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Review

RSSI Fingerprint-Based Indoor Localization Solutions Using Machine Learning Algorithms: A Comprehensive Review

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Highlights

What are the main findings?

- The review consolidates recent advances in RSSI fingerprint-based indoor localization, providing a complete view from technology choice to ML/DL model application.
- It systematically classifies radiomap generation and data preprocessing methods, compares algorithm performance, and identifies unresolved technical bottlenecks.

What is the implication of the main finding?

- The structured analysis offers a ready-to-use roadmap for researchers, helping to design efficient and adaptable localization systems.
- By mapping challenges to potential solutions, the review supports targeted innovation and faster adoption of RSSI-based positioning in diverse real-world scenarios.

Abstract

With the development of technologies and the growing need for accurate positioning inside buildings, the localization method based on Received Signal Strength Indicator (RSSI) fingerprinting is becoming increasingly popular. Its popularity is explained by the relative simplicity of implementation, low cost and the ability to use existing wireless infrastructure. This review article covers all the key aspects of building such systems: from the wireless communication technology and the creation of a radiomap to data preprocessing methods and model training using machine learning (ML) and deep learning (DL) algorithms. Specific recommendations are provided for each stage that can be useful for both researchers and practicing engineers. Particular attention is paid to such important issues as RSSI signal instability, the impact of multipath propagation, differences between devices and system scalability issues. In conclusion, the review highlights the most promising areas for further research. For smart cities, the approaches and recommendations presented in the review contribute to the development of urban services by combining indoor positioning systems with IoT platforms for automation, transport and energy management.

Keywords: indoor positioning; localization; RSSI; fingerprint; machine learning; deep learning

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1. Introduction

Localization technologies are fundamental to modern information systems, enabling accurate positioning in a wide range of applications. In open environments, global navigation satellite systems (GNSS) such as Global Positioning System (GPS) have transformed areas such as transportation, logistics, and geographic information systems [1]. However, GNSS performance declines dramatically indoors and in densely populated urban areas, where signal interference and multipath effects become serious problems. These limitations have led to the development of alternative localization approaches, resulting in innovative indoor positioning technologies [2].

Indoor localization is a key area of research in the field of positioning, requiring solutions to many unique challenges. In recent years, such systems have become an integral component of location-based services (LBS). It is also a fundamental element of smart city infrastructure, where real-time spatial data from buildings is integrated into urban IoT platforms [2]. In modern megacities, a significant part of human activity and service operation occurs in closed spaces—transport hubs, shopping malls, business complexes, educational institutions and healthcare facilities. Without precise positioning technologies in such conditions, it is impossible to fully implement the concept of "smart" urban management. In a smart city, such systems support the operation of intelligent transport hubs, emergency evacuation planning, energy-efficient building management and the provision of personalized services to residents. In healthcare facilities, they enable patient and medical equipment monitoring, in retail, they enable personalized navigation and marketing strategies [3]. Unlike outdoor positioning systems, indoor localization technologies face problems of signal attenuation, multipath propagation and high spatial heterogeneity of the environment caused by the presence of physical obstacles (walls, furniture, human flow, etc.) [4]. These factors necessitate the development of specialized methods and approaches adapted to indoor conditions.

Modern indoor localization technologies can be divided into two main categories: non-radio frequency based and radio frequency based. The first group includes methods using inertial navigation systems (INS) [5], magnetic fields [6], acoustic waves [7] and optical systems [8]. Inertial systems using accelerometers, gyroscopes, and magnetometers provide autonomous positioning, but are subject to error accumulation and require regular calibration. Magnetic navigation takes advantage of the unique variations in the magnetic field indoors, which reduces infrastructure costs but makes the method sensitive to changes in the environment. Acoustic technologies based on time-of-flight (ToF) or phase shifts of sound waves provide high accuracy, but their use is limited by noise and the need to maintain a direct line of sight between the transmitter and receiver. Optical systems using cameras or light sensors demonstrate high spatial resolution, but their effectiveness is dependent on lighting quality and environmental conditions [9]. In addition to camera-based optical methods, a rapidly growing area is visible light communication (VLC)-based localization, which uses LED lighting infrastructure both as a source of illumination and for positioning [10,11]. In such systems, the visible light received signal strength (optical RSSI) is measured to build fingerprints or perform trilateration.

The most common group of indoor positioning technologies are radio frequency methods, due to their high adaptability, cost-effectiveness and availability of the necessary infrastructure. In this category, Wi-Fi [12,13], Bluetooth [14,15], ZigBee [16], LoRa [17], Ultra-Wideband (UWB) [18], RFID [19] and NFC [20]-based systems are distinguished. Each of these technologies has unique characteristics that determine their applicability in different scenarios, taking into account the requirements for accuracy, range, and energy efficiency.

Radio frequency-based localization methods are divided into geometric and fingerprint-based. Geometric methods use triangulation, time of arrival (ToA) and angle of arrival (AoA) measurements [2]. These methods provide high accuracy, but require specialized equipment and are sensitive to interference. In contrast, fingerprinting methods rely on pre-formed databases of signal characteristics (RSSI, Channel State Information (CSI)) at various points in space, with subsequent comparison of real measurements with reference values.

