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Review

RSSI and Machine Learning-Based Indoor Localization Systems for Smart Cities

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Abstract: The rapid expansion of the Internet of Things (IoT) and Machine Learning (ML) has significantly increased the demand for Location-Based Services (LBS) in today's world. Among these services, indoor positioning and navigation have emerged as crucial components, driving the growth of indoor localization systems. However, using GPS in indoor environments is impractical, leading to a surge in interest in Received Signal Strength Indicator (RSSI) and machine learning-based algorithms for in-building localization and navigation in recent years. This paper aims to provide a comprehensive review of the technologies, applications, and future research directions of ML-based indoor localization for smart cities. Additionally, it examines the potential of ML algorithms in improving localization accuracy and performance in indoor environments.

Keywords: localization; machine learning; RSSI; algorithms; smart cities

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1. Introduction

With the technological advances in the 21st century, everyone has access to smartphones and other electronic gadgets. It is in this context that the Internet of Things (IoT) has become in vogue. The advances in IoT technologies have given rise to smart environmental monitoring [1]. New low-cost and energy-efficient devices, such as wearables and Bluetooth Low-Energy (BLE) beacons, were developed as a result of the advancements of the IoT. Such devices can connect to IoT networks with ease, enabling smart buildings to exert levels of control that were previously impossible.

One of the most interesting IoT applications is localization-based services. This has become a very useful application, as the established sensor networks are able to handle location-specific tasks through the collected data. Further IoT networks can provide customized services to users based on the device location.

Modern localization algorithms prioritize the capacity to select and place nodes in the best possible locations to maximize connectivity, data collection, and coverage. Numerous Wireless Sensor Network (WSN) applications, such as target tracking, rescue operations, disaster relief, and environmental monitoring, depend on the location estimation capabilities of sensor nodes. The effectiveness of the localization approach depends critically on how accurate the localization algorithm is [2]. The Received Signal Strength Indicator (RSSI) ranging-based localization algorithm is a straightforward and economically viable localization method that utilizes RSSI measurements to determine distances in the sensor node positions in reference to the transmitter node.

Although navigation and localization have been revolutionized by GPS, it has certain shortcomings that limit its performance in specific environment setups. For example, tall buildings, tunnels, and bridges in urban areas can block GPS signals, resulting in signal degradation, multipath errors, and signal loss. Signal attenuation and errors can also be caused by interference from forested areas, hilly terrain, and thick vegetation. Inaccurate location determination with GPS can also result from meteorological phenomena, such as solar storms that tamper with signals. Security issues related to GPS spoofing and jamming have grown, with the former involving the modification of GPS signals to offer inaccurate position data and the latter causing signal interruption [3]. In areas where GPS signals may be weak, blocked, or absent, RSSI-based localization is becoming more and more significant as a replacement for GPS-based systems. The position of a wireless device is estimated using signal strength measures, as opposed to GPS, which depends on satellite signals. As a result, it is especially helpful in enclosed spaces where GPS signals may be weak or impeded by construction materials [4]. Multiple reference points, such as Wi-Fi access points or Bluetooth beacons, can be placed strategically in these settings to deliver precise location estimates. The fact that RSSI-based methods use less power and are more economical than GPS-based ones is one of their key benefits. Additionally, even in the presence of interference from other wireless devices, RSSI-based techniques can deliver more precise location data in complex environments [5]. Although RSSI-based localization has some drawbacks, such as the potential for errors brought on by environmental factors, improvements in machine learning and statistical modeling methods are assisting in raising the precision of these systems. As a result, RSSI-based localization is a large and promising field of study that may have considerable effects on a variety of applications, such as asset monitoring, inventory control, healthcare, and emergency response [6].

The proposed statistical and probabilistic localization algorithms currently have some drawbacks, particularly in terms of their limited accuracy [7–9]. This lack of precision poses a significant challenge, making it impractical to implement these algorithms effectively in real IoT devices during the implementation phase. However, an alternative solution has emerged in the form of machine learning-based algorithms, which offer a promising approach to address these issues.

By leveraging machine learning for indoor localization, a multitude of advantages can be achieved. First and foremost, the accuracy is greatly improved, overcoming the limitations of traditional statistical and probabilistic methods. Machine learning algorithms can effectively learn from vast amounts of data, enabling them to discern patterns and relationships that result in more precise and reliable localization. In addition to enhanced accuracy, machine learning-based approaches also offer flexibility in implementation. These algorithms can adapt to various environments, accommodating different indoor settings, layouts, and architectural designs. Another notable advantage of machine learning for indoor localization is its cost efficiency. With the increasing availability of affordable computing power and the prevalence of IoT devices, the computational requirements for machine learning algorithms can be efficiently met. This cost-effectiveness enables the widespread adoption and implementation of machine learning-based localization systems, making them accessible to a broader range of applications and users. Scalability is yet another benefit offered by machine learning approaches. As the amount of data collected from IoT devices and sensors continues to grow exponentially, machine learning algorithms can efficiently process and analyze this information. This scalability ensures that the localization system can handle larger datasets and accommodate the increasing demands of modern IoT environments.

Furthermore, machine learning techniques are suitable for robust indoor applications, where accuracy and reliability are crucial. Whether it is guiding autonomous robots, facilitating asset tracking, optimizing resource allocation, or enabling seamless navigation for individuals, machine learning-based localization systems excel in meeting the demands of such complex scenarios. Moreover, when machine learning is combined with Received Signal Strength (RSS) data, additional advantages emerge. The utilization of RSS enables the exploitation of existing infrastructure, as it relies on the signals already present in the environment. This ubiquity simplifies the implementation process and reduces the need for additional hardware deployment, ultimately reducing the overall cost.

Furthermore, machine learning with RSS provides a finer level of granularity in localization. By leveraging the detailed signal strength information from multiple access points or beacons, the algorithm can precisely determine the location of IoT devices or individuals within an indoor environment. This granularity opens up possibilities for more refined applications, such as tracking movements in real time or enabling proximity-based interactions. Compatibility is yet another advantage of combining machine learning with RSS. As RSS data can be obtained from a wide range of devices and sensors, machine learning algorithms can seamlessly integrate with existing IoT infrastructure. This compatibility ensures that the localization system can be easily implemented within diverse environments and can coexist with other IoT applications without significant modifications.

Consequently, the adoption of machine learning-based algorithms for indoor localization offers numerous advantages over traditional statistical and probabilistic methods. The improved accuracy, flexibility, cost-efficiency, scalability, suitability for robust indoor applications, and the added benefits of RSS integration make machine learning an appealing choice for implementing effective and reliable localization systems in IoT environments [10].

This paper has been organized as follows: Firstly, we discuss the background of indoor wireless localization. Following that, a section on related works is included. The third section of this paper discusses parameter-based positions under distance-based, time-based, and direction-based conditions. Next, radio signal-based positioning is discussed with examples. There is then an overview of machine learning-based indoor locations. The next step is discussing performance-evaluation matrixes. Finally, after the conclusion, followed by open issues and future directions, this paper is completed.

2. Parameter-Based Positioning

2.1. Distance-Based

2.1.1. Phase of Arrival (POA)

By using POA-based methods, the phase of the incoming signal is measured. It may be possible to estimate the distance between nodes using the frequency and speed of the signal. In laser range finders, this technique is frequently used. POA-based ranging equipment detects phase changes in sinusoidally modulated infrared signals [11,12].

In order to increase precision and redundancy, POA is a high-resolution approach that may provide precise positioning. However, POA is only useful in simple interior conditions because it needs a line-of-sight (LOS) between the transmitter and receiver. The signal phase of the POA can be impacted by environmental changes, including moving objects and temperature fluctuations. The complexity and expense of POA might rise because it needs a high sample rate and processing power [13].

2.1.2. Phase Difference of Arrival (PDOA)

The PDOA technique, also known as phase difference of arrival, allows one to calculate the angle at which a signal enters a receiver. This angle of arrival and the distance between the two nodes as established by ranging may be used to estimate the transmitter's coordinates (x, y) [14].

