree was DT3(b) with test sensitivity of 66.67% and test specificity of 99.94%. The correct classification rate or accuracy remained high at 99.91%. The model produced excellent results to predict survival with a negative predictive value (NPV) of 99.920.01%, and produced satisfying results to predict neonatal death with a positive predictive value (PPV) of 87.508.09%. Overall the noMOD\_NEONATALMORT DT model did not meet the clinical expectations set by Dr. Bariciak, since the average test sensitivity is below clinical standards of 60%.

**Table 4.1:** noMOD\_NEONATALMORT decision tree results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | DT# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.7273 | | 0.9998 | | 0.8571 | | 0.9994 | | |  | | --- | | 0.5938 | | 0.9999 | | 0.9048 | | 0.9992 | | |  | | --- | | 0.6250 | | 0.9999 | | 0.9524 | | 0.9993 | | |  | | --- | | 0.5313 | | 0.9999 | | 0.9444 | | 0.9991 | | |  | | --- | | 0.5455 | | 0.9999 | | 0.9474 | | 0.9991 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6250 | | 0.9996 | | 0.7692 | | 0.9993 | | |  | | --- | | 0.6061 | | 0.9998 | | 0.8696 | | 0.9992 | | |  | | --- | | 0.5000 | | 0.9998 | | 0.8421 | | 0.9990 | | |  | | --- | | 0.5758 | | 0.9999 | | 0.9500 | | 0.9991 | | |  | | --- | | 0.5625 | | 0.9999 | | 0.9474 | | 0.9991 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6875 | | 0.9998 | | 0.8800 | | 0.9994 | | |  | | --- | | 0.6061 | | 0.9999 | | 0.9524 | | 0.9992 | | |  | | --- | | 0.5313 | | 0.9999 | | 0.9444 | | 0.9991 | | |  | | --- | | 0.7879 | | 0.9999 | | 0.9286 | | 0.9996 | | |  | | --- | | 0.5313 | | 0.9999 | | 0.8947 | | 0.9991 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6667 | | 0.9994 | | 0.7097 | | 0.9993 | | |  | | --- | | 0.5313 | | 0.9998 | | 0.8095 | | 0.9991 | | |  | | --- | | 0.5758 | | 0.9999 | | 0.9500 | | 0.9991 | | |  | | --- | | 0.4375 | | 0.9998 | | 0.8235 | | 0.9989 | | |  | | --- | | 0.6364 | | 0.9998 | | 0.8750 | | 0.9993 | |

**4.1.1.2 MOD\_NEONATALMORT DT RESULTS**

In this set, attribute(s) with nominal values were grouped, which included Mother’s Age. Out of the 13 input attributes, the attribute that was common in all datasets was AGPAR 5. The resulting test sensitivity was 62.243.28% and the test specificity was 99.950.03%, where during training it was slightly higher with TR\_sensitvity of 71.11% and TR\_specificity of. 99.96%. The highest performing decision tree was DT5(a) with test sensitivity of 68.75% and test specificity of 99.98%. The correct classification rate or accuracy remained high at 99.98%. The model produced excellent results to predict survival with a NPV of 99.930.01%, and produced satisfying results to predict neonatal death with a PPV of 72.3513.91%. Overall this model exceeds the clinical expectations set by Dr. Bariciak, since the average test sensitivity and specificity exceeds the clinical standards of 60% and 85%, respectively.

**Table 4.2:** MOD\_NEONATALMORT DT results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | DT# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6970 | | 0.9998 | | 0.8519 | | 0.9994 | | |  | | --- | | 0.5625 | | 0.9998 | | 0.8182 | | 0.9991 | | |  | | --- | | 0.8929 | | 0.9995 | | 0.7576 | | 0.9998 | | |  | | --- | | 0.8929 | | 0.9995 | | 0.7576 | | 0.9998 | | |  | | --- | | 0.6061 | | 0.9996 | | 0.7407 | | 0.9992 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6250 | | 0.9999 | | 0.9091 | | 0.9993 | | |  | | --- | | 0.6061 | | 0.9997 | | 0.8000 | | 0.9992 | | |  | | --- | | 0.6250 | | 0.9994 | | 0.6897 | | 0.9993 | | |  | | --- | | 0.6250 | | 0.9994 | | 0.6897 | | 0.9993 | | |  | | --- | | 0.5938 | | 0.9990 | | 0.5429 | | 0.9992 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.7188 | | 0.9998 | | 0.8519 | | 0.9994 | | |  | | --- | | 0.6061 | | 0.9994 | | 0.6897 | | 0.9992 | | |  | | --- | | 0.7500 | | 0.9998 | | 0.8571 | | 0.9995 | | |  | | --- | | 0.6667 | | 0.9998 | | 0.8462 | | 0.9993 | | |  | | --- | | 0.7188 | | 0.9994 | | 0.7188 | | 0.9994 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6563 | | 0.9995 | | 0.7241 | | 0.9993 | | |  | | --- | | 0.5938 | | 0.9991 | | 0.5758 | | 0.9992 | | |  | | --- | | 0.5758 | | 0.9999 | | 0.9048 | | 0.9991 | | |  | | --- | | 0.6875 | | 0.9998 | | 0.8462 | | 0.9994 | | |  | | --- | | 0.6364 | | 0.9990 | | 0.5526 | | 0.9993 | |

**4.1.1.3 COMPARING BEST PERFORMING nOMOD\_NEONATALMORT VS. MOD\_NEONATALMORT DT**

The best performing DT for noMOD\_NEONATALMORT and MOD\_NEONATALMORT prediction is presented in table 4.3. The best performing set for noMOD\_NEONATALMORT DT showed higher sensitivity, specificity, PPV and NPV compared to the MOD\_NEONATALMORT DT set. The highest increase was noted in the PPV value with an increase of 0.1365. The sensitivity, specificity and NPV values resulted in only slight increase of 0.0208, 0.0004, 0.0001 respectively, compared to the MOD\_NEONATALMORT DT set. When evaluating the best performing DT set for noMOD\_NEONATALMORT and MOD\_NEONATALMORT, both sets verify well and are clinically acceptable.

**Table 4.3:** Best performing noMOD\_NEONATALMORT vs MOD\_NEONATALMORT DT set

|  |  |  |  |
| --- | --- | --- | --- |
| DT |  | 5a | 3a |
|  |  | noMOD | MOD |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6875 | | 0.9998 | | 0.8462 | | 0.9994 | | |  | | --- | | 0.6667 | | 0.9994 | | 0.7097 | | 0.9993 | |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6667 | | 0.9998 | | 0.8462 | | 0.9993 | | |  | | --- | | 0.6875 | | 0.9998 | | 0.8800 | | 0.9994 | |

Although the best performing noMOD\_NEONATALMORT DT set exceeds the performance MOD\_NEONATALMORT DT set, the average test sensitivity, did not meet clinical expectations. The average test sensitivity of the noMOD\_NEONATALMORT DT set was 57.176.84% which is below clinical standards, even though the specificity remained high at 99.980.01%. Thus the only clinically acceptable model is the MOD\_NEONATALMORT DT set with an average test sensitivity of 62.243.28% and specificity of 99.950.03%.

**4.1.1.4 COMPARING PPV AND NPV OF nOMOD\_NEONATALMORT VS. MOD\_NEONATALMORT**

The average test PPV and NPV values for noMOD\_NEONATALMORT and MOD\_NEONATALMORT DT sets are presented in Table 4.4. The NPV results for both the noMOD\_NEONATALMORT and MOD\_NEONATALMORT DT were extremely high and stable exceeding 99.92%. The PPV values for both the noMOD\_NEONATALMORT DT and MOD\_NEONATALMORT DT set are both much higher than previous work of N.Yu of 0.34 and J.Gilchrist of 0.38, where the MOD\_NEONATALMORT DT set produced the highest average PPV of 0.85. The train PPVs were higher than the test PPVs as expected. The smaller PPV in previous work indicates that many of the positive results from the previous prediction models were false positives. Therefore any positive results in the previous work would require a follow up in the form of a more reliable assessment to determine if the neonate will survive.

**Table 4.4:** Comparing PPV and NPV of noMOD\_NEONATALMORT vs MOD\_NEONATALMORT DT

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | noMOD | MOD |
| Test | PPV  NPV | |  | | --- | | 0.7235 | | 0.9993 | | |  | | --- | | 0.8546 | | 0.9992 | |
| Train | PPV  NPV | |  | | --- | | 0.7889 | | 0.9994 | | |  | | --- | | 0.9206 | | 0.9992 | |

**4.1.1.5 nOMOD\_NEONATALMORT HYBRID ANN RESULTS**

The resulting test sensitivity and test specificity for the hybrid ANN models were 21.8512.97% and 86.5510.83%, respectively. During training, TR\_sensitvity was slightly higher at 31.61% and TR\_specificity was lower at 73.64%. The highest performing node was Fold 1(b) with test sensitivity of 57.36% and test specificity of 54.05%. The correct classification rate or accuracy 79.31%. The model produced excellent results to predict survival with a NPV of 89.840.51%, and produced poor results to predict neonatal death with a PPV of 18.145.72%. The ROC was 55.24% resulting in poor discrimination. Overall the noMOD\_NEONATALMORT hybrid ANN model did not meet the clinical expectations set by Dr. Bariciak, since the average test sensitivity is below clinical standards of 60% and resulted in poor discrimination.

**Table 4.5:** noMOD\_NEONATALMORT hybrid ANN results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Fold# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.2533 | | 0.7690 | | 0.1267 | | 0.8861 | | |  | | --- | | 0.7445 | | 0.2366 | | 0.1079 | | 0.8818 | | |  | | --- | | 0.1770 | | 0.8977 | | 0.1868 | | 0.8914 | | |  | | --- | | 0.1891 | | 0.8977 | | 0.1902 | | 0.8971 | | |  | | --- | | 0.1747 | | 0.8790 | | 0.1583 | | 0.8910 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.0245 | | 0.9039 | | 0.0251 | | 0.9018 | | |  | | --- | | 0.57356 | | 0.54053 | | 0.13412 | | 0.91084 | | |  | | --- | | 0.1912 | | 0.9020 | | 0.2011 | | 0.8963 | | |  | | --- | | 0.2288 | | 0.9011 | | 0.2315 | | 0.8997 | | |  | | --- | | 0.1862 | | 0.9001 | | 0.1947 | | 0.8951 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1799 | | 0.8885 | | 0.1691 | | 0.8958 | | |  | | --- | | 0.3745 | | 0.6698 | | 0.1237 | | 0.8959 | | |  | | --- | | 0.6707 | | 0.4127 | | 0.1310 | | 0.9047 | | |  | | --- | | 0.1716 | | 0.8723 | | 0.1450 | | 0.8930 | | |  | | --- | | 0.2263 | | 0.8406 | | 0.1560 | | 0.8930 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1985 | | 0.9008 | | 0.2064 | | 0.8964 | | |  | | --- | | 0.1875 | | 0.9001 | | 0.2024 | | 0.8912 | | |  | | --- | | 0.2053 | | 0.9016 | | 0.2071 | | 0.9007 | | |  | | --- | | 0.1934 | | 0.9027 | | 0.2061 | | 0.8955 | | |  | | --- | | 0.1962 | | 0.9021 | | 0.2058 | | 0.8967 | |

**4.1.1.6 MOD\_NEONATALMORT HYBRID ANN RESULTS**

The resulting test sensitivity was 60.740.59% and the test specificity was 91.300.65%, where during training TR\_sensitvity was slightly higher at 65.44% and TR\_specificity was lower at 80.607%. The highest performing node was Fold 1(a) with test sensitivity of 61.93% and test specificity of 91.03%. The correct classification rate or accuracy 83.33%. The model produced excellent results to predict survival with a NPV of 86.830.33%, and produced good results to predict neonatal death with a PPV of 71.141.64%. The ROC was 77.09% resulting in acceptable discrimination. Overall the noMOD\_NEONATALMORT hybrid ANN model met the clinical expectations set by Dr. Bariciak, since the average test sensitivity and specificity is above clinical standards of 60% and 85%, respectively.

**Table 4.6:** MOD\_NEONATALMORT Hybrid ANN result

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Fold# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6265 | | 0.8438 | | 0.5936 | | 0.8612 | | |  | | --- | | 0.7166 | | 0.7128 | | 0.4781 | | 0.8726 | | |  | | --- | | 0.5979 | | 0.8719 | | 0.6337 | | 0.8540 | | |  | | --- | | 0.6283 | | 0.8499 | | 0.6014 | | 0.8638 | | |  | | --- | | 0.5705 | | 0.9137 | | 0.7070 | | 0.8535 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6193 | | 0.9103 | | 0.7046 | | 0.8738 | | |  | | --- | | 0.5960 | | 0.9172 | | 0.7212 | | 0.8634 | | |  | | --- | | 0.6115 | | 0.9028 | | 0.6843 | | 0.8708 | | |  | | --- | | 0.6058 | | 0.9153 | | 0.7203 | | 0.8658 | | |  | | --- | | 0.6131 | | 0.9215 | | 0.7314 | | 0.8722 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6889 | | 0.7538 | | 0.5060 | | 0.8687 | | |  | | --- | | 0.6734 | | 0.7665 | | 0.5146 | | 0.8646 | | |  | | --- | | 0.7252 | | 0.7068 | | 0.4736 | | 0.8761 | | |  | | --- | | 0.7387 | | 0.6741 | | 0.4545 | | 0.8753 | | |  | | --- | | 0.5775 | | 0.9139 | | 0.7093 | | 0.8561 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.6034 | | 0.9004 | | 0.6835 | | 0.8643 | | |  | | --- | | 0.6068 | | 0.9201 | | 0.7326 | | 0.8664 | | |  | | --- | | 0.6057 | | 0.9123 | | 0.7042 | | 0.8704 | | |  | | --- | | 0.6069 | | 0.9145 | | 0.7129 | | 0.8692 | | |  | | --- | | 0.6056 | | 0.9156 | | 0.7185 | | 0.8671 | |

**4.1.1.7 COMPARING BEST PERFORMING nOMOD\_NEONATALMORT VS. MOD\_NEONATALMORT HYBRID ANN**

The best performing hybrid ANN for noMOD\_NEONATALMORT and MOD\_NEONATALMORT prediction is presented in Table 4.7. The best performing set for noMOD\_NEONATALMORT hybrid ANN showed higher sensitivity, specificity, and PPV compared to the MOD\_NEONATALMORT set. The highest increase was noted in the PPV value with an increase of 0.5705. The sensitivity, specificity and NPV values resulted in only slight increase of 0.0457, 0.3698, 0.0370 respectively, compared to the MOD\_NEONATALMORT hybrid ANN set.

**Table 4.7:** Best performing noMOD\_NEONATALMORT vs MOD\_NEONATALMORT hybrid ANN sets

|  |  |  |  |
| --- | --- | --- | --- |
| Fold |  | 1b | 1a |
|  |  | noMOD | MOD |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.5735 | | 0.5405 | | 0.1341 | | 0.9108 | | |  | | --- | | 0.6193 | | 0.9103 | | 0.7046 | | 0.8738 | |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.7445 | | 0.2366 | | 0.1079 | | 0.8818 | | |  | | --- | | 0.6265 | | 0.8438 | | 0.5936 | | 0.8612 | |

When evaluating the best performing hybrid ANN set for noMOD\_NEONATALMORT and MOD\_NEONATALMORT, the best performing noMOD\_NEONATALMORT does not meet clinical expectations since both the sensitivity and specificity are low.

Further the average test sensitivity of the noMOD\_NEONATALMORT set was 21.8512.97% which is below clinical standards, even though the specificity remained high at 86.5510.83%. Thus the only clinically acceptable model is the MOD\_NEONATALMORT set with an average test sensitivity 60.740.59% and test specificity of 91.300.65%

**4.1.1.8 COMPARING PPV AND NPV OF nOMOD\_NEONATALMORT VS. MOD\_NEONATALMORT HYBRID ANN**

The average test PPV and NPV values for noMOD\_NEONATALMORT and MOD\_NEONATALMORT hybrid ANN sets are presented in Table 4.8. The NPV results for both the noMOD\_NEONATALMORT and MOD\_NEONATALMORT were high and stable exceeding 86.83%. The PPV of 0.7114 in the MOD\_NEONATALMORT hybrid ANN set was higher than previous work of N.Yu of 0.34 and J.Gilchrist of 0.38; however the PPV of the noMOD\_NEONATALMORT hybrid ANN set was much lower at 0.18.

**Table 4.8:** Comparing PPV and NPV of noMOD\_NEONATALMORT vs MOD\_NEONATALMORT

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | noMOD | MOD |
| Test | PPV  NPV | |  | | --- | | 0.1814 | | 0.8984 | | |  | | --- | | 0.7114 | | 0.8683 | |
| Train | PPV  NPV | |  | | --- | | 0.1495 | | 0.8930 | | |  | | --- | | 0.5672 | | 0.8646 | |

**4.1.1.9 PREDICTING NEONATAL MORTALITY DISCUSSION**

The results of the pre-processed MOD\_NEONATALMORT DT dataset with nominal values grouped using C5.0 algorithm exceeded the performance of DT-ANN hybrid method with a higher test sensitivity and test specificity of 62.243.28% and 99.950.03%, respectively. However both the DT and hybrid ANN MOD\_NEONATALMORT met the clinical expectations set, with sensitivity and specificity exceeding 60% and 85%, respectively.

Further a high sensitivity and specificity, with a high PPV and NPV was achieved in both the DT and Hybrid ANN MOD\_NEONATALMORT. The PPV refers to the likelihood that the positive prediction is correct and that the actual disease exists given a positive prediction (section 3.8.3). The NPV refers to the likely hood that the negative prediction is correct that the non-disease of the patient is correct given the negative prediction (section 3.8.4). These values are used as direct diagnosis accuracy of a classifier which serves as a comprehensive test for physicians (Yu, 2009). There are a few similar studies available literature using AGPAR 5 as the main attribute, and although these studies often had a high sensitivity, these results were accompanied by a low specificity and in many cases a poor PPV (section 2.1.4).

The most promising neonatal mortality prediction model prior to this study was derived by J.Gilchrist, where a real-time neonatal mortality risk estimation model was created using DTs and ANN to predict neonatal mortality within the first 12 hours after NICU admission. This model contained CHEO data and used only 3 attributes: lowest serum pH, lowest blood pressure, and lowest heart rate. This study included a total of n=256 patient cases with 232 survivors and 24 neonatal death, and thus a mortality rate of 9%. The DT model produced better results on average compared to the ANN model, where a sensitivity of 75% and specificity of 96% was achieved using the DT model, whereas the ANN model resulted in a sensitivity of 68% and specificity of 97%. J.Gilchrist also examined a larger dataset using the CNN database, with a total of n=17,364 newborn cases including 16677 survivors and 687 neonatal death and a 4% mortality rate using the same attributes. The resulting model however achieved a low mean test sensitivity of 56% and a mean test specificity of 97% which did not meet the clinical usefulness guideline as per clinicians.

To date, and to our knowledge, this is the first model to predict neonatal mortality non-invasively in a heterogeneous population within the first 10 minutes of birth with clinically satisfactory results. This model was generated using a large dataset obtained from the NIDAY database where originally it contained 65 536 newborn cases, after removing 32 374 cases due data clean up procedures as outlined in section 3.7, there were 32 776 newborn cases remaining, with 32 695 survivors and 65 neonatal death. This is the largest dataset which produced a clinically acceptable model to date. This set also contains a more correct prevalence of 0.65%, in comparison with the neonatal mortality in Canada which is recorded to be 0.40% (UNICEF, 2010). All previous studies conducted consisted of a much smaller dataset, with artificially high prevalence. A dataset that is too small may lead to erroneous conclusions upon evaluating the reliability of the tree on new data. In addition, a dataset containing a higher than normal prevalence may bias the resulting decision tree and produce better performance results. However, the implications of the previous study results upon validating it on a larger dataset with normal prevalence are unclear.

Further, previous studies focused on newborns after being admitted to NICU, and attempted to predict the risk on neonatal mortality before the first 48 hours after admission. This model is the first to predict the risk of neonatal mortality within the first 10 minutes of birth in a heterogeneous population non-invasively using only 13 attributes, which resulted in clinically acceptable results. In order to not count cases where the neonatal death occurred already before 10 minutes, cases with AGPAR 10 score <1 were removed from the dataset.

The model presented by J.Gilchrist used 3 attributes; the most contributing indications was the lowest serum pH, which may only be obtained invasively via a blood test, and requires up to 48 hours to receive the results. Further, although J.Gilchrist’s model achieved a sensitivity of 75% on the highest performing tree. This was accompanied by a poor PPV of 0.38. Thus this model performed poorly with regards to predicting neonatal death.

The MOD\_NEONMORT set on average consisted of a lower mean test sensitivity of 62.243.28% compared to J.Gilchrist’s model and in total consisted of 13 attributes. However, the highest performing decision tree used only 5 attributes which included AGPAR 5, AGPAR 1, Birth Weight, Gestation, and Delivery, and had a high test sensitivity and a test specificity of 66.67% and 99.94%, respectively, with PPV and NPV exceeding clinical expectations of 0.863 and 0.998 respectively.

**4.1.2 TWINGEST DATASET**

A total of 1914 test cases were evaluated including 1591 term and 323 preterm births. A total of 21 attributes were used which included TWINGEST, MATAGE, PPRETERM, PTERM, PARITY, PREVCS, GENDER, INTBF, SMOKING, MATHP0, MATHP3, MATHP4, MATHP18, MATHP27, REPASS, FIRSTVIS, PRENCLAS, LANGUAGE\_up, MATHP\_sub, and Diagnosis. The prevalence of the dataset was 16.87%.

**4.1.2.1 noMOD\_TWINGEST DT RESULTS**

Out of the 21 input attributes, the C5.0 algorithm used 1-4 attribute(s) to generate the DTs. The attribute that was in common included LANGUAGE, and it also remained to be the most contributing factor in predicting preterm birth in twin pregnancies. The resulting average test sensitivity was 15.433.01% and the average test specificity was 99.310.29%. The sensitivity and specificity during training was slightly higher at TR\_sensitivity of 15.85% and TR\_specificity of 99.37%, respectively.The correct classification rate or accuracy was 85.150.53%. The PPV and NPV were 81.946.50% and 85.26, respectively**.** Due to the poor sensitivity, this prediction model does not meet the clinical standards set by Dr. Bariciak.

**Table 4.9:** noMOD\_TWINGEST decision tree results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | DT# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1790 | | 0.9950 | | 0.8788 | | 0.8562 | | |  | | --- | | 0.1242 | | 0.9925 | | 0.7692 | | 0.8484 | | |  | | --- | | 0.1667 | | 0.9950 | | 0.8710 | | 0.8544 | | |  | | --- | | 0.1801 | | 0.9925 | | 0.8286 | | 0.8567 | | |  | | --- | | 0.1296 | | 0.9899 | | 0.7241 | | 0.8482 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1242 | | 0.9925 | | 0.7692 | | 0.8484 | | |  | | --- | | 0.1790 | | 0.9950 | | 0.8788 | | 0.8562 | | |  | | --- | | 0.1988 | | 0.9887 | | 0.7805 | | 0.8590 | | |  | | --- | | 0.1235 | | 0.9950 | | 0.8333 | | 0.8480 | | |  | | --- | | 0.1739 | | 0.9975 | | 0.9333 | | 0.8564 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1739 | | 0.9975 | | 0.9333 | | 0.8564 | | |  | | --- | | 0.1852 | | 0.9937 | | 0.8571 | | 0.8570 | | |  | | --- | | 0.1429 | | 0.9937 | | 0.8214 | | 0.8513 | | |  | | --- | | 0.1543 | | 0.9962 | | 0.8929 | | 0.8527 | | |  | | --- | | 0.1491 | | 0.9912 | | 0.7742 | | 0.8519 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1296 | | 0.9899 | | 0.7241 | | 0.8482 | | |  | | --- | | 0.1180 | | 0.9937 | | 0.7917 | | 0.8476 | | |  | | --- | | 0.1914 | | 0.9912 | | 0.8158 | | 0.8576 | | |  | | --- | | 0.1491 | | 0.9912 | | 0.7742 | | 0.8519 | | |  | | --- | | 0.1543 | | 0.9962 | | 0.8929 | | 0.8527 | |

**4.1.2.2 MOD\_TWINGEST DT RESULTS**

The attribute(s) with nominal values grouped were TWINGEST, MATAGE, PPRETERM, PTERM and PARITY. Out of the 21 input attributes, the C5.0 algorithm used 5-13 attributes to generate the DTs. The most contributing factor in predicting preterm birth in twin pregnancies was SMOKING. The resulting average test sensitivity was 79.325.85% and the average test specificity was 91.971.20%. The sensitivity and specificity during training was much higher at TR\_sensitivity of 91.02% and TR\_specificity of 95.12%. The correct classification rate or accuracy was 90.161.42%. The PPV and NPV were 67.693.17% and 91.971.20%, respectively. The MOD\_NEONATALMORT prediction model is clinically acceptable since the average test sensitivity and specificity exceeds 65% and 80%, respectively, as determined by Dr. Bariciak.

**Table 4.10:** MOD\_TWINGEST decision tree results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | DT# | 1a | 1b | 2a | 2b | 3a |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.9444 | | 0.9611 | | 0.8315 | | 0.9884 | | |  | | --- | | 0.9068 | | 0.9421 | | 0.7604 | | 0.9804 | | |  | | --- | | 0.8765 | | 0.9623 | | 0.8256 | | 0.9746 | | |  | | --- | | 0.8696 | | 0.9572 | | 0.8046 | | 0.9731 | | |  | | --- | | 0.9753 | | 0.9284 | | 0.7349 | | 0.9946 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.7578 | | 0.9119 | | 0.6354 | | 0.9490 | | |  | | --- | | 0.7840 | | 0.9372 | | 0.7175 | | 0.9552 | | |  | | --- | | 0.7578 | | 0.9321 | | 0.6932 | | 0.9500 | | |  | | --- | | 0.7654 | | 0.9221 | | 0.6667 | | 0.9508 | | |  | | --- | | 0.9753 | | 0.9284 | | 0.7349 | | 0.9946 | |
|  |  | 3b | 4a | 4b | 5a | 5b |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.8820 | | 0.9421 | | 0.7553 | | 0.9753 | | |  | | --- | | 0.9321 | | 0.9573 | | 0.8162 | | 0.9858 | | |  | | --- | | 0.8944 | | 0.9497 | | 0.7826 | | 0.9780 | | |  | | --- | | 0.9198 | | 0.9510 | | 0.7926 | | 0.9831 | | |  | | --- | | 0.9006 | | 0.9610 | | 0.8239 | | 0.9795 | |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.7963 | | 0.9158 | | 0.6582 | | 0.9567 | | |  | | --- | | 0.8447 | | 0.9170 | | 0.6733 | | 0.9668 | | |  | | --- | | 0.7963 | | 0.9095 | | 0.6418 | | 0.9564 | | |  | | --- | | 0.7081 | | 0.9346 | | 0.6867 | | 0.9405 | | |  | | --- | | 0.7963 | | 0.9171 | | 0.6615 | | 0.9567 | |

**4.1.2.3 COMPARING BEST PERFORMING nOMOD\_TWINGEST VS. MOD\_TWINGEST**

The best performing DT for noMOD\_TWINGEST and MOD\_TWINGEST prediction is presented in table 4.7. The best performing DT classifier for the noMOD\_TWINGEST set was case 2a and MOD\_TWINGEST set was case 3a. The best performing set for MOD\_TWINGEST showed higher sensitivity and NPV compared to the noMOD\_TWINGEST set with an increase of 0.7267 and 0.1245 respectively, whereas the specificity and PPV values were slightly lower by 0.0893 and 0.1298, respectively. When evaluating the best performing sets overall in terms of sensitivity, specificity, PPV and NPV, the noMOD\_TWINGEST set does not meet the clinical standards since the resulting sensitivity is much lower than the acceptable rate of 65%.

**Table 4.11:** Best performing noMOD\_TWINGEST vs MOD\_TWINGEST

|  |  |  |  |
| --- | --- | --- | --- |
| Node |  | 2a | 3a |
|  |  | noMOD | MOD |
| Test | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1988 | | 0.9887 | | 0.7805 | | 0.8590 | | |  | | --- | | 0.9255 | | 0.8994 | | 0.6507 | | 0.9835 | |
| Train | Sensitivity  Specificity  PPV  NPV | |  | | --- | | 0.1667 | | 0.9950 | | 0.8710 | | 0.8544 | | |  | | --- | | 0.9753 | | 0.9284 | | 0.7349 | | 0.9946 | |

Further based on the average test sensitivity and average test specificity, the noMOD\_TWINGEST model did not meet clinical expectations. The average test sensitivity of the noMOD\_TWINGEST set was 15.433.01% which is much lower than the clinical standards, while the average test specificity remained high at 99.310.29%. Thus the only clinically acceptable model is the MOD\_TWINGEST set with an average test sensitivity and specificity of 79.325.85% and 91.971.20%, respectively.

**4.1.2.4 COMPARING PPV AND NPV OF nOMOD\_TWINGEST VS. MOD\_TWINGEST**

The average PPV and NPV for noMOD\_TWINGEST and MOD\_TWINGEST are presented in table 4.12. Although the PPV and NPV for the noMOD\_TWINGEST case were high, further examination of the high PPV indicates that it is due the high test specificity (99.310.29%) accompanied by a poor test sensitivity (15.433.01%), therefore the PPV in this case is not reliable. Additionally, although the PPV for the MOD\_TWINGEST case is low at 67.693.17%, this is still higher compared to the previous work of N.Yu which resulted in 43.93%. Further, upon analyzing the equation to calculate these predicative values reveals that these values are directly associated to prevalence, and therefore since both the sensitivity and specificity were high in the MOD\_TWINGEST case and the prevalene was low, this will result in a low PPV. It is also important to note that a high PPV does not necessarily indicate an accurate prediction. This can be noted in many classifiers with a high PPV but low sensitivity, including the results obtained in the noMOD\_TWINGEST case. Therefore, the PPV and NPV values alone should not be used to evaluate a classifier. Although these values can be used to obtain a good direct accuracy of a classifier, it may also be subject to a poor sensitivity value due to low prevalence. However the MOD\_TWINGEST case shows consistency in the NPVs and PPVs between each trial and is accompanied by a high sensitivity and specificity which exceed clinical expectations.

**Table 4.12:** Comparing PPV and NPV of noMOD\_TWINGEST vs MOD\_TWINGEST

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | noMOD | MOD |
| Test | PPV  NPV | |  | | --- | | 0.8194 | | 0.8526 | | |  | | --- | | 0.6685 | | 0.9566 | |
| Train | PPV  NPV | |  | | --- | | 0.8351 | | 0.8533 | | |  | | --- | | 0.7928 | | 0.9813 | |

**4.1.2.5 PREDICTING PTB IN TWIN GESTATION DISCUSSION**

The preprocessed C5.0 based DT model for predicting preterm birth in twin pregnancies non-invasively before 22 weeks gestation was able to achieve higher sensitivity and specificity than any other work in literature to our knowledge. The MOD\_TWINGEST set achieved an average test sensitivity and specificity of 81.014.66% and 91.550.03%, respectively. This was achieved using only 21 attributes. The results exceed the clinical expectation set out by Dr. Bariciak.

Previous similar work for predicting preterm birth in twin pregnancies included invasive methods, and only produced clinically acceptable predictions much later in the gestational period (section 2.2.4). Even though the scope of the previous work conducted by the MIRG group was different, the sensitivity and specificity exceeded those of previous work conducted by the MIRG group. C. Catley focused on predicting high-risk preterm birth in parous women using a 48 variable model and an integrated hybrid system which achieved a sensitivity of 65% and a specificity of 84% with an AUC of 0.80. N.Yu’s work focused on both parous and nulliparous women to predict high-risk preterm birth using an integration of decision trees and classification ANN with weight elimination and risk stratification using 19 variables. This model resulted in a test sensitivity of 65.13% and a test specificity of 84.07% for parous cases with an AUC of 0.8195. However the prediction model for nulliparous cases did not meet the clinical expectations and required further examination.

This is the first attempt at creating a prediction model for predicting preterm birth in a high risk population of twin pregnancies including both parous and nulliparous cases within the MIRG team. Many aspects of this model make this prediction model ideal. This classifier required only 21 attributes to be collected by the user. This is a great reduction in variables compared to Catley’s 48-variable model, and this is considered to be a great advantage when designing perinatal decision support systems as it greatly reduces the complexity. Further, Catley’s work was largely based upon US specific variables, and thus required these variables in order to maintain the sensitivity and specificity. N.Yu’s work only required 19 variables in parous cases and 16 for nulliparous cases, however her work included key variables (‘maternal bleeding’ and ‘previous low birth weight’) that are not captured in Ontario’s BORN nor Niday database. Therefore this is the first prediction model for PTB in twin pregnancies that are specific to Ontario. However it may be further applied as a generalized North American Model.

The PPVs and NPVs provide direct diagnostic meaning to the physicians. Current methods for predicting preterm birth in twin pregnancies which meet clinical standards include cervical length (CL) and fetal fibronectin (fFN). Both these methods are invasive, and in many cases, these methods are only able to provide clinical satisfactory predictions much later in the gestational cycle. The non-invasive prediction model presented in this thesis for predicting preterm birth in twin pregnancies not only exceeds the clinical standards, but it is also resulted in the highest average test sensitivity, specificity, PPV, NPV and AUC of 80.0%14.66%, 91.55%0.03%, 67.35%4.36%, 95.79% and 0.8129, respectively in literature. The best indicator to predicting preterm birth was ‘smoking’, followed by ‘maternal substance abuse’ and ‘previous preterm birth’.

**4.1.3 SINGLETON DATASET**

A total of 140 575 test cases were evaluated on 125 000 term and 15 575 preterm births. A total 20 attributes were used including MATAGE, PPRETERM, PTERM, PARITY, PREVCS, GENDER, INTBF, SMOKING, MATHP0, MATHP3, MATHP4, MATHP18, MATHP27, REPASS, FIRSTVIS, PRENCLAS, LANGUAGE\_up, MATHP\_sub, and Diagnosis. The prevalence of the dataset was 12.46%.

**4.1.3.1 noMOD\_SINGLETON DT RESULT**

Out of the 20 input attributes, the C5.0 algorithm used between 16-19 attributes to generate the DTs. The most common attributes among all sets were MATH27, INTBF, LANGUAGE\_up, MATHP3, MATHP4, MATAGE, PRENCLASS, GENDER, SMOKING, PPRETERM, REPASS, MATHP0 and FIRSTVIS. The most contributing attribute was MATH27 followed by MATH3 and INTBF. The resulting average test sensitivity and specificity were 11.631.58% and 74.215.36%, respectively. The sensitivity and specificity during training was slightly higher at TR\_sensitivity of 14.97% and TR\_specificity of 99.71%. The correct classification rate or accuracy was 67.274.62%. The PPV and NPR were 5.430.74% and 87.080.62%, respectively**.** The noMOD\_SINGLETON model is not acceptable, since both the sensitivity and specificity are much lower than the clinical standards.

**4.1.3.2 MOD\_SINGLETON DT RESULT**

The attributes with the nominal values grouped were MATAGE, PPRETERM, PTERM and PARITY. Out of the 20 input attributes, the C5.0 algorithm used between 18-19 attributes generate the DTs. The attributes that were common among all sets included MATH\_sub, INTBF, LANGUAGE\_up, PPRETERM, MATHP3, MATHP4, FIRSTVIS, GENDER, MATAGE, MATHP0, PRENCLAS, PREVCS, SMOKING, PTERM, PARITY, MATHP27, REPASS, and MATHP\_ment. The most contributing factor was MATH\_SUB in predicting preterm birth. The resulting average test sensitivity was higher compared to noMOD\_Singleton at 35.574.70%, however the average test specificity dropped significantly in comparison to 27.193.63%. The sensitivity and specificity during training was higher at TR\_sensitivity of 43.84% and TR\_specificity of 98.88%. The correct classification rate or accuracy was 28.132.95% andthe error rate was 71.872.95%. The PPV and NPV were 5.760.62% and 76.93, respectively. The MOD\_SINGLETON model is not acceptable, since both the sensitivity and specificity are much lower than the clinical standards.

**4.1.3.3 PREDICTING PTB IN SINGLETON DISCUSSION**

The noMOD\_Singleton and MOD\_Singleton DT prediction models did not produce clinical satisfactory results for predicting preterm birth in singletons. This was expected, in previous work to predict preterm birth in parous and nulliparous women including singleton and twins gestations, the key identifying variables in C.Catley’s work for parous women were ‘maternal bleeding’, followed by ‘plurality’ and ‘previous preterm birth’. N.Yu’s work coincided with these findings, for parous cases, all decision trees used ‘maternal bleeding’, ‘plurality’ and ‘previous preterm birth’. ‘Plurality’ and ‘previous preterm birth’ was not applicable in the nulliparous case. Further another variable that ranked highest on the contributing factors was ‘previous low birth weight’, which again was not applicable in the nulliparous case. In both the Niday and BORN database, the only key identifying variables included were ‘previous preterm birth’ and ‘plurality’, both ‘maternal bleeding’ and ‘previous low birth weight’ were not included in the BORN nor NIDAY database. All four variables above were linked as strong indicators in the prediction of preterm birth, therefore the poorer accuracy and discrimination ability of the singleton model could be attributed to this factor.

**4.2 PERINATAL DECISION SUPPORT SYSTEM (PEDSS) PROTOTYPE RESULTS**

**4.2.1 PLATFORM SELECTION**

**4.2.1.1 INTRODUCTION TO SHAREPOINT 2010 CONTENT MANAGEMENT SYSTEM**

The Microsoft based SharePoint platform provides an appealing and secure user friendly graphical interface, and when correctly implemented it can be both PIA (Privacy Impact Assessment) and TRA (Threat-Risk Assessment) approved, permitting the entry of patient sensitive information. Many of the health service providers in the Champlain region are already utilizing a SharePoint based platform. The SharePoint platform allows for rapid development and deployment of secure applications that enable the exchange of electronic submissions, digital workflow, and secured information storage. The SharePoint space can be tailored to meet the needs of a specific user by altering simple, easily maintained rule sets. The functionality of the SharePoint framework can be extended to meet hospital specific requirements through the use of custom developed components or using commercial off-the-shelf software.

The SharePoint space also supports role based access (RBAC) where in order to access the system, the user must enter a unique user identification and password. Session timeouts after a pre-set period of inactivation, as well as audit trail with an electronic signature and date-time stamp can also be incorporated.

* + - 1. **SYSTEM COMPONENT SELECTION**

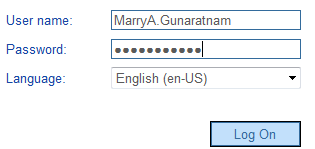
Table 4.13 below provides commercially available Microsoft based components to build web based PEDSS. It is important to choose Microsoft based components in order to be compatible with the existing infrastructure. The current See5 program executes on a Microsoft Excel document and the CBRS tool uses a Microsoft Access database. Further, Microsoft is one of the largest and most influential corporations in the computer industry, where many organizations have standardized to Microsoft based programming tools, end-user application and operating systems.