Unlike geometric approaches, fingerprinting methods demonstrate high effectiveness when combined with machine learning and deep learning algorithms, which have played a key role in advancing and improving the accuracy of indoor localization technologies. The use of ML algorithms allows modeling complex dependencies in signal data and compensating for noise distortions. Among the popular algorithms, the k-nearest neighbors (k-NN) [21], support vector machine (SVM) [22] and decision tree (DT) [23] methods can be distinguished, which are used to determine locations. More sophisticated methods, such as neural networks, can take into account signal nonlinearities and environmental dynamics. For example, convolutional neural networks (CNNs) effectively analyze spatial features of RSSI data [24], and recurrent neural networks (RNNs) are able to take into account temporal dependencies in changing conditions [25]. Although the focus of this review is on RF-based RSSI fingerprinting, we also note VLC-RSSI fingerprinting-based localization as a promising direction that complements RF approaches. In such systems, the received signal levels from LED lighting are used as “fingerprints”, which allows achieving centimeter-level accuracy in monitored premises [10].

Despite the significant amount of research devoted to the use of RSSI fingerprint and ML methods in indoor localization tasks, there remains a lack of a comprehensive analysis of existing approaches and their comparative evaluation. This review aims to fill this gap by integrating the existing solutions, critically examining the applied algorithms, and identifying the factors that determine the localization accuracy. This study covers the full development cycle of an indoor localization system—from signal propagation models to radiomap construction, including an analysis of the challenges encountered during radiomap generation, data preprocessing stages, selection and evaluation of ML models, as well as practical applications of localization technologies. In the future, recommendations for future research aimed at developing more robust and adaptive indoor positioning systems will be proposed.

The review is organized as follows: Following the Introduction, Section 2 provides a comparative analysis of existing review articles, highlighting their scope, limitations, and positioning of the current work. Section 3 presents the research methodology, describing the criteria for literature selection, data sources, and the thematic analysis approach. Section 4 outlines the principles of the RSSI fingerprint method, including signal propagation models and the fingerprinting process. Section 5 discusses the applications of indoor localization, covering a variety of use cases. Section 6 reviews the localization technologies commonly employed in indoor environments, such as Wi-Fi, Bluetooth Low Energy (BLE), ZigBee, LoRa and VLC. Section 7 explores radiomap generation techniques and data preprocessing methods. Section 8 focuses on the ML and DL models used for localization. Section 9 addresses the open challenges and future directions in RSSI-based indoor positioning. Section 10 provides structured recommendations for the development of an indoor localization system based on RSSI fingerprint. Finally, Section 11 concludes the review by summarizing the main insights and outlining potential areas for further investigation.

2. Analysis of Existing Review Articles

The existing literature on indoor localization includes both broad and focused review articles that contribute to the understanding and advancement of localization technologies. Some surveys offer comprehensive overviews of multiple technologies and methodologies, while others are dedicated to specific systems such as Wi-Fi, LoRa, or Bluetooth. Collectively, these studies form the basis for understanding the current landscape, current challenges, and potential research directions in indoor positioning systems.

The study [26] provides a comprehensive overview of indoor localization scenarios and methodologies. It focuses on the evolution from traditional techniques (e.g., trilateration) to advanced ML-based approaches. The study highlights a broad range of techniques, offering clear categorizations and performance metrics like accuracy and scalability. It also identifies key areas of improvement, such as the limited integration of ML and DL techniques. The study [27] provides a comparative analysis of indoor positioning systems. It emphasizes hybrid approaches and data fusion techniques, offering insights into their advantages and limitations. The work thoroughly explores measurement techniques and proposes evaluation frameworks. The integration of AI with wireless localization is explored in [28]. The study highlights AI's potential to address traditional challenges in localization, focusing on ML and DL synergies. It explores hybrid techniques and future trends, identifying opportunities for innovation. In the paper [29], the authors discuss localization solutions tailored for IoT applications. The review highlights hybrid methods and performance metrics relevant to IoT environments. The study [9] categorizes and evaluates various localization technologies, including radio frequency-based. It provides strong comparisons of techniques and use cases, particularly in navigation and disaster management. In [30], the focus is on fingerprint-based indoor localization using intelligent algorithms. It thoroughly explains fingerprint database creation and self-learning architectures, showcasing the potential of ML approaches. The study highlights the need for more public databases to benchmark systems effectively. Overall, it provides valuable insights but calls for further research into diverse approaches. Study [2] examines RSSI-based localization systems integrated with ML. It focuses on their scalability and robustness in smart city applications. The work highlights urban use cases and the potential for widespread implementation in dynamic environments. The transformative impact of DL is highlighted in [31]. The study covers hybrid approaches and device-free techniques, discussing DL models and their adaptability in security and healthcare. It identifies the high computational demands of DL methods as a key limitation. The study underscores the need for collaborative efforts to address these issues.

In contrast to these general surveys, some review articles focus specifically on individual wireless technologies. The study [3] explores Wi-Fi-based RSSI fingerprint methods enhanced by ML models, such as neural networks. The work identifies key challenges, including dataset variability and signal fluctuations, which can impact performance. The work on [32] emphasizes the principles and applications of Bluetooth-based localization systems. It highlights their low-cost and energy-efficient nature, making them suitable for healthcare and smart cities. The review discusses challenges such as multipath interference, which can affect performance in dynamic environments. The work [33] emphasizes LoRa-based localization techniques, discussing trilateration, fingerprinting, and time-based methods. The work highlights the unique challenges specific to IoT applications, such as signal interference and accuracy limitations. A study on localization based on communication technology in VLC presents an overview of RSSI identification methods using LED transmitters as positioning reference points [34]. The paper highlights the advantages of VLC, including high spatial resolution, immunity to radio interference, and the ability to reuse existing lighting infrastructure. It also notes the main limitations of VLC systems, such as the need for line of sight, vulnerability to shadowing, and sensitivity to ambient light, which can impact performance in dynamic environments.