An indoor localization method was developed based on PDOA and AOA using virtual stations in multipath and NLOS environments for passive UHF RFID. For indoor positioning systems, UHF RFID localization is a promising technology; however, conventional algorithms can be weak in multipath and NLOS situations. This concept offers a passive UHF RFID indoor localization solution based on the angle of arrival and phase difference of arrival (PDOA) utilizing virtual stations. In order to achieve localization, presenters utilize the array antenna to differentiate multipath signals and select the two strongest pathways based on the received signal intensity [15].

The high indoor positioning accuracy, particularly in multipath situations, is one benefit of PDOA. Additionally, it may be used with inexpensive hardware, such as ZigBee modules, and it does not require synchronization between the transmitter and receiver. PDOA, however, has a number of drawbacks. Its sensitivity to clock synchronization issues, which can lead to severe localization mistakes, is one drawback. It also needs at least three non-collinear antennas, which might be tricky to put into use in real life. Signal attenuation can also have an impact on PDOA performance, reducing its operational range [16].

2.2. Signal Based

2.2.1. Reference Signal Received Power (RSRP)

This measurement technique is of the RSSI kind. The strength of the wideband and narrowband LTE reference signals determines this. The Reference Signal Received Power (RSRP), which is the linear average of the power contributions provided by resource components that transmit cell-specific reference signals within the measurement's bandwidth, is the power received from the reference signal [17,18].

In order to assess accuracy, localization research utilizes RSRP. The study "Connected Objects Geo-Localization Based on SS-RSRP of 5G Networks" introduced a unique RSRP method-related technology. It is used to find connected objects using GPS in a 5G-covered region. To calculate the distance between two Connected Objects (COs) that are moving through a crowded metropolitan environment, they make use of the 5G SS-RSRP employed for signal quality monitoring. The overarching objective is to introduce a novel idea based on 5G SS-RSRP signaling. The suggested remedy accounts for the deterministic and stochastic effects of the signals that have been received, which had not been addressed in earlier works [19].

A crucial component of cellular networks and indoor positioning systems is the Reference Signal Received Power (RSRP). The benefits of adopting RSRP include its high precision in signal strength measurement, which allows for the exact placement of devices, and its robustness under conditions with significant interference, including interior settings. However, there are certain drawbacks to RSRP, such as its vulnerability to multi-path fading and reliance on the distance between the device and the base station. Additionally, RSRP readings may differ based on the precise location of the base station, resulting in inaccurate interior placement [20].

2.2.2. Reference Signal Received Quality (RSRQ)

The Reference Signal Received Quality (RSRQ) is an important metric for measuring the wireless signal quality used to connect IoT devices. The RSRQ is used to determine the strength and reliability of the signal received by an IoT device, which is crucial for ensuring that the device can communicate effectively with the network. A better signal is one with a higher RSRQ, whereas a weaker or less dependable signal is one with a lower RSRQ. A low RSRQ in IoT systems can have a substantial negative influence on the functionality of the devices, resulting in data loss, higher power consumption, and shortened battery life. Therefore, cellular operators need to monitor RSRQ regularly to ensure that their networks provide a stable and reliable connection for IoT devices and take necessary actions to improve the quality of coverage to meet the specific needs of IoT applications [21].

RSRQ can assist in improved decision-making procedures for handover, resource allocation, and power control, as well as provide more precise information on the radio link quality. Furthermore, it assists in the detection of interference, which can increase the dependability of communication. The usage of RSRQ, however, necessitates more intricate processing and might increase computing strain. Additionally, because RSRQ is derived from RSRP, it inherits all of RSRP's drawbacks, including multipath sensitivity and fading effects [22].

2.2.3. Channel State Information (CSI)

Channel State Information (CSI) refers to information about the characteristics of a wireless communication channel. CSI can be used to optimize the performance of wireless communication between IoT devices and networks. This can include information such as the signal strength, channel quality, and interference levels, which can be used to adjust transmission parameters and improve communication reliability. In addition, CSI can be used for advanced communication techniques, such as beamforming and MIMO [23,24].

One of CSI's key benefits is its capacity to offer comprehensive details about the wireless channel, which may be utilized to precisely predict the locations of devices. This may result in improved indoor localization performance and accuracy. CSI is helpful for applications that need real-time monitoring, because it can also be used to track a device's movement over time. Utilizing CSI for indoor localization has significant drawbacks, however. The fact that CSI data are very susceptible to environmental variables, such as multipath fading and interference, which can make it challenging to generate precise position estimations, is one of the major issues. Additionally, large-scale indoor localization systems may not be able to have the specific hardware and software that CSI requires installed [25].

2.2.4. Received Signal Strength Indicator (RSSI)

The Received Signal Strength Indicator (RSSI), which is used in wireless communication systems, such as the Internet of Things, calculates the strength of a radio signal that has been received (IoT). In the Internet of Things, it is frequently used to measure the distance between devices, improve communication, and find and discover objects. The received signal strength is expressed in dBm, and the greater the value, the stronger the signal. Nevertheless, as environmental conditions have an impact on RSSI, it should be combined with other metrics to provide a more realistic overview of wireless link quality [26].

For example, a system has been created for blind and visually impaired people to address their issue of finding it difficult to move from one place to another. This device is referred to as a crossing assistance system (CAS). It explains the principles of indoor and outdoor tracking using Bluetooth Low Energy (BLE) and the Received Signal Strength Indicator (RSSI). Additionally, this method circumvents the limitations of background noise so that we can precisely identify the individual [27]

The fact that RSSI is compatible with the majority of wireless devices and is inexpensive are two benefits of adopting it. To increase precision, it can also be used in conjunction with other technologies, such as Bluetooth and Wi-Fi. The fundamental drawback of RSSI, however, is that it is susceptible to signal attenuation, which can lead to incorrect position estimates [28].

2.3. Time-Based

2.3.1. Time of Arrival (TOA)

In wireless communication systems, the Time of Arrival (TOA) technique is used to determine the time at which a signal arrives at a receiver. It can be utilized for accurate time synchronization and location-based services in the Internet of Things (IoT) context as illustrated in Figure 1. The transmitter and the receiver both measure the time at which the signal arrives and, by determining the speed of the signal, the distance between them could be determined. TOA can also be combined with other location methods, such as the Angle of Arrival (AOA) or Received Signal Strength Indicator (RSSI), to improve location accuracy [29].

The above figure was taken from A Survey of Smartphone-Based Indoor Positioning System Using RF-Based Wireless Technologies, which describes related technologies, performances, matrices, etc. The distance between the i^{th} AP and the tag device can be calculated as follows if c = speed of light:

$$d_i = (t_i - t_0) \times c$$

where t_0 and t_1 are time instants of signal transmission and signal reception, respectively [30].

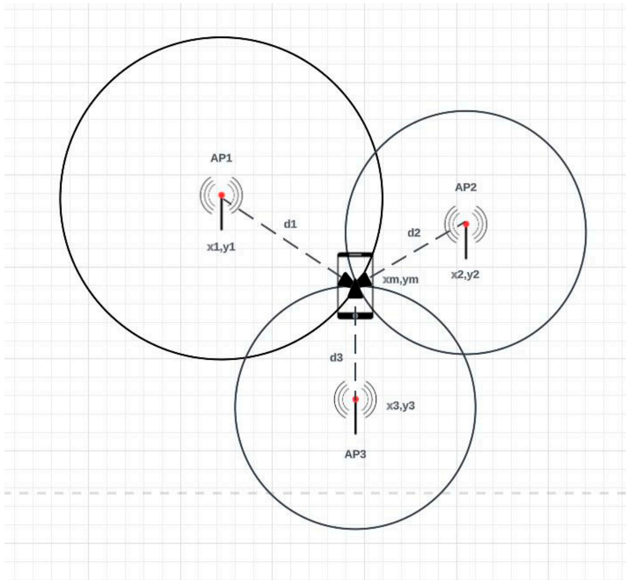

Figure 1. Localization Based on Time Of Arrival (TOA) Measurement.