**Table 4.13** Components for a web-based PEDSS

|  |  |  |
| --- | --- | --- |
| Components to Build a Web-based PEDSS | |  |
| Components | Commercially Available | Microsoft Based |
| Authentication Server | Microsoft Forefront Unified Access Gateway 2010 | Yes |
| Content Management System | SharePoint 2007/2010 | Yes |
| Workflow Engine | Nintex Workflows 2007/2010 | Yes |
| External Data Source | SQL Database 2008/2008 R2 | Yes |
| Directories | Active Directory 2003/2008 | Yes |
| Other Web Servers | Windows Server 2012, Web Front End, Development, Virtual Servers | Yes |
| ASP.Net, XML, HTML | Microsoft InfoPath 2007/2010 | Yes |

**4.2.2 PROTOTYPE OVERVIEW**

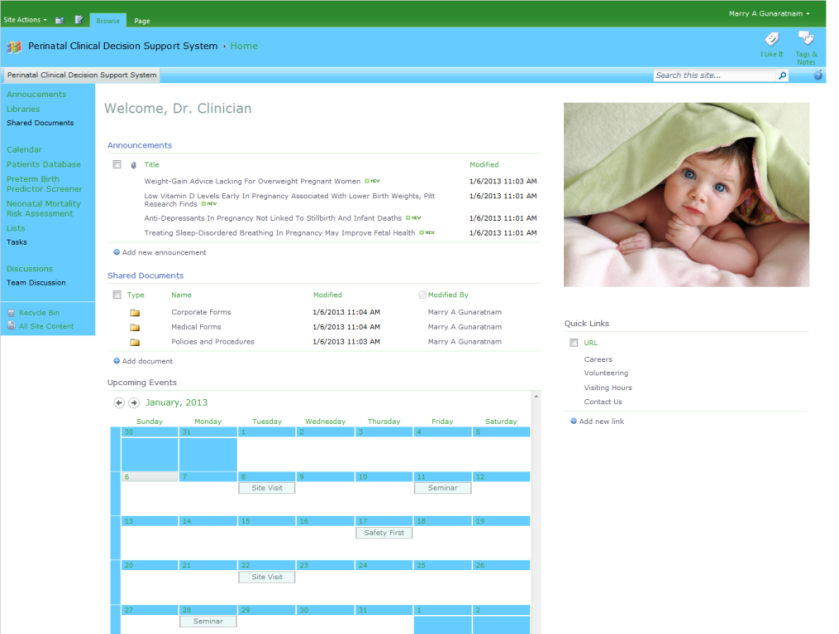
Advanced features of the content management system were utilized to develop the PEDSS tool including **audience targeting, where filters were set up for the varying user groups. All groups of users will access the tool using the same Uniform Resource Locator (URL). Based on the role of the user logged in, the user is presented with filtered views on what is relevant to them. Upon logging in, the user will be required submit a set of credentials: username and password. The login screen for the PEDDS tools is presented below in Figure 4.1.**



**Figure 4.1 Log-in screen to PEDSS**

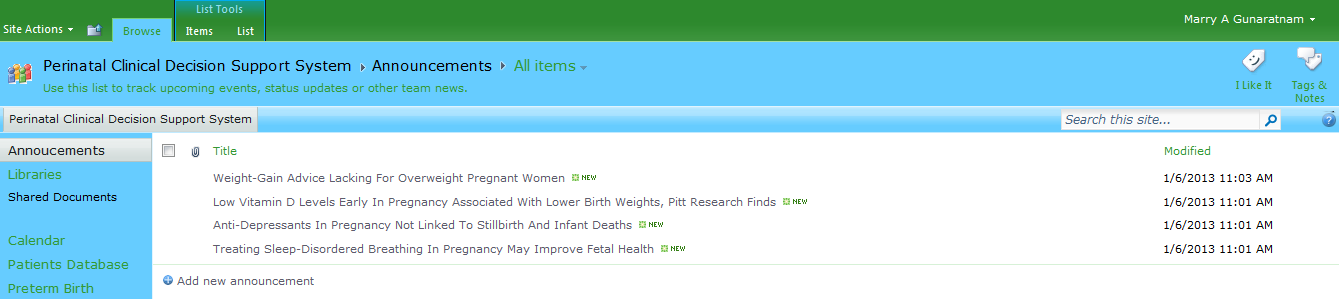
**4.2.2.1CLINICIAN’S TOOL**

**The clinician tool homepage delivers all content relevant to the clinician. A snapshot of the clinical tool homepage is presented in Figure 4.2. The clinician has permissions to add/edit and view content on PEDSS. The clinician’s home page consists of an announcements section, a shared calendar of upcoming events, a shared discussion board, a shared documents repository, a patient database, and the perinatal clinical decision support tools: (1) Neonatal Mortality Risk Assessment and (2) Preterm Birth Predictor in Twins Pregnancies.**



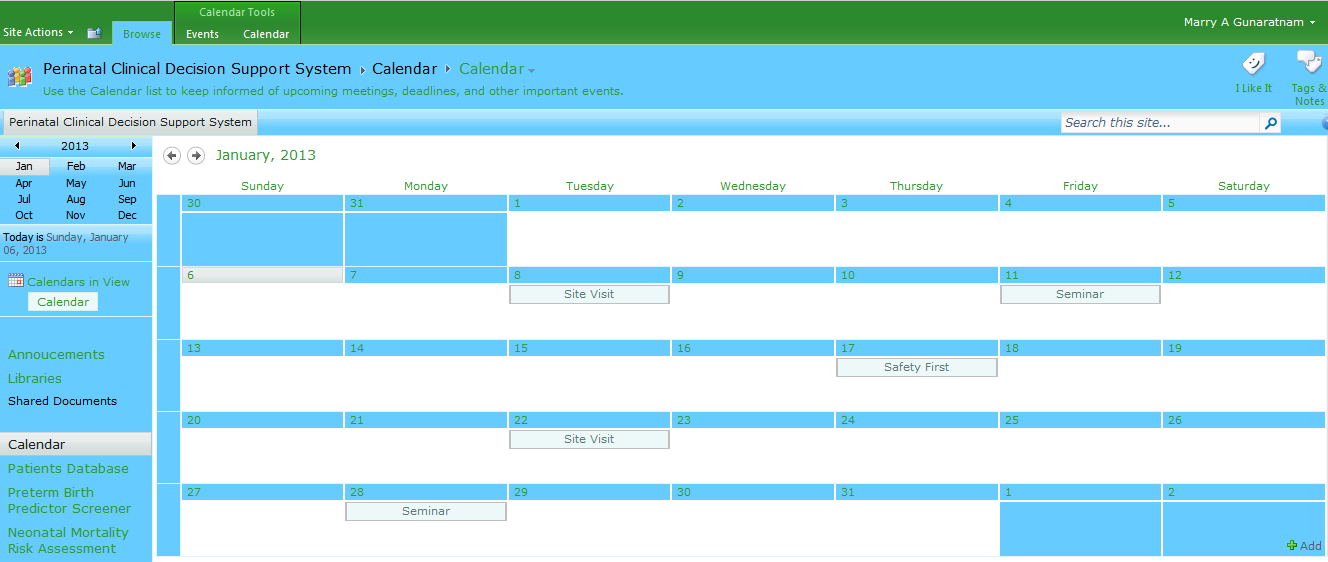
**Figure 4.2 PEDSS Homepage**

**The announcement section contains alerts and reminders relevant to the clinician user community. The clinician may add new announcements.**



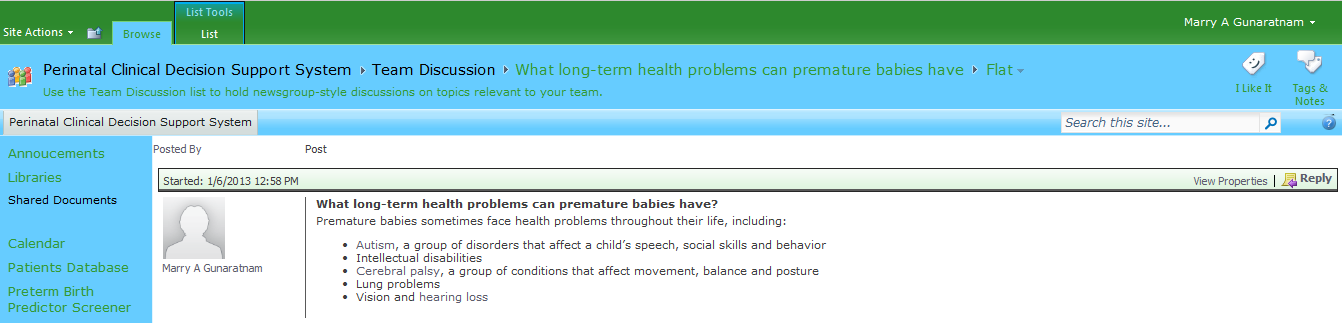
**Figure 4.3 PEDSS Announcement Section**

**The shared calendar is used to post any relevant information seminar or events of interest to the clinicians. The clinicians may add new events.**



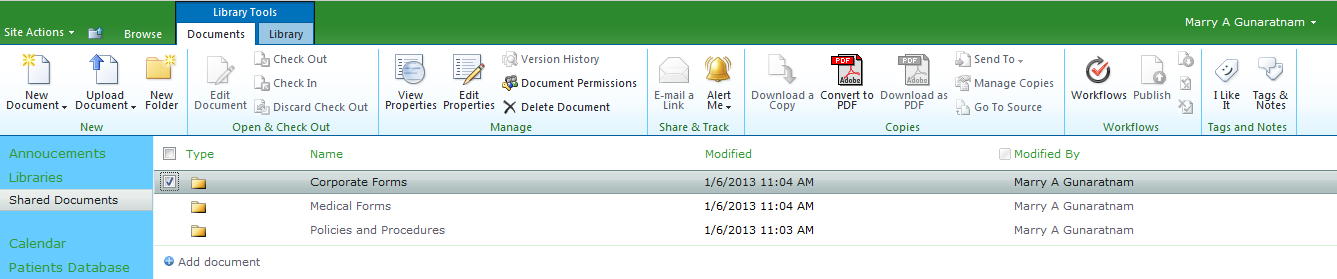
**Figure 4.4 PEDSS Shared Calendar Section**

**The shared discussion board is used to posts any discussion topics which may be relevant to the clinicians. The clinicians may use this to collaborate and gather feedback from other clinicians. The clinicians may add new discussion topics.**



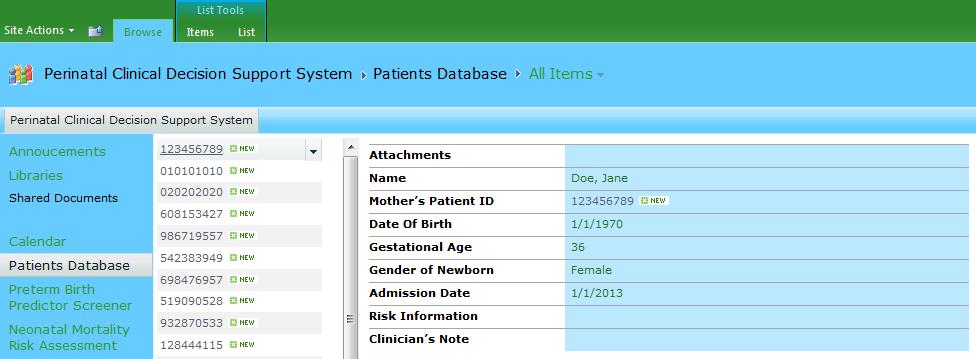
**Figure 4.5 PEDSS Discussion Board Section**

**The shared document repository contains files and folders relevant to the clinicians. Clinician’s may add, edit or delete documentation. The metadata of the following is captured: Title, Created By, Created, Modified By, and Modified.**

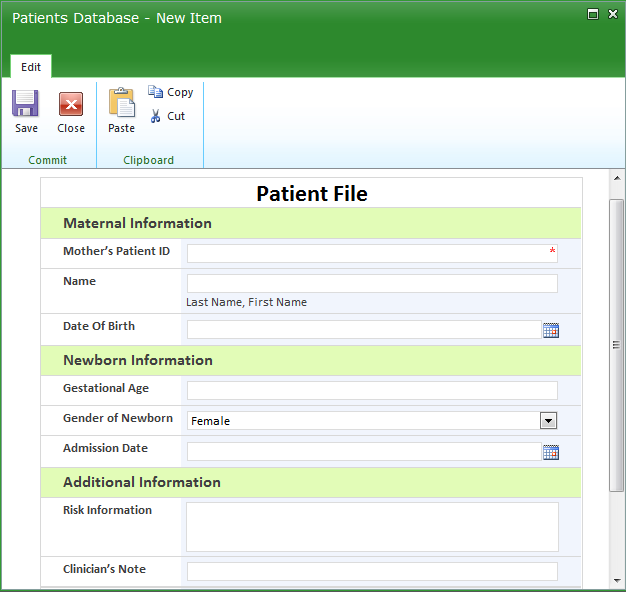


**Figure 4.6 PEDSS Shared Document Repository**

**The patient’s database contains the patient files in ascending order as shown in figure 4.7. Each patient file contains the mother’s patient ID, name, date of birth, gestational age, gender of newborn, admission date, and risk information of important outcomes including risk of preterm birth in twin pregnancies, and if applicable, risk of neonatal mortality and any relevant patient documentation. The patient file also includes a free-text clinician’s note section, where clinicians’ can write a notation specific to the patient. The patient file form was created using InfoPath 2010 and was web-enabled and published to the SharePoint environment. This form is shown in figure 4.8.**



**Figure 4.7 PEDSS Patient Database**

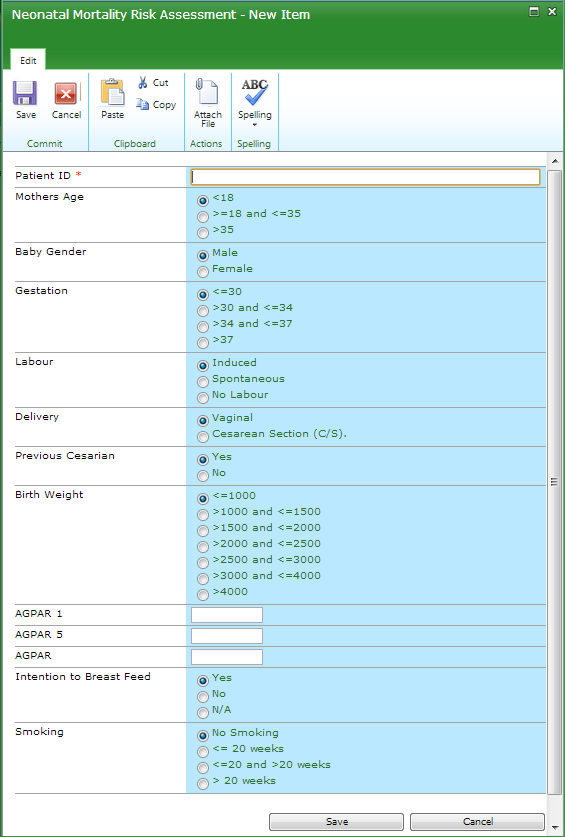


**Figure 4.8 Electronic Patient File**

There are two perinatal clinical decision support tools available to clinicians, including the **Neonatal Mortality Risk Assessment and Preterm Birth Predictor, as follows.**

**NEONATAL MORTALITY RISK ASSESSMENT**

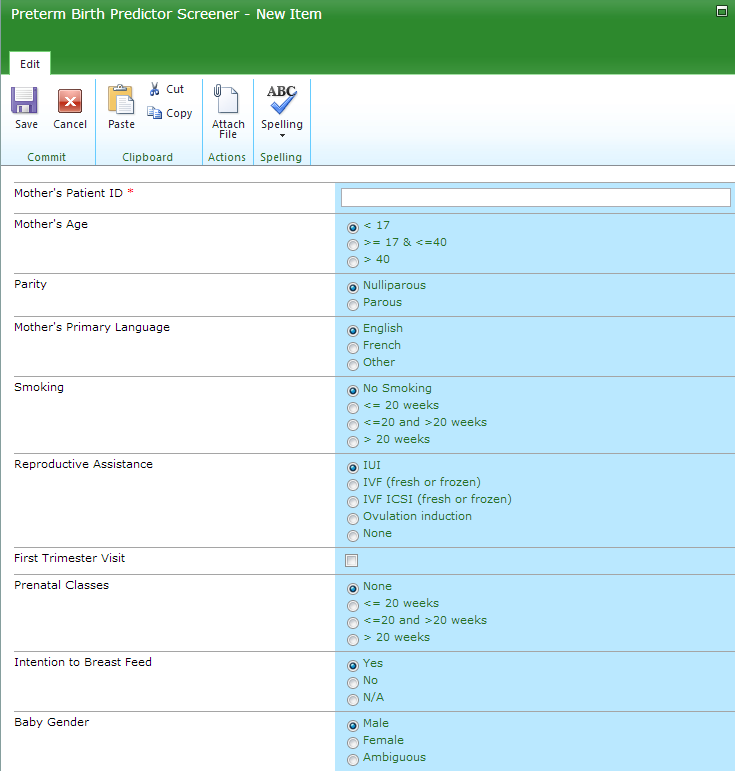
**The neonatal mortality risk assessment tool consists of a series of assessment criteria to evaluate the newborn at 10 minutes. All fields are mandatory; however certain fields may be answered as N/A if not applicable. The screener form is shown in figure 4.9.**

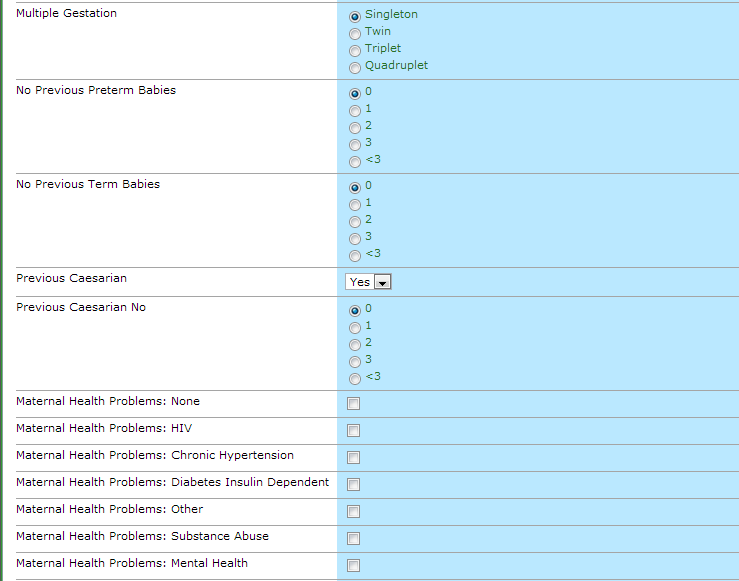


**Figure 4.9 Neonatal Mortality Risk Assessment Form**

**PRETERM BIRTH PREDICTOR IN TWINS PREGNANCIES**

**The preterm birth predictor tool consists of a series of questions for the mother pregnant with twins. All fields are mandatory; however certain fields may be answered as N/A if not applicable. The screener form is shown in figure 4.10:**





**Figure 4.10 Risk of Preterm Birth Prediction in Twins Pregnancy Form**

**Once all questions have been answered, the clinician can submit the form. A workflow is then initiated, and an outcome prediction is produced. The workflow is generated from the original C5.0 based decision tree. A sample diagram of a simple C5.0 generated decision tree is given below.**

AGPAR 5 in {3,4,5,6,7,8,9,10}: Not Applicable (16479.6/22)

AGPAR 5 = 0:

:...AGPAR 1 in {2,3,4,5,6,7,10}: Neonatal Death (0)

: AGPAR 1 in {0,1}: Neonatal Death (70.2/0.2)

: AGPAR 1 in {8,9}: Not Applicable (3)

AGPAR 5 = 2:

:...Birth Weight in {<=1000,>1500 and <=2000}: Neonatal Death (11/3)

: Birth Weight in {>1000 and <=1500,>2000 and <=2500,>2500 and <=3000, >3000 and <=4000,>4000}: Not Applicable (17.1/1)

AGPAR 5 = 1:

:...Gestation in {>30 and <=34,>37}: Not Applicable (3)

Gestation = >34 and <=37: Neonatal Death (2)

Gestation = <=30:

:...Delivery = Vaginal: Neonatal Death (4)

Delivery = Cesarean Section (C/S): Not Applicable (2)

**The decision tree can easily be** expressed as a set of nested if-statements as follows:

if (AGPAR 5 == (3 OR 4 OR 5 OR 6 OR 7 OR 8 OR 9 OR 10))

return Not Applicable;

if (AGPAR 5 == 0)

{

if (AGPAR 1== (2 OR 3 OR 4 OR 5 6 OR 7 OR 10))

return Neonatal Death;

if (AGPAR 1== (0 OR 1))

return Neonatal Death;

if (AGPAR 1== (8 OR 9))

return Not Applicable

}

if (AGPAR 5 == 2)

{

if (Birth Weight <=1000 OR >1500 OR <=2000))

return Neonatal Death;

if (Birth Weight >1000 OR <=1500 OR >2000 OR <=2500 OR >2500 OR

<=3000 OR >3000 OR <=4000 OR >4000))

return Not Applicable;

}

if (AGPAR 5 == 1)

{

if (Gestation >30 OR <=34 OR >37))

return Not Applicable;

if (Gestation >34 OR <=37))

return Neonatal Death;

if (Gestation <=30)

if (Delivery == Vaginal))

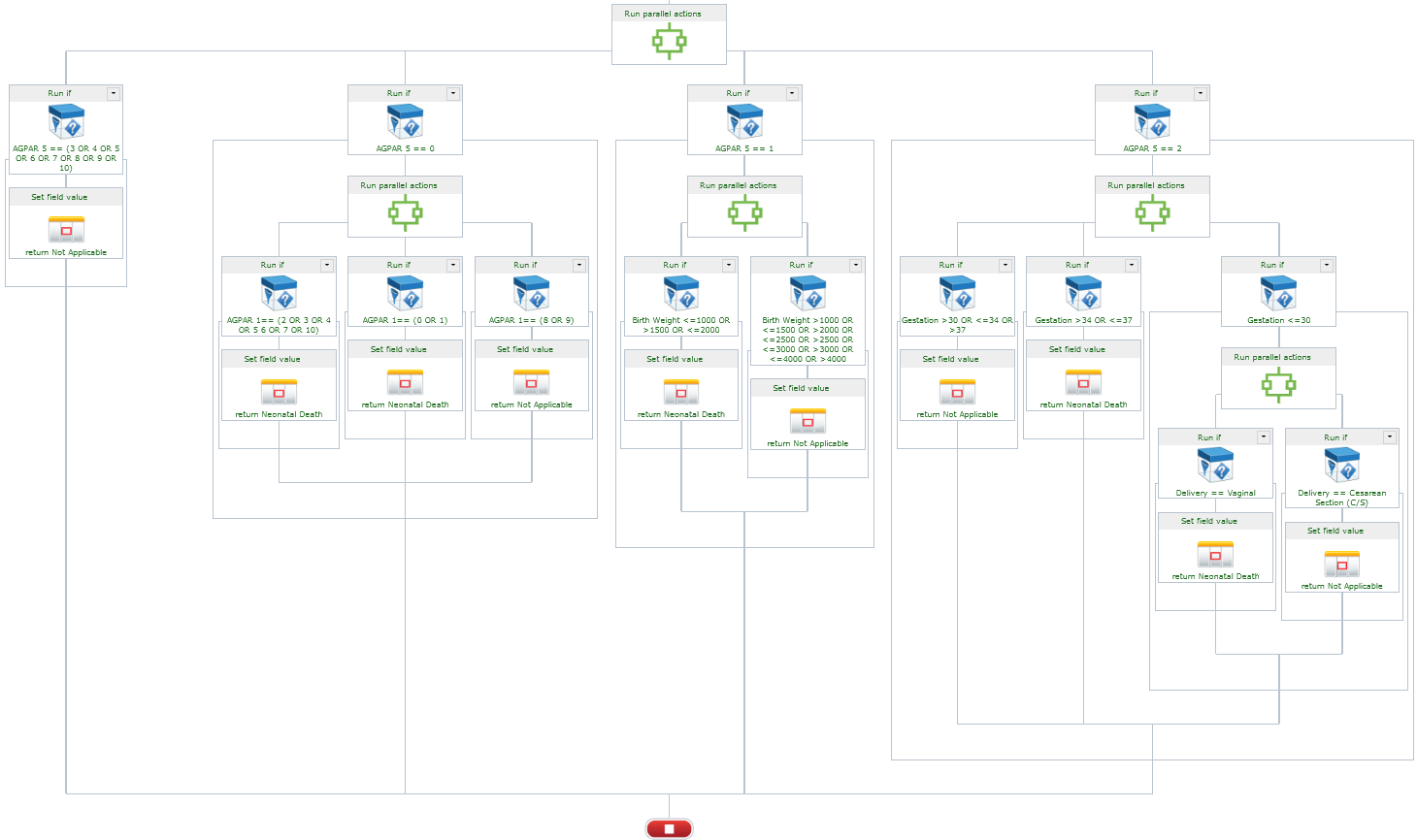
return Neonatal Death;

if (Delivery == Cesarean Section (C/S)))

return Not Applicable;

}

**The nested if statements are used to create the workflow using Nintex. Nintex is a powerful workflow designer add-on to SharePoint. Nintex allows for drag-and-drop functionality, eliminating the need to code. It also integrates to Visual Studio permitting custom actions.** Figure 4.11 shows the associated Nintex workflow for the DT presented above. The completed workflow is then published to the SharePoint environment.

****

**Figure 4.11 Workflow Diagram Using Nintex Workflows 2010**

**In the case of neonatal mortality, a decision tree was generated at each trial, and a total 10 trials were executed in the MOD\_NEONATALMORT set, thus resulting in 10 decision trees. A workflow is created for every DT, therefore resulting in 10 workflows. An additional workflow is required to predict high vs low risk of the outcome. The additional workflow is set up to produce the final outcome based on voting. If <=2 workflows resulted in neonatal death, this is marked as ‘LOW RISK’, if >2 and <7 workflows resulted in neonatal death, this is marked as ‘MODERATE RISK’ and if >=7 workflows resulted in neonatal death, this is marked as ‘HIGH RISK’. Thus, a total of (#of DTs) + 1 workflows are published, which in this case equates to 10+1=11 workflows.**

**The outcome prediction will assist clinicians and the parents in the decision making process if a patient is at high risk for any of the conditions screened. A screenshot of the outcome predictions is shown in figure 4.12.**



**Figure 4.12 Prediction Outcome Notification Message**

**In the case where a neonate has been assessed as being at high risk of neonatal mortality, one of the most difficult decisions is deciding on a change in direction of care. In this case, S.Weyand’s decision tool may be used. S.Weyand’s work included a decision support instrument in order to aid the decision making regarding change in the direction of care. S.Weyand’s decision support tool consisted of 6 steps which address various aspects of the decision that would need to be made and provides information about various options including the pros and cons of each option. It is important to note that the decision support tool is used to inform parents and physicians, assist in the decision making process by organizing decisional information, determine the information required for the decision making and bring to attention any additional information which may be required for the decision to be made. Thus it does not make the decision or produce a finalized conclusion.**

**CHAPTER 5 CONCLUDING REMARKS, CONTRIBUTING KNOWLEDGE AND FUTURE WORK**

**5.1 CONCLUSION**

An improved classification method has been derived to improve the prediction of two distinct medical problems non-invasively: neonatal mortality with information available at 10 minutes from birth and preterm birth in twin pregnancies before 22 weeks. As for the next step, in order to bring the derived classification model to clinical use in an obstetrical environment, a prototype for a secure web-based Perinatal Decision Support System (PEDSS) to assist the clinicians and parents in predicting the likelihood of neonatal mortality and preterm labour in twin pregnancies was presented. In the process of resolving the current issues, this thesis work has raised questions that require further assessment. This is discussed in the conclusion, contributing knowledge and future work sections of this chapter.

**5.1.1 ACCOMPLISHING PRELIMINARY OBJECTIVES**

The first objective of this thesis was to assess varying data mining methods with an aim to improve the classification of neonatal mortality and preterm birth in twin pregnancies. Various models were analyzed including decision trees (DTs) and hybrid ANN to see which produced better outcomes. In order to accomplish the first objective, an improved data processing step was introduced in the DT model. Concluding from the first objective, it was found that the data processing method introduced in this thesis work may be applied to many other multi-factorial medical problems to improve its classification. The new approach has provided several improvements to better predict medical problems. This thesis work has established the following:

1. Pre-processed datasets run against C5.0 algorithm produced decision trees superior to the DT-ANN hybrid method. This was shown in the increased discrimination, and accuracy of the C5.0 based method. This method should be examined as a potential principle method for future research work.
2. Created a neonatal mortality prediction system for newborn to be assessed with data available from the first 10 minutes from birth non-invasively with excellent discrimination, exceeding the results of current standard predictions. This screener tool may be used as alternative to costly and invasive methods.
3. Created a preterm birth prediction system for a high risk population (for women pregnant with twins) non-invasively before 22 weeks gestation with excellent discrimination, exceeding the results of current standard predictions. The high risk population identified is likely subject to costly and invasive screening methods (CL and fFN). This screener tool may be used as an alternative to such methods.
4. The previous neonatal prediction method only focused on newborns after admission to NICU. This is the first attempt at predicting neonatal mortality in a heterogeneous population with data available at 10 minutes from birth. To eliminate cases where neonates didn’t survive prior to 10 minutes, the cases with AGPAR 10 score <1 were removed.
5. The prediction of preterm birth in women pregnant twins included both parous and nulliparous mothers with data available before 22 weeks gestation. The resulting performance outcome was better than all previous similar studies in literature. Previous work conducted by the MIRG focused on parous and nulliparous mothers, where results for nulliparous women indicated poorer performance results compared to parous cases.
6. Preliminary results of women pregnant with singleton were poor compared women pregnant with twins. This was expected due to limited variables in both the Niday and BORN database. Both ‘maternal bleeding’ and ‘previous low birth weight’ were not included in the BORN nor did the NIDAY databases, the only key identifying variables included ‘previous preterm birth’ and ‘plurality. All four variables above were linked as strong indicators in the prediction of preterm birth, therefore the poorer accuracy and discrimination ability of the singleton model could be attributed to this factor.
7. Several improvements were made compared to past models: For the neonatal mortality case, the prediction of neonatal mortality non-invasively was reduced to data available at 10 minutes from birth using only 13 attributes, whereas the previous models required up to 12 hours from birth using 3 variables derived from invasive methods. The ability to predict preterm birth in twin pregnancies was extended to include both parous and nulliparous cases and was reduced to 22 weeks using only 21 attributes. Whereas previous prediction models predicted preterm birth in parous women pregnant with twins using 19 attributes at 23 weeks gestation with much lower sensitivity and specificity.
8. The needs for improved data pre-processing steps were emphasized: nominal inputs with many variables were grouped as appropriate according to literature to prevent spurious splits of decision trees. As an example, in the case of maternal age, in literature studies suggest that women <18 and >40 are at high risk of preterm birth. Therefore maternal age was grouped into three distinct groups: <18, >=18 and <=40 and >40. Attribute(s) with nominal values grouped improved the performance outcomes in all case. In terms of neonatal mortality, both the test average sensitivity and specificity in the neonatal mortality hybrid ANN case were higher in the MOD\_NEONATAL hybrid ANN case with 60.740.59% and 90.300.65%, respectively, compared to the noMOD\_NEONATAL hybrid ANN case of 21.8512.97% and 86.5510.83%, respectively. Improved sensitivity was also observed in the neonatal mortality DT case, where the noMOD\_NEONATALMORT DT case had an average test sensitivity of 57.176.84% and the MOD\_NEONATALMORT DT case increased to 62.243.28%, this was accompanied by a slight decrease in the average test specificity from 99.980.01% in noMOD\_NEONATALMORT DT case to 99.950.03% in MOD\_NEONATALMORT DT case. The average test sensitivity in the MOD\_TWINGEST DT case increased to 79.525.85% from 15.433.01% in the noMOD\_TWINGEST DT case, though this was accompanied by a slight decrease in average test specificity from 99.310.29% in the noMOD\_TWINGEST DT case to 91.971.20% in the MOD\_TWINGEST DT case. However, the specificity still exceeds clinical expectations.
9. The model not only performed better compared to previous methods, but it also verified well on new cases. This was achieved using 5-by-2 cross validation. This indicates that the system is not over trained and provides good generalization.

The second objective of the thesis was to derive a conceptual framework and prototype a secure web-based Perinatal Decision Support System (PEDSS). A method was developed to convert the resulting C5.0 decision tree to commercial code. This thesis work is the first to present a prototype for a secure commercial off-the-shelf solution that could be used to predict neonatal mortality 10 minutes from birth and preterm birth in twin pregnancies before 22 weeks gestation. This framework may be extended for other medical problem(s) in a perinatal environment. This thesis work has established the following:

1. A conceptual framework for a secure web-based Perinatal Decision Support System (PEDSS) was presented which provides audience targeted information and risk prediction of neonatal mortality and preterm birth in twin pregnancies.

2. A four step process for developing the framework of a Perinatal Decision Support System (PEDSS) was presented. The first step is the identifying the platform, the second step is identifying system composition including hardware/software and communication architecture, the third step is system integration, and fourth step is knowledge maintenance.

3. A high level overview of commercially available components to build a complete secure web-based perinatal decision support system is proposed, and a prototype was developed. When properly implemented, this system shall be both PIA (Privacy Impact Assessment) and TRA (Threat Risk Assessment) approved permitting the entry of patient sensitive information.

4. A web based prototype of a screener tool for non-invasively identifying the risk of neonatal mortality with data available 10 minutes from birth and preterm birth in twin pregnancies prior to 22 weeks gestation was presented.

**5.2 CONTRIBUTIONS TO KNOWLEDGE**

1. Developed an improved risk assessment model for the prediction of neonatal mortality in newborns with data available at 10 minutes from birth using DTs. The model’s average test sensitivity and specificity was 62.243.28% and99.950.03%, respectively.

2. Developed an improved risk assessment model for the prediction of preterm birth in twin pregnancies before 22 weeks gestation using DTs. The model’s average test sensitivity and specificity was 79.325.85% and 91.971.20%, respectively.

3. Demonstrated superior performance of pre-processed dataset using C5.0 based DT to predict neonatal mortality compared to DT-ANN Hybrid and ANN weight elimination methods.

4. Showed that dataset for C5.0 required less processing and adjusting of parameters, and performs well with large data in a shorter timeframe compared to DT-ANN Hybrid and ANN weight elimination methods. There is no need to normalize the data, among other time consuming pre-processing steps to create a classifier.

5. The C5.0 uses a white box model, compared to DT-ANN Hybrid and ANN weight elimination methods which use a black box model. The white box model is easier to understand and interpret. This detection may be valuable to clinicians as it could better allocate resources, provide earlier interventions and identify those at risk at an earlier stage.

6. Reduced the complexity of the prediction of preterm birth model in twin gestation by decreasing the number of input variables. The number of input variables was reduced to 21. This is a significant improvement compared to C.Catley’s work which required 48 variables, and is comparable to N.Yu’s work which required 19 variables for parous cases. The reduction in variables greatly reduces the complexity of the problem; this in turn saves time and improves the generalization of the model.

7. A conceptual framework and prototype for a secure web-based Perinatal Decision Support System (PEDSS) which included a screener tool for assessing risk for neonatal mortality and preterm birth in twin pregnancies was presented. This generalized framework may be further extended for assessing the likelihood of many other medical outcomes.

**5.3 FUTURE WORK**

1. Further work is needed to improve the prediction of preterm birth in women pregnant with singleton. Additional variables is required to improve the results, specifically,‘maternal bleeding’ and ‘previous low birth weight’

2. Apply the preprocessing step to the datasets on other perinatal databases on a national, international or global level to assess the C5.0 algorithm on different perinatal environments.

3. Throughout the duration of this thesis work, applications for ethical clearance was made and revised to the BORN database. Although we had been granted access to this database in November 2012, many indicative variables included contained corrupted values in the dataset. Further examination of the variables may reveal better improvements for the prediction of preterm births among women pregnant with singleton.

4. Perform a usability study to determine the usefulness and ease of use of the proposed Perinatal Decision Support System (PEDSS). Determine the physician views and any area of concern such as: security, privacy, ethical dilemmas etc.

5. In conjunction with physicians, implement a clinical trial of the Perinatal Decision Support System (PEDSS) and compare the screener tool findings with clinical judgment and actual maternal outcomes.

6. Use DT method with nominal values grouped in the BORN database to evaluate the risk of preterm birth in nulliparous women with singleton birth to determine whether the performance outcome can be improved compared to past methods.

**5.4 FINAL STATEMENT**

Preliminary results of the C5.0 based DT model proved to be successful for non-invasively predicting in a group of new, undifferentiated patients, including the case of: neonatal mortality using data available at 10 minutes from birth, and preterm birth in twin pregnancies using data available at 22 weeks gestation. The knowledge gained in this thesis work has proven to be advantageous to not only the data mining and artificial intelligence sector, but as well as the medical field, especially in perinatal care. Hopefully, one day the proposed perinatal decision support system is seen in clinical use and its potential benefits are experienced by those in need.

**APPENDIX**

**A 1.0 CONCEPT OF KNOWLEDGE DISCOVERY AND DATA MINING**

In the recent years, the concept of data mining and knowledge discovery has become more popular and has attracted the interest of many researchers, including the media sector. Knowledge discovery is referred to as the process to automate discovery of previously unknown patterns or rules within large volumes of data, and data mining is known as the discovery of the pattern in a dataset (Devedzic, 2000). As digital data continues to grow at an uncontrollable rate, the need for a new generation of computational tools to assist humans in extracting useful information emerged (Fayyad, 1996). It has been estimated that the amount of data in the world doubles every 20 months, with the number and size of databases increasing at a faster pace (Frawley, 1992). Knowledge Discovery in Databases (KDD) utilizes various methods in order to make sense of data. Commonly low level data that is too large to easily comprehend is converted into a more useful compact output. The core of this process includes data mining techniques used for pattern discovery and extraction (Fayyad, 1996).

Traditionally, in order to turn data into knowledge, manual analysis and interpretation is required, where commonly specialists periodically analyze current trends and changes within healthcare. The results may then become the bases for future decision making and planning within healthcare management. However, manual probing of datasets is not only slow, but it is also fairly costly and highly subjective. Further, as the volume of data grow drastically, it may be impossible to manually analyze data at times, and thus computational techniques must be used to unearth meaningful patterns and structures. KDD places an importance on patterns which are easily understandable and is interesting, where interestingness is a measure of the overall pattern value, validity, novelty, usefulness and simplicity.

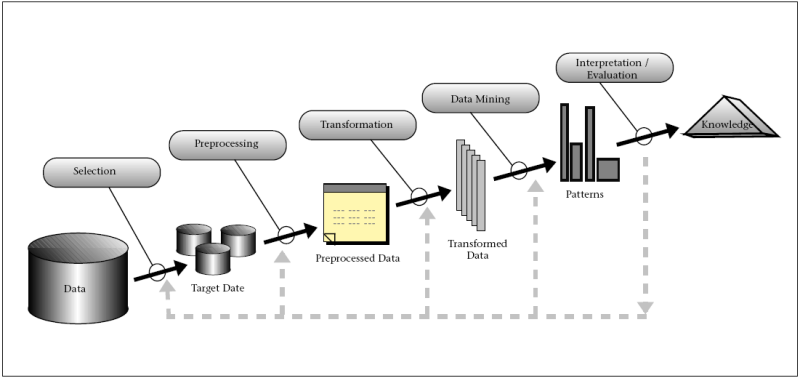
**A 1.1 CONTEXT AND RESOURCES FOR KDD**

Domain knowledge refers to the content of the data in the database, application domain and goals of the KDD process. Domain knowledge may be used to control the processes and evaluate the patterns using an appropriate knowledge representation method. Discovered knowledge may be used for database query from the application and it is typically represented using knowledge representation methods such as inference rules (IF-THEN rules), decision trees, tables, diagrams etc... (Devedzic, 2000).