To better understand the strengths and limitations of existing review articles in the field of indoor localization, we conducted a comparative analysis based on a structured set of evaluation criteria. Table 1 summarizes the coverage of key aspects across eight widely cited review articles, alongside our proposed work. The criteria include: practical applications, the range of localization technologies discussed, explanation of RSSI fingerprint principles, radiomap generation and data preprocessing techniques, the use of ML/DL algorithms, evaluation of models and discussion of open research challenges.

Table 1. Comparative analysis of existing review articles on indoor localization.

Title, Year	Applications	Localization Technologies	Principles of the RSSI Fingerprint	Radiomap Generation Techniques	Data Pre-Processing Techniques	ML/DL	Data Evaluation	Open Challenges
[2], 2023	No	Yes	No	No	No	Yes	Yes	Yes
[9], 2021	No	Yes	Yes	No	No	No	No	No
[26], 2021	No	Yes	Limited	No	Limited	Yes	Yes	Yes
[27], 2024	Yes	Yes	Yes	Limited	No	Limited	Yes	Yes
[28], 2023	No	Yes	Yes	No	No	Yes	No	Yes
[29], 2022	Yes	Yes	Yes	No	Limited	No	Yes	Yes
[30], 2020	Yes	Yes	Yes	No	No	Yes	No	Yes
[31], 2024	Limited	Yes	Yes	No	No	Yes	No	Yes
[35], 2025	Yes	Yes	No	No	No	Yes	Limited	Yes
[36], 2025	Yes	Yes	No	No	No	Yes	No	Yes
Our work, 2025	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The analysis shows that most existing reviews focus on technologies and general principles, but often do not provide a complete picture of the implementation pipeline. For example, several reviews, such as [28,30,31] provide broad technological coverage but do not go into detail on data collection, preprocessing. Similarly, some studies only address the conceptual level of ML/DL usage without addressing data processing or performance evaluation. A recent review [35] offers a comparative analysis of various localization technologies, including Wi-Fi, BLE, UWB, RFID, and hybrid solutions, with a focus on accuracy, coverage, and generalizability. However, it lacks a unified approach to consider RSSI fingerprinting, nor does it analyze key steps in its implementation, such as radio map construction methods and data preprocessing techniques. Although [36] provide a broad and up-to-date review of indoor localization technologies and their applications in various sectors, the review also does not establish uniform principles for RSSI identification and does not systematically discuss radio mapping strategies and data pre-processing methods. In contrast, our review aims to address these shortcomings by providing a comprehensive and technically detailed overview covering the entire localization process. In particular, it explains the principles of RSSI fingerprint, describes different radiomap generation strategies, and includes data preprocessing techniques required for robust ML/DL performance. We also provide an in-depth comparison of ML and DL algorithms applied in this area and highlight open challenges.

An analysis of existing review articles shows that the existing body of review literature provides important foundations for understanding indoor localization technologies, but most studies either provide general overviews without going into practical details of ML/DL integration, or they focus on individual technologies such as Wi-Fi, LoRa, or Bluetooth. Despite the significant contribution of these publications, most of them do not cover the full cycle of building and applying RSSI fingerprint systems, including the stages of generating radiomap, data preprocessing, selecting an appropriate ML or DL model.

Unlike existing works, this review provides a comprehensive and technically detailed review covering all key steps of indoor RSSI fingerprint localization. The main contributions of this study are as follows:

(i) This study presents an extensive review of various localization solutions proposed in the research literature, with a primary focus on developments last five years;
(ii) Unlike most reviews, the review covers all stages of creating localization systems: from signal propagation models to generating radiomap, data preprocessing, selecting and evaluating ML/DL models, applications of indoor localization;
(iii) Use cases in healthcare, logistics, retail, education, smart buildings, transport hubs, museums, hotels and smart cities are covered in detail;
(iv) A structured classification of radiomap generation methods is proposed: manual collection, automated, simulation, ML methods and hybrid approaches. RSSI data preprocessing methods are analyzed separately: formatting and eliminating missing values, noise filtering, detection and treatment of emissions, normalization, dimensionality reduction, data augmentation;
(v) A typology and comparative analysis of studies using ML and DL methods such as k-NN, SVM, Random Forest (RF), Bayesian, Multilayer Perceptron (MLP), CNN, RNN and hybrid architectures is presented. Specific error and accuracy values in different scenarios are given;
(vi) This review summarizes the key limitations of modern localization systems—such as signal instability, complexity of radiomap generation, device heterogeneity, noise and poor model portability—and proposes promising solutions to improve the stability and adaptability of these systems;
(vii) This review provides structured recommendations for designing RSSI fingerprint-based indoor localization systems, covering all key stages from technology selection to ML/DL algorithms.

3. Research Methodology

This study adopts a systematic review methodology in accordance with the PRISMA 2020 guidelines [37]. This review systematically collected, analyzed, and summarized existing scientific data on indoor localization based on RSSI fingerprints using machine learning (ML) methods. The methodology focuses on a broad examination of existing research, identifying patterns, trends, and knowledge gaps.