A few benefits of TOA include its precision and capacity for three-dimensional localization. It may also be utilized with many different technologies, such as Bluetooth, Wi-Fi, and ultrasonic. Additionally, a line of sight between the transmitter and receiver is not necessary for TOA. The use of TOA does have certain drawbacks, however. Clock synchronization between the transmitter and receiver is one problem that might be difficult. The multipath effect, which occurs when a signal travels through many routes before reaching the receiver and causes interference and distortion, also has an influence on TOA accuracy. This may result in inaccurate distance calculations, which will affect the localization accuracy. Another drawback of TOA is that it might be computationally expensive due to the high sample rate needed to attain high accuracy [31].

2.3.2. Time Difference on Arrival (TDOA)

A technique called Time Difference of Arrival (TDOA) is used in wireless communication systems to pinpoint the position of a device by comparing the times at which signals arrive at various receivers. In the context of the Internet of Things (IoT), TDOA can be used for location-based services and device tracking. The device's position may be determined by triangulating the times at which different receivers receive signals. TDOA may also be used in conjunction with other location techniques, such as Angle of Arrival (AOA) or Received Signal Strength Indicator (RSSI), to increase location accuracy and robustness [32,33].

From the same survey mentioned in the TOA section above, the difference in the arrival time from numerous APs is used for TDOA measurement. The following diagram, Figure 2, illustrates how TDOA-based localization determines the distance between tag devices and APs based on time difference measurements.

$$d_{i,j} = \left(t_i - t_j\right)c - \sqrt{x_i - {x_m}^2 + y_i - {y_m}^2} - \sqrt{x_j - {x_m}^2 + y_j - {y_m}^2}$$

where t_i and t_j are the time instants of signal reception from AP_i i and j, respectively. The tag device must geometrically reside on a hyperbola with a consistent range difference between the two APs for a particular TDOA measurement [30].

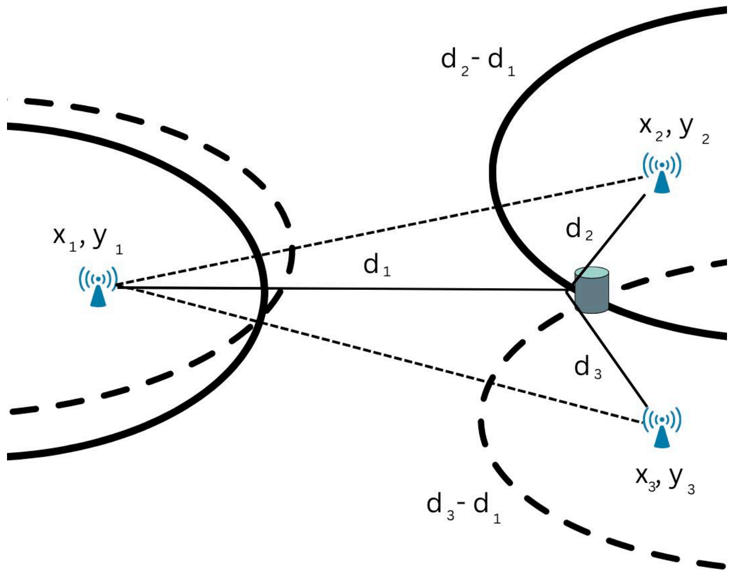

Figure 2. Localization based on Time Difference of Arrival (TDOA) measurement.

The high precision, excellent signal-to-noise ratio, and the capacity to function in non-line-of-sight situations are just a few benefits of TDoA. It also offers freedom in the selection of anchors and is compatible with a wide range of devices. However, in actual use, it might be difficult to precisely synchronize the clocks between anchors. The performance of TDoA-based systems can also be affected by multipath propagation and other environmental conditions, and the processing power and energy consumption can be rather high [31].

2.3.3. Round Trip Time (RTT)

The Round Trip Time (RTT) is a term used to describe the time it takes for a signal to go from a sender to a receiver and back again. Additionally, RTT can be used to measure the communication delay between IoT devices and a network, and can help to detect network congestion or issues with the devices. RTT can also be used to synchronize the clocks of different devices in the network. By measuring the RTT between a device and a network, the device can adjust its clock to match the network's clock, which can improve the performance of some IoT applications [34].

In terms of indoor localization, the Round-Trip Time (RTT) method provides a number of benefits. First, it is an easy procedure that does not call for any specialist gear or sophisticated algorithms. Second, it is appropriate for use with uncooperative Wi-Fi access points, allowing for usage in real-world scenarios where the position of the access points is unknown in advance. The RTT technique, however, also has significant drawbacks. First, it needs a steady and stable Wi-Fi signal, which may not always be achievable in crowded or noisy areas. Second, location estimations may be incorrect as a result of mistakes brought on by multipath interference [35].

2.4. Direction Based

2.4.1. Angle Difference of Arrival (ADOA)

A technique called Angle Difference of Arrival (ADOA) is used in wireless communication systems to pinpoint the location of a signal source using the variance in the angles at which signals arrive at various receivers. ADOA can be used for location-based services and device tracking. The direction of the signal source can be determined by measuring the angle difference between when a signal is received at multiple receivers. To increase location accuracy and robustness, ADOA may also be used in conjunction with other location techniques, such as Time Difference of Arrival (TDOA) or Received Signal Strength Indicator (RSSI) [36].

ADOA has the benefit of being more accurate than other localization techniques, particularly in multipath situations. It is also appropriate for real-time localization, because it requires less computing than some other techniques. The orientation of the transmitter and reception antennas, for example, can have an impact on ADOA. To attain optimum performance, rigorous calibration and setup might be necessary [37].

2.4.2. Direction of Arrival (DOA)

The power of the resource components that transmit cell-specific reference signals within the measurement's bandwidth is calculated as a linear average. Wireless communication systems use the Direction of Arrival (DOA) approach to pinpoint a signal source's direction based on the signal's phase difference or time delay at various receivers. DOA can be used for location-based services and device tracking. By measuring the direction of the signal at multiple receivers, the location of the signal source can be determined. To increase location accuracy and robustness, DOA may also be used in conjunction with other location techniques, such as Received Signal Strength Indicator (RSSI). It can also be used in beamforming algorithms to improve communication performance and reduce interference [38].

The benefit of DOA is that it can still deliver precise localization in a challenging multipath situation. Additionally, DOA has great resolution and can concurrently find several targets. However, employing DOA has several drawbacks. The need for an array of antennas that DOA necessitates, which can be costly to deploy, is one of its key drawbacks. In non-line-of-sight situations, DOA could also be less accurate and may be subject to interference from other wireless signals [39].

2.4.3. Angle of Arrival (AOA)

AOA measurements may be used to determine the original direction of a received radio wave. One direct finding method involves using angle-of-arrival (AOA) measurements to triangulate the receiver's position concerning emitters with known positions [40].

In terms of the angle of arrival parameter, Damir Arbula and Sandi Ljubic developed a unique sensor that uses low-range Infrared (IR) signals in a Line-of-Sight (LOS) environment to estimate the Angle of Arrival (AOA) with great accuracy. By utilizing the effective idea of a wireless sensor network, the suggested sensor is employed in a practical approach to the localization problem that overcomes NLOS propagation problems. They used it in the difficult setting of supermarket cart movement to demonstrate the recommended method [41].

Positively, AOA-based systems are able to deliver great accuracy and dependability even under challenging interior conditions with obstructions and multipath propagation. Additionally, they have modest computing demands and can handle real-time tracking. AOA-based systems do, however, have significant drawbacks, such as their restricted coverage area and susceptibility to interference from other infrared sources. To attain the needed precision, they may also call for a substantial sensor deployment, which would raise system costs and complexity [41].

Table 1 presents a summarized advantage and disadvantage comparison between different positioning parameters present in Section 2.

Table 1. Advantages and disadvantages of positioning parameters.