**A 1.2 THE KDD PROCESS**

The KDD Process is both interactive and iterative, with much of the decisions within each step made by the user (Fayyad, 1996). This process is outlined as follows:

1. Develop an understanding of the application domain
   * Identify the goal of the KDD process (Fayyad, 1996). This step is to help the user determine what should be done with the various decisions, as well as define the objectives (Maimon & Rokach, 2005).
2. Select and create a dataset on which the discovery will be performed
   * Once the goals have been defined, the data to be used for the KDD should be determined (Maimon & Rokach, 2005). This may include first determining which data is important and available, then combining all the important data into one dataset (Maimon & Rokach, 2005).
3. Create a target dataset on which the discovery is to be performed
   * This may in the form of selecting a subset of variables/data samples from a larger dataset (Fayyad, 1996).
4. Clean data and preprocess data
   * During this stage, the data reliability is enhanced (Maimon & Rokach, 2005). This may include removing noise, handling missing data etc.. (Fayyad, 1996).
5. Data transformation
   * During this step, a better dataset is generated for the data mining process (Fayyad, 1996).
6. Reduce data
   * The goal of this is to find useful features to represent the data.
7. Choose appropriate data mining tasks
   * Match the goals of the KDD process to the data-mining method (Fayyad, 1996). This step is mostly dependent on the KDD goal (Maimon & Rokach, 2005). There are two main goals in data mining known as supervised and unsupervised (Maimon & Rokach, 2005).
8. Choose the data mining algorithm
   * Perform an exploratory analysis and hypothesis selection. This may include selecting data mining algorithm(s) and choosing techniques for pattern recognition (Fayyad, 1996).
9. Employ the data mining algorithm
   * Conduct data mining and search for a pattern of interest in a specified representation (Fayyad, 1996). This may be done several times until satisfied results are obtained (Maimon & Rokach, 2005).
10. Evaluate
    * Evaluate and interpret the mined patterns as per original goal of the KDD process, this may result in re-conducting step 1-7 (Maimon & Rokach, 2005).
11. Use the discovered knowledge
    * Act on the discovered knowledge (Fayyad, 1996). Incorporate the knowledge into another system for further usage (Maimon & Rokach, 2005).



**Figure A.1 KDD Process Diagram**

**B 1.0 COMPONENTS OF DATA MINING METHODS**

There are three primary components in data mining, these include model representation, model evaluation and search method (Fayyad, 1996).

1. Model Representation – This is the language used to define the observed patterns.
2. Model Evaluation – This describes how well the pattern meets the objectives of the KDD process; these are typically quantitative statements such as fit functions.
3. Search Method – This includes both parameter and model search. First, given a fixed model representation, the algorithms must search for parameters which optimize the model evaluation criteria; this is referred to as the parameter search. Secondly, the model representation may change until the best fit is found (Fayyad, 1996).

**B 1.1 DATA MINING METHODS**

There are various data-mining methods; a few of the more popular methods are discussed as follows (Fayyad, 1996):

**Decision Trees and Rules**

These types of models are easy to comprehend. Examples of these contributions may be obtained from various disciplines. For example, artificial intelligence includes many machine-learning algorithms to create these rules (Mackinnon and Glick, 1999). Nevertheless, if a restriction is applied to a decision tree or rules, this can greatly impact the functionality of the system. Trees and rules are commonly used for predictive modelling (Fayyad, 1996).

**Nonlinear Regression and Classification Methods**

This type of model consists of various techniques for the prediction of fit linear and non-linear combination of basis function. These may include feed forward neural networks, adaptive spline methods and projection pursuit regression (Fayyad, 1996). The drawback to this method is that it minimizes the misclassification error rates at the expense of interpretability (Mackinnon and Glick, 1999).

**Example Based Methods**

In this model, new examples are derived from similar examples in the dataset, where the outcome is known. These may include nearest neighbour classification, and regression algorithms (Fayyad, 1996). The drawback to this method includes that it lacks interpretability and has scale problem in variables when creating distance measurement (Mackinnon and Glick, 1999).

**Probabilistic Graphic Dependency Models**

This type of model describes the variables that are directly dependent on each other using a graph structure. This model is often used with categorical or discrete valued variables (Fayyad, 1996). These may include Bayesian networks (Mackinnon and Glick, 1999).

**C 1.0 DECISION TREES**

Predictive modeling is one of the most useful areas of data mining, this is composed of statistics, machine learning, pattern recognition, database and optimizing techniques (Apte et al., 2002). Decision trees are primarily used in predictive modelling to discover features and extract patterns in large databases (Myles, 2004).

**C.1.1 WHAT IS A DECISION TREE?**

Decisions trees are often used for the purpose of decision making. Decision tree is a learning algorithm that has been implemented in many expert systems for the purpose of capturing knowledge to date. It is a method for evaluating discrete data-valued functions and is one of the most common methods for inductive interference (Peng, 2006). Decision trees are used to recursively partition datasets using either the depth first greedy approach or the breadth first approach until all data is categorized into a class. Based on the volume of data, memory space availability, computer resources and scalability of the algorithm, decision trees may be implemented in a serial or parallel manner (Anyanwu and Shiva, 2009). Parallel implementation may be applied in a computer architecture with many processors and is typically scalable, fast and disk resident. Serial implementation is easier to comprehend, yet fast and disk resident (Anyanwu and Shiva, 2009).

Three of the commonly used decision tree learning algorithms includes ID3, C4.5 SLIQ and SPRINT (Peng, 2006). These systems use inductive methodologies for given values of attributes of an unknown variable to determine an appropriate classification, as per the decision tree rules implementation.

**C 1.2 DECISION TREE LEARNING ALGORITHMS**

**1.2.1 ID3**

ID3 is a decision tree algorithm developed in 1983 by Ross Quinlan. The ID3 is serially implemented and constructed in two phases including tree building and pruning (Anyanwu and Shiva, 2009). During the building phase, the tree is constructed using a top-down greedy approach where for each given set, each of the attributes of the tree node are tested. A gain metric known as information gain is used to select the attribute that is most purposeful for classifying a dataset (Peng, 2006). The drawback to this method is that accurate results are hard to achieve when there is a lot of noise or extensive detail in the training dataset, and therefore intensive pre-processing of data is required prior to building a decision tree model using ID3 (Anyanwu and Shiva, 2009).

**1.2.2 C4.5**

The C4.5 algorithm is a modified and improved version of the ID3 algorithm developed by Ross Quinlan in 1993. The C4.5 is serially implemented, and is similar to the ID3. Data is sorted at every node and the best splitting attribute and gain ratio is used to evaluate the splitting attribute. Some of the advantages in the C4.5 over ID3 include an enhanced method of tree pruning, where the internal nodes are replaced by the leaf node in order to reduce the risk of errors when there is noise or extensive detail in the training set. Further, this algorithm allows for both continues and categorical data (Anyanwu and Shiva, 2009).

**1.2.3 SLIQ (Supervised Learning in Quest)**

The SLIQ algorithm was developed by Mehta in 1996. It is a fast and scalable decision tree that can be implemented both in serial and in parallel. This algorithm is used to partition a dataset recursively using the breadth-first greedy approach. This mechanism also incorporates a pre-sorting method during the tree building phase, where the trees nodes are eliminated and replaced with a one-time sort using a list data structure for each attribute, to determine the best split point. This algorithm can handle both number and categorical values. Further, this algorithm is inexpensive, since it uses the minimum description length (MDL) method for pruning the tree, and uses a bottom up approach to produce an optimized tree with the least amount of coding and is the smallest in size. However, one drawback to this technique includes that it imposes memory restrictions on the data, since it uses a class list data structure that is memory resident (Anyanwu and Shiva, 2009).

**1.2.4 SPRINT (Scalable Parallelizable Induction of Decision Tree Algorithm)**

The SPRINT algorithm was developed by Shafer et al. in 1996. This algorithm is a modified enhanced version of the SLIQ algorithm. This algorithm can be implemented both in serial and in parallel, and it is a fast and scalable decision tree classifier. A breadth-first greedy technique is used to partition the training dataset recursively, until each partition belongs to the same leaf node or class. This algorithm does not have any restriction of the input data size, and is similar to the SLIQ in the fact that it uses a one-time sort for the data items. Further, both continuous and categorical data can be handled using this algorithm, and there are no data memory restrictions, since this type of algorithm uses two data structures known as ‘attribute list’ and ‘histogram’ which are both not memory resident (Anyanwu and Shiva, 2009).

**D 1.0 HYBRID ARTIFICIAL NEURAL NETWORKS**

Hybrid methods combine the advantages of many pattern classification approaches. An artificial neural network (ANN) is essentially a ‘black box’ system with its knowledge stored in the weights biases and connection links. It has been found that combining the ANN with a knowledge-based system (which can extract domain knowledge from a dataset i.e. decision tree) will improve the generalization capability and overall performance of the ANN (Yu, 2009). Examples of where neural networks and decision trees are integrated include tree-based neural networks (TBNN) and pruning-based neural network (PBNN).

**D 1.1 TREE-BASED NEURAL NETWORK (TBNN)**

The tree-based neural network (TBNN) was originally proposed by Ivanova and Kubat, where a decision tree is used to extract knowledge that defines the feature selection and initialization weights of the ANN. A decision is created and then translated into an ANN by first converting the feature intervals created by the DT splitting value to individual input, and then training the system using a back propagation value (Yu, 2009).

The TBNN has some limitations. First, the TBNN method calculates a fixed set of weights and requires there to be as many inputs present as there are intervals, and the number of hidden nodes must equal the number of conjunctive terms in the rules. Further, the constructed network often contains redundancies and tends to be larger and more complex than necessary (Sectiono & Leow,2011).

**D 1.2 PRUNING-BASED NEURAL NETWORK (PBNN)**

Pruning-based neural network (PBNN) generates a network by mapping a decision tree from a neural network as follows: (i) the attribute intervals are extracted from the decision trees, (ii) the decision rules are extracted from the decision tree and the attribute intervals, (iii) binary training patterns are generated from the decision rules and attributes intervals, (iv) the neural network is training based on these binary patterns, and (v) the trained network is pruned (Sectiono & Leow, 2011).

Pruning-based neural network (PBNN) has several advantages over TBNN. Pruned neural networks tend to have fewer connection and hidden nodes, and the pruning process in the PBNN network compresses the internal configuration of the network and thus this method generates simpler networks compared to neural networks constructed using TBNN. Further, the weight values are derived based on training the input values for PBNN based networks, whereas TBNN networks calculates a fixed set of weights (Sectiono & Leow, 2011).

**E 1.0 INFANT MORTALITY**

The World Health Organization (WHO) predicts that the infant mortality rate around the world is ~9 million, where nearly all deaths occur in developing countries. The infant mortality rate in Canada is shockingly high in relation to its level of socio-economic development. Although the mortality rate has declined over the past few decades, other countries of similar socio-economic status have done better (Conference Board of Canada, 2001). Preterm newborns of low birth weight (LBW) weighing less than 1500g are at increased risk of infant mortality and result in nearly 70% of neonatal death in developing countries (Child Health Research Project Special Report, 1999).

**E 1.1 CLASSIFICATION**

Infant mortality (<1 year) is further classified into perinatal (>22 weeks of gestation) which includes still births (fetus death, born dead), neonatal (<28 days) and postnatal (28-364 days) periods. Neonatal period can be further subdivided into early neonatal (<7 days) and late neonatal (7-<28 days) periods (Rowley et al., 2011). Perinatal mortality commonly occurs as a result of congenital malformations, pregnancy-related complications (placenta previ or abruption placentae), delivery related complications (intrapartum asphyxia), birth trauma and infectious disease (Child Health Research Project Special Report, 1999). Neonatal mortality typically occurs as a result of surrounding events during the prenatal period and delivery. Neonatal mortality and perinatal mortality account for approximately 70% of all infant deaths. Postnatal mortality accounts for the remaining 30% of all infant deaths and occurs as a result of events that arise after delivery such as environmental factors (Rowely et al., 2011).

Infant mortality may occur due to a combination of risk factors including the maternal health, accessibility to medical care, and socioeconomic conditions. Thus, the infant mortality rate is an important indicator which represents the overall health of the nation (MacDorman, 2011).

**E 1.2 FACTORS CONTRIBUTING TO INFANT MORTALITY**

Infant mortality is strongly correlated to structural factors including economic development, general living conditions, social well-being and quality of the environment (Conference Board of Canada, 2001). Low birth weight has also been linked to increased mortality and morbidity rates among infants (Public Health Agency of Canada, 1996). The infant mortality rate among the aboriginal community in Canada is twice as high compared to non-aboriginal populations (National Union of Public and General Employees, 2011). Researchers have excluded genetics as being a factor in increased infant mortality rates among natives, and pointed to common socioeconomic factors among these groups as risk factors instead, which include low household income, poor water quality, substandard housing and lack of healthcare (CBC News, 2009).

Maternal factors which contribute to the risk of infant mortality include age, education, marital status, family income, access to medical care, and substance abuse (cigarettes, alcohol and drugs) during pregnancy. Other variables related to infant mortality include birth order, previous history of infant or fetal loss, adequacy of prenatal care, total gestational period, birth weight, Apgar score, and plurality (MacDorman, 2011). Please refer to appendix F 2.0 Table E.1 for a complete list of risk factor variables associated with infant mortality available in the BORN and NIDAY database.

**F 1.2.1 MATERNAL HEALTH & BEHAVIOURAL CHARACTERISTICS**

Maternal health factors that may increase the risk of infant mortality include the following: mother’s BMI<30, chronic diseases (i.e. diabetes, renal failure, hypertension, haemoglobinopathy, rhesus disease, thrombophialsis, antiphospholipid syndrome), infection (erythmiainfectriosum, varicella, measles) and substance abuse (i.e tobacco, alcohol and drugs) (Patient Co.Uk, 2010).

**E 1.2.2 DEMOGRAPHIC CHARACTERISTICS**

Racial and ethnic differences also play a role in infant mortality. However, race and ethnicity is not an etiological risk factor. Certain racial and ethnic groups are exposed to various risk factors socially, culturally, environmentally and economically which may put their newborns at greater risk of infant mortality. The infant mortality rate is highest among African, Native American, and Puerto Rican mothers, and is lowest among Asian mothers (MacDorman, 201).

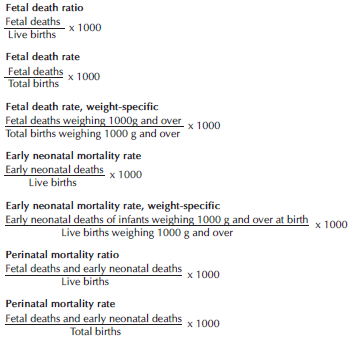
**E 2.0 Risk Factors Associated with Infant, Neonatal, Perinatal, and Postnatal Mortality**

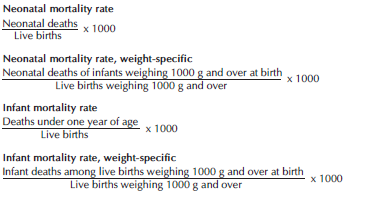
Table E.1 presents a categorized list of potential risk factors associated with infant, neonatal, perinatal and postnatal mortality derived from medical literature found in the BORN and NIDAY (Rowely et al., 2011):

**Table E.1 -** Potential risk factors associated w/ infant, neonatal, perinatal & postnatal mortality

|  |  |  |  |
| --- | --- | --- | --- |
| Risk Factor | Available before 23 week Gestation | Factor Present in | |
| **BORN** | **NIDAY** |
| Infant Mortality - MATERNAL HEALTH CHARACTERISTICS | | | |
| BMI <30 |  |  |  |
| Low Birth Weight |  | X | X |
| Diabetes |  | X | X |
| Renal Failure |  |  |  |
| Hypertension |  | X | X |
| Haemoglobinopathy |  |  |  |
| Rhesus disease |  |  |  |
| Antiphospholipid Syndrome), |  |  |  |
| Varicella |  |  |  |
| Measles |  |  |  |
| ALL Behavioural Factors | | | |
| Alcohol |  | X | X |
| Tobacco |  | X | X |
| Drugs |  | X |  |
| Infant Mortality – Socio-Economic Status | | | |
| Living Conditions |  |  |  |
| Quality of the Environment |  |  |  |
| Social Well Being |  |  |  |
| Low Household Income |  |  |  |
| Poor Water Quality |  |  |  |
| Substandard Housing |  |  |  |
| Lack of Healthcare |  |  |  |
| Infant Mortality - Demographic Factors | | | |
| Ethnicity - Black |  |  |  |
| Ethnicity - Native American |  |  | X |
| Ethnicity - Puerto Rican |  |  |  |
| NEONATAL MORTALITY | | | |
| Birth Weight <1000g |  | X | X |
| Birth Weight >3000-4500g |  | X | X |
| Complications on Delivery |  | X | X |
| Congenital Anomalies |  | X | X |
|  |  |  |  |
| Birth Defects |  |  |  |
| Neonatal Mortality - Socioeconomic Factors | | | |
| Unskilled Labour Class |  |  |  |
| Rural Area |  |  |  |
| <20 Years of Age |  | X | X |
| Multiparous (parity of 2) |  | X | X |
| Perinatal Mortality | | | |
| Complications of the Placenta |  | X | X |
| Short Gestation |  | X | X |
| Low Birth Weight |  | X | X |
| Poor Hygiene |  |  |  |
| Complications Cord or Membrane |  | X | X |
| Respiratory Distress Syndrome |  |  |  |
| Postnatal Mortality | | | |
| Sudden Infant Death Syndrome |  |  |  |
| Infections |  |  |  |

**E 2.1 Infant Mortality Ratios and Rates**





**F 1.0 PRETERM BIRTH**

**F 1.1 EPIDEMIOLOGY OF PRETERM BIRTHS**

Obstetric signs that have led to preterm birth include (1) delivery for maternal or fetal indications where the labour is induced or delivered through caesarean section, (2) spontaneous preterm birth with intact membrane, and (3) preterm premature rupture of the membrane (PPROM) irrespective of vaginal or caesarean section delivery. It is estimated that 30-35% of preterm births are indicated, 40-45% are spontaneous preterm labour, and 25-30% tail PPROM. The contribution of factors associated with preterm births varies by ethnic groups. It has been observed that spontaneous preterm birth commonly occurs in white women, whereas PPROM predominates in black women (Goldenberg et al., 2008).

**F 1.1.1 HEALTH OF PRETERM INFANTS**

Babies born prematurely are prone to several health problems due to incomplete development, and are at higher risk of morbidity and mortality compared to full-term babies of normal weight. Often, the earlier the baby is born is proportional to an increased risk in the severity of long and short term complication. Long term complication may include blindness, trouble walking and learning challenges (Alere’s Women’s & Children’s Health, 2008). Short term complications vary and may include respiratory distress, internal bleeding, poor circulation, liver failure, seizures, temperature instability, gastrointestinal complications etc… (Yu, 2009). Preterm babies are often transferred to the Neonatal Intensive Care Units (NICU) shortly after birth (Ontario’s maternal newborn and early child development resource centre, 2004). The average hospital cost of a baby admitted to NICU in 2002-2003 was $9700 (Canadian Institute for Health Information, 2006). NICU provide preterm infants with proper temperature and nutrition needed for proper growth and development (Kid’s Health, 2011).

**F 1.1.2 IMPACT ON SOCIETY**

Preterm babies often tend to use more hospital resources and require special monitoring and care during the first critical days/weeks in their lives. Often the use of specialized equipment including respirators, monitors, intravenous pumps and kidney dialysis machines are required for the survival of preterm infants. The length of stay of preterm infants is typically higher than term infants. All of these factors contribute greatly to increased healthcare costs. Further, the differential health consequences of each preterm baby typically extend far beyond infancy and childhood (Lim et al., 2009).

Often, hospital costs decrease as the birth weight and gestational age increase, where the smallest infants commonly require the longest length of stay and thus have the highest hospital costs. Newborns weighing 2,500g costs approximately $1000 in hospital resources and on average required only 2 hospital days, whereas newborns weighing less than 750g cost more than $117 000 in hospital resources and on average required more than 104 hospital days. The average hospital cost for twins born preterm is considerably higher than singleton birth (Goldenberg et al., 2008). It is estimated that in Canada, each preterm baby will use $676 800 in healthcare services throughout its lifetime (Allen et al. 2002).

Preterm babies who survive with a disability will require extensive community resources and support to achieve optimal quality of life including educational support, social services, respite care for the family and supportive housing and transportation (Allen et al. 2002). A preterm infant surviving a disability may also require special assistive devices such as a wheelchair, where a portion of the costs may be reimbursed through various financial assistance programs, but in many cases, the family bears much of these costs (Allen et al. 2002).

In addition to the various health problems many preterm infants are prone to, the family of a premature baby undergo emotional distress due to the uncertainty of their baby’s future and financial costs. Mothers often experience emotional distress and depression due to the birth and hospitalization of the baby. Parents also face challenges due to prolonged hospitalization of the baby which separates the baby from the parents during the critical newborn period (Allen et al. 2002). Further, the financial burden may impact and limit the family’s social life and lead to difficulty in maintaining proper employment and income. The strength of the family is also challenged when taking care of a baby born preterm.

**F 2.0 Risk Factors Associated with Preterm Births**

Table F.1 lists a categorized list of potential risk factors associated with preterm birth derived from medical literature found in the BORN and NIDAY database:

**Table F.1 -** Potential risk factors associated with preterm birth

|  |  |  |  |
| --- | --- | --- | --- |
| Risk Factor | Available before 23 week gestation | Factor Present in | |
| **BORN** | **NIDAY** |
| Social and Demographic Factors | | | |
| Age <18 or >35 |  | X | X |
| Ethnicity [Afro-American] |  |  |  |
| Single |  |  |  |
| Education [Not Complete HS] |  |  |  |
| Low Income |  |  |  |
| Living in Poverty |  |  |  |
| Work Condition (standing >3hr) |  |  |  |
| Stress |  | X |  |
| Genetic Factors | | | |
| Previous PTB |  | X | X |
| History of Infertility Problems |  |  |  |
| Sister/Grandmother with PTB |  |  |  |
| Health & Biological Factors | | | |
| BMI High |  |  |  |
| BMI Low <20 |  |  |  |
| Low Iron |  |  |  |
| Low Folate |  |  |  |
| Low Zinc |  |  |  |
| Insufficient Weight Gain |  |  |  |
| Diabetes |  | X | X |
| Chronic Hypertension |  | X | X |
| Cardiac Disease |  | X |  |
| Chronic Pulmonary Disease |  |  |  |
| Asymptomatic Bacteriuria |  |  |  |
| Genetic Tract Abnormalities |  |  |  |
| History of STD. |  |  |  |
| Abnormally Shaped Uterus |  |  |  |
| Excessive Uterine Contraction |  |  |  |
| >2 Third Trimester Abortions |  |  |  |
| >2 Miscarriages |  |  |  |
| Vaginal Spotting (light) |  |  |  |
| Fetal Fibronectin |  |  |  |
| Salivary Estriol |  |  |  |
| Cervical Dilation <25 mmm |  |  |  |
| Cervical Anomalies |  |  |  |
| Bacterial Vaginosis (pH >4.5) |  |  |  |
| Presence of Pyelonephritis |  |  |  |
| Presence of Pneumonia |  |  |  |
| Presence of Appendicitis |  |  |  |
| Asthma |  | X |  |
| Thyroid diseases |  | X |  |
| Severe ARDS |  |  |  |
| Severe Urinary Tract Infections |  | X | X |
| Antepartum Hemorrhage |  |  |  |
| Pregnancy Factors | | | |
| Multiparous |  | X | X |
| Nulliparous |  | X | X |
| Late or No Prenatal Care |  | X | X |
| Vaginal Bleeding (1st Trimester) |  |  |  |
| Vaginal Bleeding (2nd Trimester) |  |  |  |
| Low Pregnancy Weight |  |  |  |
| <62’’ Height |  |  |  |
| Behavioural Factors | | | |
| Smoking |  | X | X |
| Exposure to Tobacco Smoke |  |  |  |
| Alcohol Cons. Before 3rd Trimester |  |  |  |
| Cocaine |  |  |  |
| Drug Use (Heroin, Marijuana) |  | X |  |

**G1.0 Decision Tree Results**

**G1.1 nOMOD\_NEONATALMORT DT RESULTS**

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| |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | | **C5.0 Decision Tree Results** | | |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | | Cases with Mortality: | | 24 |  | ***Confusion Matrix*** | |  |  |  | | Cases without Mortality: | | 232 |  | ***TP*** | ***FP*** |  |  |  | | Total cases: |  | 256 |  | ***FN*** | ***TN*** |  |  |  | | Minority dataset: |  | **9%** |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | | 5 by 2 Cross Validation Results | | |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | |  | **Train** |  | **Test** | Std Dev |  |  |  |  | | **Accuracy:** | 1.00 |  | **1.00** | 0.00 |  |  |  |  | | **Sensitivity:** | 0.62 |  | **0.57** | 0.07 |  |  |  |  | | **Specificity:** | 1.00 |  | **1.00** | 0.00 |  |  |  |  | | **PPV/Precision:** | 0.92 |  | **0.85** | 0.08 |  |  |  |  | | **NPV:** | 1.00 |  | **1.00** | 0.00 |  |  |  |  | | **Recall:** | 0.62 |  | **0.57** | 0.07 |  |  |  |  | | **F1 score:** | 0.73 |  | **0.68** | 0.05 |  |  |  |  | | **MCC:** | 0.75 |  | **0.70** | 0.05 |  |  |  |  | | **SS1:** | 0.62 |  | **0.57** | 0.07 |  |  |  |  | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |
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| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  | *TP* | | | | | *FP* | | | | | |
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| **noMOD\_NEONATALMORT (fold a):** | | | | | | | | | | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| Train (N= 128) | | | | |  | | | |  | | | | | | | Test (N = 128) | | | | | | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| (a) | (b) | | | | <- classified as | | | | | | | | | | | (a) | | | | | (b) | | | | <- classified as | | | | | | | | | | |  | | | | |  | | | | | |
| 24 | 4 | | | | (a): class -1 | | | | | | | | | | | 20 | | | | | 6 | | | | (a): class -1 | | | | | | | | | | |  | | | | |  | | | | | |
| 9 | 16344 | | | | (b): class 1 | | | | | | | | | | | 12 | | | | | 16341 | | | | (b): class 1 | | | | | | | | | | |  | | | | |  | | | | | |
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| DT Size: |  | | | |  | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| Accuracy: | | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| Sensitivity: | | | | | 0.73 | | | |  | | | | | | |  | | | | |  | | | | 0.63 | | | | | | | | | |  |  | | | | |  | | | | | |
| Specificity: | | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| PPV/Precision: | | | | | 0.86 | | | |  | | | | | | |  | | | | |  | | | | 0.77 | | | | | | | | | |  |  | | | | |  | | | | | |
| NPV: |  | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| Recall: |  | | | | 0.73 | | | |  | | | | | | |  | | | | |  | | | | 0.63 | | | | | | | | | |  |  | | | | |  | | | | | |
| **F1 score:** | | | | | 0.79 | | | |  | | | | | | |  | | | | |  | | | | 0.69 | | | | | | | | | |  |  | | | | |  | | | | | |
| **MCC:** |  | | | | 0.79 | | | |  | | | | | | |  | | | | |  | | | | 0.69 | | | | | | | | | |  |  | | | | |  | | | | | |
| **SS1:** |  | | | | 0.73 | | | |  | | | | | | |  | | | | |  | | | | 0.62 | | | | | | | | | |  |  | | | | |  | | | | | |
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| **noMOD\_NEONATALMORT (fold b):** | | | | | | | | | | | | | | | | | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| Train (N= 128) | | | | |  | | | |  | | | | | | | Test (N = 128) | | | | | | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| (a) | (b) | | | | <- classified as | | | | | | | | | | | (a) | | | | | (b) | | | | <- classified as | | | | | | | | | | |  | | | | |  | | | | | |
| 19 | 2 | | | | (a): class -1 | | | | | | | | | | | 20 | | | | | 3 | | | | (a): class -1 | | | | | | | | | | |  | | | | |  | | | | | |
| 13 | 16345 | | | | (b): class 1 | | | | | | | | | | | 13 | | | | | 16345 | | | | (b): class 1 | | | | | | | | | | |  | | | | |  | | | | | |
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| Accuracy: | | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| Sensitivity: | | | | | 0.59 | | | |  | | | | | | |  | | | | |  | | | | 0.61 | | | | | | | | | |  |  | | | | |  | | | | | |
| Specificity: | | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| PPV/Precision: | | | | | 0.90 | | | |  | | | | | | |  | | | | |  | | | | 0.87 | | | | | | | | | |  |  | | | | |  | | | | | |
| NPV: |  | | | | 1.00 | | | |  | | | | | | |  | | | | |  | | | | 1.00 | | | | | | | | | |  |  | | | | |  | | | | | |
| Recall: |  | | | | 0.59 | | | |  | | | | | | |  | | | | |  | | | | 0.61 | | | | | | | | | |  |  | | | | |  | | | | | |
| **F1 score:** | | | | | 0.72 | | | |  | | | | | | |  | | | | |  | | | | 0.71 | | | | | | | | | |  |  | | | | |  | | | | | |
| **MCC:** |  | | | | 0.73 | | | |  | | | | | | |  | | | | |  | | | | 0.73 | | | | | | | | | |  |  | | | | |  | | | | | |
| **SS1:** |  | | | | 0.59 | | | |  | | | | | | |  | | | | |  | | | | 0.61 | | | | | | | | | |  |  | | | | |  | | | | | |
|  |  | | | |  | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
|  |  | | | |  | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
|  |  | | | |  | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
|  |  | | | |  | | | |  | | | | | | |  | | | | |  | | | |  | | | | | | | | | |  |  | | | | |  | | | | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | | *TP* | | | | | | *FP* | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | | *FN* | | | | | | *TN* | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| **noMOD\_NEONATALMORT (fold a):** | | | | | | | | | | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| Train (N= 128) | | | | |  | | | |  | | | | | | Test (N = 128) | | | | | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| (a) | (b) | | | | <- classified as | | | | | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | | | | | |  | | | | | |  | | | |
| 20 | 1 | | | | (a): class -1 | | | | | | | | | | 16 | | | | 3 | | | | (a): class -1 | | | | | | | | | | |  | | | | | |  | | | |
| 12 | 16347 | | | | (b): class 1 | | | | | | | | | | 16 | | | | 16344 | | | | (b): class 1 | | | | | | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| DT Size: |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| Accuracy: | | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| Sensitivity: | | | | | 0.63 | | | |  | | | | | |  | | | |  | | | | 0.50 | | | | |  | | | | | |  | | | | | |  | | | |
| Specificity: | | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| PPV/Precision: | | | | | 0.95 | | | |  | | | | | |  | | | |  | | | | 0.84 | | | | |  | | | | | |  | | | | | |  | | | |
| NPV: |  | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| Recall: |  | | | | 0.63 | | | |  | | | | | |  | | | |  | | | | 0.50 | | | | |  | | | | | |  | | | | | |  | | | |
| **F1 score:** | | | | | 0.75 | | | |  | | | | | |  | | | |  | | | | 0.63 | | | | |  | | | | | |  | | | | | |  | | | |
| **MCC:** |  | | | | 0.77 | | | |  | | | | | |  | | | |  | | | | 0.65 | | | | |  | | | | | |  | | | | | |  | | | |
| **SS1:** |  | | | | 0.62 | | | |  | | | | | |  | | | |  | | | | 0.50 | | | | |  | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| **noMOD\_NEONATALMORT (fold b):** | | | | | | | | | | | | | | | | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| Train (N= 128) | | | | |  | | | |  | | | | | | Test (N = 128) | | | | | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| (a) | (b) | | | | <- classified as | | | | | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | | | | | |  | | | | | |  | | | |
| 17 | 1 | | | | (a): class -1 | | | | | | | | | | 19 | | | | 1 | | | | (a): class -1 | | | | | | | | | | |  | | | | | |  | | | |
| 15 | 16346 | | | | (b): class 1 | | | | | | | | | | 14 | | | | 16347 | | | | (b): class 1 | | | | | | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| DT Size: |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| Accuracy: | | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| Sensitivity: | | | | | 0.53 | | | |  | | | | | |  | | | |  | | | | 0.58 | | | | |  | | | | | |  | | | | | |  | | | |
| Specificity: | | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| PPV/Precision: | | | | | 0.94 | | | |  | | | | | |  | | | |  | | | | 0.95 | | | | |  | | | | | |  | | | | | |  | | | |
| NPV: |  | | | | 1.00 | | | |  | | | | | |  | | | |  | | | | 1.00 | | | | |  | | | | | |  | | | | | |  | | | |
| Recall: |  | | | | 0.53 | | | |  | | | | | |  | | | |  | | | | 0.58 | | | | |  | | | | | |  | | | | | |  | | | |
| **F1 score:** | | | | | 0.68 | | | |  | | | | | |  | | | |  | | | | 0.72 | | | | |  | | | | | |  | | | | | |  | | | |
| **MCC:** |  | | | | 0.71 | | | |  | | | | | |  | | | |  | | | | 0.74 | | | | |  | | | | | |  | | | | | |  | | | |
| **SS1:** |  | | | | 0.53 | | | |  | | | | | |  | | | |  | | | | 0.58 | | | | |  | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
|  |  | | | |  | | | |  | | | | | |  | | | |  | | | |  | | | | |  | | | | | |  | | | | | |  | | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | | | |
| *Options: Default Boosting* | | | | | | | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | | *TP* | | | | | | *FP* | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | | *FN* | | | | | | *TN* | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| **noMOD\_NEONATALMORT (fold a):** | | | | | | | | | | | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| Train (N= 128) | | | | | |  | | | |  | | Test (N = 128) | | | | | | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| (a) | | (b) | | | | <- classified as | | | | | | (a) | | | | | (b) | | | | | <- classified as | | | | | | | | | |  | | | | | |  | | | | |
| 18 | | 1 | | | | (a): class -1 | | | | | | 18 | | | | | 1 | | | | | (a): class -1 | | | | | | | | | |  | | | | | |  | | | | |
| 15 | | 16347 | | | | (b): class 1 | | | | | | 14 | | | | | 16346 | | | | | (b): class 1 | | | | | | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| DT Size: | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| Accuracy: | | | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| Sensitivity: | | | | | | 0.55 | | | |  | |  | | | | |  | | | | | 0.56 | | | | |  | | | | |  | | | | | |  | | | | |
| Specificity: | | | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| PPV/Precision: | | | | | | 0.95 | | | |  | |  | | | | |  | | | | | 0.95 | | | | |  | | | | |  | | | | | |  | | | | |
| NPV: | |  | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| Recall: | |  | | | | 0.55 | | | |  | |  | | | | |  | | | | | 0.56 | | | | |  | | | | |  | | | | | |  | | | | |
| **F1 score:** | | | | | | 0.69 | | | |  | |  | | | | |  | | | | | 0.71 | | | | |  | | | | |  | | | | | |  | | | | |
| **MCC:** | |  | | | | 0.72 | | | |  | |  | | | | |  | | | | | 0.73 | | | | |  | | | | |  | | | | | |  | | | | |
| **SS1:** | |  | | | | 0.55 | | | |  | |  | | | | |  | | | | | 0.56 | | | | |  | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| **noMOD\_NEONATALMORT (fold b):** | | | | | | | | | | | | | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| Train (N= 128) | | | | | |  | | | |  | | Test (N = 128) | | | | | | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| (a) | | (b) | | | | <- classified as | | | | | | (a) | | | | | (b) | | | | | <- classified as | | | | | | | | | |  | | | | | |  | | | | |
| 22 | | 3 | | | | (a): class -1 | | | | | | 22 | | | | | 9 | | | | | (a): class -1 | | | | | | | | | |  | | | | | |  | | | | |
| 10 | | 16344 | | | | (b): class 1 | | | | | | 11 | | | | | 16339 | | | | | (b): class 1 | | | | | | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| DT Size: | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| Accuracy: | | | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| Sensitivity: | | | | | | 0.69 | | | |  | |  | | | | |  | | | | | 0.67 | | | | |  | | | | |  | | | | | |  | | | | |
| Specificity: | | | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| PPV/Precision: | | | | | | 0.88 | | | |  | |  | | | | |  | | | | | 0.71 | | | | |  | | | | |  | | | | | |  | | | | |
| NPV: | |  | | | | 1.00 | | | |  | |  | | | | |  | | | | | 1.00 | | | | |  | | | | |  | | | | | |  | | | | |
| Recall: | |  | | | | 0.69 | | | |  | |  | | | | |  | | | | | 0.67 | | | | |  | | | | |  | | | | | |  | | | | |
| **F1 score:** | | | | | | 0.77 | | | |  | |  | | | | |  | | | | | 0.69 | | | | |  | | | | |  | | | | | |  | | | | |
| **MCC:** | |  | | | | 0.78 | | | |  | |  | | | | |  | | | | | 0.69 | | | | |  | | | | |  | | | | | |  | | | | |
| **SS1:** | |  | | | | 0.69 | | | |  | |  | | | | |  | | | | | 0.67 | | | | |  | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
|  | |  | | | |  | | | |  | |  | | | | |  | | | | |  | | | | |  | | | | |  | | | | | |  | | | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | | | |
| *Options: Default Boosting* | | | | | | | | | | |  | | |  | | | |  | | | | | |  | | | | |  | | *TP* | | | | | | *FP* | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | | *FN* | | | | | | *TN* | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| **noMOD\_NEONATALMORT (fold a):** | | | | | | | | | | | | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| Train (N= 128) | | | | | | |  | | | |  | | | Test (N = 128) | | | | | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| (a) | | | (b) | | | | <- classified as | | | | | | | (a) | | | | (b) | | | | | | <- classified as | | | | | | |  | | | | | |  | | | | |
| 20 | | | 1 | | | | (a): class -1 | | | | | | | 17 | | | | 4 | | | | | | (a): class -1 | | | | | | |  | | | | | |  | | | | |
| 13 | | | 16347 | | | | (b): class 1 | | | | | | | 15 | | | | 16343 | | | | | | (b): class 1 | | | | | | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| DT Size: | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| Accuracy: | | | | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| Sensitivity: | | | | | | | 0.61 | | | |  | | |  | | | |  | | | | | | 0.53 | | | | |  | |  | | | | | |  | | | | |
| Specificity: | | | | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| PPV/Precision: | | | | | | | 0.95 | | | |  | | |  | | | |  | | | | | | 0.81 | | | | |  | |  | | | | | |  | | | | |
| NPV: | | |  | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| Recall: | | |  | | | | 0.61 | | | |  | | |  | | | |  | | | | | | 0.53 | | | | |  | |  | | | | | |  | | | | |
| **F1 score:** | | | | | | | 0.74 | | | |  | | |  | | | |  | | | | | | 0.64 | | | | |  | |  | | | | | |  | | | | |
| **MCC:** | | |  | | | | 0.76 | | | |  | | |  | | | |  | | | | | | 0.66 | | | | |  | |  | | | | | |  | | | | |
| **SS1:** | | |  | | | | 0.61 | | | |  | | |  | | | |  | | | | | | 0.53 | | | | |  | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| **noMOD\_NEONATALMORT (fold b):** | | | | | | | | | | | | | | | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| Train (N= 128) | | | | | | |  | | | |  | | | Test (N = 128) | | | | | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| (a) | | | (b) | | | | <- classified as | | | | | | | (a) | | | | (b) | | | | | | <- classified as | | | | | | |  | | | | | |  | | | | |
| 17 | | | 1 | | | | (a): class -1 | | | | | | | 19 | | | | 1 | | | | | | (a): class -1 | | | | | | |  | | | | | |  | | | | |
| 15 | | | 16346 | | | | (b): class 1 | | | | | | | 14 | | | | 16347 | | | | | | (b): class 1 | | | | | | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| DT Size: | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| Accuracy: | | | | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| Sensitivity: | | | | | | | 0.53 | | | |  | | |  | | | |  | | | | | | 0.58 | | | | |  | |  | | | | | |  | | | | |
| Specificity: | | | | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| PPV/Precision: | | | | | | | 0.94 | | | |  | | |  | | | |  | | | | | | 0.95 | | | | |  | |  | | | | | |  | | | | |
| NPV: | | |  | | | | 1.00 | | | |  | | |  | | | |  | | | | | | 1.00 | | | | |  | |  | | | | | |  | | | | |
| Recall: | | |  | | | | 0.53 | | | |  | | |  | | | |  | | | | | | 0.58 | | | | |  | |  | | | | | |  | | | | |
| **F1 score:** | | | | | | | 0.68 | | | |  | | |  | | | |  | | | | | | 0.72 | | | | |  | |  | | | | | |  | | | | |
| **MCC:** | | |  | | | | 0.71 | | | |  | | |  | | | |  | | | | | | 0.74 | | | | |  | |  | | | | | |  | | | | |
| **SS1:** | | |  | | | | 0.53 | | | |  | | |  | | | |  | | | | | | 0.58 | | | | |  | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
|  | | |  | | | |  | | | |  | | |  | | | |  | | | | | |  | | | | |  | |  | | | | | |  | | | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | | | | |
| *Options: Default Boosting* | | | | | | | | | | | | |  | | |  | | | |  | | | | | |  | | | |  | | | *TP* | | | | | | *FP* | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | | *FN* | | | | | | *TN* | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| **noMOD\_NEONATALMORT (fold a):** | | | | | | | | | | | | | | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| Train (N= 128) | | | | | | | |  | | | | |  | | | Test (N = 128) | | | | | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| (a) | | | | (b) | | | | <- classified as | | | | | | | | (a) | | | | (b) | | | | | | <- classified as | | | | | | |  | | | | | |  | | | | | |
| 26 | | | | 2 | | | | (a): class -1 | | | | | | | | 14 | | | | 3 | | | | | | (a): class -1 | | | | | | |  | | | | | |  | | | | | |
| 7 | | | | 16346 | | | | (b): class 1 | | | | | | | | 18 | | | | 16344 | | | | | | (b): class 1 | | | | | | |  | | | | | |  | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| DT Size: | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| Accuracy: | | | | | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| Sensitivity: | | | | | | | | 0.79 | | | | |  | | |  | | | |  | | | | | | 0.44 | | | |  | | |  | | | | | |  | | | | | |
| Specificity: | | | | | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| PPV/Precision: | | | | | | | | 0.93 | | | | |  | | |  | | | |  | | | | | | 0.82 | | | |  | | |  | | | | | |  | | | | | |
| NPV: | | | |  | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| Recall: | | | |  | | | | 0.79 | | | | |  | | |  | | | |  | | | | | | 0.44 | | | |  | | |  | | | | | |  | | | | | |
| **F1 score:** | | | | | | | | 0.85 | | | | |  | | |  | | | |  | | | | | | 0.57 | | | |  | | |  | | | | | |  | | | | | |
| **MCC:** | | | |  | | | | 0.85 | | | | |  | | |  | | | |  | | | | | | 0.60 | | | |  | | |  | | | | | |  | | | | | |
| **SS1:** | | | |  | | | | 0.79 | | | | |  | | |  | | | |  | | | | | | 0.44 | | | |  | | |  | | | | | |  | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| **noMOD\_NEONATALMORT (fold b):** | | | | | | | | | | | | | | | | | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| Train (N= 128) | | | | | | | |  | | | | |  | | | Test (N = 128) | | | | | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| (a) | | | | (b) | | | | <- classified as | | | | | | | | (a) | | | | (b) | | | | | | <- classified as | | | | | | |  | | | | | |  | | | | | |
| 17 | | | | 2 | | | | (a): class -1 | | | | | | | | 21 | | | | 3 | | | | | | (a): class -1 | | | | | | |  | | | | | |  | | | | | |
| 15 | | | | 16345 | | | | (b): class 1 | | | | | | | | 12 | | | | 16345 | | | | | | (b): class 1 | | | | | | |  | | | | | |  | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| DT Size: | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
| Accuracy: | | | | | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| Sensitivity: | | | | | | | | 0.53 | | | | |  | | |  | | | |  | | | | | | 0.64 | | | |  | | |  | | | | | |  | | | | | |
| Specificity: | | | | | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| PPV/Precision: | | | | | | | | 0.89 | | | | |  | | |  | | | |  | | | | | | 0.88 | | | |  | | |  | | | | | |  | | | | | |
| NPV: | | | |  | | | | 1.00 | | | | |  | | |  | | | |  | | | | | | 1.00 | | | |  | | |  | | | | | |  | | | | | |
| Recall: | | | |  | | | | 0.53 | | | | |  | | |  | | | |  | | | | | | 0.64 | | | |  | | |  | | | | | |  | | | | | |
| **F1 score:** | | | | | | | | 0.67 | | | | |  | | |  | | | |  | | | | | | 0.74 | | | |  | | |  | | | | | |  | | | | | |
| **MCC:** | | | |  | | | | 0.69 | | | | |  | | |  | | | |  | | | | | | 0.75 | | | |  | | |  | | | | | |  | | | | | |
| **SS1:** | | | |  | | | | 0.53 | | | | |  | | |  | | | |  | | | | | | 0.64 | | | |  | | |  | | | | | |  | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |
|  | | | |  | | | |  | | | | |  | | |  | | | |  | | | | | |  | | | |  | | |  | | | | | |  | | | | | |