The literature search was conducted using databases such as IEEE Xplore, Elsevier, MDPI, Springer, etc. The following keywords and their combinations were used: "RSSI fingerprint", "indoor localization", "machine learning based localization", "indoor positioning" and "machine learning-based localization". An iterative approach was used to refine the search results, including citation tracking and link chaining, which provided an extensive and thorough overview.

Two independent reviewers screened titles, abstracts, and full texts to assess eligibility, with discrepancies resolved by discussion. The selection process followed the PRISMA 2020 flow diagram (Figure 1). A total of 2582 records were initially identified from major databases. After removing non-research articles, duplicates, non-English publications, and papers outside the time span, 887 records remained for screening. Based on titles and abstracts, 491 records were excluded. Of 396 reports sought for retrieval, 265 were assessed for eligibility. Finally, 188 studies met the inclusion criteria and were included in this review.

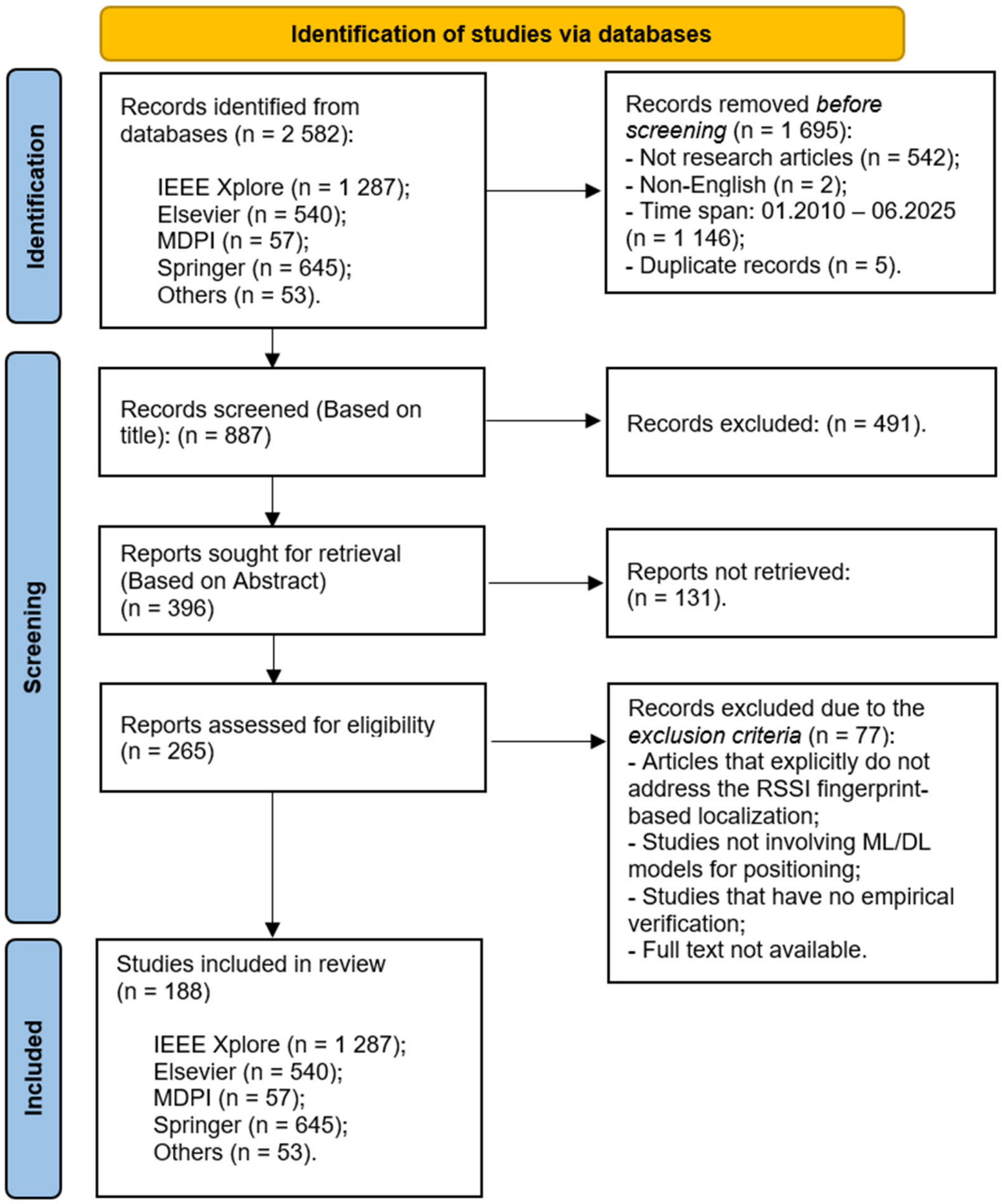

Figure 1. PRISMA 2020 flow diagram.

For each included study, data extraction included publication details, algorithms used, dataset type, evaluation metrics, and claimed performance. A thematic synthesis was then conducted to group studies by applied methods, identify emerging trends, assess challenges, and identify future research directions in the field of RSSI fingerprint-based indoor localization.