Parameters	Advantages	Disadvantages
POA	High-accuracy positioning. Redundancy with multiple antennas. Resistant to multi-path fading and interference.	Requires line-of-sight (LOS). Sensitive to changes in the environment. Requires high sampling rate and processing power.
PDOA	High indoor positioning accuracy. No synchronization needed. Low-cost hardware.	Incorrect clock synchronization. Requires at least three non-collinear antennas. Signal attenuation may affect performance.
RSRP	RSRP is used for signal strength measurement in wireless networks. Suitable for indoor positioning in areas with poor GPS coverage. Less impacted by multipath fading and interference than RSSI.	Obstructions impact RSRP and positioning accuracy. Environmental factors affect RSRP. Measurement tool and antenna choice impact RSRP.
RSRQ	Precise signal quality assessment. Helps to detect signal interference and noise levels. Improves mobile network decision-making during handover.	Higher measurement noise level than RSRP. Compared with RSRP, requires more resources and computing power for computation. Some devices and networking hardware might not support it.
CSI	Highly precise localization. Effective in dense indoor environments. Can handle multiple users. Suitable for localization, movement, and gesture detection.	Requires specific hardware and software for CSI data collection and processing. Environmental changes and barriers can affect accuracy, requiring ongoing calibration and monitoring. Susceptible to multipath interference and RF noise.
RSSI	Low-cost solution. Simple implementation. Available in most wireless devices. Good for determining signal strength differences. Can be used for fingerprinting-based positioning.	Multipath interference vulnerability.Surroundings and device orientation impact accuracy. Limited coverage area. Challenging accuracy in dynamic environments. Unable to block noise and interference from other wireless devices.
TOA	Accurate distance measurement. Works in noisy and multipath environments. Precise 3D localization.	Sync needed between transmitter and receiver. Line-of-sight necessary for accurate distance estimation. Requires high sampling rate and precision clocks.
TDOA	Accurate positioning. Resistant to barriers and reflections. Suitable for long-range communication. Works with various signal types.	Requires precise synchronization. High processing complexity. Limited coverage area. Requires line-of-sight. Vulnerable to signal issues.

Table 1. *Cont.*

Parameters	Advantages	Disadvantages
RTT	High accuracy achievable. Suitable for multi-story buildings. Uses existing Wi-Fi infrastructure. Real-time location updates available.	Requires precise synchronization of clocks. Can be affected by environmental factors, such as signal attenuation and interference. Can have reduced accuracy in crowded areas with high signal interference. Can be resource-intensive for mobile devices.
ADOA	High accuracy. Can work in non-line-of-sight environments. Can be used for multi-user localization.	Limited range. Sensitive to interference. Requires multiple antennas or radios.
DOA	Precise localization possible. No additional hardware required. Suitable for line-of-sight and non-line-of-sight. Effective in multipath scenarios. Provides location and direction information.	Affected by surroundings and item positioning. Requires advanced processing and computation. May not be effective in highly reflective environments. Susceptible to interference from other transmissions. Limited in crowded, high-signal areas.
AOA	Precise and accurate location estimates. Resistant to multipath and interference. Provides detailed device location information. Energy-efficient with low-power sensors Works for both indoor and outdoor localization.	Limited range. Multiple sensors required. Line-of-sight necessary. Expensive and complex. Limited commercial availability.

3. Radio Signals-Based Positioning

3.1. Wi-Fi

Wi-Fi is a radio signal that can be used to connect various devices together. A connected router sends signals to nearby devices. For its signal, the 2.4 GHz or 5 GHz frequency bands are used by Wi-Fi. With dual-band devices, one may choose the frequency they want to use for their Wi-Fi network. The IEEE (Institute of Electrical and Electronics Engineers) 802.11 standards cover Wi-Fi or wireless LAN. As a result, there are several subcategories of Wi-Fi protocols, including 802.11a, 802.11b, 802.11g, 802.11n, 802.11ac, and 802.11ax. Each Wi-Fi frequency band has several channels that devices may use to transmit and receive data [42,43]. Wi-Fi-based indoor positioning methods provide a number of benefits, including low cost, ubiquitous infrastructure availability, and the capacity for real-time location updates. As Wi-Fi signals may pass through walls and other obstructions, precise indoor localization is still achievable, even when there is no direct line of sight. Wi-Fi-based devices, however, might lose accuracy due to external variables, including signal attenuation and interference. Additionally, the necessity for several access points to cover a vast region might make their deployment and maintenance more difficult. Finally, modifications to the physical surroundings or network setup can have an impact on the precision of Wi-Fi-based location estimation [44].

3.2. ZigBee

This is a wireless standard-based technology that was created to support low-cost, low-power Machine-to-Machine (M2M) and Internet of Things (IoT) networks. As a result, low-data-rate and low-power applications use this open standard. The 2.4 GHz, 900 MHz, and 868 MHz unlicensed radio bands are used by the IEEE 802.15.4 physical board radio specification for the Zigbee communication standard. ZigBee provides outstanding adaptability and scalability for both developers and end-users. The wireless range of ZigBee is 400 m outside and 70 m inside. It supports both point-to-point and point-to-multipoint mesh networks, among other types [45].

The benefits of Zigbee include its low cost, low power consumption, and capacity for numerous concurrent users. Furthermore, Zigbee is appropriate for larger interior areas because it has a greater coverage area than Bluetooth. Zigbee's negative aspects include its constrained capacity, which can result in decreased accuracy in high-density settings where several devices are vying for bandwidth. In addition, its location accuracy can be impacted by interference from other wireless devices in the surroundings, and Zigbee requires a more complicated network architecture than alternative localization methods, such as Wi-Fi or Bluetooth [46].

3.3. RFID

The two components of the wireless technology known as Radio-Frequency Identification are tags and readers. RFID uses radio waves to carry out AIDC (Automatic Identification and Data Capture technology) operations. An electrical device called a reader uses radio waves to send and receive signals from RFID tags. One or more antennas could be present. Either passive or active tags employ radio waves to transmit their identity and other data to nearby readers [47].

RFID has several benefits for interior localization, including high precision, affordability, and ease of deployment. RFID systems may be utilized for a variety of purposes and can function effectively under challenging conditions. The restricted read range of RFID systems, which can be impacted by ambient variables, such as radio signal interference from other devices, is one drawback of the technology. The cost of RFID tags can also be high, and their small size might make it challenging to find them in large interior environments [48].

3.4. Bluetooth Low Energy

In order to function at incredibly low power levels, Bluetooth Low-Energy (LE) radios have been designed. By delivering data over 40 channels in the 2.4 GHz unlicensed ISM frequency space, Bluetooth LE radios provide manufacturers with a substantial degree of flexibility to develop devices that meet the unique connectivity needs of their market. Moreover, they support a range of communication topologies, including point-to-point, broadcast, and, most recently, mesh, enabling Bluetooth technology to facilitate the creation of reliable, vast device networks. Bluetooth Low Energy is now being extensively used in the Internet of Things and the business advertising industry. Some of such applications are highlighted in Figure 3. Bluetooth LE is the best option for longer-lasting devices that only need to occasionally communicate small amounts of data because it slows down data transmission and uses 0.01 to 0.5 Watts of power [49,50].

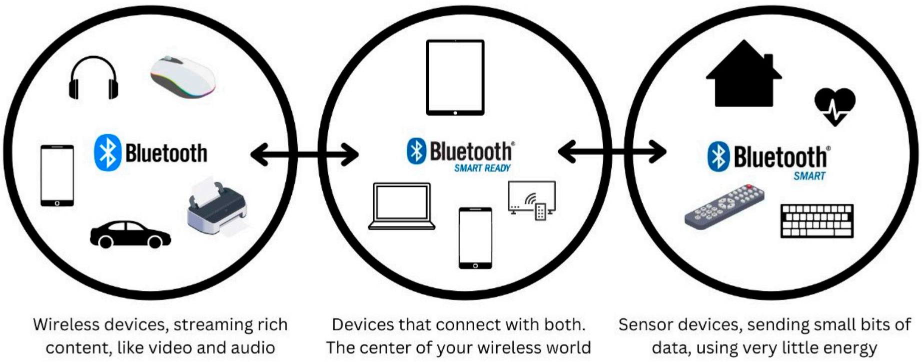

Figure 3. Bluetooth low energy usage.