**G1.2 MOD\_NEONATALMORT DT RESULTS**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **C5.0 Decision Tree Results** | | |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| Cases with Mortality: | | 24 |  | ***Confusion Matrix*** | |  |  |
| Cases without Mortality: | | 232 |  | ***TP*** | ***FP*** |  |  |
| Total cases: |  | 256 |  | ***FN*** | ***TN*** |  |  |
| Minority dataset: |  | **9%** |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| 5 by 2 Cross Validation Results | | |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
|  | **Train** |  | **Test** | Std Dev |  |  |  |
| **Accuracy:** | 0.9979 |  | **0.9974** | 0.00 |  |  |  |
| **Sensitivity:** | 0.7323 |  | **0.7013** | 0.04 |  |  |  |
| **Specificity:** | 0.9997 |  | **0.9993** | 0.00 |  |  |  |
| **PPV/Precision:** | 0.9380 |  | **0.8817** | 0.08 |  |  |  |
| **NPV:** | 0.9983 |  | **0.9981** | 0.00 |  |  |  |
| **Recall:** | 0.7323 |  | **0.7013** | 0.04 |  |  |  |
| **F1 score:** | 0.8204 |  | **0.7781** | 0.03 |  |  |  |
| **MCC:** | 0.8262 |  | **0.7830** | 0.03 |  |  |  |
| **SS1:** | 0.7320 |  | **0.7006** | 0.04 |  |  |  |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | |
| *Options: Default Boosting* | | | | | | |  | |  | | |  | | |  | | | | |  | *TP* | | | *FP* | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  | *FN* | | | *TN* | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| **MOD\_NEONATALMORT (fold a):** | | | | | | | | |  | | |  | | |  | | | | |  |  | | |  | | |
| Train (N= 128) | | | |  | | |  | | Test (N = 128) | | | | | |  | | | | |  |  | | |  | | |
| (a) | | (b) | | <- classified as | | | | | (a) | | | (b) | | | <- classified as | | | | | |  | | |  | | |
| 65 | | 3 | | (a): class -1 | | | | | 73 | | | 1 | | | (a): class -1 | | | | | |  | | |  | | |
| 43 | | 16483 | | (b): class 1 | | | | | 34 | | | 16484 | | | (b): class 1 | | | | | |  | | |  | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| DT Size: | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| Accuracy: | | | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| Sensitivity: | | | | 0.60 | | |  | |  | | |  | | | 0.68 | | | | |  |  | | |  | | |
| Specificity: | | | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| PPV/Precision: | | | | 0.96 | | |  | |  | | |  | | | 0.99 | | | | |  |  | | |  | | |
| NPV: | |  | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| Recall: | |  | | 0.60 | | |  | |  | | |  | | | 0.68 | | | | |  |  | | |  | | |
| **F1 score:** | | | | 0.74 | | |  | |  | | |  | | | 0.81 | | | | |  |  | | |  | | |
| **MCC:** | |  | | 0.76 | | |  | |  | | |  | | | 0.82 | | | | |  |  | | |  | | |
| **SS1:** | |  | | 0.60 | | |  | |  | | |  | | | 0.68 | | | | |  |  | | |  | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| **MOD\_NEONATALMORT (fold b):** | | | | | | | | | | | |  | | |  | | | | |  |  | | |  | | |
| Train (N= 128) | | | |  | | |  | | Test (N = 128) | | | | | |  | | | | |  |  | | |  | | |
| (a) | | (b) | | <- classified as | | | | | (a) | | | (b) | | | <- classified as | | | | | |  | | |  | | |
| 91 | | 4 | | (a): class -1 | | | | | 79 | | | 17 | | | (a): class -1 | | | | | |  | | |  | | |
| 16 | | 16481 | | (b): class 1 | | | | | 29 | | | 16469 | | | (b): class 1 | | | | | |  | | |  | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| DT Size: | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| Accuracy: | | | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| Sensitivity: | | | | 0.85 | | |  | |  | | |  | | | 0.73 | | | | |  |  | | |  | | |
| Specificity: | | | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| PPV/Precision: | | | | 0.96 | | |  | |  | | |  | | | 0.82 | | | | |  |  | | |  | | |
| NPV: | |  | | 1.00 | | |  | |  | | |  | | | 1.00 | | | | |  |  | | |  | | |
| Recall: | |  | | 0.85 | | |  | |  | | |  | | | 0.73 | | | | |  |  | | |  | | |
| **F1 score:** | | | | 0.90 | | |  | |  | | |  | | | 0.77 | | | | |  |  | | |  | | |
| **MCC:** | |  | | 0.90 | | |  | |  | | |  | | | 0.77 | | | | |  |  | | |  | | |
| **SS1:** | |  | | 0.85 | | |  | |  | | |  | | | 0.73 | | | | |  |  | | |  | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
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|  | |  | |  | | |  | |  | | |  | | |  | | | | |  |  | | |  | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | |
| *Options: Default Boosting* | | | | | | |  |  | | |  | | |  | | | |  | *TP* | | | | *FP* | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  | *FN* | | | | *TN* | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| **MOD\_NEONATALMORT (fold a):** | | | | | | | |  | | |  | | |  | | | |  |  | | | |  | | |
| Train (N= 128) | | | |  | | |  | Test (N = 128) | | | | | |  | | | |  |  | | | |  | | |
| (a) | | (b) | | <- classified as | | | | (a) | | | (b) | | | <- classified as | | | | |  | | | |  | | |
| 80 | | 8 | | (a): class -1 | | | | 72 | | | 6 | | | (a): class -1 | | | | |  | | | |  | | |
| 28 | | 16478 | | (b): class 1 | | | | 35 | | | 16479 | | | (b): class 1 | | | | |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| DT Size: | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| Accuracy: | | | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| Sensitivity: | | | | 0.74 | | |  |  | | |  | | | 0.67 | | | |  |  | | | |  | | |
| Specificity: | | | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| PPV/Precision: | | | | 0.91 | | |  |  | | |  | | | 0.92 | | | |  |  | | | |  | | |
| NPV: | |  | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| Recall: | |  | | 0.74 | | |  |  | | |  | | | 0.67 | | | |  |  | | | |  | | |
| **F1 score:** | | | | 0.82 | | |  |  | | |  | | | 0.78 | | | |  |  | | | |  | | |
| **MCC:** | |  | | 0.82 | | |  |  | | |  | | | 0.79 | | | |  |  | | | |  | | |
| **SS1:** | |  | | 0.74 | | |  |  | | |  | | | 0.67 | | | |  |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| **MOD\_NEONATALMORT (fold b):** | | | | | | | | | | |  | | |  | | | |  |  | | | |  | | |
| Train (N= 128) | | | |  | | |  | Test (N = 128) | | | | | |  | | | |  |  | | | |  | | |
| (a) | | (b) | | <- classified as | | | | (a) | | | (b) | | | <- classified as | | | | |  | | | |  | | |
| 83 | | 4 | | (a): class -1 | | | | 81 | | | 15 | | | (a): class -1 | | | | |  | | | |  | | |
| 24 | | 16481 | | (b): class 1 | | | | 27 | | | 16471 | | | (b): class 1 | | | | |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| DT Size: | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| Accuracy: | | | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| Sensitivity: | | | | 0.78 | | |  |  | | |  | | | 0.75 | | | |  |  | | | |  | | |
| Specificity: | | | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| PPV/Precision: | | | | 0.95 | | |  |  | | |  | | | 0.84 | | | |  |  | | | |  | | |
| NPV: | |  | | 1.00 | | |  |  | | |  | | | 1.00 | | | |  |  | | | |  | | |
| Recall: | |  | | 0.78 | | |  |  | | |  | | | 0.75 | | | |  |  | | | |  | | |
| **F1 score:** | | | | 0.86 | | |  |  | | |  | | | 0.79 | | | |  |  | | | |  | | |
| **MCC:** | |  | | 0.86 | | |  |  | | |  | | | 0.79 | | | |  |  | | | |  | | |
| **SS1:** | |  | | 0.78 | | |  |  | | |  | | | 0.75 | | | |  |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
|  | |  | |  | | |  |  | | |  | | |  | | | |  |  | | | |  | | |
| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | |  |  | | | |  | | |  | | |  | *TP* | | | | | *FP* | | |
|  |  | |  | |  |  | | | |  | | |  | | |  | *FN* | | | | | *TN* | | |
|  |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| **MOD\_NEONATALMORT (fold a):** | | | | | |  | | | |  | | |  | | |  |  | | | | |  | | |
| Train (N= 128) | | |  | |  | Test (N = 128) | | | | | | |  | | |  |  | | | | |  | | |
| (a) | (b) | | <- classified as | | | (a) | | | | (b) | | | <- classified as | | | |  | | | | |  | | |
| 79 | 9 | | (a): class -1 | | | 76 | | | | 9 | | | (a): class -1 | | | |  | | | | |  | | |
| 29 | 16477 | | (b): class 1 | | | 31 | | | | 16476 | | | (b): class 1 | | | |  | | | | |  | | |
|  |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| DT Size: |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| Accuracy: | | | 1.00 | |  |  | | | |  | | | 1.00 | | |  |  | | | | |  | | |
| Sensitivity: | | | 0.73 | |  |  | | | |  | | | 0.71 | | |  |  | | | | |  | | |
| Specificity: | | | 1.00 | |  |  | | | |  | | | 1.00 | | |  |  | | | | |  | | |
| PPV/Precision: | | | 0.90 | |  |  | | | |  | | | 0.89 | | |  |  | | | | |  | | |
| NPV: |  | | 1.00 | |  |  | | | |  | | | 1.00 | | |  |  | | | | |  | | |
| Recall: |  | | 0.73 | |  |  | | | |  | | | 0.71 | | |  |  | | | | |  | | |
| **F1 score:** | | | 0.81 | |  |  | | | |  | | | 0.79 | | |  |  | | | | |  | | |
| **MCC:** |  | | 0.81 | |  |  | | | |  | | | 0.80 | | |  |  | | | | |  | | |
| **SS1:** |  | | 0.73 | |  |  | | | |  | | | 0.71 | | |  |  | | | | |  | | |
|  |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| **MOD\_NEONATALMORT (fold b):** | | | | | | | | | |  | | |  | | |  |  | | | | |  | | |
| Train (N= 128) | | |  | |  | Test (N = 128) | | | | | | |  | | |  |  | | | | |  | | |
| (a) | (b) | | <- classified as | | | (a) | | | | (b) | | | <- classified as | | | |  | | | | |  | | |
| 84 | 3 | | (a): class -1 | | | 82 | | | | 13 | | | (a): class -1 | | | |  | | | | |  | | |
| 23 | 16482 | | (b): class 1 | | | 26 | | | | 16473 | | | (b): class 1 | | | |  | | | | |  | | |
|  |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| DT Size: |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |
| Accuracy: | | | 1.00 | |  |  | | | |  | | | 1.00 | | |  |  | | | | |  | | |
| Sensitivity: | | | 0.79 | |  |  | | | |  | | | 0.75926 | | |  |  | | | | |  | | |
| Specificity: | | | 1.00 | |  |  | | | |  | | | 0.99921 | | |  |  | | | | |  | | |
| PPV/Precision: | | | 0.97 | |  |  | | | |  | | | 0.86316 | | |  |  | | | | |  | | |
| NPV: |  | | 1.00 | |  |  | | | |  | | | 0.99842 | | |  |  | | | | |  | | |
| Recall: |  | | 0.79 | |  |  | | | |  | | | 0.76 | | |  |  | | | | |  | | |
| **F1 score:** | | | 0.87 | |  |  | | | |  | | | 0.81 | | |  |  | | | | |  | | |
| **MCC:** |  | | 0.87 | |  |  | | | |  | | | 0.81 | | |  |  | | | | |  | | |
| **SS1:** |  | | 0.78 | |  |  | | | |  | | | 0.76 | | |  |  | | | | |  | | |
|  |  | |  | |  |  | | | |  | | |  | | |  |  | | | | |  | | |

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| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | | | *Confusion Matrix* | | | |
| *Options: Default Boosting* | | |  | |  | |  | |  | | |  | *TP* | | *FP* | |
|  |  |  |  | |  | |  | |  | | |  | *FN* | | *TN* | |
|  |  |  |  | |  | |  | |  | | |  |  | |  | |
| **MOD\_NEONATALMORT (fold a):** | | | | |  | |  | |  | | |  |  | |  | |
| Train (N= 128) | |  |  | | Test (N = 128) | | | |  | | |  |  | |  | |
| (a) | (b) | <- classified as | | | (a) | | (b) | | <- classified as | | | |  | |  | |
| 70 | 2 | (a): class -1 | | | 68 | | 1 | | (a): class -1 | | | |  | |  | |
| 38 | 16484 | (b): class 1 | | | 39 | | 16484 | | (b): class 1 | | | |  | |  | |
|  |  |  |  | |  | |  | |  | | |  |  | |  | |
| DT Size: |  |  |  | |  | |  | |  | | |  |  | |  | |
| Accuracy: | | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| Sensitivity: | | 0.65 |  | |  | |  | | 0.64 | | |  |  | |  | |
| Specificity: | | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| PPV/Precision: | | 0.97 |  | |  | |  | | 0.99 | | |  |  | |  | |
| NPV: |  | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| Recall: |  | 0.65 |  | |  | |  | | 0.64 | | |  |  | |  | |
| **F1 score:** | | 0.78 |  | |  | |  | | 0.77 | | |  |  | |  | |
| **MCC:** |  | 0.79 |  | |  | |  | | 0.79 | | |  |  | |  | |
| **SS1:** |  | 0.65 |  | |  | |  | | 0.64 | | |  |  | |  | |
|  |  |  |  | |  | |  | |  | | |  |  | |  | |
| **MOD\_NEONATALMORT (fold b):** | | | | | | |  | |  | | |  |  | |  | |
| Train (N= 128) | |  |  | | Test (N = 128) | | | |  | | |  |  | |  | |
| (a) | (b) | <- classified as | | | (a) | | (b) | | <- classified as | | | |  | |  | |
| 83 | 8 | (a): class -1 | | | 76 | | 32 | | (a): class -1 | | | |  | |  | |
| 24 | 16477 | (b): class 1 | | | 32 | | 16461 | | (b): class 1 | | | |  | |  | |
|  |  |  |  | |  | |  | |  | | |  |  | |  | |
| DT Size: |  |  |  | |  | |  | |  | | |  |  | |  | |
| Accuracy: | | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| Sensitivity: | | 0.78 |  | |  | |  | | 0.70 | | |  |  | |  | |
| Specificity: | | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| PPV/Precision: | | 0.91 |  | |  | |  | | 0.70 | | |  |  | |  | |
| NPV: |  | 1.00 |  | |  | |  | | 1.00 | | |  |  | |  | |
| Recall: |  | 0.78 |  | |  | |  | | 0.70 | | |  |  | |  | |
| **F1 score:** | | 0.84 |  | |  | |  | | 0.70 | | |  |  | |  | |
| **MCC:** |  | 0.84 |  | |  | |  | | 0.70 | | |  |  | |  | |
| **SS1:** |  | 0.78 |  | |  | |  | | 0.70 | | |  |  | |  | |
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| **Decision Tree Results - Mortality (13 attributes)** | | | | | | | | | | | *Confusion Matrix* | | | | |
| *Options: Default Boosting* | | |  |  | |  | |  | |  | *TP* | | | *FP* | |
|  |  |  |  |  | |  | |  | |  | *FN* | | | *TN* | |
|  |  |  |  |  | |  | |  | |  |  | | |  | |
| **MOD\_NEONATALMORT (fold a):** | | | |  | |  | |  | |  |  | | |  | |
| Train (N= 128) | |  |  | Test (N = 128) | | | |  | |  |  | | |  | |
| (a) | (b) | <- classified as | | (a) | | (b) | | <- classified as | | |  | | |  | |
| 75 | 4 | (a): class -1 | | 74 | | 11 | | (a): class -1 | | |  | | |  | |
| 33 | 16482 | (b): class 1 | | 33 | | 16474 | | (b): class 1 | | |  | | |  | |
|  |  |  |  |  | |  | |  | |  |  | | |  | |
| DT Size: |  |  |  |  | |  | |  | |  |  | | |  | |
| Accuracy: | | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| Sensitivity: | | 0.69 |  |  | |  | | 0.69 | |  |  | | |  | |
| Specificity: | | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| PPV/Precision: | | 0.95 |  |  | |  | | 0.87 | |  |  | | |  | |
| NPV: |  | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| Recall: |  | 0.69 |  |  | |  | | 0.69 | |  |  | | |  | |
| **F1 score:** | | 0.80 |  |  | |  | | 0.77 | |  |  | | |  | |
| **MCC:** |  | 0.81 |  |  | |  | | 0.77 | |  |  | | |  | |
| **SS1:** |  | 0.69 |  |  | |  | | 0.69 | |  |  | | |  | |
|  |  |  |  |  | |  | |  | |  |  | | |  | |
| **MOD\_NEONATALMORT (fold b):** | | | | | |  | |  | |  |  | | |  | |
| Train (N= 128) | |  |  | Test (N = 128) | | | |  | |  |  | | |  | |
| (a) | (b) | <- classified as | | (a) | | (b) | | <- classified as | | |  | | |  | |
| 77 | 8 | (a): class -1 | | 73 | | 6 | | (a): class -1 | | |  | | |  | |
| 30 | 16477 | (b): class 1 | | 35 | | 16480 | | (b): class 1 | | |  | | |  | |
|  |  |  |  |  | |  | |  | |  |  | | |  | |
| DT Size: |  |  |  |  | |  | |  | |  |  | | |  | |
| Accuracy: | | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| Sensitivity: | | 0.72 |  |  | |  | | 0.68 | |  |  | | |  | |
| Specificity: | | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| PPV/Precision: | | 0.91 |  |  | |  | | 0.92 | |  |  | | |  | |
| NPV: |  | 1.00 |  |  | |  | | 1.00 | |  |  | | |  | |
| Recall: |  | 0.72 |  |  | |  | | 0.68 | |  |  | | |  | |
| **F1 score:** | | 0.80 |  |  | |  | | 0.78 | |  |  | | |  | |
| **MCC:** |  | 0.81 |  |  | |  | | 0.79 | |  |  | | |  | |
| **SS1:** |  | 0.72 |  |  | |  | | 0.68 | |  |  | | |  | |
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**G1.3 noMOD\_MULTGEST DT RESULTS**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | | **C5.0 Decision Tree Results** | | |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | | Cases with Mortality: | | 24 |  | ***Confusion Matrix*** | |  |  |  | | Cases without Mortality: | | 232 |  | ***TP*** | ***FP*** |  |  |  | | Total cases: |  | 256 |  | ***FN*** | ***TN*** |  |  |  | | Minority dataset: |  | **9%** |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | | 5 by 2 Cross Validation Results | | |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  | |  | **Train** |  | **Test** | Std Dev |  |  |  |  | | **Accuracy:** | 0.8528 |  | **0.8515** | 0.0053 |  |  |  |  | | **Sensitivity:** | 0.1585 |  | **0.1542** | 0.0301 |  |  |  |  | | **Specificity:** | 0.9937 |  | **0.9931** | 0.0029 |  |  |  |  | | **PPV/Precision:** | 0.8351 |  | **0.8194** | 0.0650 |  |  |  |  | | **NPV:** | 0.8533 |  | **0.8526** | 0.0044 |  |  |  |  | | **Recall:** | 0.1585 |  | **0.1542** | 0.0301 |  |  |  |  | | **F1 score:** | 0.2661 |  | **0.2585** | 0.0435 |  |  |  |  | | **MCC:** | 0.2997 |  | **0.2906** | 0.0394 |  |  |  |  | | **SS1:** | 0.1522 |  | **0.1473** | 0.0298 |  |  |  |  | | | | | | | | | | |  |  |  |  |  |  |
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|  | | | | | | | |  |  |  |  |  |  |  |  |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold a):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 29 | 4 | (a): class -1 | | 20 | 6 | (a): class -1 |
| 133 | 792 | (b): class 1 | | 141 | 789 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8570 |  |  |  | 0.8462 |
| Sensitivity: | | 0.1790 |  |  |  | 0.1242 |
| Specificity: | | 0.9950 |  |  |  | 0.9925 |
| PPV/Precision: | | 0.8788 |  |  |  | 0.7692 |
| NPV: |  | 0.8562 |  |  |  | 0.8484 |
| Recall: |  | 0.1790 |  |  |  | 0.1242 |
| **F1 score:** | | 0.2974 |  |  |  | 0.2139 |
| **MCC:** |  | 0.3317 |  |  |  | 0.2482 |
| **SS1:** |  | 0.1740 |  |  |  | 0.1167 |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold b):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 20 | 6 | (a): class -1 | | 29 | 4 | (a): class -1 |
| 141 | 789 | (b): class 1 | | 133 | 792 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8462 |  |  |  | 0.8570 |
| Sensitivity: | | 0.1242 |  |  |  | 0.1790 |
| Specificity: | | 0.9925 |  |  |  | 0.9950 |
| PPV/Precision: | | 0.7692 |  |  |  | 0.8788 |
| NPV: |  | 0.8484 |  |  |  | 0.8562 |
| Recall: |  | 0.1242 |  |  |  | 0.1790 |
| **F1 score:** | | 0.2139 |  |  |  | 0.2974 |
| **MCC:** |  | 0.2482 |  |  |  | 0.3317 |
| **SS1:** |  | 0.1167 |  |  |  | 0.1740 |

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| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold a):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 27 | 4 | (a): class -1 | | 32 | 9 | (a): class -1 |
| 135 | 792 | (b): class 1 | | 129 | 786 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8549 |  |  |  | 0.8556 |
| Sensitivity: | | 0.1667 |  |  |  | 0.1988 |
| Specificity: | | 0.9950 |  |  |  | 0.9887 |
| PPV/Precision: | | 0.8710 |  |  |  | 0.7805 |
| NPV: |  | 0.8544 |  |  |  | 0.8590 |
| Recall: |  | 0.1667 |  |  |  | 0.1988 |
| **F1 score:** | | 0.2798 |  |  |  | 0.3168 |
| **MCC:** |  | 0.3173 |  |  |  | 0.3227 |
| **SS1:** |  | 0.1616 |  |  |  | 0.1874 |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold b):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 29 | 6 | (a): class -1 | | 20 | 4 | (a): class -1 |
| 132 | 789 | (b): class 1 | | 142 | 792 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8556 |  |  |  | 0.8476 |
| Sensitivity: | | 0.1801 |  |  |  | 0.1235 |
| Specificity: | | 0.9925 |  |  |  | 0.9950 |
| PPV/Precision: | | 0.8286 |  |  |  | 0.8333 |
| NPV: |  | 0.8567 |  |  |  | 0.8480 |
| Recall: |  | 0.1801 |  |  |  | 0.1235 |
| **F1 score:** | | 0.2959 |  |  |  | 0.2151 |
| **MCC:** |  | 0.3195 |  |  |  | 0.2622 |
| **SS1:** |  | 0.1726 |  |  |  | 0.1184 |

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| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold a):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 21 | 8 | (a): class -1 | | 28 | 2 | (a): class -1 |
| 141 | 788 | (b): class 1 | | 133 | 793 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8445 |  |  |  | 0.8588 |
| Sensitivity: | | 0.1296 |  |  |  | 0.1739 |
| Specificity: | | 0.9899 |  |  |  | 0.9975 |
| PPV/Precision: | | 0.7241 |  |  |  | 0.9333 |
| NPV: |  | 0.8482 |  |  |  | 0.8564 |
| Recall: |  | 0.1296 |  |  |  | 0.1739 |
| **F1 score:** | | 0.2199 |  |  |  | 0.2932 |
| **MCC:** |  | 0.2422 |  |  |  | 0.3409 |
| **SS1:** |  | 0.1196 |  |  |  | 0.1714 |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold b):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 28 | 2 | (a): class -1 | | 21 | 8 | (a): class -1 |
| 133 | 793 | (b): class 1 | | 141 | 788 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8588 |  |  |  | 0.8445 |
| Sensitivity: | | 0.1739 |  |  |  | 0.1296 |
| Specificity: | | 0.9975 |  |  |  | 0.9899 |
| PPV/Precision: | | 0.9333 |  |  |  | 0.7241 |
| NPV: |  | 0.8564 |  |  |  | 0.8482 |
| Recall: |  | 0.1739 |  |  |  | 0.1296 |
| **F1 score:** | | 0.2932 |  |  |  | 0.2199 |
| **MCC:** |  | 0.3409 |  |  |  | 0.2422 |
| **SS1:** |  | 0.1714 |  |  |  | 0.1196 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold a):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 30 | 5 | (a): class -1 | | 19 | 5 | (a): class -1 |
| 132 | 791 | (b): class 1 | | 142 | 790 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8570 |  |  |  | 0.8462 |
| Sensitivity: | | 0.1852 |  |  |  | 0.1180 |
| Specificity: | | 0.9937 |  |  |  | 0.9937 |
| PPV/Precision: | | 0.8571 |  |  |  | 0.7917 |
| NPV: |  | 0.8570 |  |  |  | 0.8476 |
| Recall: |  | 0.1852 |  |  |  | 0.1180 |
| **F1 score:** | | 0.3046 |  |  |  | 0.2054 |
| **MCC:** |  | 0.3319 |  |  |  | 0.2468 |
| **SS1:** |  | 0.1789 |  |  |  | 0.1117 |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold b):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 23 | 5 | (a): class -1 | | 31 | 7 | (a): class -1 |
| 138 | 790 | (b): class 1 | | 131 | 789 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8504 |  |  |  | 0.8559 |
| Sensitivity: | | 0.1429 |  |  |  | 0.1914 |
| Specificity: | | 0.9937 |  |  |  | 0.9912 |
| PPV/Precision: | | 0.8214 |  |  |  | 0.8158 |
| NPV: |  | 0.8513 |  |  |  | 0.8576 |
| Recall: |  | 0.1429 |  |  |  | 0.1914 |
| **F1 score:** | | 0.2434 |  |  |  | 0.3100 |
| **MCC:** |  | 0.2805 |  |  |  | 0.3261 |
| **SS1:** |  | 0.1366 |  |  |  | 0.1826 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold a):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 25 | 3 | (a): class -1 | | 24 | 7 | (a): class -1 |
| 137 | 793 | (b): class 1 | | 137 | 788 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8539 |  |  |  | 0.8494 |
| Sensitivity: | | 0.1543 |  |  |  | 0.1491 |
| Specificity: | | 0.9962 |  |  |  | 0.9912 |
| PPV/Precision: | | 0.8929 |  |  |  | 0.7742 |
| NPV: |  | 0.8527 |  |  |  | 0.8519 |
| Recall: |  | 0.1543 |  |  |  | 0.1491 |
| **F1 score:** | | 0.2632 |  |  |  | 0.2500 |
| **MCC:** |  | 0.3100 |  |  |  | 0.2747 |
| **SS1:** |  | 0.1506 |  |  |  | 0.1403 |
|  |  |  |  |  |  |  |
| **noMOD\_TWINGEST (fold b):** | | | |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 24 | 7 | (a): class -1 | | 25 | 3 | (a): class -1 |
| 137 | 788 | (b): class 1 | | 137 | 793 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.8494 |  |  |  | 0.8539 |
| Sensitivity: | | 0.1491 |  |  |  | 0.1543 |
| Specificity: | | 0.9912 |  |  |  | 0.9962 |
| PPV/Precision: | | 0.7742 |  |  |  | 0.8929 |
| NPV: |  | 0.8519 |  |  |  | 0.8527 |
| Recall: |  | 0.1491 |  |  |  | 0.1543 |
| **F1 score:** | | 0.2500 |  |  |  | 0.2632 |
| **MCC:** |  | 0.2747 |  |  |  | 0.3100 |
| **SS1:** |  | 0.1403 |  |  |  | 0.1506 |

**G1.4 MOD\_MULTGEST DT RESULTS**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **MOD\_MULTGEST RESULTS** | | |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
| Cases with Mortality: | | 24 |  | ***Confusion Matrix*** | |  |  |  |
| Cases without Mortality: | | 232 |  | ***TP*** | ***FP*** |  |  |  |
| Total cases: |  | 256 |  | ***FN*** | ***TN*** |  |  |  |
| Minority dataset: |  | **9%** |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
| 5 by 2 Cross Validation Results | | |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  | **Train** |  | **Test** | Std Dev |  |  |  |  |
| **Accuracy:** | 0.9443 |  | **0.8983** | 0.0074 |  |  |  |  |
| **Sensitivity:** | 0.9102 |  | **0.7932** | 0.0585 |  |  |  |  |
| **Specificity:** | 0.9512 |  | **0.9197** | 0.0120 |  |  |  |  |
| **PPV/Precision:** | 0.7928 |  | **0.6685** | 0.0251 |  |  |  |  |
| **NPV:** | 0.9813 |  | **0.9566** | 0.0117 |  |  |  |  |
| **Recall:** | 0.9102 |  | **0.7932** | 0.0585 |  |  |  |  |
| **F1 score:** | 0.8467 |  | **0.7242** | 0.0236 |  |  |  |  |
| **MCC:** | 0.8291 |  | **0.6807** | 0.0364 |  |  |  |  |
| **SS1:** | 0.8614 |  | **0.7129** | 0.0506 |  |  |  |  |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold a):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 153 | 31 | (a): class -1 | | 122 | 70 | (a): class -1 |
| 9 | 765 | (b): class 1 | | 39 | 725 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9582 |  |  |  | 0.8860 |
| Sensitivity: | | 0.9444 |  |  |  | 0.7578 |
| Specificity: | | 0.9611 |  |  |  | 0.9119 |
| PPV/Precision: | | 0.8315 |  |  |  | 0.6354 |
| NPV: |  | 0.9884 |  |  |  | 0.9490 |
| Recall: |  | 0.9444 |  |  |  | 0.7578 |
| **F1 score:** | | 0.8844 |  |  |  | 0.6912 |
| **MCC:** |  | 0.8738 |  |  |  | 0.6382 |
| **SS1:** |  | 0.9055 |  |  |  | 0.6697 |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold b):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 146 | 46 | (a): class -1 | | 127 | 50 | (a): class -1 |
| 15 | 749 | (b): class 1 | | 35 | 746 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9362 |  |  |  | 0.9113 |
| Sensitivity: | | 0.9068 |  |  |  | 0.7840 |
| Specificity: | | 0.9421 |  |  |  | 0.9372 |
| PPV/Precision: | | 0.7604 |  |  |  | 0.7175 |
| NPV: |  | 0.9804 |  |  |  | 0.9552 |
| Recall: |  | 0.9068 |  |  |  | 0.7840 |
| **F1 score:** | | 0.8272 |  |  |  | 0.7493 |
| **MCC:** |  | 0.8090 |  |  |  | 0.7032 |
| **SS1:** |  | 0.8490 |  |  |  | 0.7211 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold a):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 142 | 30 | (a): class -1 | | 122 | 54 | (a): class -1 |
| 20 | 766 | (b): class 1 | | 39 | 741 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9478 |  |  |  | 0.9027 |
| Sensitivity: | | 0.8765 |  |  |  | 0.7578 |
| Specificity: | | 0.9623 |  |  |  | 0.9321 |
| PPV/Precision: | | 0.8256 |  |  |  | 0.6932 |
| NPV: |  | 0.9746 |  |  |  | 0.9500 |
| Recall: |  | 0.8765 |  |  |  | 0.7578 |
| **F1 score:** | | 0.8503 |  |  |  | 0.7240 |
| **MCC:** |  | 0.8245 |  |  |  | 0.6725 |
| **SS1:** |  | 0.8389 |  |  |  | 0.6898 |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold b):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 140 | 34 | (a): class -1 | | 124 | 62 | (a): class -1 |
| 21 | 761 | (b): class 1 | | 38 | 734 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9425 |  |  |  | 0.8956 |
| Sensitivity: | | 0.8696 |  |  |  | 0.7654 |
| Specificity: | | 0.9572 |  |  |  | 0.9221 |
| PPV/Precision: | | 0.8046 |  |  |  | 0.6667 |
| NPV: |  | 0.9731 |  |  |  | 0.9508 |
| Recall: |  | 0.8696 |  |  |  | 0.7654 |
| **F1 score:** | | 0.8358 |  |  |  | 0.7126 |
| **MCC:** |  | 0.8085 |  |  |  | 0.6616 |
| **SS1:** |  | 0.8268 |  |  |  | 0.6875 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold a):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 158 | 57 | (a): class -1 | | 149 | 80 | (a): class -1 |
| 4 | 739 | (b): class 1 | | 12 | 715 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9363 |  |  |  | 0.9038 |
| Sensitivity: | | 0.9753 |  |  |  | 0.9255 |
| Specificity: | | 0.9284 |  |  |  | 0.8994 |
| PPV/Precision: | | 0.7349 |  |  |  | 0.6507 |
| NPV: |  | 0.9946 |  |  |  | 0.9835 |
| Recall: |  | 0.9753 |  |  |  | 0.9255 |
| **F1 score:** | | 0.8382 |  |  |  | 0.7641 |
| **MCC:** |  | 0.8404 |  |  |  | 0.7563 |
| **SS1:** |  | 0.9037 |  |  |  | 0.8248 |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold b):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 142 | 46 | (a): class -1 | | 129 | 67 | (a): class -1 |
| 19 | 749 | (b): class 1 | | 33 | 729 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9320 |  |  |  | 0.8956 |
| Sensitivity: | | 0.8820 |  |  |  | 0.7963 |
| Specificity: | | 0.9421 |  |  |  | 0.9158 |
| PPV/Precision: | | 0.7553 |  |  |  | 0.6582 |
| NPV: |  | 0.9753 |  |  |  | 0.9567 |
| Recall: |  | 0.8820 |  |  |  | 0.7963 |
| **F1 score:** | | 0.8138 |  |  |  | 0.7207 |
| **MCC:** |  | 0.7895 |  |  |  | 0.6763 |
| **SS1:** |  | 0.8241 |  |  |  | 0.7121 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold a):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 151 | 34 | (a): class -1 | | 136 | 66 | (a): class -1 |
| 11 | 762 | (b): class 1 | | 25 | 729 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9530 |  |  |  | 0.9048 |
| Sensitivity: | | 0.9321 |  |  |  | 0.8447 |
| Specificity: | | 0.9573 |  |  |  | 0.9170 |
| PPV/Precision: | | 0.8162 |  |  |  | 0.6733 |
| NPV: |  | 0.9858 |  |  |  | 0.9668 |
| Recall: |  | 0.9321 |  |  |  | 0.8447 |
| **F1 score:** | | 0.8703 |  |  |  | 0.7493 |
| **MCC:** |  | 0.8570 |  |  |  | 0.7170 |
| **SS1:** |  | 0.8894 |  |  |  | 0.7617 |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold b):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 144 | 40 | (a): class -1 | | 129 | 72 | (a): class -1 |
| 17 | 755 | (b): class 1 | | 33 | 724 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9404 |  |  |  | 0.8904 |
| Sensitivity: | | 0.8944 |  |  |  | 0.7963 |
| Specificity: | | 0.9497 |  |  |  | 0.9095 |
| PPV/Precision: | | 0.7826 |  |  |  | 0.6418 |
| NPV: |  | 0.9780 |  |  |  | 0.9564 |
| Recall: |  | 0.8944 |  |  |  | 0.7963 |
| **F1 score:** | | 0.8348 |  |  |  | 0.7107 |
| **MCC:** |  | 0.8131 |  |  |  | 0.6663 |
| **SS1:** |  | 0.8441 |  |  |  | 0.7058 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Twins Gestation (21 attributes)** | | | | | | |
| *Options: Default Boosting* | | |  |  |  |  |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold a):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 149 | 39 | (a): class -1 | | 114 | 52 | (a): class -1 |
| 13 | 757 | (b): class 1 | | 47 | 743 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9457 |  |  |  | 0.8964 |
| Sensitivity: | | 0.9198 |  |  |  | 0.7081 |
| Specificity: | | 0.9510 |  |  |  | 0.9346 |
| PPV/Precision: | | 0.7926 |  |  |  | 0.6867 |
| NPV: |  | 0.9831 |  |  |  | 0.9405 |
| Recall: |  | 0.9198 |  |  |  | 0.7081 |
| **F1 score:** | | 0.8514 |  |  |  | 0.6972 |
| **MCC:** |  | 0.8356 |  |  |  | 0.6369 |
| **SS1:** |  | 0.8708 |  |  |  | 0.6427 |
|  |  |  |  |  |  |  |
| **MOD\_TWINGEST (fold b):** | | |  |  |  |  |
| Train (N= 128) | |  |  | Test (N = 128) | |  |
| (a) | (b) | <- classified as | | (a) | (b) | <- classified as |
| 145 | 31 | (a): class -1 | | 129 | 66 | (a): class -1 |
| 16 | 764 | (b): class 1 | | 33 | 730 | (b): class 1 |
|  |  |  |  |  |  |  |
| DT Size: |  |  |  |  |  |  |
| Accuracy: | | 0.9508 |  |  |  | 0.8967 |
| Sensitivity: | | 0.9006 |  |  |  | 0.7963 |
| Specificity: | | 0.9610 |  |  |  | 0.9171 |
| PPV/Precision: | | 0.8239 |  |  |  | 0.6615 |
| NPV: |  | 0.9795 |  |  |  | 0.9567 |
| Recall: |  | 0.9006 |  |  |  | 0.7963 |
| **F1 score:** | | 0.8605 |  |  |  | 0.7227 |
| **MCC:** |  | 0.8399 |  |  |  | 0.6783 |
| **SS1:** |  | 0.8616 |  |  |  | 0.7134 |