After applying the inclusion and exclusion criteria for the review article, a total of 188 relevant scientific publications were identified. The pie chart illustrates the distribution of these publications by publisher (Figure 2). This distribution clearly demonstrates that the majority of research on RSSI fingerprint and ML algorithms for indoor localization is published in IEEE journals. Figure 3 shows the distribution of articles included in our review, with a particular focus on the last five years, during which we aimed to cover as much research as possible. The relatively small number of articles in 2025 is due to the fact that many articles for the current year have not yet been published or are still unavailable.

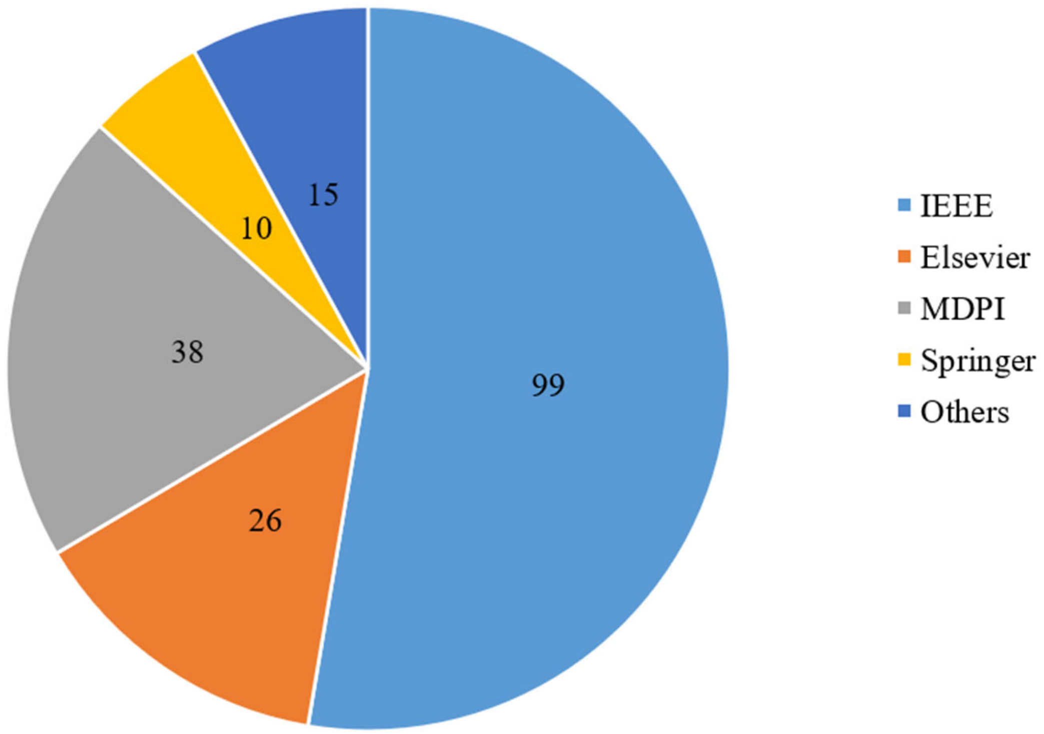

Figure 2. Distribution of selected publications by Publisher.

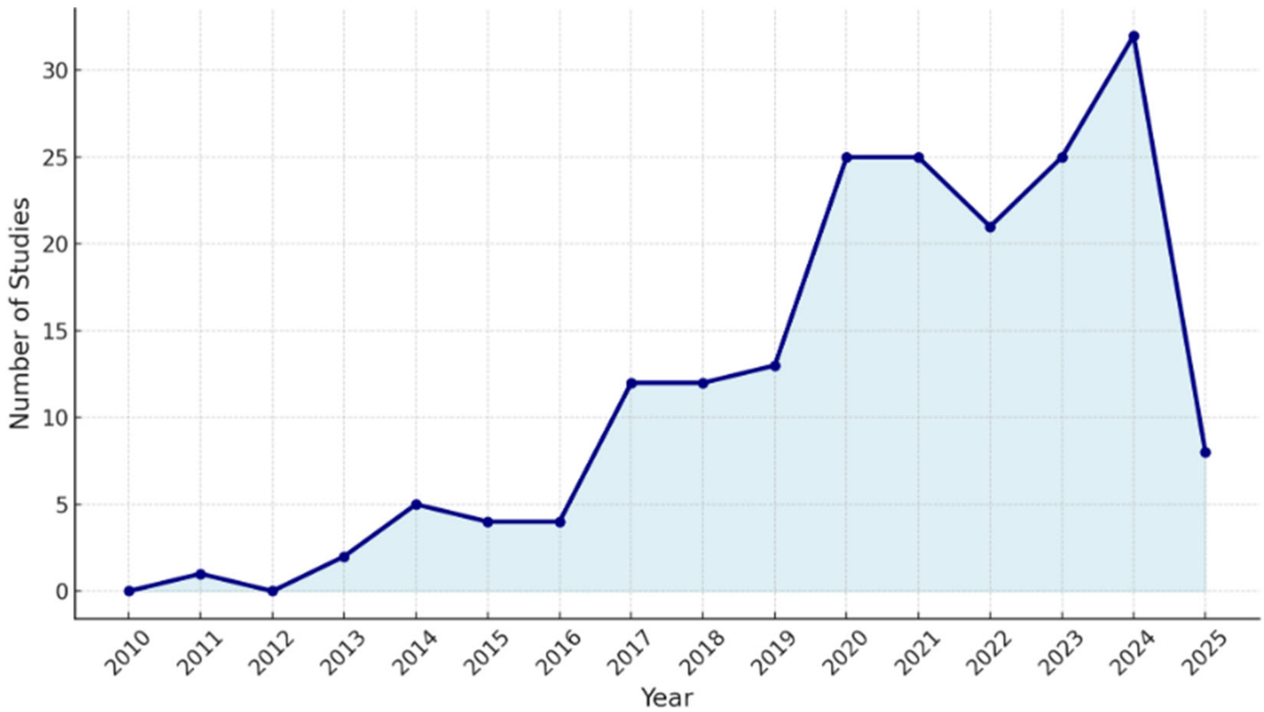

Figure 3. Distribution of reviewed articles by year.