They can reach sub-meter accuracy and provide exceptional accuracy and precision in indoor settings. Additionally, low-power BLE beacons may run for extended periods of time on modest batteries. Furthermore, they provide easy connection with current wireless networks and may accommodate numerous concurrent users. However, using BLE beacons for indoor localization is not without its problems. They need a large number of beacons to be installed in order to accomplish precise and dependable localization. Their performance may also be impacted by signal interference from other wireless devices, and their implementation may be time-consuming and expensive [51].

3.5. UWB (Ultra-Wide Band)

UWB is a radio wave-based short-range wireless communication technology similar to Bluetooth or Wi-Fi. The fact that it runs at an extremely high frequency, however, makes it easily distinct. Using the broad-spectrum frequency, a UWB transmitter sends billions of pulses (UWB was once known as "pulse radio"). The real-time accuracy of UWB is enhanced by its capacity to transmit pulses at a rate of one per two nanoseconds. UWB can send a large amount of data from a host device to other devices up to around 30 feet away while using very little power because of its wide bandwidth (500 MHz) [45].

Other indoor positioning technologies cannot compete with UWB's high precision, high dependability, and ability to function under challenging conditions. Walls and other obstructions cannot block UWB signals, making it possible to communicate effectively, even under difficult interior conditions. Additionally, UWB technology uses less power, resulting in a long battery life and little energy use. UWB technology, however, also has certain drawbacks. The high cost of UWB infrastructure and hardware is one of its key drawbacks, which may render it unusable for various applications. The precision of the positioning system may also be impacted by the interference that UWB technology may experience from other wireless signals, such as Wi-Fi and Bluetooth. Finally, some applications may be constrained by UWB technology's restricted range, which normally operates over a distance of only a few meters [52].

3.6. Long-Range Radio (LoRa)

This is a method of wireless modulation. LoRa devices are affordable and simple to integrate into a network because they have a long range and require little infrastructure. It enables chirp spread spectrum communication over vast distances. It limits interference from other devices by using specialized radios, which are uncommon in end-user devices. In comparison with other network technologies, it costs 20% less. LoRa uses unlicensed RF bands for operation. Moreover, LoRa employs Forward Error Correction (FEC) to lessen signal noise significantly [53–55].

LoRa's low power requirements, long-range capabilities, and inexpensive cost make it a good choice for indoor localization. Systems for indoor localization that use LoRa technology are simple to set up and can function under a variety of conditions. However, compared with other technologies, LoRa's biggest flaw is its poor precision, which makes it difficult to pinpoint a specific place. Furthermore, LoRa may be limited in places with significant levels of signal attenuation and may be subject to interference from other wireless devices [56].

3.7. Sigfox

The LPWAN family of technologies includes the Sigfox technology. Long-range wireless cellular communication is called Sigfox. Sigfox offers specialized solutions, particularly for low-throughput Internet of Things (IoT) and M2M applications, using its end-to-end IoT connection services and distinctive technology. The Sigfox network was created to make efficient communication possible while using minimum power. With the help of Sigfox, IoT devices can communicate over large distances and broadcast using few base stations. According to frequency and geographical region limits, the duty cycle of Sigfox technology ranges from 0.1% to 10% inside the transmitting spectrum. The client server hosting the application and the nodes and gateways that send communications from the node side to the Sigfox Cloud make up the architecture [57,58]. Figure 4 illustrates a general layout of a Sigfox System.

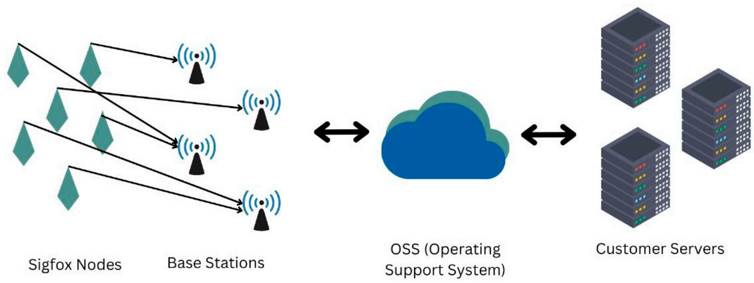

Figure 4. Sigfox system.

Sigfox is a LPWAN (Low-Power Wide-Area Network) system that can deliver long-distance communication with little power usage. However, Sigfox has a lower data rate and a smaller capacity than other LPWAN technologies, making it suitable for straightforward applications that do not need high-speed data transfer. In addition, Sigfox uses the unlicensed ISM band, which might lead to interference problems in congested areas. However, for low-power, low-bandwidth indoor localization applications that do not need great precision, Sigfox may be a financially viable option [59].

3.8. Near-Field Communication

Data interchange between electronic devices is possible across a short range of up to 4 cm due to a group of radio transmission protocols known as Near-Field Communication (NFC) (1.6 in.). Devices can be physically touched or brought close enough to transmit data using this technology. Operating at a 13.56 MHz frequency, which is an unlicensed band, this method takes advantage of inductive coupling. NFC systems may function following three different methods: the NFC card emulation approach, P2P method, and the reader/writer method.

Two-way communication between electronic devices is made possible by NFC. Additionally, it has the capacity to write to an RFID chip. As a result, an NFC-enabled mobile phone and NFC reader may establish a bidirectional connection [60,61].

Owing to its low power usage, excellent precision, and low cost, NFC technology has several benefits for indoor localization. Owing to its short-range transmission, it is less sensitive to interference from outside signals and can function in locations where GPS signals are not accessible. It is simple to install and maintain NFC tags because they may be placed on items or walls. NFC does have certain drawbacks, however, such as its limited coverage due to its low communication range. Additionally, because line-of-sight communication is required for NFC, it cannot pass through barriers, such as walls. For vast and complicated interior situations, it might not be the best option [62].

3.9. Cellular Networks

A cellular network is made up of several cells, each of which covers a specific geographic area. Each cell also has a base station that functions similarly to an 802.11 AP in that it aids mobile users in connecting to the network, and each cell and base station have an air interface that combines the physical and link layer protocols. Cellular networks might be a useful choice for SMs and utilities to communicate with one another. The expansion of smart metering deployments into a large-scale setting is also made possible by cellular network technologies. The cellular communications technologies that are accessible to utilities for the implementation of smart meters include 3G and LTE [63,64].

The benefits include extensive coverage, which makes it simpler to find devices in various locations. Additionally, cellular networks may offer time-of-flight and signal strength metrics with high levels of precision. Cellular networks can, however, have drawbacks for interior localization, such as expensive implementation and maintenance costs. Another drawback is the poor accuracy in densely crowded or high-interference locations [65].

Table 2 presents a comparative summary in terms of the advantages and disadvantages of various communication technologies used in Radio Signals-Based Positioning.

Table 2. Advantages and disadvantages of Communication technologies.

Technologies	Advantages	Disadvantages
Wi-Fi	High accuracy Low cost Multi-user support Flexibility Ease of deployment	Signal interference Limited coverage Environmental factors Privacy concerns
ZigBee	Low power consumption Supports large networks of devices Can be used in areas with high signal interference Can operate over longer distances	Limited data rates Limited coverage area Requires specialized hardware
RFID	Precise localization in small areas Affordable and easy to install Can operate in harsh environmentsSuitable for object tracking	Limited range of operation Susceptible to interference from metals and other objects Signal attenuation can occur in dense environments Requires direct line of sight for accurate localization

Table 2. *Cont.*

Technologies	Advantages	Disadvantages
Bluetooth low energy	High accuracy Low cost Multi-user support Wide availability Easy to deploy	Limited range Signal interference Environmental factors Privacy concerns
UWB	High accuracy Low latency High update rate Resistant to interference	Expensive Limited range Limited availability of devices Line-of-sight dependency
Long-rangeradio (LoRa)	Long-range communication Low power consumption Low cost Ability to penetrate walls and obstacles Scalability and flexibility Simple network architecture Open standard	Limited bandwidth and data rate Susceptibility to interference and noise Limited number of available channels Not suitable for high-precision localization Limited availability of LoRa-enabled devices and gateways
Sigfox	Low-power consumption Long battery life Low cost Wide coverage area	Limited bandwidth and data rate Limited availability in certain regions Limited support for real-time tracking Limited integration with other technologies
Near-field communication	Low cost High accuracy No need for additional hardware	Limited range Interference from metallic objects and electromagnetic fields Limited availability
Cellular networks	Wide coverage High accuracy No extra hardware Suitable for high-density environments	Limited accuracy in some areas High power consumption Dependence on external infrastructure Privacy concerns

4. Machine Learning for Indoor Applications

4.1. k-Nearest Neighbor (kNN)

The k-nearest neighbor algorithm, sometimes referred to as KNN or k-NN, is a supervised learning classifier that makes predictions or classifications about how a single data point will be grouped. It is frequently used as a classification approach because it is predicated on the assumption that similar points may be found adjacent to one another; however, it can be applied to classification or regression problems.