**G1.5 noMOD\_SINGLETON DT RESULTS**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **C5.0 Decision Tree Results** | | |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
| Cases with Mortality: | | 24 |  | ***Confusion Matrix*** | |  |  |  |
| Cases without Mortality: | | 232 |  | ***TP*** | ***FP*** |  |  |  |
| Total cases: |  | 256 |  | ***FN*** | ***TN*** |  |  |  |
| Minority dataset: |  | **9%** |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
| 5 by 2 Cross Validation Results | | |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  | **Train** |  | **Test** | Std Dev |  |  |  |  |
| **Accuracy:** | 0.90 |  | **0.67** | 0.05 |  |  |  |  |
| **Sensitivity:** | 0.15 |  | **0.12** | 0.02 |  |  |  |  |
| **Specificity:** | 1.00 |  | **0.74** | 0.05 |  |  |  |  |
| **PPV/Precision:** | 0.86 |  | **0.05** | 0.01 |  |  |  |  |
| **NPV:** | 0.90 |  | **0.87** | 0.01 |  |  |  |  |
| **Recall:** | 0.15 |  | **0.12** | 0.02 |  |  |  |  |
| **F1 score:** | 0.25 |  | **0.07** | 0.01 |  |  |  |  |
| **MCC:** | 0.32 |  | **-0.11** | 0.03 |  |  |  |  |
| **SS1:** | 0.15 |  | **-0.14** | 0.04 |  |  |  |  |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | |  | | | | | |  | | | |  | |  | | | | | | |  | | *TP* | | | | *FP* | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | | *FN* | | | | *TN* | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| **NICU CDR first 12 hours (fold a):** | | | | | | | | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | | | Test (N = 128) | | | | | |  | | | | | | |  | |  | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | | | (a) | | | | (b) | | <- classified as | | | | | | | | |  | | | |  | | | |
| 1428 | 218 | | | (a): class -1 | | | | | | | | | 947 | | | | 18711 | | (a): class -1 | | | | | | | | |  | | | |  | | | |
| 6360 | 62282 | | | (b): class 1 | | | | | | | | | 6840 | | | | 43789 | | (b): class 1 | | | | | | | | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| DT Size: |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Accuracy: | | | | 0.91 | | |  | | | | | |  | | | |  | | 0.64 | | | | | | |  | |  | | | |  | | | |
| Sensitivity: | | | | 0.18 | | |  | | | | | |  | | | |  | | 0.12 | | | | | | |  | |  | | | |  | | | |
| Specificity: | | | | 1.00 | | |  | | | | | |  | | | |  | | 0.70 | | | | | | |  | |  | | | |  | | | |
| PPV/Precision: | | | | 0.87 | | |  | | | | | |  | | | |  | | 0.05 | | | | | | |  | |  | | | |  | | | |
| NPV: |  | | | 0.91 | | |  | | | | | |  | | | |  | | 0.86 | | | | | | |  | |  | | | |  | | | |
| Recall: |  | | | 0.18 | | |  | | | | | |  | | | |  | | 0.12 | | | | | | |  | |  | | | |  | | | |
| **F1 score:** | | | | 0.30 | | |  | | | | | |  | | | |  | | 0.07 | | | | | | |  | |  | | | |  | | | |
| **MCC:** |  | | | 0.36 | | |  | | | | | |  | | | |  | | -0.14 | | | | | | |  | |  | | | |  | | | |
| **SS1:** |  | | | 0.18 | | |  | | | | | |  | | | |  | | -0.18 | | | | | | |  | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| **noMOD\_Singleton (fold b):** | | | | | | | | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | | | Test (N = 128) | | | | | |  | | | | | | |  | |  | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | | | (a) | | | | (b) | | <- classified as | | | | | | | | |  | | | |  | | | |
| 1221 | 122 | | | (a): class -1 | | | | | | | | | 925 | | | | 19065 | | (a): class -1 | | | | | | | | |  | | | |  | | | |
| 6566 | 62378 | | | (b): class 1 | | | | | | | | | 6863 | | | | 43435 | | (b): class 1 | | | | | | | | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| DT Size: |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Accuracy: | | | | 0.90 | | |  | | | | | |  | | | |  | | 0.63 | | | | | | |  | |  | | | |  | | | |
| Sensitivity: | | | | 0.16 | | |  | | | | | |  | | | |  | | 0.12 | | | | | | |  | |  | | | |  | | | |
| Specificity: | | | | 1.00 | | |  | | | | | |  | | | |  | | 0.69 | | | | | | |  | |  | | | |  | | | |
| PPV/Precision: | | | | 0.91 | | |  | | | | | |  | | | |  | | 0.05 | | | | | | |  | |  | | | |  | | | |
| NPV: |  | | | 0.90 | | |  | | | | | |  | | | |  | | 0.86 | | | | | | |  | |  | | | |  | | | |
| Recall: |  | | | 0.16 | | |  | | | | | |  | | | |  | | 0.12 | | | | | | |  | |  | | | |  | | | |
| **F1 score:** | | | | 0.27 | | |  | | | | | |  | | | |  | | 0.07 | | | | | | |  | |  | | | |  | | | |
| **MCC:** |  | | | 0.34 | | |  | | | | | |  | | | |  | | -0.14 | | | | | | |  | |  | | | |  | | | |
| **SS1:** |  | | | 0.15 | | |  | | | | | |  | | | |  | | -0.19 | | | | | | |  | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
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|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | |
| *Options: Default Boosting* | | | | | | |  | | | |  | | | |  | | |  | | |  | | | | *TP* | | | | | *FP* | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | | *FN* | | | | | *TN* | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **noMOD\_SINGLETON (fold a):** | | | | | | | | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | Test (N = 128) | | | | | | |  | | |  | | | |  | | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | (a) | | | | (b) | | | <- classified as | | | | | | |  | | | | |  | | | |
| 1295 | 184 | | | (a): class -1 | | | | | | | 1116 | | | | 20393 | | | (a): class -1 | | | | | | |  | | | | |  | | | |
| 6493 | 62316 | | | (b): class 1 | | | | | | | 6671 | | | | 42107 | | | (b): class 1 | | | | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| DT Size: |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Accuracy: | | | | 0.91 | | |  | | | |  | | | |  | | | 0.61 | | |  | | | |  | | | | |  | | | |
| Sensitivity: | | | | 0.17 | | |  | | | |  | | | |  | | | 0.14 | | |  | | | |  | | | | |  | | | |
| Specificity: | | | | 1.00 | | |  | | | |  | | | |  | | | 0.67 | | |  | | | |  | | | | |  | | | |
| PPV/Precision: | | | | 0.88 | | |  | | | |  | | | |  | | | 0.05 | | |  | | | |  | | | | |  | | | |
| NPV: |  | | | 0.91 | | |  | | | |  | | | |  | | | 0.86 | | |  | | | |  | | | | |  | | | |
| Recall: |  | | | 0.17 | | |  | | | |  | | | |  | | | 0.14 | | |  | | | |  | | | | |  | | | |
| **F1 score:** | | | | 0.28 | | |  | | | |  | | | |  | | | 0.08 | | |  | | | |  | | | | |  | | | |
| **MCC:** |  | | | 0.34 | | |  | | | |  | | | |  | | | -0.14 | | |  | | | |  | | | | |  | | | |
| **SS1:** |  | | | 0.16 | | |  | | | |  | | | |  | | | -0.18 | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **noMOD\_Singleton (fold b):** | | | | | | | | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | Test (N = 128) | | | | | | |  | | |  | | | |  | | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | (a) | | | | (b) | | | <- classified as | | | | | | |  | | | | |  | | | |
| 1115 | 212 | | | (a): class -1 | | | | | | | 761 | | | | 15033 | | | (a): class -1 | | | | | | |  | | | | |  | | | |
| 6672 | 62288 | | | (b): class 1 | | | | | | | 7027 | | | | 47467 | | | (b): class 1 | | | | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| DT Size: |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Accuracy: | | | | 0.90 | | |  | | | |  | | | |  | | | 0.69 | | |  | | | |  | | | | |  | | | |
| Sensitivity: | | | | 0.14 | | |  | | | |  | | | |  | | | 0.10 | | |  | | | |  | | | | |  | | | |
| Specificity: | | | | 1.00 | | |  | | | |  | | | |  | | | 0.76 | | |  | | | |  | | | | |  | | | |
| PPV/Precision: | | | | 0.84 | | |  | | | |  | | | |  | | | 0.05 | | |  | | | |  | | | | |  | | | |
| NPV: |  | | | 0.90 | | |  | | | |  | | | |  | | | 0.87 | | |  | | | |  | | | | |  | | | |
| Recall: |  | | | 0.14 | | |  | | | |  | | | |  | | | 0.10 | | |  | | | |  | | | | |  | | | |
| **F1 score:** | | | | 0.24 | | |  | | | |  | | | |  | | | 0.06 | | |  | | | |  | | | | |  | | | |
| **MCC:** |  | | | 0.31 | | |  | | | |  | | | |  | | | -0.12 | | |  | | | |  | | | | |  | | | |
| **SS1:** |  | | | 0.14 | | |  | | | |  | | | |  | | | -0.14 | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
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|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | |
| *Options: Default Boosting* | | | | | | | |  | |  | | | |  | | | |  | | | |  | | *TP* | | | | | *FP* | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | | *FN* | | | | | *TN* | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **noMOD\_SINGLETON (fold a):** | | | | | | | | | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Train (N= 128) | | | | |  | | |  | | Test (N = 128) | | | | | | | |  | | | |  | |  | | | | |  | | | |
| (a) | | (b) | | | <- classified as | | | | | (a) | | | | (b) | | | | <- classified as | | | | | |  | | | | |  | | | |
| 1043 | | 178 | | | (a): class -1 | | | | | 770 | | | | 11173 | | | | (a): class -1 | | | | | |  | | | | |  | | | |
| 6745 | | 62322 | | | (b): class 1 | | | | | 7017 | | | | 51327 | | | | (b): class 1 | | | | | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| DT Size: | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Accuracy: | | | | | 0.90 | | |  | |  | | | |  | | | | 0.74 | | | |  | |  | | | | |  | | | |
| Sensitivity: | | | | | 0.13 | | |  | |  | | | |  | | | | 0.10 | | | |  | |  | | | | |  | | | |
| Specificity: | | | | | 1.00 | | |  | |  | | | |  | | | | 0.82 | | | |  | |  | | | | |  | | | |
| PPV/Precision: | | | | | 0.85 | | |  | |  | | | |  | | | | 0.06 | | | |  | |  | | | | |  | | | |
| NPV: | |  | | | 0.90 | | |  | |  | | | |  | | | | 0.88 | | | |  | |  | | | | |  | | | |
| Recall: | |  | | | 0.13 | | |  | |  | | | |  | | | | 0.10 | | | |  | |  | | | | |  | | | |
| **F1 score:** | | | | | 0.23 | | |  | |  | | | |  | | | | 0.08 | | | |  | |  | | | | |  | | | |
| **MCC:** | |  | | | 0.30 | | |  | |  | | | |  | | | | -0.07 | | | |  | |  | | | | |  | | | |
| **SS1:** | |  | | | 0.13 | | |  | |  | | | |  | | | | -0.08 | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **noMOD\_Singleton (fold b):** | | | | | | | | | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Train (N= 128) | | | | |  | | |  | | Test (N = 128) | | | | | | | |  | | | |  | |  | | | | |  | | | |
| (a) | | (b) | | | <- classified as | | | | | (a) | | | | (b) | | | | <- classified as | | | | | |  | | | | |  | | | |
| 901 | | 189 | | | (a): class -1 | | | | | 728 | | | | 9840 | | | | (a): class -1 | | | | | |  | | | | |  | | | |
| 6886 | | 62311 | | | (b): class 1 | | | | | 7060 | | | | 52660 | | | | (b): class 1 | | | | | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| DT Size: | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Accuracy: | | | | | 0.90 | | |  | |  | | | |  | | | | 0.76 | | | |  | |  | | | | |  | | | |
| Sensitivity: | | | | | 0.12 | | |  | |  | | | |  | | | | 0.09 | | | |  | |  | | | | |  | | | |
| Specificity: | | | | | 1.00 | | |  | |  | | | |  | | | | 0.84 | | | |  | |  | | | | |  | | | |
| PPV/Precision: | | | | | 0.83 | | |  | |  | | | |  | | | | 0.07 | | | |  | |  | | | | |  | | | |
| NPV: | |  | | | 0.90 | | |  | |  | | | |  | | | | 0.88 | | | |  | |  | | | | |  | | | |
| Recall: | |  | | | 0.12 | | |  | |  | | | |  | | | | 0.09 | | | |  | |  | | | | |  | | | |
| **F1 score:** | | | | | 0.20 | | |  | |  | | | |  | | | | 0.08 | | | |  | |  | | | | |  | | | |
| **MCC:** | |  | | | 0.27 | | |  | |  | | | |  | | | | -0.06 | | | |  | |  | | | | |  | | | |
| **SS1:** | |  | | | 0.11 | | |  | |  | | | |  | | | | -0.06 | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | | *TP* | | | | *FP* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | | *FN* | | | | *TN* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **noMOD\_SINGLETON (fold a):** | | | | | | | | | | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 1098 | | | 176 | | | (a): class -1 | | | | | | 975 | | | | 16280 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 6690 | | | 62324 | | | (b): class 1 | | | | | | 6812 | | | | 46220 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.90 | | |  | | |  | | | |  | | | | 0.67 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.14 | | |  | | |  | | | |  | | | | 0.13 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 1.00 | | |  | | |  | | | |  | | | | 0.74 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.86 | | |  | | |  | | | |  | | | | 0.06 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.90 | | |  | | |  | | | |  | | | | 0.87 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.14 | | |  | | |  | | | |  | | | | 0.13 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.24 | | |  | | |  | | | |  | | | | 0.08 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.31 | | |  | | |  | | | |  | | | | -0.11 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.14 | | |  | | |  | | | |  | | | | -0.14 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **noMOD\_Singleton (fold b):** | | | | | | | | | | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 1102 | | | 196 | | | (a): class -1 | | | | | | 867 | | | | 16499 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 6685 | | | 62304 | | | (b): class 1 | | | | | | 6921 | | | | 46001 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.90 | | |  | | |  | | | |  | | | | 0.67 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.14 | | |  | | |  | | | |  | | | | 0.11 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 1.00 | | |  | | |  | | | |  | | | | 0.74 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.85 | | |  | | |  | | | |  | | | | 0.05 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.90 | | |  | | |  | | | |  | | | | 0.87 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.14 | | |  | | |  | | | |  | | | | 0.11 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.24 | | |  | | |  | | | |  | | | | 0.07 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.31 | | |  | | |  | | | |  | | | | -0.12 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.14 | | |  | | |  | | | |  | | | | -0.15 | | |  | | | |  | | | |  | | | |
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| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | | *TP* | | | | *FP* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | | *FN* | | | | *TN* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **noMOD\_SINGLETON (fold a):** | | | | | | | | | | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 1288 | | | 166 | | | (a): class -1 | | | | | | 1006 | | | | 17263 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 6500 | | | 62334 | | | (b): class 1 | | | | | | 6781 | | | | 45237 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.91 | | |  | | |  | | | |  | | | | 0.66 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.17 | | |  | | |  | | | |  | | | | 0.13 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 1.00 | | |  | | |  | | | |  | | | | 0.72 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.89 | | |  | | |  | | | |  | | | | 0.06 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.91 | | |  | | |  | | | |  | | | | 0.87 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.17 | | |  | | |  | | | |  | | | | 0.13 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.28 | | |  | | |  | | | |  | | | | 0.08 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.34 | | |  | | |  | | | |  | | | | -0.12 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.16 | | |  | | |  | | | |  | | | | -0.15 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **noMOD\_Singleton (fold b):** | | | | | | | | | | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 1170 | | | 177 | | | (a): class -1 | | | | | | 964 | | | | 16945 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 6617 | | | 62323 | | | (b): class 1 | | | | | | 6824 | | | | 45555 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.90 | | |  | | |  | | | |  | | | | 0.66 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.15 | | |  | | |  | | | |  | | | | 0.12 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 1.00 | | |  | | |  | | | |  | | | | 0.73 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.87 | | |  | | |  | | | |  | | | | 0.05 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.90 | | |  | | |  | | | |  | | | | 0.87 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.15 | | |  | | |  | | | |  | | | | 0.12 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.26 | | |  | | |  | | | |  | | | | 0.08 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.32 | | |  | | |  | | | |  | | | | -0.12 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.15 | | |  | | |  | | | |  | | | | -0.15 | | |  | | | |  | | | |  | | | |
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**G1.6 MOD\_SINGLETON DT RESULTS**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | |  | |  | |  | |  | |  | |  |  | |  | |
| **C5.0 Decision Tree Results** | | | | | |  | |  | |  | |  | | |  | |  | |
|  | |  | |  | |  | |  | |  | |  | | |  | |  | |
| Cases with Mortality: | | | | 24 | |  | | ***Confusion Matrix*** | | | |  | | |  | |  | |
| Cases without Mortality: | | | | 232 | |  | | ***TP*** | | ***FP*** | |  | | |  | |  | |
| Total cases: | |  | | 256 | |  | | ***FN*** | | ***TN*** | |  | | |  | |  | |
| Minority dataset: | |  | | **9%** | |  | |  | |  | |  | | |  | |  | |
|  | |  | |  | |  | |  | |  | |  | | |  | |  | |
|  | |  | |  | |  | |  | |  | |  | | |  | |  | |
| 5 by 2 Cross Validation Results | | | | | |  | |  | |  | |  | | |  | |  | |
|  | |  | |  | |  | |  | |  | |  | | |  | |  | |
|  | | **Train** | |  | | **Test** | | Std Dev | |  | |  | | |  | |  | |
| **Accuracy:** | | 0.93 | |  | | **0.28** | | 0.03 | |  | |  | | |  | |  | |
| **Sensitivity:** | | 0.44 | |  | | **0.36** | | 0.05 | |  | |  | | |  | |  | |
| **Specificity:** | | 0.99 | |  | | **0.27** | | 0.04 | |  | |  | | |  | |  | |
| **PPV/Precision:** | | 0.85 | |  | | **0.06** | | 0.01 | |  | |  | | |  | |  | |
| **NPV:** | | 0.94 | |  | | **0.77** | | 0.03 | |  | |  | | |  | |  | |
| **Recall:** | | 0.44 | |  | | **0.36** | | 0.05 | |  | |  | | |  | |  | |
| **F1 score:** | | 0.54 | |  | | **0.10** | | 0.01 | |  | |  | | |  | |  | |
| **MCC:** | | 0.55 | |  | | **-0.43** | | 0.08 | |  | |  | | |  | |  | |
| **SS1:** | | 0.43 | |  | | **-0.37** | | 0.04 | |  | |  | | |  | |  | |

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | |  | | | | | |  | | | |  | |  | | | | | | |  | | *TP* | | | | *FP* | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | | *FN* | | | | *TN* | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| **MOD\_SINGLETON (fold a):** | | | | | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | | | Test (N = 128) | | | | | |  | | | | | | |  | |  | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | | | (a) | | | | (b) | | <- classified as | | | | | | | | |  | | | |  | | | |
| 3518 | 347 | | | (a): class -1 | | | | | | | | | 2438 | | | | 45381 | | (a): class -1 | | | | | | | | |  | | | |  | | | |
| 4270 | 62153 | | | (b): class 1 | | | | | | | | | 5349 | | | | 17119 | | (b): class 1 | | | | | | | | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| DT Size: |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Accuracy: | | | | 0.93 | | |  | | | | | |  | | | |  | | 0.28 | | | | | | |  | |  | | | |  | | | |
| Sensitivity: | | | | 0.45 | | |  | | | | | |  | | | |  | | 0.31 | | | | | | |  | |  | | | |  | | | |
| Specificity: | | | | 0.99 | | |  | | | | | |  | | | |  | | 0.27 | | | | | | |  | |  | | | |  | | | |
| PPV/Precision: | | | | 0.91 | | |  | | | | | |  | | | |  | | 0.05 | | | | | | |  | |  | | | |  | | | |
| NPV: |  | | | 0.94 | | |  | | | | | |  | | | |  | | 0.76 | | | | | | |  | |  | | | |  | | | |
| Recall: |  | | | 0.45 | | |  | | | | | |  | | | |  | | 0.31 | | | | | | |  | |  | | | |  | | | |
| **F1 score:** | | | | 0.60 | | |  | | | | | |  | | | |  | | 0.09 | | | | | | |  | |  | | | |  | | | |
| **MCC:** |  | | | 0.60 | | |  | | | | | |  | | | |  | | -0.46 | | | | | | |  | |  | | | |  | | | |
| **SS1:** |  | | | 0.45 | | |  | | | | | |  | | | |  | | -0.41 | | | | | | |  | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| **MOD\_SINGLETON (fold b):** | | | | | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | | | Test (N = 128) | | | | | |  | | | | | | |  | |  | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | | | (a) | | | | (b) | | <- classified as | | | | | | | | |  | | | |  | | | |
| 3467 | 380 | | | (a): class -1 | | | | | | | | | 2562 | | | | 46104 | | (a): class -1 | | | | | | | | |  | | | |  | | | |
| 4320 | 62120 | | | (b): class 1 | | | | | | | | | 5226 | | | | 16396 | | (b): class 1 | | | | | | | | |  | | | |  | | | |
|  |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| DT Size: |  | | |  | | |  | | | | | |  | | | |  | |  | | | | | | |  | |  | | | |  | | | |
| Accuracy: | | | | 0.93 | | |  | | | | | |  | | | |  | | 0.27 | | | | | | |  | |  | | | |  | | | |
| Sensitivity: | | | | 0.45 | | |  | | | | | |  | | | |  | | 0.33 | | | | | | |  | |  | | | |  | | | |
| Specificity: | | | | 0.99 | | |  | | | | | |  | | | |  | | 0.26 | | | | | | |  | |  | | | |  | | | |
| PPV/Precision: | | | | 0.90 | | |  | | | | | |  | | | |  | | 0.05 | | | | | | |  | |  | | | |  | | | |
| NPV: |  | | | 0.93 | | |  | | | | | |  | | | |  | | 0.76 | | | | | | |  | |  | | | |  | | | |
| Recall: |  | | | 0.45 | | |  | | | | | |  | | | |  | | 0.33 | | | | | | |  | |  | | | |  | | | |
| **F1 score:** | | | | 0.60 | | |  | | | | | |  | | | |  | | 0.09 | | | | | | |  | |  | | | |  | | | |
| **MCC:** |  | | | 0.59 | | |  | | | | | |  | | | |  | | -0.47 | | | | | | |  | |  | | | |  | | | |
| **SS1:** |  | | | 0.44 | | |  | | | | | |  | | | |  | | -0.41 | | | | | | |  | |  | | | |  | | | |
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| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | |
| *Options: Default Boosting* | | | | | | |  | | | |  | | | |  | | |  | | |  | | | | *TP* | | | | | *FP* | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | | *FN* | | | | | *TN* | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **MOD\_SINGLETON (fold a):** | | | | | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | Test (N = 128) | | | | | | |  | | |  | | | |  | | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | (a) | | | | (b) | | | <- classified as | | | | | | |  | | | | |  | | | |
| 1115 | 212 | | | (a): class -1 | | | | | | | 2792 | | | | 43665 | | | (a): class -1 | | | | | | |  | | | | |  | | | |
| 6672 | 62288 | | | (b): class 1 | | | | | | | 4995 | | | | 18835 | | | (b): class 1 | | | | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| DT Size: |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Accuracy: | | | | 0.90 | | |  | | | |  | | | |  | | | 0.31 | | |  | | | |  | | | | |  | | | |
| Sensitivity: | | | | 0.14 | | |  | | | |  | | | |  | | | 0.36 | | |  | | | |  | | | | |  | | | |
| Specificity: | | | | 1.00 | | |  | | | |  | | | |  | | | 0.30 | | |  | | | |  | | | | |  | | | |
| PPV/Precision: | | | | 0.84 | | |  | | | |  | | | |  | | | 0.06 | | |  | | | |  | | | | |  | | | |
| NPV: |  | | | 0.90 | | |  | | | |  | | | |  | | | 0.79 | | |  | | | |  | | | | |  | | | |
| Recall: |  | | | 0.14 | | |  | | | |  | | | |  | | | 0.36 | | |  | | | |  | | | | |  | | | |
| **F1 score:** | | | | 0.24 | | |  | | | |  | | | |  | | | 0.10 | | |  | | | |  | | | | |  | | | |
| **MCC:** |  | | | 0.31 | | |  | | | |  | | | |  | | | -0.37 | | |  | | | |  | | | | |  | | | |
| **SS1:** |  | | | 0.14 | | |  | | | |  | | | |  | | | -0.34 | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **MOD\_SINGLETON (fold b):** | | | | | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Train (N= 128) | | | |  | | |  | | | | Test (N = 128) | | | | | | |  | | |  | | | |  | | | | |  | | | |
| (a) | (b) | | | <- classified as | | | | | | | (a) | | | | (b) | | | <- classified as | | | | | | |  | | | | |  | | | |
| 3202 | 408 | | | (a): class -1 | | | | | | | 3101 | | | | 45484 | | | (a): class -1 | | | | | | |  | | | | |  | | | |
| 4585 | 62092 | | | (b): class 1 | | | | | | | 4687 | | | | 17016 | | | (b): class 1 | | | | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| DT Size: |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| Accuracy: | | | | 0.93 | | |  | | | |  | | | |  | | | 0.29 | | |  | | | |  | | | | |  | | | |
| Sensitivity: | | | | 0.41 | | |  | | | |  | | | |  | | | 0.40 | | |  | | | |  | | | | |  | | | |
| Specificity: | | | | 0.99 | | |  | | | |  | | | |  | | | 0.27 | | |  | | | |  | | | | |  | | | |
| PPV/Precision: | | | | 0.89 | | |  | | | |  | | | |  | | | 0.06 | | |  | | | |  | | | | |  | | | |
| NPV: |  | | | 0.93 | | |  | | | |  | | | |  | | | 0.78 | | |  | | | |  | | | | |  | | | |
| Recall: |  | | | 0.41 | | |  | | | |  | | | |  | | | 0.40 | | |  | | | |  | | | | |  | | | |
| **F1 score:** | | | | 0.56 | | |  | | | |  | | | |  | | | 0.11 | | |  | | | |  | | | | |  | | | |
| **MCC:** |  | | | 0.56 | | |  | | | |  | | | |  | | | -0.38 | | |  | | | |  | | | | |  | | | |
| **SS1:** |  | | | 0.40 | | |  | | | |  | | | |  | | | -0.33 | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
|  |  | | |  | | |  | | | |  | | | |  | | |  | | |  | | | |  | | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | | |
| *Options: Default Boosting* | | | | | | | |  | |  | | | |  | | | |  | | | |  | | *TP* | | | | | *FP* | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | | *FN* | | | | | *TN* | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **MOD\_SINGLETON (fold a):** | | | | | | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Train (N= 128) | | | | |  | | |  | | Test (N = 128) | | | | | | | |  | | | |  | |  | | | | |  | | | |
| (a) | | (b) | | | <- classified as | | | | | (a) | | | | (b) | | | | <- classified as | | | | | |  | | | | |  | | | |
| 3566 | | 354 | | | (a): class -1 | | | | | 3106 | | | | 45401 | | | | (a): class -1 | | | | | |  | | | | |  | | | |
| 4222 | | 62146 | | | (b): class 1 | | | | | 4681 | | | | 17099 | | | | (b): class 1 | | | | | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| DT Size: | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Accuracy: | | | | | 0.93 | | |  | |  | | | |  | | | | 0.29 | | | |  | |  | | | | |  | | | |
| Sensitivity: | | | | | 0.46 | | |  | |  | | | |  | | | | 0.40 | | | |  | |  | | | | |  | | | |
| Specificity: | | | | | 0.99 | | |  | |  | | | |  | | | | 0.27 | | | |  | |  | | | | |  | | | |
| PPV/Precision: | | | | | 0.91 | | |  | |  | | | |  | | | | 0.06 | | | |  | |  | | | | |  | | | |
| NPV: | |  | | | 0.94 | | |  | |  | | | |  | | | | 0.79 | | | |  | |  | | | | |  | | | |
| Recall: | |  | | | 0.46 | | |  | |  | | | |  | | | | 0.40 | | | |  | |  | | | | |  | | | |
| **F1 score:** | | | | | 0.61 | | |  | |  | | | |  | | | | 0.11 | | | |  | |  | | | | |  | | | |
| **MCC:** | |  | | | 0.60 | | |  | |  | | | |  | | | | -0.38 | | | |  | |  | | | | |  | | | |
| **SS1:** | |  | | | 0.45 | | |  | |  | | | |  | | | | -0.33 | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **MOD\_SINGLETON (fold b):** | | | | | | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Train (N= 128) | | | | |  | | |  | | Test (N = 128) | | | | | | | |  | | | |  | |  | | | | |  | | | |
| (a) | | (b) | | | <- classified as | | | | | (a) | | | | (b) | | | | <- classified as | | | | | |  | | | | |  | | | |
| 3170 | | 385 | | | (a): class -1 | | | | | 2719 | | | | 46088 | | | | (a): class -1 | | | | | |  | | | | |  | | | |
| 4617 | | 62115 | | | (b): class 1 | | | | | 5069 | | | | 15412 | | | | (b): class 1 | | | | | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| DT Size: | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| Accuracy: | | | | | 0.93 | | |  | |  | | | |  | | | | 0.26 | | | |  | |  | | | | |  | | | |
| Sensitivity: | | | | | 0.41 | | |  | |  | | | |  | | | | 0.35 | | | |  | |  | | | | |  | | | |
| Specificity: | | | | | 0.99 | | |  | |  | | | |  | | | | 0.25 | | | |  | |  | | | | |  | | | |
| PPV/Precision: | | | | | 0.89 | | |  | |  | | | |  | | | | 0.06 | | | |  | |  | | | | |  | | | |
| NPV: | |  | | | 0.93 | | |  | |  | | | |  | | | | 0.75 | | | |  | |  | | | | |  | | | |
| Recall: | |  | | | 0.41 | | |  | |  | | | |  | | | | 0.35 | | | |  | |  | | | | |  | | | |
| **F1 score:** | | | | | 0.56 | | |  | |  | | | |  | | | | 0.10 | | | |  | |  | | | | |  | | | |
| **MCC:** | |  | | | 0.56 | | |  | |  | | | |  | | | | -0.48 | | | |  | |  | | | | |  | | | |
| **SS1:** | |  | | | 0.40 | | |  | |  | | | |  | | | | -0.40 | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
|  | |  | | |  | | |  | |  | | | |  | | | |  | | | |  | |  | | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | | *TP* | | | | *FP* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | | *FN* | | | | *TN* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **MOD\_SINGLETON (fold a):** | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 3207 | | | 428 | | | (a): class -1 | | | | | | 2836 | | | | 48444 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 4581 | | | 62072 | | | (b): class 1 | | | | | | 4951 | | | | 12056 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.93 | | |  | | |  | | | |  | | | | 0.22 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.41 | | |  | | |  | | | |  | | | | 0.36 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 0.99 | | |  | | |  | | | |  | | | | 0.20 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.88 | | |  | | |  | | | |  | | | | 0.06 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.93 | | |  | | |  | | | |  | | | | 0.71 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.41 | | |  | | |  | | | |  | | | | 0.36 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.56 | | |  | | |  | | | |  | | | | 0.10 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.56 | | |  | | |  | | | |  | | | | -0.61 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.40 | | |  | | |  | | | |  | | | | -0.44 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **MOD\_SINGLETON (fold b):** | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 3102 | | | 389 | | | (a): class -1 | | | | | | 2676 | | | | 43372 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 4685 | | | 62111 | | | (b): class 1 | | | | | | 5112 | | | | 19128 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.93 | | |  | | |  | | | |  | | | | 0.31 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.40 | | |  | | |  | | | |  | | | | 0.34 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 0.99 | | |  | | |  | | | |  | | | | 0.31 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.89 | | |  | | |  | | | |  | | | | 0.06 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.93 | | |  | | |  | | | |  | | | | 0.79 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.40 | | |  | | |  | | | |  | | | | 0.34 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.55 | | |  | | |  | | | |  | | | | 0.10 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.55 | | |  | | |  | | | |  | | | | -0.37 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.39 | | |  | | |  | | | |  | | | | -0.35 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **Decision Tree Results - Singleton (20 attributes)** | | | | | | | | | | | | | | | | | | | | | | | | | | | *Confusion Matrix* | | | | | | | |
| *Options: Default Boosting* | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | | *TP* | | | | *FP* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | | *FN* | | | | *TN* | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **MOD\_SINGLETON (fold a):** | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 2758 | | | 283 | | | (a): class -1 | | | | | | 2098 | | | | 41837 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 5030 | | | 62217 | | | (b): class 1 | | | | | | 5689 | | | | 20663 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.92 | | |  | | |  | | | |  | | | | 0.32 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.35 | | |  | | |  | | | |  | | | | 0.27 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 1.00 | | |  | | |  | | | |  | | | | 0.33 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.91 | | |  | | |  | | | |  | | | | 0.05 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.93 | | |  | | |  | | | |  | | | | 0.78 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.35 | | |  | | |  | | | |  | | | | 0.27 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.51 | | |  | | |  | | | |  | | | | 0.08 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.52 | | |  | | |  | | | |  | | | | -0.40 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.35 | | |  | | |  | | | |  | | | | -0.40 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| **MOD\_SINGLETON (fold b):** | | | | | | | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Train (N= 128) | | | | | |  | | |  | | | Test (N = 128) | | | | | | | |  | | |  | | | |  | | | |  | | | |
| (a) | | | (b) | | | <- classified as | | | | | | (a) | | | | (b) | | | | <- classified as | | | | | | |  | | | |  | | | |
| 3747 | | | 4030 | | | (a): class -1 | | | | | | 3373 | | | | 46938 | | | | (a): class -1 | | | | | | |  | | | |  | | | |
| 401 | | | 62099 | | | (b): class 1 | | | | | | 4415 | | | | 15562 | | | | (b): class 1 | | | | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| DT Size: | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
| Accuracy: | | | | | | 0.94 | | |  | | |  | | | |  | | | | 0.27 | | |  | | | |  | | | |  | | | |
| Sensitivity: | | | | | | 0.90 | | |  | | |  | | | |  | | | | 0.43 | | |  | | | |  | | | |  | | | |
| Specificity: | | | | | | 0.94 | | |  | | |  | | | |  | | | | 0.25 | | |  | | | |  | | | |  | | | |
| PPV/Precision: | | | | | | 0.48 | | |  | | |  | | | |  | | | | 0.07 | | |  | | | |  | | | |  | | | |
| NPV: | | |  | | | 0.99 | | |  | | |  | | | |  | | | | 0.78 | | |  | | | |  | | | |  | | | |
| Recall: | | |  | | | 0.90 | | |  | | |  | | | |  | | | | 0.43 | | |  | | | |  | | | |  | | | |
| **F1 score:** | | | | | | 0.63 | | |  | | |  | | | |  | | | | 0.12 | | |  | | | |  | | | |  | | | |
| **MCC:** | | |  | | | 0.65 | | |  | | |  | | | |  | | | | -0.39 | | |  | | | |  | | | |  | | | |
| **SS1:** | | |  | | | 0.84 | | |  | | |  | | | |  | | | | -0.32 | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |
|  | | |  | | |  | | |  | | |  | | | |  | | | |  | | |  | | | |  | | | |  | | | |