Figure 4 is a mind map that depicts the structure and main components of the topic of indoor localization based on RSSI fingerprint. The study consists of ten interrelated sections, each of which focuses on an aspect of the localization process, from theoretical principles to implementation issues and future directions.

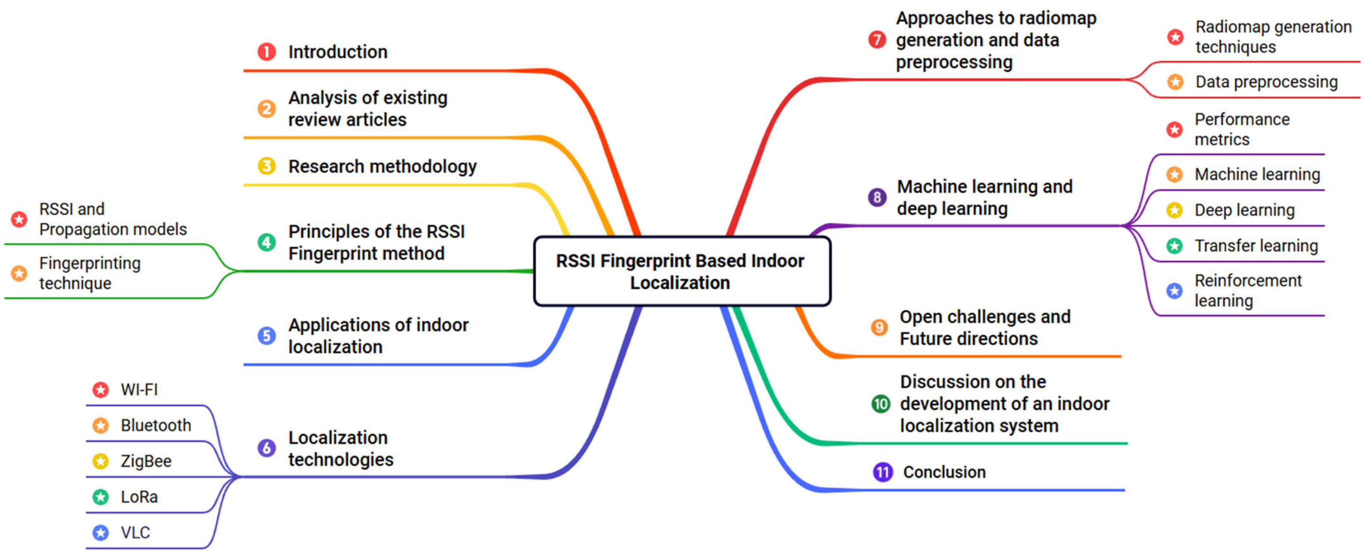

Figure 4. Review structure.

4. Principles of the RSSI Fingerprint Method

This section lays the theoretical groundwork for understanding how RSSI-based fingerprinting enables indoor localization. It begins by examining the physical nature of RSSI signals and their propagation models in various environments, highlighting the challenges associated with signal variability and multipath effects. It then introduces the fingerprinting technique as a data-driven alternative to geometric methods, explaining its operational phases and advantages in indoors.

4.1. RSSI and Propagation Models

RSSI is a fundamental parameter in wireless communication, representing the power level of a received radio signal in decibels relative to a milliwatt (dBm). The basic principle of RSSI-based localization relies on the fact that as the distance between the transmitter and receiver increases, the received signal strength decreases due to path loss.

RSSI-based localization methods rely on various propagation models to estimate the relationship between distance and received signal strength. These models describe how radio waves behave in different environments and account for factors such as path loss, reflections, and obstacles.

1. The simplest free-space path loss model assumes an unobstructed line-of-sight (LoS) between the transmitter and receiver. This model was first introduced by Harald T. Friis in May 1946 [38]. The received power in this case is given by Friis' transmission Equation (1):

$$P_r(d) = P_t + G_t + G_r - L - 20log_{10}d - 20log_{10}f + 20log_{10}c \quad (1)$$

where $P_r(d)$—received power at distance d, P_t—transmitted power, G_t—gain of the transmitting antenna, G_r—gain of the receiving antenna, L—system loss factor, f—signal frequency, c—speed of light, d—distance between the transmitter and receiver.

This model, however, does not consider real-world environmental factors such as reflections and obstacles. In urban and indoor environments, signal propagation is more complex due to multipath effects and shadowing.