KNN is used as a classifier most frequently. It is employed to classify data based on local or adjacent training samples in a particular location. Due to its quick computation and simplicity, this method is used [66,67].

The simplicity, adaptability, and capability of the KNN algorithm to handle non-linear data are its advantages. A flexible tool for indoor localization, it may also be utilized for regression and classification problems. However, there are also certain restrictions on the KNN algorithm. Good accuracy, for example, necessitates a large amount of data, and the algorithm's performance may be affected by the choice of distance measure and k value. The KNN approach is also vulnerable to the "curse of dimensionality", which can result in subpar performance in high-dimensional feature fields [46].

4.2. Support Vector Machine (SVM)

The support vector machine approach aims to find a hyperplane in an N-dimensional space (where N is the number of characteristics) that unambiguously classifies the data points. Support Vector Machine (SVM) is a deep learning system that uses supervised learning to categorize or forecast the behavior of data groups. SVMs are exceptional in delivering balanced projected performance, even in investigations with possibly limited sample sizes. This is because they are very straightforward and adaptable in how they approach different categorization problems. Binary classification problems may be resolved with SVMs. As the number of computationally challenging multiclass problems increases, several binary classifiers are being developed and integrated to produce SVMs that can execute such multiclass classifications using binary techniques [68].

SVMs work well in high-dimensional domains, even with more dimensions than samples. They have good memory capacity and are adaptive. If the number of attributes is much higher than the number of samples, the technique is likely to perform poorly. SVMs were originally developed to deal with classification challenges, but using an insensitive loss function may also be extended to solve nonlinear regression problems. The input x is initially translated into a higher-dimensional feature space in support vector regression using a kernel function. Within the linear, polynomial, radial basis, and sigmoid functions, the sigmoid function is a kernel function frequently employed in SVM. The linear model of the feature space, f(x), is denoted by

$$f(x, \omega) = \sum_{j=1}^{m} \omega_i + g_j(x) + b$$

SVM has benefits such as its capacity to handle high-dimensional data, generalize effectively to unknown samples, and prevent overfitting. SVM also has the ability to handle nonlinear connections between features and the target variable, which is a significant benefit in indoor localization. However, SVM-based techniques can be computationally demanding and need a long training time and a large amount of computing power. Additionally, when dealing with unbalanced data or when the training dataset does not accurately reflect the test dataset, SVM may not perform as expected [69].

4.3. Decision Tree

The classifier expression of a decision tree is a recursive split of the instance space. A decision tree is automatically generated from a dataset using methods referred to as decision tree inducers. Generally, lowering the generalization error leads to the discovery of the optimum decision tree. Making a better logical judgment or attribute choice is essential for creating a decision tree. Which characteristics are selected depends on the method used to measure impurities on the different instances of the subset. Methods for measuring impurities include information gain, the gain ratio, Gini-index, distance measurement, X2 statistics, the weight of evidence, the minimum description length, etc. As the fundamental process for building decision trees does not consider noise, the produced decision tree perfectly matches training instances, which results in excessive fitting and destroys predictive performance [70,71].

The benefits of decision trees include their readability and simplicity, as well as their capacity to manage missing data. In comparison with other machine learning techniques, they require fewer computations. The drawbacks of decision trees, however, include overfitting, which can result in subpar generalization, and instability, particularly when working with noisy data. If the training data are not representative of the complete dataset, decision trees may potentially experience biased categorization [46].

4.4. Extra Tree

The Train Using AutoML tool employs the ensemble supervised machine learning technique known as extra trees, sometimes excessively randomized trees, which uses decision trees. The highly randomized trees classifier is a type of ensemble learning strategy that integrates the results of various de-correlated decision trees gathered in a "forest" to obtain its classification result. Unpruned decision trees are produced using the extra-trees classifier. When splitting a tree node, it substantially randomizes both attribute and cut-point selection to create trees. Originally evolved from the Random Forest (RF) model, Extra Tree Regression (ETR) is a refined technique. The Extra Tree Regression (ETR) methodology follows the conventional top-down approach to produce a collection of unpruned judgments or regression trees.

Additional trees are beneficial, especially when considering the cost of computation. Extra trees would be preferable to other ensemble tree-based models for building models that need substantial feature engineering/feature selection pre-modeling operations when computational expense is a factor [72–76].

4.5. Random Forest

In a random forest, every tree depends on the values of a random vector sampled independently and uniformly across every tree in the forest. The values of a random vector that was sampled randomly and with the same distribution for all the trees in the forest determine the values of each tree in a random forest. A random forest is an ensemble classifier that constructs various unique decision trees using the idea of randomness. Random forest defines the importance of a value by randomly permuting (rearranging) a given variable. The generalization error converges as a limit as a forest's number of trees grows. The generalization error of a forest of tree classifiers depends on the strength of each tree inside the forest and the correlation between them. Random forests are an effective prediction method. The law of big numbers prevents them from overfitting. They function well as classifiers and regressors when the right amount of randomness is present. For a while, it was thought that forests could not match the precision of arcing-type algorithms [77,77].

As it can manage nonlinear connections between features and accommodate missing data, random forest provides a number of benefits for indoor localization. However, random forest can be expensive to compute, especially for large datasets. Additionally, if the input is noisy or the number of trees in the forest is too great, the method may be prone to overfitting [78].

4.6. Neural Network (NN)

Artificial Neural Networks (ANNs) or Simulated Neural Networks (SNNs), a subset of machine learning and the foundation of deep learning techniques, are based on neural networks. A neural network is a group of algorithms that attempts to find hidden connections in a data set by mimicking how the human brain works. The network is made up of several highly connected processing units called neurons that collaborate in parallel to address a specific issue. Neural networks are capable of learning from examples. They cannot be forced to perform a specified task. To prevent wasting time or, worse still, having the network behave poorly, the examples must be carefully picked. One or more hidden layers, an output layer, and a node layer are the components of an artificial neural network (ANN) as presented in Figure 5. The weight and threshold associated with each node, or artificial neuron, are linked to other nodes. For machine learning systems, such as artificial neural networks, to be useful in practical applications, they need to be trained on and learn from a large amount of data. Neural networks and conventional computers use distinct approaches to problem-solving [79–81].

Among the benefits are NN's capacity for handling complicated data with high accuracy and flexibility in terms of the quantity and configuration of hidden layers. Both classification and regression problems may be solved using neural networks. The risk of overfitting if the model is too complicated or there are not enough training data is one of the drawbacks of employing NNs for indoor localization, on the other hand. It might be challenging to grasp how the network came to make its predictions because of the model's interpretability. In addition, training neural networks may be time- and resource-intensive, especially for large datasets [82].

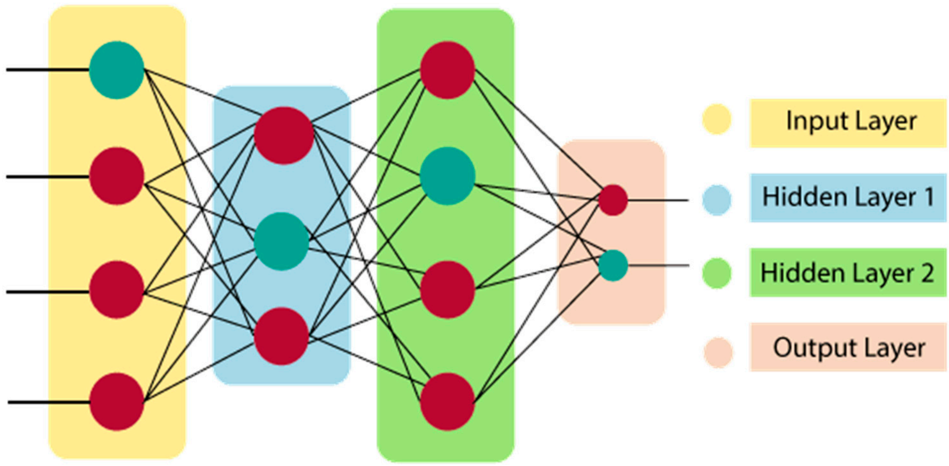

Figure 5. Neural Network Structure.