**H1.0 Hybrid ANN Results**

**H1.1 nOMOD\_NEONATALMORT HYBRID ANN RESULTS (TRAIN)**

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 5 by 2 Cross Validation Results | | | | | | |  |  | |  | |
|  | |  | | |  | |  |  | |  | |
|  | | **Verification** | | | Std Dev | | Confidence Interval (95%) | | | | |
| **Accuracy:** | | 0.6883 | | | 0.1722 | | 0.11 |  | |  | |
| **Sensitivity/Recall:** | | 0.3161 | | | 0.2048 | | 0.13 |  | |  | |
| **Specificity:** | | 0.7364 | | | 0.2202 | | 0.14 |  | |  | |
| **PPV/Precision:** | | 0.1495 | | | 0.0261 | | 0.02 |  | |  | |
| **NPV:** | | 0.8930 | | | 0.0059 | | 0.00 |  | |  | |
| **F1 score:** | | 0.1816 | | | 0.0161 | | 0.01 |  | |  | |
| **MCC:** | | 0.0467 | | | 0.0283 | | 0.02 |  | |  | |
| **SS1:** | | 0.0525 | | | 0.0304 | | 0.02 |  | |  | |
| **Fold 1A** |  | | **Fold 1B** |  | | **Fold 2A** | | |  | | **Fold 2B** | |  | **Fold 3A** |  |
| 11124 | 1430 | | 3448 | 462 | | 13020 | | | 1586 | | 13047 | | 1497 | 12738 | 1559 |
| 3342 | 485 | | 11123 | 1346 | | 1484 | | | 341 | | 1486 | | 349 | 1754 | 330 |
|  |  | |  |  | |  | | |  | |  | |  |  |  |
| *Accuracy:* | 0.709 | | *Accuracy:* | 0.293 | | *Accuracy:* | | | 0.813 | | *Accuracy:* | | 0.818 | *Accuracy:* | 0.798 |
| *Sens:* | 0.2533 | | *Sens:* | 0.7445 | | *Sens:* | | | 0.1770 | | *Sens:* | | 0.1891 | *Sens:* | 0.1747 |
| *Spec:* | 0.7690 | | *Spec:* | 0.2366 | | *Spec:* | | | 0.8977 | | *Spec:* | | 0.8977 | *Spec:* | 0.8790 |
| *PPV:* | 0.1267 | | *PPV:* | 0.1079 | | *PPV:* | | | 0.1868 | | *PPV:* | | 0.1902 | *PPV:* | 0.1583 |
| *NPV:* | 0.8861 | | *NPV:* | 0.8818 | | *NPV:* | | | 0.8914 | | *NPV:* | | 0.8971 | *NPV:* | 0.8910 |
| *F1 score:* | 0.169 | | *F1 score:* | 0.189 | | *F1 score:* | | | 0.182 | | *F1 score:* | | 0.190 | *F1 score:* | 0.166 |
| *MCC:* | 0.017 | | *MCC:* | -0.014 | | *MCC:* | | | 0.076 | | *MCC:* | | 0.087 | *MCC:* | 0.051 |
| *SS1:* | 0.022 | | *SS1:* | -0.019 | | *SS1:* | | | 0.075 | | *SS1:* | | 0.087 | *SS1:* | 0.054 |
| *Fold 3B* |  | | *Fold 4A* |  | | *Fold 4B* | | |  | | *Fold 5A* | |  | *Fold 5B* |  |
| *12923* | 1504 | | *9758* | 1134 | | *5972* | | | 629 | | *12688* | | 1521 | *12182* | 1460 |
| *1622* | 330 | | *4810* | 679 | | *8497* | | | 1281 | | *1857* | | 315 | *2310* | 427 |
|  |  | |  |  | |  | | |  | |  | |  |  |  |
| *Accuracy:* | 0.809 | | *Accuracy:* | 0.637 | | *Accuracy:* | | | 0.443 | | *Accuracy:* | | 0.794 | *Accuracy:* | 0.770 |
| *Sens:* | 0.1799 | | *Sens:* | 0.3745 | | *Sens:* | | | 0.6707 | | *Sens:* | | 0.1716 | *Sens:* | 0.2263 |
| *Spec:* | 0.8885 | | *Spec:* | 0.6698 | | *Spec:* | | | 0.4127 | | *Spec:* | | 0.8723 | *Spec:* | 0.8406 |
| *PPV:* | 0.1691 | | *PPV:* | 0.1237 | | *PPV:* | | | 0.1310 | | *PPV:* | | 0.1450 | *PPV:* | 0.1560 |
| *NPV:* | 0.8958 | | *NPV:* | 0.8959 | | *NPV:* | | | 0.9047 | | *NPV:* | | 0.8930 | *NPV:* | 0.8930 |
| *F1 score:* | 0.174 | | *F1 score:* | 0.186 | | *F1 score:* | | | 0.219 | | *F1 score:* | | 0.157 | *F1 score:* | 0.185 |
| *MCC:* | 0.067 | | *MCC:* | 0.029 | | *MCC:* | | | 0.055 | | *MCC:* | | 0.041 | *MCC:* | 0.057 |
| *SS1:* | 0.068 | | *SS1:* | 0.044 | | *SS1:* | | | 0.083 | | *SS1:* | | 0.044 | *SS1:* | 0.067 |

**H1.2 nOMOD\_NEONATALMORT HYBRID ANN RESULTS (TEST)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 5 by 2 Cross Validation Results | | |  |  |
|  |  |  |  |  |
|  | **Verification** | Std Dev | Confidence Interval (95%) | |
| **Accuracy:** | 0.7931 | 0.0830 | 0.05 |  |
| **Sensitivity/Recall:** | 0.2185 | 0.1297 | 0.08 |  |
| **Specificity:** | 0.8655 | 0.1083 | 0.07 |  |
| **PPV/Precision:** | 0.1814 | 0.0572 | 0.04 |  |
| **NPV:** | 0.8984 | 0.0051 | 0.00 |  |
| **F1 score:** | 0.1862 | 0.0550 | 0.03 |  |
| **MCC:** | 0.0811 | 0.0531 | 0.03 |  |
| **SS1:** | 0.0840 | 0.0533 | 0.03 |  |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Fold 1A** |  | **Fold 1B** |  | **Fold 2A** |  | **Fold 2B** |  | **Fold 3A** |  |
| 6587 | 717 | 7876 | 771 | 6543 | 757 | 6530 | 728 | 6526 | 765 |
| 700 | 18 | 6695 | 1037 | 711 | 179 | 717 | 216 | 724 | 175 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.823 | *Accuracy:* | 0.544 | *Accuracy:* | 0.821 | *Accuracy:* | 0.824 | *Accuracy:* | 0.818 |
| *Sens:* | 0.0245 | *Sens:* | 0.57356 | *Sens:* | 0.1912 | *Sens:* | 0.2288 | *Sens:* | 0.1862 |
| *Spec:* | 0.9039 | *Spec:* | 0.54053 | *Spec:* | 0.9020 | *Spec:* | 0.9011 | *Spec:* | 0.9001 |
| *PPV:* | 0.0251 | *PPV:* | 0.13412 | *PPV:* | 0.2011 | *PPV:* | 0.2315 | *PPV:* | 0.1947 |
| *NPV:* | 0.9018 | *NPV:* | 0.91084 | *NPV:* | 0.8963 | *NPV:* | 0.8997 | *NPV:* | 0.8951 |
| *F1 score:* | 0.025 | *F1 score:* | 0.217 | *F1 score:* | 0.196 | *F1 score:* | 0.230 | *F1 score:* | 0.190 |
| *MCC:* | -0.072 | *MCC:* | 0.072 | *MCC:* | 0.095 | *MCC:* | 0.131 | *MCC:* | 0.088 |
| *SS1:* | -0.072 | *SS1:* | 0.114 | *SS1:* | 0.093 | *SS1:* | 0.130 | *SS1:* | 0.086 |
| *Fold 3B* |  | *Fold 4A* |  | *Fold 4B* |  | *Fold 5A* |  | *Fold 5B* |  |
| *6530* | 755 | *6493* | 793 | *6564* | 724 | *6538* | 763 | *6543* | 754 |
| *719* | 187 | *721* | 183 | *716* | 187 | *705* | 183 | *710* | 184 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.820 | *Accuracy:* | 0.815 | *Accuracy:* | 0.824 | *Accuracy:* | 0.821 | *Accuracy:* | 0.821 |
| *Sens:* | 0.1985 | *Sens:* | 0.1875 | *Sens:* | 0.2053 | *Sens:* | 0.1934 | *Sens:* | 0.1962 |
| *Spec:* | 0.9008 | *Spec:* | 0.9001 | *Spec:* | 0.9016 | *Spec:* | 0.9027 | *Spec:* | 0.9021 |
| *PPV:* | 0.2064 | *PPV:* | 0.2024 | *PPV:* | 0.2071 | *PPV:* | 0.2061 | *PPV:* | 0.2058 |
| *NPV:* | 0.8964 | *NPV:* | 0.8912 | *NPV:* | 0.9007 | *NPV:* | 0.8955 | *NPV:* | 0.8967 |
| *F1 score:* | 0.202 | *F1 score:* | 0.195 | *F1 score:* | 0.206 | *F1 score:* | 0.200 | *F1 score:* | 0.201 |
| *MCC:* | 0.101 | *MCC:* | 0.091 | *MCC:* | 0.107 | *MCC:* | 0.099 | *MCC:* | 0.100 |
| *SS1:* | 0.099 | *SS1:* | 0.088 | *SS1:* | 0.107 | *SS1:* | 0.096 | *SS1:* | 0.098 |

**H1.3 nOMOD\_NEONATALMORT HYBRID ANN OVERALL RESULTS nOMOD\_NEONATALMORT RESULTS Set 1a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 17 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0049473

lr\_inc = 1.01

lr\_dec = 0.7726

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2188

lambda\_dec = 0.8595

wnot = 0.2659

momentum = 0.048

err\_ratio = 1.1231

max\_epoch = 432

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda\_dec = 0.8595

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

7550 990

6916 925

Test Confusion Matrix

3766 459

3521 444

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.023825

maxTrainSENS = 0

bestTrainEpoch = 265

currTestSENS\_bestTrain = 0.29014

currTrainSPEC\_bestTrain = 0.76898

currTestSPEC\_bestTrain = 0.76575

currTrainCR\_bestTrain = 70.8687

currTestCR\_bestTrain = 71.3309

currTrainASE\_bestTrain = 1.1547

currTestASE\_bestTrain = 1.1387

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.03166

Train Confusion Matrix - Epoch: 265

11124 1430

3342 485

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.018431

maxTestSENS = 0

bestTestEpoch = 431

currTestSENS = 0.20598

currTrainSENS = 0.16867

currTestSPEC = 0.90394

currTrainSPEC = 0.89327

currTestCR = 82.6984

currTrainCR = 80.8559

currTestASE = 0.68928

currTrainASE = 0.76391

currTrain\_Log\_Sensitivity\_Index = 0.011962

Test Confusion Matrix - Epoch: 431

6587 717

700 186

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5366

ROC\_test =

0.5582

dirName =

Results\exp20130207\_2005\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 9.0409e-027

Final weight decay constant: lambda = 23.1638

Final weight scale: wnot = 0.2659

momentum = 0.048

err\_ratio = 1.1231

Data Statistics

Training Set Apriori Probabilities

trprob =

88.3096

11.6904

Test Set Apriori Probabilities

teprob =

88.9744

11.0256

MDC Training Set Classification Rate

bayes\_train = 88.3585

MDC Test Set Classification Rate

bayes\_test = 89.0842

Network Outputs

---------------

W1 =

Columns 1 through 8

2.3035 4.9938 -6.1466 -8.2222 7.4750 9.3612 -3.5388 -3.1949

-6.5818 3.7660 -6.2680 5.4024 -7.0751 -4.7428 -4.3918 8.4766

-5.6328 23.3809 6.5339 -3.5324 5.3992 4.4997 3.4231 -9.2053

-2.0651 -6.2017 39.5588 -3.3282 -12.9986 9.0379 -8.4988 -27.3915

-19.4283 -4.1168 -19.0391 -5.0378 -1.5451 2.5175 6.4062 -5.7816

2.6669 2.8834 4.2462 3.4236 2.9109 -5.1375 -6.7646 -3.3404

-1.9521 5.3148 -5.1851 4.9917 2.4617 2.7755 -8.7026 -3.2328

-13.1208 6.0417 -8.5032 9.1046 10.6959 -30.4253 20.2751 9.1272

8.8237 3.3509 2.4122 16.2920 8.1180 -9.7137 -5.8716 4.9691

6.2860 -16.2090 -7.5456 5.1206 -5.0126 -5.7698 10.7590 3.6105

-5.0346 -3.3562 -4.7331 3.9977 10.9911 10.2331 4.9961 8.9853

6.7169 15.4043 -4.6184 2.8449 4.9374 17.1660 -2.1923 -0.0879

8.0940 -5.2483 -2.5353 -3.0647 -2.8780 -8.8351 7.7583 -5.6133

34.6415 -7.8816 -1.3678 3.5132 7.9758 -3.1007 -12.8552 4.1610

19.7310 4.0940 3.5594 4.2208 -9.0956 -13.0497 10.6952 4.2116

-4.4577 -11.0183 4.5182 -7.1222 11.6078 -15.3315 -5.9592 6.7976

-8.9759 -30.0171 -1.0833 1.1858 -16.3021 -7.9268 -26.2272 -7.1582

Columns 9 through 11

-6.7272 3.6654 -7.1495

3.0498 5.4454 -12.1419

-4.5194 -3.2611 -4.7183

-21.9397 5.1321 7.1712

-3.1540 -7.2110 4.5464

-13.3789 8.0363 -4.5606

-3.5102 -13.2812 -3.3020

-0.1808 -1.8038 -23.5812

2.3790 7.1825 7.2049

5.6755 -6.2047 -1.6006

-9.1335 2.8499 -6.5077

7.4622 -1.3948 -12.7612

8.6162 -1.9197 33.6559

-11.6846 3.2441 4.5465

-4.0155 6.4781 -5.6993

7.2640 -9.2198 4.2539

3.9192 -4.6139 4.5481

B1 =

0.6967

-6.8408

-2.7577

15.3432

6.0940

9.3721

3.5385

6.6257

-2.1969

-15.6429

-5.7981

-4.1580

5.6404

4.6067

-9.9666

-9.2334

9.4429

W2 =

Columns 1 through 8

-39.9863 54.1330 -19.4823 -26.4231 -16.7875 46.8950 14.7338 -13.0998

Columns 9 through 16

-33.7123 19.3048 5.6471 35.0764 -28.8612 -40.7356 -18.0445 35.1762

Column 17

18.1128

B2 =

-61.4235

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambdaDec = 0.8595

Best Test Log\_Sensitivity Index = 0.018431

Best Test Epoch = 431

Current Train Log\_Sensitivity Index = 0.011962

Current Test Log\_Sensitivity Index\_BestTrain = 0.03166

Current Test SENSITIVITY = 0.20598

Current Train SENSITIVITY = 0.16867

Current Test SPECIFICITY = 0.90394

Current Train SPECIFICITY = 0.89327

Current Test CR = 82.6984

Current Train CR = 80.8559

Current Test ASE = 0.68928

Current Train ASE = 0.76391

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 1b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 17 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0049473

lr\_inc = 1.01

lr\_dec = 0.7726

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2188

lambda\_dec = 0.8595

wnot = 0.2659

momentum = 0.048

err\_ratio = 1.1231

max\_epoch = 432

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda\_dec = 0.8595

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

7550 990

6916 925

Test Confusion Matrix

3766 459

3521 444

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.023825

maxTrainSENS = 0

bestTrainEpoch = 265

currTestSENS\_bestTrain = 0.29014

currTrainSPEC\_bestTrain = 0.76898

currTestSPEC\_bestTrain = 0.76575

currTrainCR\_bestTrain = 70.8687

currTestCR\_bestTrain = 71.3309

currTrainASE\_bestTrain = 1.1547

currTestASE\_bestTrain = 1.1387

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.03166

Train Confusion Matrix - Epoch: 265

11124 1430

3342 485

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.018431

maxTestSENS = 0

bestTestEpoch = 431

currTestSENS = 0.20598

currTrainSENS = 0.16867

currTestSPEC = 0.90394

currTrainSPEC = 0.89327

currTestCR = 82.6984

currTrainCR = 80.8559

currTestASE = 0.68928

currTrainASE = 0.76391

currTrain\_Log\_Sensitivity\_Index = 0.011962

Test Confusion Matrix - Epoch: 431

6587 717

700 186

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5366

ROC\_test =

0.5582

dirName =

Results\exp20130207\_2005\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 9.0409e-027

Final weight decay constant: lambda = 23.1638

Final weight scale: wnot = 0.2659

momentum = 0.048

err\_ratio = 1.1231

Data Statistics

Training Set Apriori Probabilities

trprob =

88.3096

11.6904

Test Set Apriori Probabilities

teprob =

88.9744

11.0256

MDC Training Set Classification Rate

bayes\_train = 88.3585

MDC Test Set Classification Rate

bayes\_test = 89.0842

Network Outputs

---------------

W1 =

Columns 1 through 8

2.3035 4.9938 -6.1466 -8.2222 7.4750 9.3612 -3.5388 -3.1949

-6.5818 3.7660 -6.2680 5.4024 -7.0751 -4.7428 -4.3918 8.4766

-5.6328 23.3809 6.5339 -3.5324 5.3992 4.4997 3.4231 -9.2053

-2.0651 -6.2017 39.5588 -3.3282 -12.9986 9.0379 -8.4988 -27.3915

-19.4283 -4.1168 -19.0391 -5.0378 -1.5451 2.5175 6.4062 -5.7816

2.6669 2.8834 4.2462 3.4236 2.9109 -5.1375 -6.7646 -3.3404

-1.9521 5.3148 -5.1851 4.9917 2.4617 2.7755 -8.7026 -3.2328

-13.1208 6.0417 -8.5032 9.1046 10.6959 -30.4253 20.2751 9.1272

8.8237 3.3509 2.4122 16.2920 8.1180 -9.7137 -5.8716 4.9691

6.2860 -16.2090 -7.5456 5.1206 -5.0126 -5.7698 10.7590 3.6105

-5.0346 -3.3562 -4.7331 3.9977 10.9911 10.2331 4.9961 8.9853

6.7169 15.4043 -4.6184 2.8449 4.9374 17.1660 -2.1923 -0.0879

8.0940 -5.2483 -2.5353 -3.0647 -2.8780 -8.8351 7.7583 -5.6133

34.6415 -7.8816 -1.3678 3.5132 7.9758 -3.1007 -12.8552 4.1610

19.7310 4.0940 3.5594 4.2208 -9.0956 -13.0497 10.6952 4.2116

-4.4577 -11.0183 4.5182 -7.1222 11.6078 -15.3315 -5.9592 6.7976

-8.9759 -30.0171 -1.0833 1.1858 -16.3021 -7.9268 -26.2272 -7.1582

Columns 9 through 11

-6.7272 3.6654 -7.1495

3.0498 5.4454 -12.1419

-4.5194 -3.2611 -4.7183

-21.9397 5.1321 7.1712

-3.1540 -7.2110 4.5464

-13.3789 8.0363 -4.5606

-3.5102 -13.2812 -3.3020

-0.1808 -1.8038 -23.5812

2.3790 7.1825 7.2049

5.6755 -6.2047 -1.6006

-9.1335 2.8499 -6.5077

7.4622 -1.3948 -12.7612

8.6162 -1.9197 33.6559

-11.6846 3.2441 4.5465

-4.0155 6.4781 -5.6993

7.2640 -9.2198 4.2539

3.9192 -4.6139 4.5481

B1 =

0.6967

-6.8408

-2.7577

15.3432

6.0940

9.3721

3.5385

6.6257

-2.1969

-15.6429

-5.7981

-4.1580

5.6404

4.6067

-9.9666

-9.2334

9.4429

W2 =

Columns 1 through 8

-39.9863 54.1330 -19.4823 -26.4231 -16.7875 46.8950 14.7338 -13.0998

Columns 9 through 16

-33.7123 19.3048 5.6471 35.0764 -28.8612 -40.7356 -18.0445 35.1762

Column 17

18.1128

B2 =

-61.4235

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambdaDec = 0.8595

Best Test Log\_Sensitivity Index = 0.018431

Best Test Epoch = 431

Current Train Log\_Sensitivity Index = 0.011962

Current Test Log\_Sensitivity Index\_BestTrain = 0.03166

Current Test SENSITIVITY = 0.20598

Current Train SENSITIVITY = 0.16867

Current Test SPECIFICITY = 0.90394

Current Train SPECIFICITY = 0.89327

Current Test CR = 82.6984

Current Train CR = 80.8559

Current Test ASE = 0.68928

Current Train ASE = 0.76391

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 2a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 1

h1 = 0 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.005025

lr\_inc = 1.01

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2461

lambda\_dec = 0.6251

wnot = 0.4996

momentum = 0.5

err\_ratio = 1.02

max\_epoch = 121

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

wnot = 0.4996

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

3613 589

10891 1288

Test Confusion Matrix

1934 250

5320 686

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_3

actual\_epoch = 120

Train Confusion Matrix

13020 1536

1484 341

Test Confusion Matrix

6543 757

711 179

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_3

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.014047

maxTrainSENS = 0

bestTrainEpoch = 120

currTestSENS\_bestTrain = 0.19124

currTrainSPEC\_bestTrain = 0.89768

currTestSPEC\_bestTrain = 0.90199

currTrainCR\_bestTrain = 81.564

currTestCR\_bestTrain = 82.0757

currTrainASE\_bestTrain = 0.73859

currTestASE\_bestTrain = 0.71504

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.015725

Train Confusion Matrix - Epoch: 120

13020 1536

1484 341

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.015725

maxTestSENS = 0

bestTestEpoch = 120

currTestSENS = 0.19124

currTrainSENS = 0.18167

currTestSPEC = 0.90199

currTrainSPEC = 0.89768

currTestCR = 82.0757

currTrainCR = 81.564

currTestASE = 0.71504

currTrainASE = 0.73859

currTrain\_Log\_Sensitivity\_Index = 0.014047

Test Confusion Matrix - Epoch: 120

6543 757

711 179

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5485

ROC\_test =

0.5529

dirName =

Results\exp20130207\_2010\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 0.012751

Final weight decay constant: lambda = 94.3704

Final weight scale: wnot = 0.4996

momentum = 0.5

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

88.5416

11.4584

Test Set Apriori Probabilities

teprob =

88.5714

11.4286

MDC Training Set Classification Rate

bayes\_train = 88.6088

MDC Test Set Classification Rate

bayes\_test = 88.6203

Network Outputs

---------------

W1 =

Columns 1 through 8

-257.8479 4.1393 14.8582 -10.1450 14.1487 39.6343 -7.8916 45.0420

Columns 9 through 11

90.9609 -102.6412 -61.8019

B1 =

-60.4360

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

weightScale = 0.4996

Best Test Log\_Sensitivity Index = 0.015725

Best Test Epoch = 120

Current Train Log\_Sensitivity Index = 0.014047

Current Test Log\_Sensitivity Index\_BestTrain = 0.015725

Current Test SENSITIVITY = 0.19124

Current Train SENSITIVITY = 0.18167

Current Test SPECIFICITY = 0.90199

Current Train SPECIFICITY = 0.89768

Current Test CR = 82.0757

Current Train CR = 81.564

Current Test ASE = 0.71504

Current Train ASE = 0.73859

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 2b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 1

h1 = 0 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0049473

lr\_inc = 1.01

lr\_dec = 0.877

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.1563

lambda\_dec = 0.918

wnot = 0.01

momentum = 0.5

err\_ratio = 1.125

max\_epoch = 92

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lr\_dec = 0.877

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

3739 535

10794 1311

Test Confusion Matrix

1867 264

5380 680

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_3

actual\_epoch = 91

Train Confusion Matrix

13037 1500

1496 346

Test Confusion Matrix

6530 728

717 216

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_3

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.015272

maxTrainSENS = 0

bestTrainEpoch = 73

currTestSENS\_bestTrain = 0.22246

currTrainSPEC\_bestTrain = 0.89775

currTestSPEC\_bestTrain = 0.9023

currTrainCR\_bestTrain = 81.7877

currTestCR\_bestTrain = 82.3953

currTrainASE\_bestTrain = 0.72762

currTestASE\_bestTrain = 0.70127

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.021646

Train Confusion Matrix - Epoch: 73

13047 1497

1486 349

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.022944

maxTestSENS = 0

bestTestEpoch = 91

currTestSENS = 0.22881

currTrainSENS = 0.18743

currTestSPEC = 0.90106

currTrainSPEC = 0.89706

currTestCR = 82.3587

currTrainCR = 81.7083

currTestASE = 0.70409

currTrainASE = 0.73585

currTrain\_Log\_Sensitivity\_Index = 0.014985

Test Confusion Matrix - Epoch: 91

6530 728

717 216

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5463

ROC\_test =

0.5705

dirName =

Results\exp20130207\_2010\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 0.0016948

Final weight decay constant: lambda = 108.4421

Final weight scale: wnot = 0.01

momentum = 0.5

err\_ratio = 1.125

Data Statistics

Training Set Apriori Probabilities

trprob =

88.7295

11.2705

Test Set Apriori Probabilities

teprob =

88.4752

11.5248

MDC Training Set Classification Rate

bayes\_train = 88.7966

MDC Test Set Classification Rate

bayes\_test = 88.6094

Network Outputs

---------------

W1 =

Columns 1 through 8

-259.6375 1.7828 -2.0002 -9.4137 8.0094 41.7605 19.3792 44.8852

Columns 9 through 11

-0.7663 -1.7104 -1.8022

B1 =

-49.4670

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

learnRateDec = 0.877

Best Test Log\_Sensitivity Index = 0.022944

Best Test Epoch = 91

Current Train Log\_Sensitivity Index = 0.014985

Current Test Log\_Sensitivity Index\_BestTrain = 0.021646

Current Test SENSITIVITY = 0.22881

Current Train SENSITIVITY = 0.18743

Current Test SPECIFICITY = 0.90106

Current Train SPECIFICITY = 0.89706

Current Test CR = 82.3587

Current Train CR = 81.7083

Current Test ASE = 0.70409

Current Train ASE = 0.73585

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 3a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 21 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0003622

lr\_inc = 0.8204

lr\_dec = 1.0586

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.001

lambda\_dec = 0.7835

wnot = 0.01

momentum = 0.999

err\_ratio = 1.02

max\_epoch = 630

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lr\_dec = 1.0586

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

10375 1274

4117 615

Test Confusion Matrix

5209 630

2041 310

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

12745 1564

1747 325

Test Confusion Matrix

6361 741

889 199

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.012648

maxTrainSENS = 0

bestTrainEpoch = 489

currTestSENS\_bestTrain = 0.2117

currTrainSPEC\_bestTrain = 0.87897

currTestSPEC\_bestTrain = 0.87669

currTrainCR\_bestTrain = 79.7753

currTestCR\_bestTrain = 80.0366

currTrainASE\_bestTrain = 0.8061

currTestASE\_bestTrain = 0.79431

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.018876

Train Confusion Matrix - Epoch: 489

12738 1559

1754 330

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.01483

maxTestSENS = 0

bestTestEpoch = 629

currTestSENS = 0.18617

currTrainSENS = 0.14664

currTestSPEC = 0.90014

currTrainSPEC = 0.90367

currTestCR = 81.8193

currTrainCR = 81.6373

currTestASE = 0.72509

currTrainASE = 0.73224

currTrain\_Log\_Sensitivity\_Index = 0.009053

Test Confusion Matrix - Epoch: 629

6526 765

724 175

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5274

ROC\_test =

0.5434

dirName =

Results\exp20130214\_2144\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 8.3928e-058

Final weight decay constant: lambda = 0.003519

Final weight scale: wnot = 0.01

momentum = 0.999

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

88.4683

11.5317

Test Set Apriori Probabilities

teprob =

88.5226

11.4774

MDC Training Set Classification Rate

bayes\_train = 88.5477

MDC Test Set Classification Rate

bayes\_test = 88.6203

Network Outputs

---------------

W1 =

Columns 1 through 9

3.1545 -2.1518 0.7330 11.7167 -2.5482 -1.9098 -1.4769 -3.2163 0.7397

17.3442 38.2265 4.1006 -0.7494 0.9335 -1.7394 -1.0034 -1.5735 0.7751

-7.5154 -2.4521 -42.2661 1.0349 -0.6023 -1.5866 6.3381 -2.2329 3.1353

-24.6122 -0.4102 -1.6122 -1.0125 0.9360 1.1737 -3.2888 1.4825 11.1371

-2.7498 5.4425 -22.5551 0.5784 2.1686 2.0150 1.4337 3.9838 1.2204

22.8964 -0.2718 0.9521 30.6119 2.7470 1.3780 0.7808 1.6944 -0.2992

-0.7829 12.4184 14.0200 1.1793 1.8563 1.5392 -2.1845 -1.9316 0.9064

12.3059 2.4367 0.8058 -1.6579 -3.5395 -2.1722 -5.3271 -3.5125 -2.6083

-13.0213 -2.1034 -0.9818 4.9676 0.7280 1.5595 0.5496 7.9046 25.1917

23.1997 -0.3061 0.8626 1.6477 4.4787 -1.8447 2.8534 1.9299 6.2794

3.1051 10.9133 -0.7664 -20.3547 -0.2158 -0.9586 -2.1840 -1.6371 -0.9275

6.9382 -0.6124 3.1496 20.0414 -4.7730 3.5495 -1.2125 -35.6149 17.9722

34.2639 4.9327 -0.6619 1.6453 0.9912 4.2354 2.0304 2.9871 -3.1300

0.8732 1.5828 0.2548 0.6448 2.5807 -4.1105 0.5403 -1.0058 0.7703

0.7605 -0.8705 6.8176 5.6051 -1.1115 -1.9517 -0.8011 1.1395 0.5832

-8.1053 -1.6747 -43.4046 1.6712 -2.9081 2.5820 -2.1759 -3.0394 0.1964

-0.9049 -2.3947 -1.4153 -1.4172 -1.6811 -2.0371 -43.7526 -0.9395 1.0225

-0.6600 5.1135 7.4993 -0.7081 0.7158 -2.2948 2.5075 0.5522 6.1882

-4.5200 2.3601 2.2622 -1.2570 -6.1259 -1.8617 -0.4564 -1.8071 -18.3884

-6.4182 0.3042 -10.2576 9.3222 1.5534 0.9068 0.9841 1.5448 0.6702

5.1024 2.7928 -6.8488 -2.9928 -5.0101 -5.1135 -3.0963 -4.6342 -0.5456

Columns 10 through 11

-26.3173 -33.0329

-18.9885 0.9481

0.6482 17.4131

-3.4023 4.8069

-1.3773 -8.6846

4.2130 -0.8726

-22.5993 -0.6029

-19.9107 -0.6181

0.9345 -8.3112

-0.6949 1.5332

-6.3790 0.5905

0.8966 8.1996

-3.6782 -8.1873

-0.1380 0.3631

14.7101 3.1986

-0.7078 0.2240

0.9310 1.8236

-0.2522 0.6742

0.4617 -27.5014

-35.4141 15.4109

0.6903 -2.9711

B1 =

3.3643

1.8789

3.3487

-2.0844

-1.8691

-12.3297

4.1133

4.1263

-0.5516

-1.4573

-3.8721

-2.6738

-2.5619

1.9397

2.9879

4.9454

1.4717

-0.8444

2.0866

3.2685

6.6096

W2 =

Columns 1 through 9

13.1767 -26.9244 59.5041 38.6517 27.2137 -16.1599 21.8278 62.1839 -63.0336

Columns 10 through 18

-15.1661 28.0003 -60.1220 -36.4463 -67.9502 -32.5858 -38.8630 42.9889 51.6717

Columns 19 through 21

-24.5805 17.8821 -30.2276

B2 =

-89.8606

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

learnRateDec = 1.0586

Best Test Log\_Sensitivity Index = 0.01483

Best Test Epoch = 629

Current Train Log\_Sensitivity Index = 0.009053

Current Test Log\_Sensitivity Index\_BestTrain = 0.018876

Current Test SENSITIVITY = 0.18617

Current Train SENSITIVITY = 0.14664

Current Test SPECIFICITY = 0.90014

Current Train SPECIFICITY = 0.90367

Current Test CR = 81.8193

Current Train CR = 81.6373

Current Test ASE = 0.72509

Current Train ASE = 0.73224

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 3b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 23 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0053554

lr\_inc = 0.8165

lr\_dec = 0.7515

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.001

lambda\_dec = 0.66

wnot = 0.01

momentum = 0.984

err\_ratio = 1.02

max\_epoch = 425

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda\_dec = 0.66

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

2594 299

11951 1535

Test Confusion Matrix

1285 140

5964 802

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.013613

maxTrainSENS = 0

bestTrainEpoch = 419

currTestSENS\_bestTrain = 0.19321

currTrainSPEC\_bestTrain = 0.88848

currTestSPEC\_bestTrain = 0.90081

currTrainCR\_bestTrain = 80.9146

currTestCR\_bestTrain = 81.9436

currTrainASE\_bestTrain = 0.76326

currTestASE\_bestTrain = 0.7218

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.016044

Train Confusion Matrix - Epoch: 419

12923 1504

1622 330

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.016986

maxTestSENS = 0

bestTestEpoch = 424

currTestSENS = 0.19851

currTrainSENS = 0.17666

currTestSPEC = 0.90081

currTrainSPEC = 0.89007

currTestCR = 82.0046

currTrainCR = 81.0184

currTestASE = 0.71979

currTrainASE = 0.75903

currTrain\_Log\_Sensitivity\_Index = 0.013126

Test Confusion Matrix - Epoch: 424

6530 755

719 187

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5338

ROC\_test =

0.5499

dirName =

Results\exp20130214\_2146\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 2.3024e-040

Final weight decay constant: lambda = 0.0050365

Final weight scale: wnot = 0.01

momentum = 0.984

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

88.8027

11.1973

Test Set Apriori Probabilities

teprob =

88.4996

11.5004

MDC Training Set Classification Rate

bayes\_train = 88.8943

MDC Test Set Classification Rate

bayes\_test = 88.585

Network Outputs

---------------

W1 =

Columns 1 through 9

-0.9362 -2.1310 3.3942 13.0631 -2.3159 -28.8527 -15.4220 -32.9037 4.2571

1.0621 -4.7146 2.5099 -45.6575 -68.7630 -60.8421 -40.4106 -66.2804 1.7213

-1.0241 4.3918 5.2862 -9.3166 12.6528 37.8416 20.7241 47.5373 -8.6048

1.1373 -9.5073 0.8614 14.1409 15.9714 14.1677 8.1049 15.6619 1.6348

-15.5340 8.4640 0.5576 -14.9923 -21.3028 -29.0106 -22.0447 -28.5197 -4.3897

1.2845 9.7045 2.3634 -35.9821 -47.7444 -63.7266 -42.7820 -71.2421 -11.1336

-0.9983 5.3463 3.0878 -10.6821 5.3468 6.5884 -1.9530 6.5401 0.4246

0.6382 2.6822 -8.0007 -30.2369 -48.6896 -50.9846 -36.0204 -59.6942 0.4126

1.2387 -5.0212 4.7141 -40.7343 -64.2433 -96.3311 -68.8957 -99.7250 3.3748

1.3656 -14.5712 2.3944 -5.9262 -20.4744 -25.3029 -14.6182 -31.7001 2.5459

-0.9384 -1.8264 -2.8295 -12.4995 3.2227 23.4644 9.3892 30.7407 -2.4807

-7.2110 -1.3547 -2.9548 -4.0441 -6.6916 -12.6527 -5.3247 -15.3305 3.0954

-7.4370 -6.0460 -7.3224 -8.9898 -12.3675 -18.9692 -12.8809 -21.3738 0.4804

-0.4098 -3.1231 -1.5702 -5.3100 6.3744 11.6410 0.9398 7.2580 0.6921

2.0761 11.8239 5.7850 -4.5163 4.4458 18.5738 -8.4846 19.1381 -5.1052

1.7032 -1.8734 -4.3757 16.1745 -0.6243 -5.7704 -0.4533 -12.7352 0.5811

-2.1537 12.2035 -2.2273 21.7317 40.8459 53.1702 35.0222 66.5669 -0.4335

8.9748 0.5014 4.0734 2.4578 -3.1604 1.5617 1.4352 -2.6653 -2.3088

-5.6386 5.5641 -2.0541 27.9428 30.6593 72.4276 50.9209 69.6733 -0.3947

-1.0465 11.2232 2.0414 -7.1152 -7.5501 -25.3941 -22.5438 -24.3297 1.0465

6.6732 5.3097 3.1743 -13.5655 -20.6169 -35.1134 -27.1956 -33.2877 1.5983

-1.7909 0.8436 1.7325 -4.6539 -23.2443 -35.2775 -19.8028 -41.4232 5.7056

-1.8674 7.6104 -1.4950 10.9309 16.0472 18.8005 13.6222 21.4048 -1.6598

Columns 10 through 11

2.8635 2.3343

2.9594 2.4905

-1.3823 -2.5880

-1.7059 -1.3023

1.3046 8.2365

2.3079 6.4806

5.8128 0.1768

1.0900 0.8909

6.4531 8.7093

-11.2088 2.0517

-2.3070 -6.1734

-16.1499 7.1606

-0.6154 0.9793

-15.8309 4.6394

3.9526 0.7422

0.9712 1.4093

-1.4825 3.8879

-2.0890 5.4534

-1.5188 -0.8459

-0.2594 2.2637

3.8138 3.0643

2.2345 1.7695

-1.3685 -1.5288

B1 =

42.4437

83.5926

-56.6412

-16.7545

33.6791

75.8964

-12.4671

70.7289

119.6675

39.6403

-36.9233

17.9114

22.2228

-9.0600

-26.2173

22.0144

-71.6391

2.9283

-75.2771

32.1725

42.8443

51.4654

-26.6691

W2 =

1.0e+003 \*

Columns 1 through 9

1.0135 0.3753 0.7611 -1.1102 -0.7296 0.1734 1.3900 -0.0039 -0.0315

Columns 10 through 18

0.6730 -1.1589 -0.7809 -0.2938 1.2339 1.2020 1.0303 0.1529 -0.8682

Columns 19 through 23

0.2602 1.0714 0.5355 0.5719 -0.4439

B2 =

-1.9122e+003

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambdaDec = 0.66

Best Test Log\_Sensitivity Index = 0.016986

Best Test Epoch = 424

Current Train Log\_Sensitivity Index = 0.013126

Current Test Log\_Sensitivity Index\_BestTrain = 0.016044

Current Test SENSITIVITY = 0.19851

Current Train SENSITIVITY = 0.17666

Current Test SPECIFICITY = 0.90081

Current Train SPECIFICITY = 0.89007

Current Test CR = 82.0046

Current Train CR = 81.0184

Current Test ASE = 0.71979

Current Train ASE = 0.75903

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 4a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 21 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0038227

lr\_inc = 0.9766

lr\_dec = 1.1622

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.0665

lambda\_dec = 0.0099

wnot = 0.086

momentum = 0.937

err\_ratio = 1.25

max\_epoch = 291

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.937

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

10510 1211

4058 602

Test Confusion Matrix

5170 679

2044 297

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.046979

maxTrainSENS = 0

bestTrainEpoch = 280

currTestSENS\_bestTrain = 0.42008

currTrainSPEC\_bestTrain = 0.66982

currTestSPEC\_bestTrain = 0.66842

currTrainCR\_bestTrain = 63.7141

currTestCR\_bestTrain = 63.8828

currTrainASE\_bestTrain = 1.4531

currTestASE\_bestTrain = 1.4446

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.060133

Train Confusion Matrix - Epoch: 280

9758 1134

4810 679

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.015051

maxTestSENS = 0

bestTestEpoch = 290

currTestSENS = 0.1875

currTrainSENS = 0.13789

currTestSPEC = 0.90006

currTrainSPEC = 0.90349

currTestCR = 81.514

currTrainCR = 81.8753

currTestASE = 0.73942

currTrainASE = 0.7281

currTrain\_Log\_Sensitivity\_Index = 0.0079683

Test Confusion Matrix - Epoch: 290

6493 793

721 183

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5248

ROC\_test =

0.5477

dirName =

Results\exp20130214\_2147\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 5.6409e-006