2. A more realistic model that considers reflections from surfaces is the two-ray ground reflection model, which extends the free-space model by incorporating both the direct signal and the reflected signal from the ground [39]. The received power in this model is given by (2):

$$P_r(d) = \frac{P_t G_t C_r h_t^2 h_r^2}{d^4 L} \quad (2)$$

where $P_r(d)$—received power at distance d, P_t—transmitted power, G_t—gain of the transmitting antenna, C_r—gain of the receiving antenna, L—system loss factor, d—distance between the transmitter and receiver, h_t—height of the transmitting antenna, h_t—height of the receiving antenna.

3. To address the randomness in real-world signal propagation, the log-normal shadowing model introduces a stochastic component to account for environmental variations [40]. The received power is expressed as (3):

$$P_r(d) = P_t - PL(d_0) - 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\sigma \quad (3)$$

where $P_r(d)$—received power at distance d, P_t—transmitted power, $PL(d_0)$—path loss at a reference distance d_0, n—path loss exponent, which depends on the propagation environment, d—distance between the transmitter and receiver, X_σ-zero-mean Gaussian random variable representing random shadowing effects.

This model is widely used for indoor and urban localization because it better represents random fluctuations in signal strength caused by obstacles and multipath effects.

Selecting the appropriate propagation model is crucial for accurate RSSI-based localization, as different environments require different modeling approaches. While the free-space model is suitable for open areas, the log-normal shadowing model is more appropriate for complex indoor environments. However, even with an appropriate propagation model, the accuracy of RSSI-based localization can still be compromised by various environmental and system-specific factors. Due to these challenges, accurately estimating distance using RSSI alone is difficult, as environmental factors and device-specific variations introduce significant uncertainties. To address these limitations and enhance localization accuracy, it is essential to employ more robust approaches, such as accurate propagation models tailored to the environment, RSSI fingerprint methods that leverage pre-collected signal data, or ML-based calibration techniques that dynamically adjust for signal variations and environmental changes.

In addition to radio frequency propagation, similar principles can be extended to the visible light spectrum. In VLC systems, the received signal strength also decreases with distance due to optical loss, absorption, and reflection from surfaces. Since visible light cannot penetrate walls, propagation is limited to line-of-sight conditions, which provides strong spatial limitation, but also increases sensitivity to shadowing and ambient light [41].

4.2. Fingerprinting Technique

The RSSI fingerprint method is a widely used indoor localization technique in which the location of a device is estimated by comparing real-time RSSI measurements with a pre-recorded database of signal strength values. Unlike distance-based localization methods that rely on propagation models, fingerprinting is data-driven, making it more suitable for multipath environments and non-line-of-sight (NLoS) conditions [42]. RSSI fingerprint method does not require additional hardware, as most smartphones, IoT devices, and Wi-Fi-enabled systems can measure RSSI using built-in wireless modules. Figure 5 illustrates the typical workflow of RSSI fingerprint-based indoor localization using a ML. The process is divided into two main phases: the offline phase and the online phase.

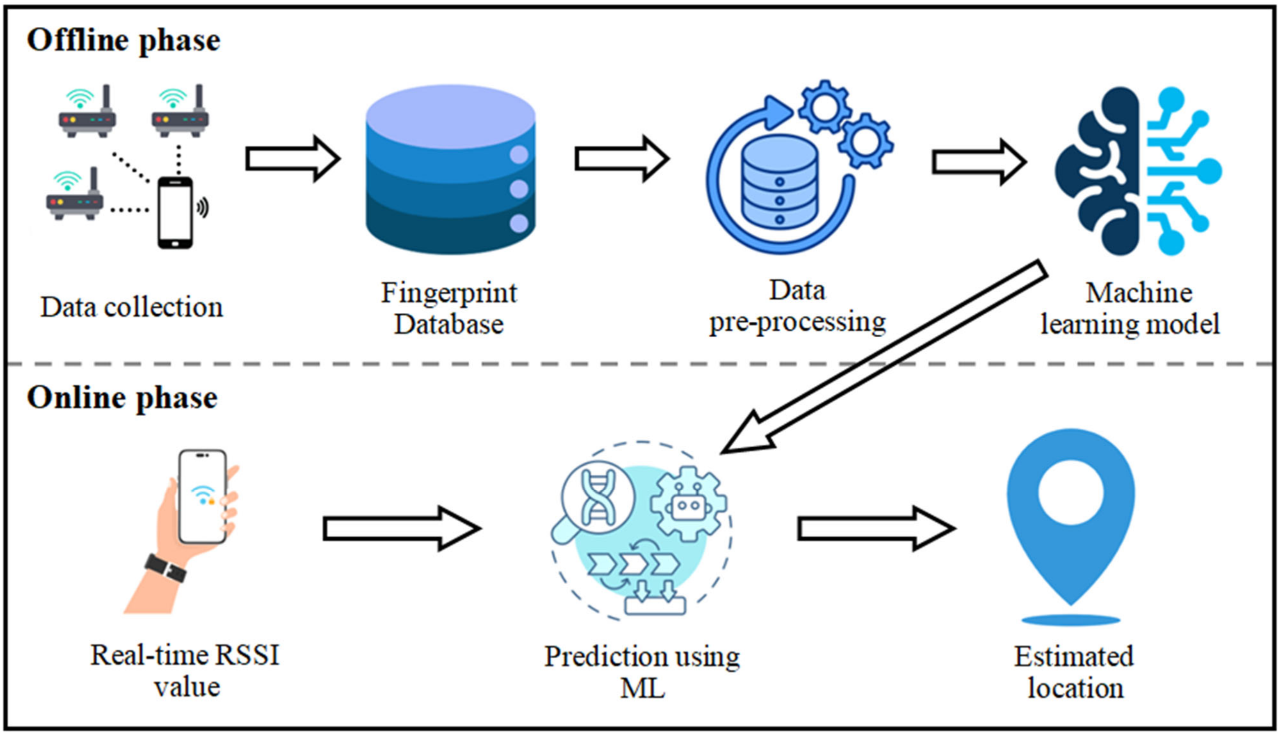

Figure 5. Workflow of RSSI fingerprint-based indoor localization.