4.7. Feed-Forward Neural Network (FFNN)

Feed-forward neural networks and recurrent neural networks are the two main categories of network architectures, depending on the type of connections between the neurons. The network is referred to as a "feed-forward neural network" if there is no "feedback" from the outputs of the neurons toward the inputs throughout the network. Feed-forward neural networks fall under the "single layer" or "multi-layer" classifications, depending on how many layers they have. Figure 6 illustrates a single layer feed-forward neural network. Feed-forward neural network models for classification often employ single-layer perceptrons. Machine learning may also be used with single-layer perceptrons. By being trained to adjust their weights based on a property known as the delta rule, neural networks may be used to compare their outputs with the intended values [83,84].

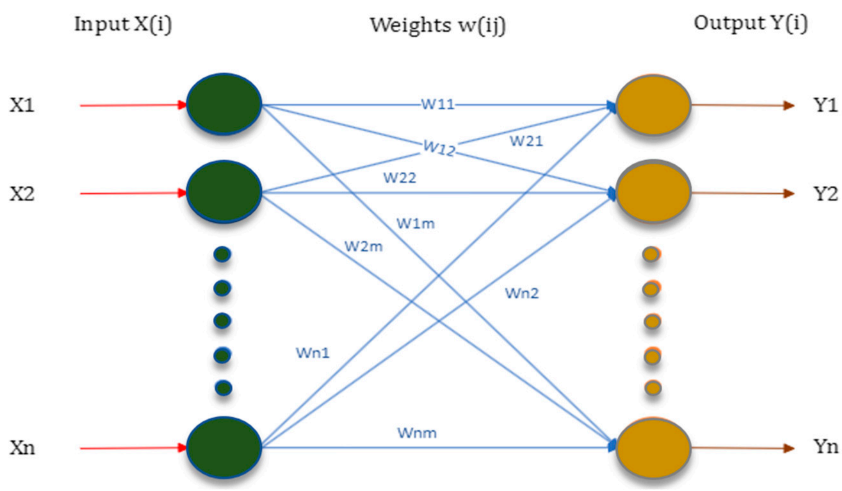

Figure 6. A single-layer feed-forward neural network.

When correctly trained, FFNNs can manage large and complicated datasets with ease and offer excellent accuracy in indoor localization. For indoor localization using Wi-Fi signals, FFNN is a good choice because it can capture non-linear correlations between features. Utilizing FFNNs for indoor localization has several drawbacks, however. In addition to taking a lot of time, training FFNNs may be computationally costly. If the test data are not a good representation of the training data, FFNNs may potentially overfit. Understanding how FFNNs generate their predictions might be problematic because the model's underlying workings can be tricky to grasp. Last, but not least, obtaining decent performance necessitates a sizable amount of labeled training data [85]. Table 3 presents a comparative summary of various machine learning techniques in general.

Table 3. Advantages and disadvantages of machine learning algorithms.

ML	Advantages	Disadvantages
k-Nearest Neighbor (kNN)	Simple and easy to implement. Effective in reducing noise and outliers. Can work well with different types of data.	Performance highly dependent on the choice of k. Sensitive to the number of dimensions in the data. Can be computationally expensive for large datasets.
Support Vector Machine (SVM)	Accurate and robust. Effective in high-dimensional spaces. Handles noisy and missing data well.	Computationally expensive. Requires careful selection of kernel function and tuning of hyperparameters. Can be sensitive to overfitting. May not perform well with imbalanced data.
Decision Tree	Simple to understand and interpret. Suitable for real-time applications. Can handle both continuous and discrete data. Can handle missing data without requiring imputation.	Prone to overfitting. May not perform well on complex data with many features. Sensitive to small variations in data. Unstable, as small changes in the data can lead to significant changes in the model.
Extra Tree	Can be used for both classification and regression problems. Can capture nonlinear relationships. Dealing with non-linear data does not need any feature modification, as decision trees do not simultaneously consider numerous weighted combinations.	Millions of records with regard to the decision tree split for numerical variables. Random forest ensemble approach, overfit pruning (pre, post), and growing with the tree from the training set.Method of overfitting.
Random Forest	Easy to understand, interpret, and visualize. Handles large datasets and irrelevant data well. Deals with missing data. Provides feature importance information.	Can be computationally expensive. May overfit or perform poorly with highly correlated features.
Neural Network (NN)	Handles non-linear relationships. Provides high accuracy. Adaptable to new conditions and input types.	Requires significant computation time. May overfit without representative training data. Difficult to interpret and understand. Requires a large amount of labeled training data.
Forward Neural Network (FFNN)	Fast and efficient processing of large amounts of data. Versatile for both classification and regression tasks. Can capture complex non-linear relationships between input features. Can handle a variety of input data types, improving accuracy in multi-building environments.	Prone to overfitting. Requires a large amount of training data. Difficult to interpret and explain.Requires significant computation power and time to train.

5. Performance Evaluation Matrices

5.1. Performance Metrics

5.1.1. Accuracy

Accuracy in indoor localization is the system's capacity to correctly estimate the user's position. The primary parameter for gauging accuracy is the Mean Error Distance (MED), which computes the average distance between the user's projected position and actual location. For indoor localization, accuracy is a crucial performance indicator that can be impacted by a number of variables, including signal intensity, interference, and multipath effects.

The authors emphasize the use of machine learning methods, including k-Nearest Neighbor (kNN) algorithms, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs), to increase accuracy. These methods may be used to increase the precision of indoor localization by learning a map between sensor data and the user's position [46].

$$\text{Accuracy} = \frac{\text{Number of corect predictions}}{\text{Total number of predictions}} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN}}$$

5.1.2. Precision

The accuracy with which the indoor localization system can pinpoint the user's position is known as precision. Precision is referred to as TP/(TP + FP), or the ratio of True Positive (TP) measurements to the total number of true positives plus False Positives (FPs). In terms of indoor localization, TP denotes the quantity of accurate location estimates, whereas FP denotes the quantity of inaccurate location estimations.

Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and k-Nearest Neighbor (kNN) methods can all be used to increase precision in machine learning. These methods may be used to increase the accuracy of indoor localization by learning a mapping between sensor data and the user's position [46].

$$\text{Precision} = \frac{\text{Number of correct positive results}}{\text{Total number of positive resullts}} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

5.1.3. Average Localization Error

The ALE is a measurement of the typical gap between a user's real location and their estimated location. The precision of the indoor localization system is clearly demonstrated by the ALE, making it a crucial performance metric. This study points out that the ALE can be impacted by a number of variables, including multipath effects, the geometry of the interior environment, and signal quality.

Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and k-Nearest Neighbor (kNN) methods can all be utilized to enhance the ALE. These algorithms may be used to discover a relationship between location-based sensor data and user location [46].

5.1.4. Mean-Squared Error (MSE)

The average squared difference between the estimated values and the real values is measured by the MSE performance metric, which is widely used in machine learning and signal processing. MSE is a tool that may be used to assess the precision of location estimations produced by a machine learning algorithm in the context of indoor positioning and localization.

Among the machine learning algorithms that can utilize MSE as a performance indicator are neural networks, support vector regression, decision trees, and linear regression. To reduce the MSE and boost performance, these algorithms may be trained using a variety of optimization techniques, such as gradient descent [86].