Final weight decay constant: lambda = 55.3309

Final weight scale: wnot = 0.086

momentum = 0.937

err\_ratio = 1.25

Data Statistics

Training Set Apriori Probabilities

trprob =

88.9323

11.0677

Test Set Apriori Probabilities

teprob =

88.0830

11.9170

MDC Training Set Classification Rate

bayes\_train = 89.0361

MDC Test Set Classification Rate

bayes\_test = 88.1563

Network Outputs

---------------

W1 =

1.0e+003 \*

Columns 1 through 9

-0.4085 -0.0111 -0.0200 -0.0082 -0.0147 -0.0147 -0.0084 -0.0169 0.0358

-0.1614 -0.0193 0.0774 0.0393 -0.0089 -0.0112 -0.0055 -0.0115 -0.0224

-0.0159 -0.0410 0.0186 0.0056 -0.3956 -0.0077 0.0719 -0.0137 0.0074

0.0090 -1.1076 0.0102 -0.0033 -0.1042 0.0063 0.0276 0.0093 -0.0058

0.0137 -0.0104 0.0617 0.0516 0.0092 0.0191 0.0079 0.0262 0.0088

-0.0205 -0.0096 -0.0239 -0.0503 0.0362 -0.0419 -0.2296 0.0057 -0.0568

-0.0163 -0.3134 -0.0341 -0.3273 0.0099 0.0027 -0.0266 -0.4431 -1.0042

-1.1961 0.0152 -0.0578 -0.0081 -0.0120 -0.0211 -0.0095 -0.0251 -0.0044

0.0495 -0.0108 -0.0380 -0.0923 0.0065 0.0094 0.0991 0.0067 0.1235

-0.0983 1.6515 -0.3908 0.0052 0.0088 0.0095 0.0034 0.0122 0.1433

-0.2002 0.2380 -0.1432 0.0260 -0.0079 0.0142 -1.8693 -0.0080 -0.0221

0.0849 -0.0091 -0.0458 -0.0247 -0.0501 -0.0640 0.0315 -0.0120 -0.0842

0.0048 -0.0170 -0.2808 0.0125 0.0117 0.0292 0.0180 0.0263 -0.0068

-0.0169 0.0139 0.1917 -0.0748 -0.0063 0.0148 -1.2315 -1.5868 -0.0126

-0.0093 -0.0087 -0.0552 0.0392 -0.0102 -0.0123 -0.0040 -0.0134 -0.0062

-0.0139 -0.0165 -0.0135 -0.0126 -0.0225 -0.0239 -0.0128 -0.0268 -0.1077

-0.0736 -0.0141 0.5934 -0.0075 -0.0133 -0.0144 -0.0050 -0.0129 -0.3051

0.0053 0.0179 -0.0274 0.0458 -0.3337 -0.1275 0.0258 -0.3128 -0.0224

0.2957 -0.0731 0.0289 0.2633 -0.0083 -0.0117 -0.0072 -0.0130 -0.0501

0.0383 0.0987 0.2683 -0.0171 0.0053 0.0045 -0.0158 0.0074 -0.0099

0.7771 -0.0810 -0.0069 -0.0309 -0.0406 -0.0388 -0.0252 -0.0433 0.0067

Columns 10 through 11

-0.0937 0.0284

-0.0291 0.0089

-0.0288 -0.0263

-0.7228 -0.4926

0.0228 -0.1058

-0.2070 0.0247

0.3426 0.0349

0.0333 0.0113

-0.0089 -0.0053

0.0100 0.2214

-0.0178 -0.0143

0.0278 -0.0366

0.0194 -0.0420

-0.0092 0.0149

2.0487 0.1457

0.0113 0.1100

0.0110 0.0043

-0.1308 -1.1032

0.1580 -0.0294

0.0030 -0.4894

0.0237 -0.2766

B1 =

1.0e+003 \*

0.0233

0.0151

0.0152

-0.0165

-0.0294

0.0953

-0.0124

0.0254

-0.0131

-0.0147

0.0093

0.0314

-0.0273

0.0120

0.0185

0.0338

0.0191

-1.3279

0.0180

-0.0092

0.0485

W2 =

Columns 1 through 9

112.1725 -223.2929 486.9363 319.8108 231.1462 -108.0822 180.8289 510.3345 -515.6655

Columns 10 through 18

-119.1681 226.3958 -490.8167 -296.1371 -557.2413 -268.8444 -323.0722 359.7521 468.0847

Columns 19 through 21

-197.4833 162.3464 -242.1887

B2 =

-727.1479

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.937

Best Test Log\_Sensitivity Index = 0.015051

Best Test Epoch = 290

Current Train Log\_Sensitivity Index = 0.0079683

Current Test Log\_Sensitivity Index\_BestTrain = 0.060133

Current Test SENSITIVITY = 0.1875

Current Train SENSITIVITY = 0.13789

Current Test SPECIFICITY = 0.90006

Current Train SPECIFICITY = 0.90349

Current Test CR = 81.514

Current Train CR = 81.8753

Current Test ASE = 0.73942

Current Train ASE = 0.7281

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 4b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 20 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 8.89e-005

lr\_inc = 1.01

lr\_dec = 0.999

lambda = 8.95e-005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2383

lambda\_dec = 0.801

wnot = 0.01

momentum = 0.405

err\_ratio = 1.375

max\_epoch = 1312

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.405

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

7221 888

7248 1022

Test Confusion Matrix

3708 415

3572 496

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

12585 1592

1884 318

Test Confusion Matrix

6313 772

967 139

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1000

Train Confusion Matrix

694 121

13775 1789

Test Confusion Matrix

314 69

6966 842

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.094401

maxTrainSENS = 0

bestTrainEpoch = 695

currTestSENS\_bestTrain = 0.70033

currTrainSPEC\_bestTrain = 0.41274

currTestSPEC\_bestTrain = 0.42747

currTrainCR\_bestTrain = 44.2823

currTestCR\_bestTrain = 45.782

currTrainASE\_bestTrain = 4998842074877280800000000000000000000000

currTestASE\_bestTrain = 2.1687

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.10821

Train Confusion Matrix - Epoch: 695

5972 629

8497 1281

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.018245

maxTestSENS = 0

bestTestEpoch = 1311

currTestSENS = 0.20527

currTrainSENS = 0.18482

currTestSPEC = 0.90165

currTrainSPEC = 0.89073

currTestCR = 82.4197

currTrainCR = 80.8413

currTestASE = 0.70321

currTrainASE = 7578916769934784900000000000000000000000000000000000000000000000000000000000000000000000000000000

currTrain\_Log\_Sensitivity\_Index = 0.014437

Test Confusion Matrix - Epoch: 1311

6564 724

716 187

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5378

ROC\_test =

0.5535

dirName =

Results\exp20130214\_2148\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 15.8658

Final weight decay constant: lambda = 153716466808487590000000000000000000000000000000000000000000000000000000000000000000000000000000000000

Final weight scale: wnot = 0.01

momentum = 0.405

err\_ratio = 1.375

Data Statistics

Training Set Apriori Probabilities

trprob =

88.3387

11.6613

Test Set Apriori Probabilities

teprob =

88.8780

11.1220

MDC Training Set Classification Rate

bayes\_train = 88.412

MDC Test Set Classification Rate

bayes\_test = 89.0123

Network Outputs

---------------

W1 =

1.0e+045 \*

Columns 1 through 9

0.0253 -0.0103 -0.0199 0.0059 -0.0236 -0.0084 -0.0229 -0.0103 -0.0000

-0.1085 -0.0071 0.0022 0.0055 -0.0127 -0.0094 0.0177 0.0125 0.0000

0.0066 0.0102 0.0276 0.0110 0.0196 1.6269 -0.0157 -0.0134 -0.0014

0.0063 -0.0000 0.0175 0.0096 0.0101 0.0153 0.0106 0.0036 0.0044

0.0000 -0.1314 -0.0331 -0.0026 0.0678 0.0029 -0.0107 0.0060 0.0148

-0.0044 0.0125 -0.0104 -0.0132 0.0016 -0.0311 0.0123 0.0116 0.0061

0.0136 -0.0183 0.0164 -0.0132 -0.0250 -0.0492 0.0223 -0.0085 -0.0147

0.0081 0.0131 -0.0134 0.1221 0.0019 -0.0140 -0.0060 0.0141 0.0113

-0.0419 0.0211 0.0142 -0.2838 0.0121 0.0306 -0.0075 -0.3432 0.0099

-0.0140 0.0164 -0.0172 0.0162 -0.0370 -0.0209 0.0238 0.0119 -0.0065

-0.0071 -0.0188 0.0142 -0.0182 -0.0258 0.0233 -0.0000 -0.0000 0.0082

0.0132 0.0072 -0.0200 -0.0103 0.0139 -0.0098 0.0174 -0.0065 -0.0000

0.0091 0.0066 0.0074 0.0046 0.0213 0.6340 -0.0086 -0.0083 0.0000

0.1535 0.0142 -0.0257 -0.0090 -0.1209 0.0235 0.0000 -0.0211 -0.0012

-0.0137 0.0000 0.0198 0.0135 0.0143 -0.0008 0.0000 -0.0000 0.0320

-0.0130 0.0000 0.0081 -0.0220 0.0103 -0.0023 0.0000 -0.0139 -0.0145

-0.0111 -0.1406 -0.0121 -0.0153 0.0251 -0.0000 -0.0050 0.0275 -0.0130

0.0176 -0.0140 -0.0135 0.0151 -0.0105 -0.0000 0.0174 0.0509 0.0170

-0.0000 -0.0175 0.0064 -0.0186 0.0159 0.0188 0.0232 -0.0106 0.0175

-0.2172 -0.0000 -0.0007 0.0238 -0.0150 0.1112 0.0095 -0.0133 -0.0059

Columns 10 through 11

0.0151 -0.0126

0.0046 0.0070

0.0252 -0.0134

-0.0000 0.0000

0.0191 0.0025

0.0079 0.0109

-0.0058 0.0136

0.0096 0.0002

0.0302 -0.0034

0.0000 -0.0139

-0.0212 0.0045

0.0328 -0.0131

0.0508 -0.0253

0.0611 0.0013

0.0179 0.0113

0.0976 0.0085

-0.0066 0.0163

-0.0516 -0.3291

0.0240 0.0078

0.0130 -0.0127

B1 =

1.0e+043 \*

-0.0000

-3.7301

1.2314

-3.0673

-1.2933

-1.8375

1.3349

1.2040

1.2179

2.6877

0.0404

0.8693

2.0218

-0.4309

1.0005

-1.4538

1.3890

0.9024

0.0000

0.5187

W2 =

1.0e+043 \*

Columns 1 through 9

0.2226 7.6934 -2.2579 1.2473 -1.5620 -1.3498 -1.3753 0.0000 -1.4378

Columns 10 through 18

0.8495 -0.3650 -0.0000 1.2486 -1.2622 -1.4835 -2.0684 2.6366 0.7576

Columns 19 through 20

1.3124 3.2259

B2 =

-1.8026e+043

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.405

Best Test Log\_Sensitivity Index = 0.018245

Best Test Epoch = 1311

Current Train Log\_Sensitivity Index = 0.014437

Current Test Log\_Sensitivity Index\_BestTrain = 0.10821

Current Test SENSITIVITY = 0.20527

Current Train SENSITIVITY = 0.18482

Current Test SPECIFICITY = 0.90165

Current Train SPECIFICITY = 0.89073

Current Test CR = 82.4197

Current Train CR = 80.8413

Current Test ASE = 0.70321

Current Train ASE = 7578916769934784900000000000000000000000000000000000000000000000000000000000000000000000000000000

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 5a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 20 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.31e-005

lr\_inc = 0.75

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.0079

lambda\_dec = 0.9205

wnot = 0.0918

momentum = 0.992

err\_ratio = 1.02

max\_epoch = 342

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

wnot = 0.0918

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

7276 855

7269 981

Test Confusion Matrix

3725 448

3519 498

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.01208

maxTrainSENS = 0

bestTrainEpoch = 297

currTestSENS\_bestTrain = 0.22727

currTrainSPEC\_bestTrain = 0.87233

currTestSPEC\_bestTrain = 0.87148

currTrainCR\_bestTrain = 79.3785

currTestCR\_bestTrain = 79.707

currTrainASE\_bestTrain = 0.79622

currTestASE\_bestTrain = 0.78032

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.021786

Train Confusion Matrix - Epoch: 297

12688 1521

1857 315

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.016123

maxTestSENS = 0

bestTestEpoch = 341

currTestSENS = 0.19345

currTrainSENS = 0.14216

currTestSPEC = 0.90268

currTrainSPEC = 0.89962

currTestCR = 82.0757

currTrainCR = 81.4724

currTestASE = 0.68306

currTrainASE = 0.70915

currTrain\_Log\_Sensitivity\_Index = 0.008448

Test Confusion Matrix - Epoch: 341

6539 763

705 183

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5081

ROC\_test =

0.5441

dirName =

Results\exp20130214\_2005\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 3.0105e-043

Final weight decay constant: lambda = 0.0030587

Final weight scale: wnot = 0.0918

momentum = 0.992

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

88.7919

11.2081

Test Set Apriori Probabilities

teprob =

88.4493

11.5507

MDC Training Set Classification Rate

bayes\_train = 88.8529

MDC Test Set Classification Rate

bayes\_test = 88.5592

Network Outputs

---------------

W1 =

Columns 1 through 9

-0.0000 0.0000 0.0000 -0.0000 1.2168 0.0000 0.0000 -0.0000 1.7431

-0.0000 1.0435 0.0000 -0.0000 0.0000 -0.0000 0.0000 1.2740 -1.3827

-1.7399 -0.0000 -0.0000 -0.2878 1.3166 0.0000 0.0000 1.6286 0.0000

-0.7901 -0.0000 -0.0000 -0.0000 0.5924 1.0418 0.0000 -0.0000 -0.8037

-0.0000 0.0000 -0.0000 0.0000 -0.0000 -0.0000 -0.0000 0.0027 0.0000

0.0000 0.0000 -0.0000 -1.4147 0.0000 -0.0000 1.8001 1.2296 0.0000

0.0000 -0.6700 -0.0000 -0.0000 -0.0696 0.0000 -0.0000 0.0000 -0.0000

0.0000 -0.0000 -0.0000 -1.4546 0.0000 0.0000 0.0000 -0.0000 -0.0000

0.8784 0.0000 -0.0000 -0.0000 -0.0000 -0.0000 0.0000 -0.0000 0.0000

-0.3973 0.0000 -0.0000 -2.2510 -0.0000 0.0000 0.0000 -1.6271 -0.8686

0.0000 -0.0000 0.0000 -0.0000 0.5038 0.0000 -1.5832 1.5815 -0.0000

-0.0000 0.0000 -0.0000 0.0000 -0.0000 0.0000 -0.9391 0.6141 0.4383

-0.4014 -0.0000 0.0000 -0.0000 0.0000 0.5607 0.0000 0.0000 -0.0000

-0.3747 0.5594 -0.0000 -1.9640 0.0000 0.0000 -0.0000 0.0014 0.4194

2.1999 -0.0000 0.0000 0.0000 -0.0000 -0.0611 -0.0000 0.0000 -0.6781

2.2631 0.1088 -0.0000 0.0000 0.0000 0.0360 -0.0000 -0.0000 -0.0000

-0.0000 -0.6600 0.0000 -0.0000 -0.0022 -0.0000 -0.0000 -0.0000 -0.0000

2.1257 0.0000 -0.0000 -0.0000 0.0002 -0.4110 1.6436 0.0000 -0.0000

-0.0000 0.0000 -0.0000 0.0000 -0.0000 1.1351 0.0000 -0.0000 0.0698

0.0000 -0.0000 0.0000 -0.0000 0.0000 0.0000 0.0000 0.0000 -0.8623

Columns 10 through 11

-0.0000 0.0000

-0.0000 -0.0000

-0.0000 0.6196

-0.0000 -0.0000

-1.1947 0.0000

0.0000 -0.0000

0.0000 0.0000

0.0001 -0.0000

-0.0000 0.0000

-0.0000 0.0000

-0.0000 -0.0000

0.0000 -1.0368

0.0000 -0.0000

0.0000 0.0000

0.0000 -0.0000

2.0065 0.1092

-0.0000 -0.0000

-1.5644 2.1530

0.0000 0.0000

0.0000 -0.0000

B1 =

-0.0000

0.0000

-2.2105

-0.0000

-0.0000

0.0000

-0.0000

0.5445

-1.6618

-0.0000

-0.0000

0.0000

-0.0000

0.0000

-0.0000

-0.0000

-0.0000

0.0000

-1.0507

1.2853

W2 =

Columns 1 through 9

-9.2103 -4.2028 -4.2994 3.5987 10.7278 -3.5755 4.7685 -0.0000 4.1223

Columns 10 through 18

-2.2412 -0.0000 9.6742 9.6441 9.2562 0.0000 -8.7898 -7.2543 -8.2422

Columns 19 through 20

1.1953 -11.2652

B2 =

-18.2675

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

weightScale = 0.0918

Best Test Log\_Sensitivity Index = 0.016123

Best Test Epoch = 341

Current Train Log\_Sensitivity Index = 0.008448

Current Test Log\_Sensitivity Index\_BestTrain = 0.021786

Current Test SENSITIVITY = 0.19345

Current Train SENSITIVITY = 0.14216

Current Test SPECIFICITY = 0.90268

Current Train SPECIFICITY = 0.89962

Current Test CR = 82.0757

Current Train CR = 81.4724

Current Test ASE = 0.68306

Current Train ASE = 0.70915

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**nOMOD\_NEONATALMORT RESULTS Set 5b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 16 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0005159

lr\_inc = 0.7656

lr\_dec = 1.0313

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.001

lambda\_dec = 0.7818

wnot = 0.01

momentum = 0.999

err\_ratio = 1.02

max\_epoch = 419

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda\_dec = 0.7818

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

7731 1000

6761 887

Test Confusion Matrix

3786 504

3467 434

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.020735

maxTrainSENS = 0

bestTrainEpoch = 383

currTestSENS\_bestTrain = 0.242

currTrainSPEC\_bestTrain = 0.8406

currTestSPEC\_bestTrain = 0.84972

currTrainCR\_bestTrain = 76.9827

currTestCR\_bestTrain = 78.0125

currTrainASE\_bestTrain = 0.91934

currTestASE\_bestTrain = 0.87787

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.024196

Train Confusion Matrix - Epoch: 383

12182 1460

2310 427

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.016591

maxTestSENS = 0

bestTestEpoch = 418

currTestSENS = 0.19616

currTrainSENS = 0.16746

currTestSPEC = 0.90211

currTrainSPEC = 0.89787

currTestCR = 82.1267

currTrainCR = 81.3725

currTestASE = 0.7145

currTrainASE = 0.7442

currTrain\_Log\_Sensitivity\_Index = 0.01185

Test Confusion Matrix - Epoch: 418

6543 754

710 184

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.5333

ROC\_test =

0.5507

dirName =

Results\exp20130209\_1208\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 2.2634e-052

Final weight decay constant: lambda = 0.0059303

Final weight scale: wnot = 0.01

momentum = 0.999

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

88.4792

11.5208

Test Set Apriori Probabilities

teprob =

88.5484

11.4516

MDC Training Set Classification Rate

bayes\_train = 88.6074

MDC Test Set Classification Rate

bayes\_test = 88.6217

Network Outputs

---------------

W1 =

Columns 1 through 9

20.3242 4.6194 11.2189 -1.7822 -3.4603 -5.0695 -2.5475 -4.6507 13.6798

-0.5013 22.8036 18.2997 4.3613 5.9245 4.3655 2.3646 5.8715 0.5209

-51.1395 -9.9741 -13.8440 -4.3372 -8.3493 -8.2155 -5.3877 -8.0123 0.4362

0.3698 -1.8818 0.9766 24.2445 -5.5211 -1.7992 -1.8485 -3.4956 0.6687

0.2518 10.7610 0.5937 -7.3772 5.7687 6.4295 3.5582 -5.3843 8.3023

-29.0177 3.3037 -0.8511 4.7901 6.8020 9.0143 5.7104 10.2119 1.3534

50.8783 1.0259 21.5310 1.7977 -0.7151 -2.0671 1.5818 -3.6044 -3.8111

0.1926 -8.7237 -0.9481 1.6549 -12.5275 3.4423 2.5459 -8.9826 4.8544

1.6424 -4.6468 0.5008 3.8766 8.8345 10.7168 4.4051 9.0283 -3.5651

-0.4805 4.3881 -7.2133 8.3858 3.6584 10.8940 6.6292 4.9983 -0.8004

3.5689 4.1866 0.9838 -3.0908 -5.0768 1.5596 -4.8210 -7.7284 10.9103

14.3742 2.9012 64.9471 1.8389 2.1832 4.5502 3.1825 -5.6736 -38.0649

8.9472 1.0913 -2.2254 1.1747 2.4116 -8.0751 1.0386 1.3464 3.2092

0.6789 2.3461 12.6329 1.8683 -0.8768 -2.4545 -0.6737 -2.7191 -0.5245

1.1843 -1.3826 34.6482 1.4983 3.4392 -13.5278 -2.1552 -3.8908 0.0855

0.6377 -1.0701 0.9287 2.6914 3.3998 8.2918 8.5297 9.1951 0.3473

Columns 10 through 11

0.7493 -0.6188

32.7978 -15.6337

0.3061 33.4342

-23.3842 0.8252

39.0960 -16.8395

-0.6361 26.6722

-21.8426 0.3023

0.7149 -2.0833

0.7052 22.5275

-0.4504 0.5802

-5.9447 -0.6245

-0.8873 38.6993

-18.1569 5.8863

4.1231 28.6310

79.8757 1.0822

6.1929 10.8924

B1 =

5.9752

5.2176

6.9518

10.3777

-7.0278

-10.5718

6.3316

-12.8120

-11.0278

-5.7959

10.7130

-14.5059

-2.4726

3.4636

5.8187

-9.3429

W2 =

Columns 1 through 9

-106.6898 -46.1678 17.0701 159.9149 -9.2792 50.6675 -153.0171 28.5593 -90.2257

Columns 10 through 16

75.9377 -52.4508 -21.7961 18.6569 -153.3849 107.3265 -154.8718

B2 =

-273.0017

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambdaDec = 0.7818

Best Test Log\_Sensitivity Index = 0.016591

Best Test Epoch = 418

Current Train Log\_Sensitivity Index = 0.01185

Current Test Log\_Sensitivity Index\_BestTrain = 0.024196

Current Test SENSITIVITY = 0.19616

Current Train SENSITIVITY = 0.16746

Current Test SPECIFICITY = 0.90211

Current Train SPECIFICITY = 0.89787

Current Test CR = 82.1267

Current Train CR = 81.3725

Current Test ASE = 0.7145

Current Train ASE = 0.7442

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**H1.4 MOD\_NEONATALMORT HYBRID RESULTS (TRAIN)**

|  |  |  |  |
| --- | --- | --- | --- |
| 5 by 2 Cross Validation Results | | |  |
|  |  |  |  |
|  |  |  |  |
|  | **Verification** | Std Dev | Confidence Interval (95%) |
| **Accuracy:** | 0.76 | 0.05 | 0.03 |
| **Sensitivity/Recall:** | 0.6544 | 0.0593 | 0.0367 |
| **Specificity:** | 0.8007 | 0.0842 | 0.0522 |
| **PPV/Precision:** | 0.5672 | 0.0905 | 0.0561 |
| **NPV:** | 0.8646 | 0.0081 | 0.0050 |
| **F1 score:** | 0.60 | 0.02 | 0.02 |
| **MCC:** | 0.44 | 0.05 | 0.03 |
| **SS1:** | 0.46 | 0.03 | 0.02 |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Fold 1A** |  | **Fold 1B** |  | **Fold 2A** |  | **Fold 2B** |  | **Fold 3A** |  |
| 10113 | 1630 | 8524 | 1244 | 10399 | 1778 | 10212 | 1610 | 10942 | 1878 |
| 1872 | 2734 | 3434 | 3146 | 1528 | 2644 | 1804 | 2722 | 1034 | 2495 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.786 | *Accuracy:* | 0.714 | *Accuracy:* | 0.798 | *Accuracy:* | 0.791 | *Accuracy:* | 0.822 |
| *Sens:* | 0.6265 | *Sens:* | 0.7166 | *Sens:* | 0.5979 | *Sens:* | 0.6283 | *Sens:* | 0.5705 |
| *Spec:* | 0.8438 | *Spec:* | 0.7128 | *Spec:* | 0.8719 | *Spec:* | 0.8499 | *Spec:* | 0.9137 |
| *PPV:* | 0.5936 | *PPV:* | 0.4781 | *PPV:* | 0.6337 | *PPV:* | 0.6014 | *PPV:* | 0.7070 |
| *NPV:* | 0.8612 | *NPV:* | 0.8726 | *NPV:* | 0.8540 | *NPV:* | 0.8638 | *NPV:* | 0.8535 |
| *F1 score:* | 0.610 | *F1 score:* | 0.574 | *F1 score:* | 0.615 | *F1 score:* | 0.615 | *F1 score:* | 0.631 |
| *MCC:* | 0.462 | *MCC:* | 0.388 | *MCC:* | 0.479 | *MCC:* | 0.472 | *MCC:* | 0.521 |
| *SS1:* | 0.470 | *SS1:* | 0.429 | *SS1:* | 0.470 | *SS1:* | 0.478 | *SS1:* | 0.484 |
| *Fold 3B* |  | *Fold 4A* |  | *Fold 4B* |  | *Fold 5A* |  | *Fold 5B* |  |
| *9021* | 1363 | *9164* | 1435 | *8473* | 1198 | *8059* | 1148 | *10956* | 1842 |
| *2946* | 3018 | *2791* | 2959 | *3515* | 3162 | *3896* | 3246 | *1032* | 2518 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.736 | *Accuracy:* | 0.742 | *Accuracy:* | 0.712 | *Accuracy:* | 0.691 | *Accuracy:* | 0.824 |
| *Sens:* | 0.6889 | *Sens:* | 0.6734 | *Sens:* | 0.7252 | *Sens:* | 0.7387 | *Sens:* | 0.5775 |
| *Spec:* | 0.7538 | *Spec:* | 0.7665 | *Spec:* | 0.7068 | *Spec:* | 0.6741 | *Spec:* | 0.9139 |
| *PPV:* | 0.5060 | *PPV:* | 0.5146 | *PPV:* | 0.4736 | *PPV:* | 0.4545 | *PPV:* | 0.7093 |
| *NPV:* | 0.8687 | *NPV:* | 0.8646 | *NPV:* | 0.8761 | *NPV:* | 0.8753 | *NPV:* | 0.8561 |
| *F1 score:* | 0.583 | *F1 score:* | 0.583 | *F1 score:* | 0.573 | *F1 score:* | 0.563 | *F1 score:* | 0.637 |
| *MCC:* | 0.407 | *MCC:* | 0.408 | *MCC:* | 0.389 | *MCC:* | 0.369 | *MCC:* | 0.527 |
| *SS1:* | 0.443 | *SS1:* | 0.440 | *SS1:* | 0.432 | *SS1:* | 0.413 | *SS1:* | 0.491 |

**H1.5 MOD\_NEONATALMORT HYBRID RESULTS (TEST)**

|  |  |  |  |
| --- | --- | --- | --- |
| 5 by 2 Cross Validation Results | | |  |
|  |  |  |  |
|  |  |  |  |
|  | **Verification** | Std Dev | Confidence Interval (95%) |
| **Accuracy:** | 0.8333 | 0.0049 | 0.00 |
| **Sensitivity/Recall:** | 0.60741 | 0.00588 | 0.00 |
| **Specificity:** | 0.91300 | 0.00651 | 0.00 |
| **PPV/Precision:** | 0.71135 | 0.01638 | 0.01 |
| **NPV:** | 0.86834 | 0.00329 | 0.00 |
| **F1 score:** | 0.66 | 0.01 | 0.00 |
| **MCC:** | 0.55 | 0.01 | 0.01 |
| **SS1:** | 0.52 | 0.01 | 0.01 |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Fold 1A** |  | **Fold 1B** |  | **Fold 2A** |  | **Fold 2B** |  | **Fold 3A** |  |
| 5530 | 799 | 5516 | 873 | 5488 | 814 | 5502 | 853 | 5584 | 818 |
| 545 | 1300 | 498 | 1288 | 591 | 1281 | 509 | 1311 | 476 | 1296 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.836 | *Accuracy:* | 0.832 | *Accuracy:* | 0.828 | *Accuracy:* | 0.833 | *Accuracy:* | 0.842 |
| *Sens:* | 0.6193 | *Sens:* | 0.5960 | *Sens:* | 0.6115 | *Sens:* | 0.6058 | *Sens:* | 0.6131 |
| *Spec:* | 0.9103 | *Spec:* | 0.9172 | *Spec:* | 0.9028 | *Spec:* | 0.9153 | *Spec:* | 0.9215 |
| *PPV:* | 0.7046 | *PPV:* | 0.7212 | *PPV:* | 0.6843 | *PPV:* | 0.7203 | *PPV:* | 0.7314 |
| *NPV:* | 0.8738 | *NPV:* | 0.8634 | *NPV:* | 0.8708 | *NPV:* | 0.8658 | *NPV:* | 0.8722 |
| *F1 score:* | 0.659 | *F1 score:* | 0.653 | *F1 score:* | 0.646 | *F1 score:* | 0.658 | *F1 score:* | 0.667 |
| *MCC:* | 0.553 | *MCC:* | 0.548 | *MCC:* | 0.534 | *MCC:* | 0.553 | *MCC:* | 0.568 |
| *SS1:* | 0.530 | *SS1:* | 0.513 | *SS1:* | 0.514 | *SS1:* | 0.521 | *SS1:* | 0.535 |
| *Fold 3B* |  | *Fold 4A* |  | *Fold 4B* |  | *Fold 5A* |  | *Fold 5B* |  |
| *5427* | 852 | *5527* | 852 | *5547* | 826 | *5537* | 833 | *5521* | 846 |
| *600* | 1296 | *480* | 1315 | *533* | 1269 | *518* | 1286 | *509* | 1299 |
|  |  |  |  |  |  |  |  |  |  |
| *Accuracy:* | 0.822 | *Accuracy:* | 0.837 | *Accuracy:* | 0.834 | *Accuracy:* | 0.835 | *Accuracy:* | 0.834 |
| *Sens:* | 0.6034 | *Sens:* | 0.6068 | *Sens:* | 0.6057 | *Sens:* | 0.6069 | *Sens:* | 0.6056 |
| *Spec:* | 0.9004 | *Spec:* | 0.9201 | *Spec:* | 0.9123 | *Spec:* | 0.9145 | *Spec:* | 0.9156 |
| *PPV:* | 0.6835 | *PPV:* | 0.7326 | *PPV:* | 0.7042 | *PPV:* | 0.7129 | *PPV:* | 0.7185 |
| *NPV:* | 0.8643 | *NPV:* | 0.8664 | *NPV:* | 0.8704 | *NPV:* | 0.8692 | *NPV:* | 0.8671 |
| *F1 score:* | 0.641 | *F1 score:* | 0.664 | *F1 score:* | 0.651 | *F1 score:* | 0.656 | *F1 score:* | 0.657 |
| *MCC:* | 0.525 | *MCC:* | 0.562 | *MCC:* | 0.546 | *MCC:* | 0.551 | *MCC:* | 0.552 |
| *SS1:* | 0.504 | *SS1:* | 0.527 | *SS1:* | 0.518 | *SS1:* | 0.521 | *SS1:* | 0.521 |

**H1.6 MOD\_NEONATALMORT OVERALL RESULTS**

**MOD\_NEONATALMORT RESULTS Set 1a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 13 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.71e-005

lr\_inc = 0.7598

lr\_dec = 1.0313

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2198

lambda\_dec = 0.176

wnot = 0.01

momentum = 0.625

err\_ratio = 1.02

max\_epoch = 200

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.625

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11447 4059

538 305

Test Confusion Matrix

5801 1938

274 161

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.20464

maxTrainSENS = 0

bestTrainEpoch = 10

currTestSENS\_bestTrain = 0.66794

currTrainSPEC\_bestTrain = 0.8438

currTestSPEC\_bestTrain = 0.84379

currTrainCR\_bestTrain = 78.5797

currTestCR\_bestTrain = 79.863

currTrainASE\_bestTrain = 0.56416

currTestASE\_bestTrain = 0.52708

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.24053

Train Confusion Matrix - Epoch: 10

10113 1630

1872 2734

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.22315

maxTestSENS = 0

bestTestEpoch = 199

currTestSENS = 0.61934

currTrainSENS = 0.57516

currTestSPEC = 0.91029

currTrainSPEC = 0.9164

currTestCR = 83.5576

currTrainCR = 82.531

currTestASE = 0.54148

currTrainASE = 0.56716

currTrain\_Log\_Sensitivity\_Index = 0.18705

Test Confusion Matrix - Epoch: 199

5530 799

545 1300

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7628

ROC\_test =

0.7857

dirName =

Results\exp20130212\_2049\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 3.4421e-026

Final weight decay constant: lambda = 0.078644

Final weight scale: wnot = 0.01

momentum = 0.625

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

73.3072

26.6928

Test Set Apriori Probabilities

teprob =

74.3210

25.6790

MDC Training Set Classification Rate

bayes\_train = 86.6414

MDC Test Set Classification Rate

bayes\_test = 87.9374

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.5578 0.8149 -0.6235 -0.8605 -0.7539 0.9426 0.5180 0.8413

-0.3918 0.8332 -0.5932 0.8747 -0.3585 0.6889 -0.4578 -0.6493

-0.3506 0.5668 0.6386 0.2830 -0.5466 0.7746 -0.9279 -0.3716

0.3826 -0.9682 -0.8595 0.7745 0.7430 -0.6172 -1.0063 0.8779

0.6381 -0.6684 -0.6762 0.3848 -0.4514 0.9215 -0.3352 -0.4929

0.5577 0.9377 -2.6039 0.2409 2.1689 -0.7239 0.8679 -0.4506

-0.7810 -0.3158 -0.6574 0.4949 -0.1118 -0.3151 1.0329 -0.2344

-0.8204 0.1872 2.4106 0.2300 0.2099 1.0095 0.2543 -0.7439

0.2832 -0.8751 -0.9133 0.9769 -0.5613 0.8459 0.5666 -0.7596

0.7329 -0.7791 0.6776 0.5334 -0.5629 -1.7824 0.5862 0.9950

1.1982 -2.0659 0.6515 0.6943 0.5525 0.6070 -0.2206 0.5642

0.3560 -0.8121 -0.7384 -0.9600 0.2614 -0.7320 0.4114 -0.7538

-0.1679 0.8166 -0.5190 -0.3564 -0.2583 -0.9479 0.6432 0.7465

Columns 9 through 11

-0.1612 0.8410 0.6065

-0.5983 -0.6690 0.3810

-0.3263 -0.5045 -0.3922

0.5233 -0.3448 0.4468

0.4434 -0.3345 -0.3779

-0.8292 0.5955 1.3744

0.2862 -0.5913 0.4076

0.8622 -1.7292 -0.9462

0.4911 -0.4643 -0.3811

0.2888 0.3515 0.3063

-0.5750 -0.3570 1.4492

-0.2351 0.2587 -0.8153

-0.1647 0.8503 0.4855

B1 =

0.4039

0.7606

0.6011

-0.4415

0.2495

0.6483

-0.6176

0.3299

0.9070

1.0050

-0.6273

-0.5479

-0.7176

W2 =

Columns 1 through 8

0.4783 0.0463 0.4216 0.3517 -0.2738 0.1195 -0.1286 0.1876

Columns 9 through 13

0.1658 0.2334 0.1593 -0.2483 0.3587

B2 =

0.1262

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.625

Best Test Log\_Sensitivity Index = 0.22315

Best Test Epoch = 199

Current Train Log\_Sensitivity Index = 0.18705

Current Test Log\_Sensitivity Index\_BestTrain = 0.24053

Current Test SENSITIVITY = 0.61934

Current Train SENSITIVITY = 0.57516

Current Test SPECIFICITY = 0.91029

Current Train SPECIFICITY = 0.9164

Current Test CR = 83.5576

Current Train CR = 82.531

Current Test ASE = 0.54148

Current Train ASE = 0.56716

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 1b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 8 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.62e-005

lr\_inc = 0.8417

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.001

lambda\_dec = 0.999

wnot = 0.01

momentum = 0.999

err\_ratio = 1.0821

max\_epoch = 582

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lr\_inc = 0.8417

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11826 4053

132 337

Test Confusion Matrix

5957 1997

57 164

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

9867 1539

2091 2851

Test Confusion Matrix

4958 729

1056 1432

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.22254

maxTrainSENS = 0

bestTrainEpoch = 233

currTestSENS\_bestTrain = 0.73947

currTrainSPEC\_bestTrain = 0.71283

currTestSPEC\_bestTrain = 0.70984

currTrainCR\_bestTrain = 71.3849

currTestCR\_bestTrain = 71.7676

currTrainASE\_bestTrain = 0.84789

currTestASE\_bestTrain = 0.83222

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.23902

Train Confusion Matrix - Epoch: 233

8524 1244

3434 3146

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.20478

maxTestSENS = 0

bestTestEpoch = 581

currTestSENS = 0.59602

currTrainSENS = 0.57927

currTestSPEC = 0.91719

currTrainSPEC = 0.90893

currTestCR = 83.2294

currTrainCR = 82.0406

currTestASE = 0.67375

currTrainASE = 0.70687

currTrain\_Log\_Sensitivity\_Index = 0.18809

Test Confusion Matrix - Epoch: 581

5516 873

498 1288

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7303

ROC\_test =

0.7427

dirName =

Results\exp20130212\_2049\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 6.0134e-025

Final weight decay constant: lambda = 0.00475

Final weight scale: wnot = 0.01

momentum = 0.999

err\_ratio = 1.0821

Data Statistics

Training Set Apriori Probabilities

trprob =

73.1466

26.8534

Test Set Apriori Probabilities

teprob =

73.5657

26.4343

MDC Training Set Classification Rate

bayes\_train = 86.347

MDC Test Set Classification Rate

bayes\_test = 87.315

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.4482 -3.8398 -0.9031 -0.8492 -0.6643 0.8501 0.4961 -0.3522

4.3445 -5.9989 -0.6101 0.5584 -17.1196 -0.9218 0.6744 4.4658

2.0488 1.7153 10.6612 -0.5157 4.2737 0.8314 -0.8191 -1.9783

-1.4111 -1.5774 -3.6790 -5.0015 0.6424 -3.9880 -9.7503 -9.3871

0.6006 -3.4464 -3.3973 0.4912 0.6329 -9.0040 -0.6803 -0.4953

0.4601 0.8184 -0.8809 -0.8166 -0.7483 0.4304 -0.1209 16.2244

-0.7964 0.8169 -0.7295 -0.6717 -0.3045 2.4609 -0.5173 0.5131

-16.3218 0.4070 1.5092 3.5380 -0.9203 0.9825 0.7210 4.2562

Columns 9 through 11

-5.1635 0.8746 -1.0475

-1.9353 0.6482 -1.1307

0.7141 -13.9456 -0.6102

0.4079 -2.8468 1.1822

-0.5218 -0.8279 0.8871

0.8695 6.4320 -7.6228

-0.7454 0.4795 0.5122

-15.1413 0.2729 0.7710

B1 =

-0.8009

-3.8731

0.6615

0.8810

22.7454

-1.5188

0.8851

9.6998

W2 =

-0.3219 -0.4413 -0.8656 0.7696 -0.2985 2.9143 0.8116 0.3189

B2 =

1.8150

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

learnRateInc = 0.8417

Best Test Log\_Sensitivity Index = 0.20478

Best Test Epoch = 581

Current Train Log\_Sensitivity Index = 0.18809

Current Test Log\_Sensitivity Index\_BestTrain = 0.23902

Current Test SENSITIVITY = 0.59602

Current Train SENSITIVITY = 0.57927

Current Test SPECIFICITY = 0.91719

Current Train SPECIFICITY = 0.90893

Current Test CR = 83.2294

Current Train CR = 82.0406

Current Test ASE = 0.67375

Current Train ASE = 0.70687

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 2a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 8 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0002055

lr\_inc = 0.877

lr\_dec = 0.9693

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.1231

lambda\_dec = 0.5861

wnot = 0.01

momentum = 0.5

err\_ratio = 1.02

max\_epoch = 380

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lr = 0.0002055

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11808 4083

119 339

Test Confusion Matrix

6019 1936

60 159

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.19131

maxTrainSENS = 0

bestTrainEpoch = 305

currTestSENS\_bestTrain = 0.62959

currTrainSPEC\_bestTrain = 0.87189

currTestSPEC\_bestTrain = 0.88057

currTrainCR\_bestTrain = 79.7786

currTestCR\_bestTrain = 81.6247

currTrainASE\_bestTrain = 0.5148

currTestASE\_bestTrain = 0.47184

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.22102

Train Confusion Matrix - Epoch: 305

10399 1778

1528 2644

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.21323

maxTestSENS = 0

bestTestEpoch = 379

currTestSENS = 0.61146

currTrainSENS = 0.57463

currTestSPEC = 0.90278

currTrainSPEC = 0.89453

currTestCR = 82.8114

currTrainCR = 80.8

currTestASE = 0.49094

currTrainASE = 0.52979

currTrain\_Log\_Sensitivity\_Index = 0.18008

Test Confusion Matrix - Epoch: 379

5488 814

591 1281

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7705

ROC\_test =

0.7914

dirName =

Results\exp20130212\_2049\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 2.8025e-023