5.1.5. Root-Mean-Squared Error (RMSE)

A performance statistic in machine learning and indoor localization is called Root-Mean-Squared Error (RMSE). A lower RMSE suggests a more accurate indoor positioning system. The RMSE is used to assess the difference between the actual and forecasted location estimations. In machine learning algorithms that perform regression tasks, the RMSE performance statistic is frequently utilized [46].

5.1.6. R-Squared

R^2 is a statistical index that shows how much of the variance in the dependent variable in a regression model can be accounted for by the independent variables. R2 may be used to evaluate the goodness of fit of a regression model in indoor localization that estimates the user's position using sensor data or other factors. The accuracy of the model's predictions is indicated by a greater R2 value, which also shows how well the independent variables predict the target variable. In machine learning algorithms that incorporate regression problems, R-squared (R2) is a frequently used performance indicator [46].

5.2. Performance Issues

5.2.1. Scalability

Scalability is the capacity of a system or algorithm to manage growing volumes of data or users without sacrificing its effectiveness or performance. Scalability can provide considerable difficulty in indoor localization, particularly in large or complicated interior environments with numerous users and devices. The study "A Review of Indoor Localization Techniques and Wireless Technologies" pointed out that some indoor localization methods, such as fingerprinting and triangulation, may not be scalable because they rely heavily on manual calibration and infrastructure deployment. On the other hand, machine learning methods, such as deep learning and neural networks, have demonstrated promising outcomes when scaling huge datasets and intricate interior situations. In comparison with conventional localization methods, these algorithms are more scalable because they can learn from vast amounts of sensor data and adapt to changes in the environment [46].

The performance of machine learning- and RSSI-based indoor localization and navigation systems must be maintained; thus, it is critical to solve scalability challenges, including data processing speed, system complexity, and the need for more computational power. In this context, several recent research studies have examined the scalability of machine learning and RSSI-based indoor localization systems and proposed ways to solve these challenges. One such study is "Scalable indoor localization using deep learning" [20].

5.2.2. Robustness

The term "robustness" describes a system's capacity to operate precisely and consistently in the face of interference, noise, and other possible external conditions that might impact a wireless signal. A system is said to be robust if it can withstand changes in signal intensity and quality, as well as alterations in the environment, without suffering serious performance losses. The wireless environment may be complicated and dynamic, and there may be a variety of sources of interference and noise; in other words, a reliable indoor localization system should be able to function well in real-world situations.

The paper titled "A Review of Indoor Localization Techniques and Wireless Technologies" discussed the significance of robustness in indoor localization systems, as they should be able to manage various noise, interference, and environmental changes while maintaining accurate and reliable performance. The study also discussed a number of machine learning methods, such as decision trees, support vector machines, and neural networks, that have been applied to increase the resilience of indoor localization systems.

Any system or process, including machine learning's localization, should be robust. It speaks to a system's capacity to continue operating or being accurate, despite interruptions from outside sources, uncertainties, or mistakes. Robustness is essential for localization because a variety of mistakes or disruptions, including environmental changes, signal noise, and sensor failures, can reduce the precision of the localization system. The robustness of vehicle localization using cameras and LiDAR under various weather and illumination circumstances was examined in the study, "Investigation on Robustness of Vehicle Localization Using Cameras and LiDAR". The accuracy and resilience of various algorithms' localization abilities were measured by the authors under various conditions, such as heavy snowfall, rain, and fog, which emphasized the significance of the aforementioned point [87].

6. Open Issues and Future Directions

Despite the significant advancements in RSSI and machine learning for indoor localization, there are still several challenges that need to be addressed. These challenges have limited progress in the field, resulting in a lack of comprehensive coverage in some research publications regarding unanswered questions and future directions. One of the primary problems is the interference caused by wireless devices, which can introduce errors to RSSI readings. This interference can affect the accuracy of the position estimates and pose a significant hurdle in achieving reliable indoor localization. Additionally, the varying radio signal conditions across different locations further hinder the accuracy of indoor localization systems.

The movement of objects and people within indoor environments can also impact the accuracy of localization. Fast-moving objects or individuals can disrupt the RSSI signal, leading to inaccurate position estimates. Overcoming these dynamic factors poses a considerable challenge in achieving precise and real-time indoor localization. Furthermore, the cost of implementing indoor localization systems, along with their power requirements and the need for real-time data processing, present additional obstacles. These factors limit the scalability and practicality of their widespread adoption in smart cities.

To address these issues, future research efforts can focus on developing novel machine learning algorithms specifically designed for indoor localization. By leveraging additional technologies, such as Wi-Fi, Bluetooth, and Zigbee, researchers can explore new approaches to improve accuracy and overcome interference challenges. Moreover, cloud-based services can enable real-time data processing, offering a potential solution for handling the computational demands of indoor localization systems.

Ultimately, the development of indoor localization systems that are affordable, low-power, and suitable for broad usage in smart cities heavily relies on resolving these outstanding challenges. By tackling interference issues, accounting for dynamic environmental factors, and optimizing cost and power requirements, researchers can pave the way for more efficient and reliable indoor localization solutions.

7. Discussion

The ideal parameter for a location-based service will vary depending on the particular needs of the application. Every one of the stated parameters has advantages and disadvantages, and whether or not they are appropriate for a certain application will depend on the context in which they are utilized. For example, when the accuracy requirements are not too stringent and the propagation circumstances are steady, RSS can be used for localization in areas with a large density of access points or beacons. Applications that need high accuracy and do not have a lot of multipath effects are good candidates for TOA and TDOA. In outdoor localization systems, they are frequently employed. In environments with a large number of obstacles and constrained line-of-sight propagation, AOA and DOA are appropriate for indoor localization systems. When accuracy standards are high and there are lots of impediments present, POA and PDOA are appropriate. ADOA is appropriate for outdoor settings with a variety of access points or base stations. As line-of-sight propagation is constrained and the environment is dynamic, RTT can be employed for both indoor and outdoor localization. When there are few access points and there are strong multipath effects in the surroundings, indoor localization systems are a good fit for CSI.

For outdoor localization applications, RSRP and RSRQ are frequently employed in cellular networks.

When discussing machine learning-based indoor localization, algorithms are very important. As discussed in the above sections, there are various kinds of machine learning algorithms contributing to localization research and new findings. As the best ML method relies on the particular problem being addressed and the data at hand, it is challenging to name any one approach as the best. As it is straightforward and simple to use, k-Nearest Neighbor (kNN) might be a viable option when the dataset is small and the issue is non-linear. Support Vector Machine (SVM) is an excellent option in situations when the issue is non-linear and the dataset is highly dimensional, because it performs well under these conditions. Decision trees might be a suitable option if the interpretability of the model is vital, as they are simple to comprehend and interpret. Random forest can be a suitable option if the dataset is huge and prone to overfitting, because it does so by aggregating several trees, which lessens overfitting. The Forward Neural Network (FFNN), which can learn complicated non-linear correlations between the input and output, might be a useful option if the dataset is very unbalanced and improved performance is required.

8. Conclusions

Indoor localization has gained significant importance due to the rising demand for precise positioning and navigation solutions in smart cities. Various technologies, including RSSI, machine learning, and others, have been proposed to tackle indoor localization challenges, each offering its own advantages and limitations. RSSI-based methods are favored for their simplicity and cost-effectiveness, but they suffer from high variability and limited accuracy. Conversely, machine learning methods show promise in delivering more precise indoor localization outcomes by leveraging historical data and adapting to dynamic environments. However, these approaches can be computationally intensive and require substantial training data. Combining different technologies, such as integrating RSSI with machine learning algorithms, holds the potential to enhance accuracy and robustness in indoor localization solutions. The choice of technique should be based on specific application requirements, considering factors such as the desired accuracy levels, cost considerations, and system complexity. Further research is imperative to fully explore the potential of these technologies and address their inherent limitations. This research should focus on refining RSSI-based methods to reduce variability and enhance accuracy. Simultaneously, efforts should be made to develop more efficient and optimized machine learning algorithms tailored specifically for indoor localization. Additionally, investigations into the fusion of multiple technologies and the development of hybrid approaches could yield superior results. By delving deeper into these areas, researchers can advance the field of indoor localization, enabling the development of more reliable, accurate, and cost-effective solutions for smart cities.

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