Final weight decay constant: lambda = 0.10314

Final weight scale: wnot = 0.01

momentum = 0.5

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

72.9525

27.0475

Test Set Apriori Probabilities

teprob =

74.3700

25.6300

MDC Training Set Classification Rate

bayes\_train = 86.3233

MDC Test Set Classification Rate

bayes\_test = 87.8762

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.4959 0.2768 -0.9301 -0.8527 -0.6693 0.8813 0.5547 -0.4555

-0.3515 0.2148 -0.6517 0.9352 0.4165 -0.2659 0.7146 0.4704

-0.2923 -0.2375 0.4132 -0.5304 -0.6473 0.8429 -0.8873 -0.3096

0.2513 -0.5224 -0.4133 -0.5508 0.5737 0.2583 -0.4463 -0.3241

0.5751 0.4452 -0.3341 0.5790 0.6103 0.5034 -0.7572 -0.5943

0.4889 0.8208 -0.9039 -0.8569 -0.8000 0.4753 -0.4141 0.2412

-0.8109 0.8273 -0.7522 -0.7147 -0.4375 0.2340 -0.5537 0.5737

-0.1829 0.5134 0.3337 0.0021 -0.9918 0.9405 0.7290 0.8549

Columns 9 through 11

0.7514 0.9210 -1.0144

0.1997 0.6863 -1.1166

0.7222 -0.1765 -0.5463

0.6546 0.2909 0.9582

-0.6233 -0.6783 1.0622

0.8630 -2.3077 0.2976

-0.7385 0.5620 0.5616

0.9517 -0.3738 0.7300

B1 =

0.9227

-0.7763

0.6863

0.9885

-0.2422

-0.3563

0.8954

-0.6646

W2 =

-0.1501 -0.2764 -0.4373 0.5884 0.3687 -0.3318 0.1872 0.2270

B2 =

0.1364

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

learnRate = 0.0002055

Best Test Log\_Sensitivity Index = 0.21323

Best Test Epoch = 379

Current Train Log\_Sensitivity Index = 0.18008

Current Test Log\_Sensitivity Index\_BestTrain = 0.22102

Current Test SENSITIVITY = 0.61146

Current Train SENSITIVITY = 0.57463

Current Test SPECIFICITY = 0.90278

Current Train SPECIFICITY = 0.89453

Current Test CR = 82.8114

Current Train CR = 80.8

Current Test ASE = 0.49094

Current Train ASE = 0.52979

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 2b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 13 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.13e-005

lr\_inc = 0.7735

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 0.9688

lambda\_dec = 0.999

wnot = 0.01

momentum = 0.5

err\_ratio = 1.0157

max\_epoch = 99

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

err\_ratio = 1.0157

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11459 4028

557 304

Test Confusion Matrix

5749 2007

262 157

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.20838

maxTrainSENS = 0

bestTrainEpoch = 8

currTestSENS\_bestTrain = 0.65481

currTrainSPEC\_bestTrain = 0.84987

currTestSPEC\_bestTrain = 0.83713

currTrainCR\_bestTrain = 79.1167

currTestCR\_bestTrain = 78.8869

currTrainASE\_bestTrain = 0.60357

currTestASE\_bestTrain = 0.59844

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.22592

Train Confusion Matrix - Epoch: 8

10212 1610

1804 2722

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.21275

maxTestSENS = 0

bestTestEpoch = 98

currTestSENS = 0.60582

currTrainSENS = 0.57341

currTestSPEC = 0.91532

currTrainSPEC = 0.91669

currTestCR = 83.3394

currTrainCR = 82.5728

currTestASE = 0.59019

currTrainASE = 0.59224

currTrain\_Log\_Sensitivity\_Index = 0.18572

Test Confusion Matrix - Epoch: 98

5502 853

509 1311

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7851

ROC\_test =

0.7952

dirName =

Results\exp20130212\_2050\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 7.7646e-012

Final weight decay constant: lambda = 0.00069691

Final weight scale: wnot = 0.01

momentum = 0.5

err\_ratio = 1.0157

Data Statistics

Training Set Apriori Probabilities

trprob =

73.5013

26.4987

Test Set Apriori Probabilities

teprob =

73.5291

26.4709

MDC Training Set Classification Rate

bayes\_train = 86.665

MDC Test Set Classification Rate

bayes\_test = 87.3272

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.5537 0.8177 -0.6241 -0.8780 -0.7474 0.1940 0.5272 0.8467

-0.4053 0.8311 -0.5986 0.8684 -0.3744 0.6868 -0.4706 0.1384

-0.3664 0.5664 0.6373 -0.2210 -0.5536 0.7730 -0.9316 -0.3848

0.3964 -0.9658 -0.8573 0.7758 0.7484 -0.6158 -1.0042 0.8809

0.6337 -0.6759 -0.6836 0.3986 -0.4647 0.9167 -0.3561 -0.4023

0.5553 -0.1975 -0.2009 0.1619 -0.1328 -0.7309 0.8618 -0.4633

-0.7912 -0.3402 -0.6670 0.5093 0.2347 -0.2389 1.0229 -0.2780

-0.1399 0.2467 -0.1199 0.2722 0.2059 1.0215 0.2891 0.1806

0.3031 -0.8743 -0.5417 0.9872 -0.5663 0.8458 0.5659 -0.1020

0.1800 -0.7796 0.6800 0.5344 -0.1634 -0.1079 0.5961 -0.1450

0.1958 -0.1675 0.6502 0.6915 0.5601 0.1665 -0.4660 0.5691

0.5833 -0.8143 -0.7407 -0.9587 0.1534 -0.7372 0.0485 -0.1050

0.1405 -0.2000 -0.5106 -0.3703 -0.2698 -0.1253 0.6594 0.7592

Columns 9 through 11

0.1038 0.8369 0.6020

-0.3920 -0.6632 0.4063

-0.3469 -0.5052 -0.0891

0.5322 0.1429 0.4515

0.4340 -0.3396 -0.0284

-0.8399 -0.1191 -0.1285

-0.0983 -0.5869 0.1059

0.8552 0.0928 -0.9348

0.4858 -0.4704 -0.2515

0.3221 0.3623 0.3172

-0.5741 -0.3725 -0.1029

-0.2743 0.2905 -0.8127

-0.2041 0.8383 0.4672

B1 =

0.4049

0.7661

0.6070

-0.1424

0.1687

-0.1944

-0.6112

0.3326

0.9095

0.9984

-0.6338

-0.5457

-0.7347

W2 =

Columns 1 through 8

0.4477 0.2393 0.2117 0.3785 -0.2600 0.1713 -0.1830 0.2610

Columns 9 through 13

-0.1623 0.2334 0.0990 -0.2532 0.3564

B2 =

0.1373

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

errorRatio = 1.0157

Best Test Log\_Sensitivity Index = 0.21275

Best Test Epoch = 98

Current Train Log\_Sensitivity Index = 0.18572

Current Test Log\_Sensitivity Index\_BestTrain = 0.22592

Current Test SENSITIVITY = 0.60582

Current Train SENSITIVITY = 0.57341

Current Test SPECIFICITY = 0.91532

Current Train SPECIFICITY = 0.91669

Current Test CR = 83.3394

Current Train CR = 82.5728

Current Test ASE = 0.59019

Current Train ASE = 0.59224

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 3a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 19 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.46e-005

lr\_inc = 0.877

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.2344

lambda\_dec = 0.4689

wnot = 0.0026

momentum = 0.516

err\_ratio = 1.02

max\_epoch = 297

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.516

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11797 4320

179 53

Test Confusion Matrix

5971 2092

89 22

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.18253

maxTrainSENS = 0

bestTrainEpoch = 296

currTestSENS\_bestTrain = 0.61306

currTrainSPEC\_bestTrain = 0.91366

currTestSPEC\_bestTrain = 0.92145

currTrainCR\_bestTrain = 82.1885

currTestCR\_bestTrain = 84.1693

currTrainASE\_bestTrain = 0.55852

currTestASE\_bestTrain = 0.51497

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.22157

Train Confusion Matrix - Epoch: 296

10942 1878

1034 2495

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.22157

maxTestSENS = 0

bestTestEpoch = 296

currTestSENS = 0.61306

currTrainSENS = 0.57055

currTestSPEC = 0.92145

currTrainSPEC = 0.91366

currTestCR = 84.1693

currTrainCR = 82.1885

currTestASE = 0.51497

currTrainASE = 0.55852

currTrain\_Log\_Sensitivity\_Index = 0.18253

Test Confusion Matrix - Epoch: 296

5584 818

476 1296

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7591

ROC\_test =

0.7802

dirName =

Results\exp20130215\_1724\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 2.0682e-018

Final weight decay constant: lambda = 0.13397

Final weight scale: wnot = 0.0026

momentum = 0.516

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

73.2522

26.7478

Test Set Apriori Probabilities

teprob =

74.1375

25.8625

MDC Training Set Classification Rate

bayes\_train = 86.4151

MDC Test Set Classification Rate

bayes\_test = 87.8028

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.5189 -0.3869 -0.4713 -0.0820 -0.7436 1.3967 -0.5508 0.4102

-0.4236 -0.0953 -0.9389 0.2636 -2.2255 -0.4881 -0.3081 3.8624

-0.3670 -0.8784 0.8634 0.1746 0.5711 -0.2940 0.2196 -0.1218

0.4003 -0.7538 0.7671 -0.5678 -0.5133 0.1082 0.7680 0.6460

0.6635 0.1360 0.8405 -0.1388 -0.9034 0.1965 -0.5752 -0.9175

0.5448 -0.8469 0.3998 0.5744 -0.9600 0.1140 -0.4618 0.7842

-0.8970 19.6752 0.1211 0.1345 -0.4652 0.4970 -2.0450 0.1608

-0.2142 -0.6169 0.4966 -0.2169 0.8109 -0.3443 -0.3094 -0.1331

0.3259 -0.5832 0.2876 0.2130 1.0171 0.8809 -0.2372 -0.7373

0.1953 0.6191 0.9902 0.6711 0.2554 -0.8853 -0.5747 0.3468

-0.1127 -0.8587 0.5095 0.7591 0.5039 -0.1271 -0.6279 0.3245

-3.8896 -0.7195 0.6700 -0.5449 0.5714 -0.4463 -0.5504 0.6954

0.2095 -0.2148 -0.9406 0.8940 -0.5945 0.5903 0.3467 0.6295

0.8283 -0.6977 -0.3531 -0.7418 -0.1314 0.3564 -0.4335 -0.2142

0.8674 -0.0956 -0.6879 -0.4378 0.7891 -0.8011 -0.2858 0.2547

0.5510 0.2003 -0.3878 0.9835 0.8760 -0.1695 0.7614 -0.1668

-0.9315 0.7083 -0.5590 0.8239 -0.0873 0.8713 0.5324 -0.5647

-0.7155 0.6663 0.7957 0.3697 -0.4218 0.4382 0.4259 0.3458

-0.3768 -0.7714 -0.4893 0.1494 0.8980 0.3643 -0.0912 0.8986

Columns 9 through 11

0.9930 -0.3553 0.3097

-0.6351 -0.0993 0.6677

-0.5133 -0.6227 -0.4614

-0.8181 0.9982 0.5506

0.5447 -0.1072 -0.4184

-0.6213 0.1884 -0.3199

-0.4113 0.9335 0.4858

-0.0964 -0.8400 0.9052

-0.8984 -0.3122 -0.6976

0.6345 -2.2626 0.2568

0.3336 1.0242 0.9363

0.6392 0.8096 0.4240

0.4465 0.6885 -0.5669

-0.3296 0.9356 0.2609

0.6679 -0.3208 0.1611

0.6424 0.5541 -0.4240

0.7810 0.8023 -0.5627

0.8813 -0.6632 0.6797

-0.4518 0.2247 0.3288

B1 =

0.7281

0.2613

0.9759

0.4694

-0.2664

-0.5519

-0.8300

-0.7067

-0.7160

0.3608

-0.3179

0.7274

-0.3093

0.4871

0.5974

-0.5768

0.6281

-0.4363

0.7728

W2 =

Columns 1 through 8

-0.1409 0.6182 0.1983 0.6406 -0.2588 -0.3240 0.4482 0.1269

Columns 9 through 16

-0.3565 0.1893 0.5180 0.5341 -0.1329 0.3606 -0.2983 -0.1014

Columns 17 through 19

0.2873 0.1907 0.3028

B2 =

-0.1032

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

momentum = 0.516

Best Test Log\_Sensitivity Index = 0.22157

Best Test Epoch = 296

Current Train Log\_Sensitivity Index = 0.18253

Current Test Log\_Sensitivity Index\_BestTrain = 0.22157

Current Test SENSITIVITY = 0.61306

Current Train SENSITIVITY = 0.57055

Current Test SPECIFICITY = 0.92145

Current Train SPECIFICITY = 0.91366

Current Test CR = 84.1693

Current Train CR = 82.1885

Current Test ASE = 0.51497

Current Train ASE = 0.55852

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 3b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 3 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.25e-005

lr\_inc = 0.9688

lr\_dec = 0.8125

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.086

lambda\_dec = 0.9212

wnot = 0.9369

momentum = 0.953

err\_ratio = 1.1246

max\_epoch = 462

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

wnot = 0.9369

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11844 4265

123 116

Test Confusion Matrix

5953 2117

74 31

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.21915

maxTrainSENS = 0

bestTrainEpoch = 48

currTestSENS\_bestTrain = 0.71508

currTrainSPEC\_bestTrain = 0.75382

currTestSPEC\_bestTrain = 0.74

currTrainCR\_bestTrain = 73.642

currTestCR\_bestTrain = 73.3456

currTrainASE\_bestTrain = 0.98482

currTestASE\_bestTrain = 0.98483

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.23393

Train Confusion Matrix - Epoch: 48

9021 1363

2946 3018

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.20535

maxTestSENS = 0

bestTestEpoch = 461

currTestSENS = 0.60335

currTrainSENS = 0.57681

currTestSPEC = 0.90045

currTrainSPEC = 0.89989

currTestCR = 82.2385

currTrainCR = 81.331

currTestASE = 0.66355

currTrainASE = 0.68103

currTrain\_Log\_Sensitivity\_Index = 0.18338

Test Confusion Matrix - Epoch: 461

5427 852

600 1296

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7568

ROC\_test =

0.7652

dirName =

Results\exp20130215\_1724\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 1.4735e-026

Final weight decay constant: lambda = 0.98359

Final weight scale: wnot = 0.9369

momentum = 0.953

err\_ratio = 1.1246

Data Statistics

Training Set Apriori Probabilities

trprob =

73.2016

26.7984

Test Set Apriori Probabilities

teprob =

73.7248

26.2752

MDC Training Set Classification Rate

bayes\_train = 86.5733

MDC Test Set Classification Rate

bayes\_test = 87.3761

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.0069 0.7830 -0.0495 -0.0091 0.0705 0.0024 9.9024 -1.8697

7.6938 0.1410 4.2175 9.5367 14.1863 -14.4336 0.0056 -2.7892

0.0582 0.0042 -0.0070 5.1959 0.0097 4.5378 9.9127 -0.5199

Columns 9 through 11

-0.1197 -9.3526 -13.2564

-10.9581 -0.0007 -8.2006

14.3247 -13.8424 -13.8617

B1 =

8.8967

0.0092

-4.4441

W2 =

-13.3745 -0.0001 -13.3638

B2 =

0.0094

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

weightScale = 0.9369

Best Test Log\_Sensitivity Index = 0.20535

Best Test Epoch = 461

Current Train Log\_Sensitivity Index = 0.18338

Current Test Log\_Sensitivity Index\_BestTrain = 0.23393

Current Test SENSITIVITY = 0.60335

Current Train SENSITIVITY = 0.57681

Current Test SPECIFICITY = 0.90045

Current Train SPECIFICITY = 0.89989

Current Test CR = 82.2385

Current Train CR = 81.331

Current Test ASE = 0.66355

Current Train ASE = 0.68103

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 4a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 13 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.13e-005

lr\_inc = 0.877

lr\_dec = 0.999

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.125

lambda\_dec = 0.8595

wnot = 0.01

momentum = 0.508

err\_ratio = 1.02

max\_epoch = 310

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lr\_inc = 0.877

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

11423 4091

532 303

Test Confusion Matrix

5743 2019

264 148

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.21235

maxTrainSENS = 0

bestTrainEpoch = 235

currTestSENS\_bestTrain = 0.70281

currTrainSPEC\_bestTrain = 0.76654

currTestSPEC\_bestTrain = 0.76411

currTrainCR\_bestTrain = 74.1513

currTestCR\_bestTrain = 74.7859

currTrainASE\_bestTrain = 0.60997

currTestASE\_bestTrain = 0.58671

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.23505

Train Confusion Matrix - Epoch: 235

9164 1435

2791 2959

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.21537

maxTestSENS = 0

bestTestEpoch = 309

currTestSENS = 0.60683

currTrainSENS = 0.56645

currTestSPEC = 0.92009

currTrainSPEC = 0.9166

currTestCR = 83.7044

currTrainCR = 82.2497

currTestASE = 0.50952

currTrainASE = 0.54277

currTrain\_Log\_Sensitivity\_Index = 0.18016

Test Confusion Matrix - Epoch: 309

5527 852

480 1315

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7651

ROC\_test =

0.7836

dirName =

Results\exp20130215\_1724\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 4.1711e-015

Final weight decay constant: lambda = 0.0090472

Final weight scale: wnot = 0.01

momentum = 0.508

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

73.1237

26.8763

Test Set Apriori Probabilities

teprob =

73.4891

26.5109

MDC Training Set Classification Rate

bayes\_train = 86.2193

MDC Test Set Classification Rate

bayes\_test = 87.4847

Network Outputs

---------------

W1 =

Columns 1 through 8

-0.5214 0.7912 -0.6463 -0.8581 -0.7221 1.8570 0.5318 0.8534

-0.3935 0.8259 -0.5985 0.8667 -0.3594 0.6838 -0.4694 1.3449

-0.3555 0.5569 0.6292 -0.1794 -0.5536 0.7655 -0.9305 -0.3693

0.4042 -0.9465 -0.8379 0.7711 0.7656 -0.5924 -1.0094 0.8745

0.6190 -0.6793 -0.6869 0.3768 -0.4666 0.9045 -0.3288 -0.1797

0.5448 0.2420 -1.1034 -0.2093 -0.7812 -0.7338 0.8561 -0.4582

-0.8001 -0.3070 -0.6557 0.4972 0.2018 -0.1139 1.0157 -0.2420

1.5597 0.0528 -0.9813 0.1732 -0.1306 0.9565 0.1940 0.4701

0.2602 -0.8671 -0.6006 0.9900 -0.5679 0.8381 0.5570 0.4454

-1.4837 -0.7781 0.6773 0.5340 3.5121 -0.7576 0.6110 -0.6052

-0.2224 3.7289 0.6424 0.6870 0.5683 -1.1480 -0.4887 0.5705

0.5375 -0.7981 -0.7245 -0.9704 0.8724 -0.7512 1.6386 0.4518

-0.7294 -0.2944 -0.4922 -0.3436 -0.1892 -0.2561 0.6383 0.7378

Columns 9 through 11

-1.4905 0.8547 0.6328

-0.2400 -0.6546 0.4026

-0.3219 -0.4995 3.0897

0.5173 -0.6487 0.4652

0.4284 -0.3171 -0.1731

-0.8368 0.4752 0.8708

-0.5837 -0.5861 -1.1681

0.8592 -1.3997 -1.0000

0.4772 -0.4634 -0.3059

0.3037 0.3537 0.3292

-0.5564 -0.3388 0.4938

-0.2446 0.2188 -0.8346

-0.6910 0.8526 0.4925

B1 =

0.3627

0.7646

0.6090

-0.9914

-0.1974

0.9614

-0.5966

0.3827

0.9151

0.9672

-0.6446

-0.5244

-0.7464

W2 =

Columns 1 through 8

0.3974 0.1090 0.2474 0.4300 -0.4360 -0.5359 -0.3533 -0.2198

Columns 9 through 13

0.2056 -0.0678 -0.2143 -0.1699 0.4449

B2 =

0.5212

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

learnRateInc = 0.877

Best Test Log\_Sensitivity Index = 0.21537

Best Test Epoch = 309

Current Train Log\_Sensitivity Index = 0.18016

Current Test Log\_Sensitivity Index\_BestTrain = 0.23505

Current Test SENSITIVITY = 0.60683

Current Train SENSITIVITY = 0.56645

Current Test SPECIFICITY = 0.92009

Current Train SPECIFICITY = 0.9166

Current Test CR = 83.7044

Current Train CR = 82.2497

Current Test ASE = 0.50952

Current Train ASE = 0.54277

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 4b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 18 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0001181

lr\_inc = 0.9708

lr\_dec = 0.999

lambda = 2.05e-005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.1719

lambda\_dec = 0.3908

wnot = 0.01

momentum = 0.501

err\_ratio = 1.3594

max\_epoch = 1801

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda2 = 0.0005

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

279 118

11709 4242

Test Confusion Matrix

139 50

5941 2045

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

173 181

11815 4179

Test Confusion Matrix

82 66

5998 2029

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1000

Train Confusion Matrix

190 1334

11798 3026

Test Confusion Matrix

79 652

6001 1443

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1500

Train Confusion Matrix

10346 3909

1642 451

Test Confusion Matrix

5225 1872

855 223

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.22634

maxTrainSENS = 0

bestTrainEpoch = 1797

currTestSENS\_bestTrain = 0.74988

currTrainSPEC\_bestTrain = 0.70679

currTestSPEC\_bestTrain = 0.70148

currTrainCR\_bestTrain = 71.1708

currTestCR\_bestTrain = 71.3884

currTrainASE\_bestTrain = 645756365407588530000000000000000000000000000000000000000000000000000000000000000000000000000000000000000

currTestASE\_bestTrain = 1.1445

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.24315

Train Confusion Matrix - Epoch: 1797

8473 1198

3515 3162

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.2116

maxTestSENS = 0

bestTestEpoch = 1800

currTestSENS = 0.60573

currTrainSENS = 0.5867

currTestSPEC = 0.91234

currTrainSPEC = 0.91024

currTestCR = 83.3761

currTrainCR = 82.3954

currTestASE = 0.66495

currTrainASE = 1039298639107325300000000000000000000000000000000000000000000000000000000000000000000000000000000000000000

currTrain\_Log\_Sensitivity\_Index = 0.19458

Test Confusion Matrix - Epoch: 1800

5547 826

533 1269

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7485

ROC\_test =

0.7590

dirName =

Results\exp20130215\_1724\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 1.4689e-027

Final weight decay constant: lambda = 19911113220877107000000000000000000000000000000000000000000000000000000000000000000000000000000000000000000000

Final weight scale: wnot = 0.01

momentum = 0.501

err\_ratio = 1.3594

Data Statistics

Training Set Apriori Probabilities

trprob =

73.3301

26.6699

Test Set Apriori Probabilities

teprob =

74.3731

25.6269

MDC Training Set Classification Rate

bayes\_train = 86.769

MDC Test Set Classification Rate

bayes\_test = 87.6942

Network Outputs

---------------

W1 =

1.0e+049 \*

Columns 1 through 8

0.0169 0.0228 -0.0096 -0.0000 -0.0197 -0.0860 0.0000 0.0123

2.7193 -0.0110 0.0334 -0.0231 0.0000 -0.0102 -0.0300 -0.0466

-0.0170 -0.0118 0.0218 0.0075 0.0053 -0.0000 -0.0034 -0.1508

-0.0120 0.0078 0.4326 0.0235 -0.0247 0.0192 1.0052 0.0151

-0.0013 0.0173 0.0146 -0.0208 0.0220 0.0159 -0.0152 -0.0317

0.0189 -0.0136 -0.0144 0.0000 0.0103 0.0042 0.0114 0.0154

-0.0166 0.0058 -0.0176 -0.0204 0.0256 -0.0171 -0.0719 0.0229

-0.0192 0.0175 0.0176 -0.0000 -0.0000 0.0160 -0.0435 -0.0029

-0.0197 0.0340 0.0087 0.0108 -0.0117 0.0232 -0.0034 0.0060

0.0098 -0.0019 -0.0194 0.1595 -0.0095 -0.0169 0.0220 -0.0130

-0.0078 -0.0168 -0.0000 0.0135 0.0444 0.0212 0.0183 -0.0636

0.0170 0.0178 0.0213 -0.0039 -0.1112 0.0216 -0.0124 0.0206

-0.0918 -0.0236 -0.0158 0.0654 -0.1244 0.7603 0.0270 0.0260

-0.0196 -0.0026 0.0078 -0.0173 -0.0209 0.0232 -0.0256 -0.0087

0.0068 0.0189 -0.0151 0.0146 0.0000 -0.1033 0.0000 0.2267

-0.0136 -0.0138 0.0150 0.0165 0.0196 -0.0458 0.0086 -0.0183

0.5170 -0.0109 -0.0214 -0.0231 -0.0149 0.0211 0.0091 -0.0386

0.0000 -0.0853 -0.0000 -0.0204 0.0116 -0.0246 0.0152 0.0020

Columns 9 through 11

-0.0205 -0.0176 -0.0199

-0.0195 0.0253 -0.0073

-0.0352 -0.0248 -0.0162

-0.0084 -0.0267 0.0086

0.0091 -0.0133 0.0045

-0.0141 0.0011 -0.0218

0.0155 -0.0133 -0.0037

1.4205 -0.0000 0.0347

-0.0317 0.0145 0.0152

0.0193 -0.0269 0.0308

-0.0153 0.0000 -0.0511

-0.0198 0.0296 -0.0501

-0.0140 -0.0219 -0.0510

0.0204 -0.0150 -0.0599

0.0292 0.0177 0.0223

0.0043 -0.0071 0.0222

0.0293 -0.0166 0.0000

0.0000 -0.0123 0.0245

B1 =

1.0e+047 \*

3.9888

-3.9481

1.3644

3.7547

-1.4390

-2.3136

2.6127

-1.8510

2.9144

0.0000

-1.8183

0.0000

4.5483

-0.0000

-2.7739

-2.2936

0.4570

2.5186

W2 =

1.0e+048 \*

Columns 1 through 8

-0.0029 0.0364 -2.4033 -0.1016 -0.1336 -0.0000 0.2790 0.2582

Columns 9 through 16

0.1763 0.2043 -0.3121 -0.1699 -0.1387 -0.0694 0.1461 -0.1781

Columns 17 through 18

-0.2951 -0.1959

B2 =

2.1471e+048

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda = 2.05e-005

Best Test Log\_Sensitivity Index = 0.2116

Best Test Epoch = 1800

Current Train Log\_Sensitivity Index = 0.19458

Current Test Log\_Sensitivity Index\_BestTrain = 0.24315

Current Test SENSITIVITY = 0.60573

Current Train SENSITIVITY = 0.5867

Current Test SPECIFICITY = 0.91234

Current Train SPECIFICITY = 0.91024

Current Test CR = 83.3761

Current Train CR = 82.3954

Current Test ASE = 0.66495

Current Train ASE = 1039298639107325300000000000000000000000000000000000000000000000000000000000000000000000000000000000000000

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 5a**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 6 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 5.97e-005

lr\_inc = 0.8125

lr\_dec = 1.0938

lambda = 5.24e-005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.001

lambda\_dec = 0.999

wnot = 0.7064

momentum = 0.998

err\_ratio = 1.02

max\_epoch = 1846

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda2 = 0.0005

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

55 6

11900 4388

Test Confusion Matrix

31 3

6024 2116

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

10510 3560

1445 834

Test Confusion Matrix

5340 1720

715 399

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1000

Train Confusion Matrix

4300 3290

7655 1104

Test Confusion Matrix

2223 1617

3832 502

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1500

Train Confusion Matrix

4296 3287

7659 1107

Test Confusion Matrix

2223 1617

3832 502

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.22109

maxTrainSENS = 0

bestTrainEpoch = 1641

currTestSENS\_bestTrain = 0.75696

currTrainSPEC\_bestTrain = 0.67411

currTestSPEC\_bestTrain = 0.6659

currTrainCR\_bestTrain = 69.148

currTestCR\_bestTrain = 68.9503

currTrainASE\_bestTrain = 0.87863

currTestASE\_bestTrain = 0.87374

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.23055

Train Confusion Matrix - Epoch: 1641

8059 1148

3896 3246

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.21339

maxTestSENS = 0

bestTestEpoch = 1845

currTestSENS = 0.60689

currTrainSENS = 0.57601

currTestSPEC = 0.91445

currTrainSPEC = 0.91351

currTestCR = 83.472

currTrainCR = 82.2803

currTestASE = 0.97905

currTrainASE = 0.97964

currTrain\_Log\_Sensitivity\_Index = 0.18686

Test Confusion Matrix - Epoch: 1845

5537 833

518 1286

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7448

ROC\_test =

0.7607

dirName =

Results\exp20130218\_1616\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 8.2518e-171

Final weight decay constant: lambda = 0.00032865

Final weight scale: wnot = 0.7064

momentum = 0.998

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

73.1237

26.8763

Test Set Apriori Probabilities

teprob =

74.0763

25.9237

MDC Training Set Classification Rate

bayes\_train = 86.5496

MDC Test Set Classification Rate

bayes\_test = 87.5336

Network Outputs

---------------

W1 =

Columns 1 through 8

0.0018 -0.0001 -0.0007 0.0000 -0.0001 0.0002 -0.0003 -0.0019

0.0017 0.0000 0.0018 0.0010 0.0001 -0.0000 0.0001 -0.0017

0.0020 -0.0015 -0.0019 -0.0000 0.0003 -0.0001 0.0024 0.0000

-0.0020 -0.0003 -0.0001 0.0025 0.0006 -0.0001 0.0022 -0.0006

-0.0006 -0.0001 0.0024 -0.0000 -0.0005 0.0001 -0.0024 -0.0006

-0.0011 -0.0000 0.0432 -0.0000 -0.0541 -0.0664 0.0001 0.1023

Columns 9 through 11

-0.0003 -0.0000 -0.0018

-0.0025 0.0078 0.0000

0.0025 0.0015 -0.0007

0.0013 0.0003 -0.0000

-0.0001 -0.0000 -0.0001

0.0024 0.0008 0.1619

B1 =

-0.0009

-0.0001

0.0000

-0.0025

0.0004

-0.0001

W2 =

-6.2898 0.5320 -0.0001 -0.0001 -0.0001 -0.0024

B2 =

4.1710e-005

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda = 5.24e-005

Best Test Log\_Sensitivity Index = 0.21339

Best Test Epoch = 1845

Current Train Log\_Sensitivity Index = 0.18686

Current Test Log\_Sensitivity Index\_BestTrain = 0.23055

Current Test SENSITIVITY = 0.60689

Current Train SENSITIVITY = 0.57601

Current Test SPECIFICITY = 0.91445

Current Train SPECIFICITY = 0.91351

Current Test CR = 83.472

Current Train CR = 82.2803

Current Test ASE = 0.97905

Current Train ASE = 0.97964

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

**MOD\_NEONATALMORT RESULTS Set 5b**

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\* Start of next Iteration \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

AUTO\_ANN = 0 -- 0 = simple ANN, 1 = auto ANN

STOP\_CRITERION = 4 -- 0 = best Test CR, 1 = best Test ASE, 2 = best Test SENSITIVITY, 3 = exact epoch stop at max\_epoch, \n

4 = Maximize Sensitivity and Specificity using Log\_Sensitivity\_Index

MAX\_EPOCH\_INTERVAL = 500 -- # epochs after the best class. rate attained

SENSITIVITY\_VALUE = 0.75

layers = 2

h1 = 9 -- number of hidden layer

decay = 1 -- 0 = no, 1 = yes

wterrs = 1 -- 0 = OFF, 1 = ON. turn on/off weights

wtwhat = 0 -- 0 = weight output, 1 = weight variable #wtvar

wtvar = 1 -- if weight variable, then select which variable for weight

wtfact = 1 -- 1 = same as set wterrs=0, sounds like no weight. If weight, then select weight fact

roc = 1 -- 0 = no roc calculation, 1 = yes

maxi = 41

incr = 0.05

MIN\_SENS\_INCR = 0.01

delete\_variables = 1 -- 0 = do not delete variables, 1 = yes

remove\_indices = 1

lr = 0.0001583

lr\_inc = 0.875

lr\_dec = 0.8145

lambda = 0.005

lambda2 = 0.0005

LAMBDA2\_START\_PT = 2000

lambda\_inc = 1.25

lambda\_dec = 0.5483

wnot = 0.01

momentum = 0.5

err\_ratio = 1.02

max\_epoch = 1830

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

Best parameter value

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambda\_dec = 0.5483

Use TANSIG to calculate transfer function derivatives.

Transfer functions now calculate their own derivatives.

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 0

Train Confusion Matrix

5390 1919

6598 2441

Test Confusion Matrix

2778 998

3252 1147

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 500

Train Confusion Matrix

11765 2161

223 2199

Test Confusion Matrix

5925 989

105 1156

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1000

Train Confusion Matrix

11798 2244

190 2116

Test Confusion Matrix

5933 1035

97 1110

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

\_\_\_\_\_\_\_\_\_\_\_\_\_1

actual\_epoch = 1500

Train Confusion Matrix

11395 1985

593 2375

Test Confusion Matrix

5751 909

279 1236

Confusion Matrix Labels:

TN FN

FP TP

\_\_\_\_\_\_\_\_\_\_\_\_\_1

The Best Train Set Results:

--------------------------

maxTrain\_Log\_Sensitivity\_Index = 0.1882

maxTrainSENS = 0

bestTrainEpoch = 1829

currTestSENS\_bestTrain = 0.60559

currTrainSPEC\_bestTrain = 0.91391

currTestSPEC\_bestTrain = 0.91559

currTrainCR\_bestTrain = 82.4199

currTestCR\_bestTrain = 83.4251

currTrainASE\_bestTrain = 0.59487

currTestASE\_bestTrain = 0.57166

currTest\_Log\_Sensitivity\_Index\_bestTrain = 0.21264

Train Confusion Matrix - Epoch: 1829

10956 1842

1032 2518

Confusion Matrix Labels:

TN FN

FP TP

The Best Test Set Results:

-------------------------

maxTest\_Log\_Sensitivity\_Index = 0.21264

maxTestSENS = 0

bestTestEpoch = 1829

currTestSENS = 0.60559

currTrainSENS = 0.57752

currTestSPEC = 0.91559

currTrainSPEC = 0.91391

currTestCR = 83.4251

currTrainCR = 82.4199

currTestASE = 0.57166

currTrainASE = 0.59487

currTrain\_Log\_Sensitivity\_Index = 0.1882

Test Confusion Matrix - Epoch: 1829

5521 846

509 1299

Confusion Matrix Labels:

TN FN

FP TP

ROC\_training =

0.7349

ROC\_test =

0.7421

dirName =

Results\exp20130218\_1616\_Seq\MODNeonatalMORTALITY\_NeonatalMortality\\bestResultOverAllStructures

Run Parameters

--------------

Final learning rate value: lr = 7.1414e-126

Final weight decay constant: lambda = 0.16693

Final weight scale: wnot = 0.01

momentum = 0.5

err\_ratio = 1.02

Data Statistics

Training Set Apriori Probabilities

trprob =

73.3301

26.6699

Test Set Apriori Probabilities

teprob =

73.7615

26.2385

MDC Training Set Classification Rate

bayes\_train = 86.4387

MDC Test Set Classification Rate

bayes\_test = 87.633

Network Outputs

---------------

W1 =

Columns 1 through 8

2.1835 -3.3389 3.8796 -5.2034 0.4517 0.6176 -13.2426 -0.6553

-6.7069 -1.0267 1.5325 1.2229 1.1490 -2.3075 9.9357 1.6965

-17.4210 -3.4741 3.2073 0.7066 -1.6916 0.6785 3.3703 18.9310

1.0527 -5.4599 3.2616 1.4555 -0.6880 -3.0435 3.5809 -1.0883

0.7941 -1.0701 -3.5007 -1.3696 1.1313 2.2042 -1.0560 3.1612

6.0879 -3.0764 -0.3087 0.9908 -1.0252 -0.6626 2.2075 -2.0327

-0.9759 12.7236 8.0427 -0.4443 -169.3200 -1.9319 1.5782 8.9762

3.4234 -0.6595 -0.3970 32.3212 -2.0258 -14.2615 2.3190 -48.7116

-1.1309 3.1520 2.5359 8.0202 -2.5007 -10.2159 1.7007 -4.8921

Columns 9 through 11

0.5952 -0.3742 -7.0457

-0.5270 -6.7757 -2.0752

-7.1053 -0.9028 -1.9786

2.5491 0.9100 0.9280

-0.6182 0.6323 1.0179

-2.5812 0.9222 -11.1250

1.2968 2.3537 -20.8180

1.9447 39.9173 112.9910

-0.5391 1.7356 -3.0913

B1 =

6.0492

-1.4287

-6.9928

-2.3167

0.7734

-1.8583

6.5520

39.3359

0.9774

W2 =

Columns 1 through 8

0.5116 -0.4014 1.2304 -0.6867 1.7407 -0.6240 -0.7825 0.6774

Column 9

1.2017

B2 =

1.1452

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

BEST Log\_Sensitivity INDEX OUTCOME :

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

lambdaDec = 0.5483

Best Test Log\_Sensitivity Index = 0.21264

Best Test Epoch = 1829

Current Train Log\_Sensitivity Index = 0.1882

Current Test Log\_Sensitivity Index\_BestTrain = 0.21264

Current Test SENSITIVITY = 0.60559

Current Train SENSITIVITY = 0.57752

Current Test SPECIFICITY = 0.91559

Current Train SPECIFICITY = 0.91391

Current Test CR = 83.4251

Current Train CR = 82.4199

Current Test ASE = 0.57166

Current Train ASE = 0.59487

\*\*\*\*\*\*\*\*\*\*\*\*\*\* SPECIFIC EPOCH STOP - WEIGHTS PULLED \*\*\*\*\*\*\*\*\*\*\*\*\*\*

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1. Preterm: Birth of a baby of less than 37 weeks gestational age [↑](#footnote-ref-1)
2. Terminally ill: a disease or a condition that cannot be cured or adequately treated and that is reasonably expected to result in the death of the patient within a short period of time [↑](#footnote-ref-2)
3. **Critically ill**: A patient experiencing an acute life-threatening episode or who is believed to be in imminent danger of such an episode.  [↑](#footnote-ref-3)
4. **Case Controlled Study:** A case-control study is an analytical study which compares individuals who have a specific disease ("cases") with a group of individuals without the disease ("controls") [↑](#footnote-ref-4)
5. **Parous**: A medical term a women who has previous give birth one or more times. [↑](#footnote-ref-5)
6. **Nulliparous**: A medical term used to describe a woman who has never given birth to a viable, or live, infant. [↑](#footnote-ref-6)