In the offline phase, RSSI values are collected at known reference points from multiple access points (AP), creating a fingerprint database. These measurements are then cleaned and processed during the data pre-processing stage to address noise and fluctuations. The refined dataset is subsequently used to train a ML model capable of associating signal patterns with spatial coordinates. During the online phase, the system receives real-time RSSI values from the user's mobile device in an unknown location. These values are input into the trained ML model, which performs pattern matching to predict the most probable location by comparing the real-time data against the previously recorded fingerprint.

The accuracy of fingerprinting-based localization depends on several factors, including the density of reference points, the number of access points, and the quality of the fingerprint database [43]. Increasing the number of APs generally improves accuracy but also raises computational complexity and localization costs. Since RSSI values fluctuate over time, periodic updates to the fingerprint database are required to maintain accuracy. Addressing these challenges on fingerprinting remains an ongoing research area aimed at improving its scalability and real-world deployment.

While the definition of RSSI has traditionally been applied to radio frequency technologies such as Wi-Fi, Bluetooth, ZigBee and LoRa, the same approach can be used for visible light [44]. In VLC-based systems, optical RSSI values obtained from LED luminaires serve as fingerprints, which are then compared with real-time measurements. This method uses existing lighting infrastructure, provides centimeter-level accuracy, and guarantees immunity to electromagnetic interference, although it requires line-of-sight and stable lighting conditions [45].

5. Applications of Indoor Localization

Indoor localization technologies are widely used in various fields of activity, providing increased efficiency, safety and user convenience. These systems are used in healthcare [46], logistics [47], retail [48], autonomous vehicle [49], emergency [50], providing the ability to track objects and optimize processes based on spatial data. In smart city ecosystems, indoor localization systems are important elements that connect physical space with digital management platforms. Integrating positioning systems with IoT and AI management systems allows municipalities to optimize urban infrastructure, improve the quality of services provided, and ensure a higher level of safety for residents and visitors [2].

Below are the possible applications and real-world scenarios of indoor localization (Figure 6):

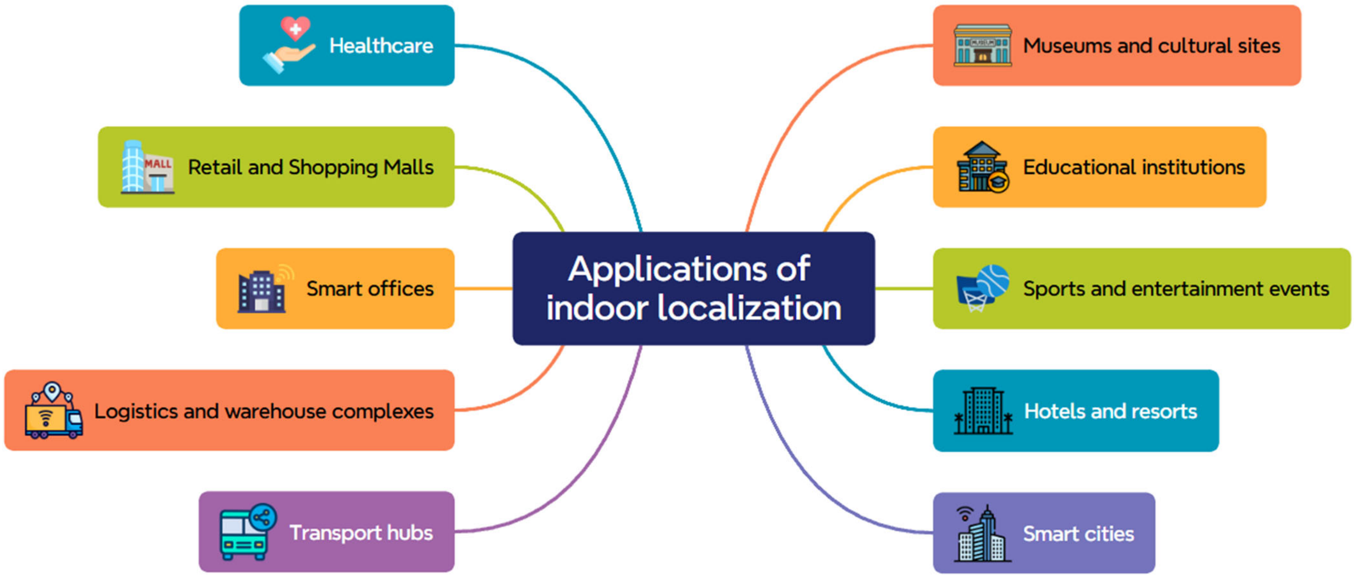

Figure 6. Applications of indoor localization.

1. Healthcare. In healthcare facilities, indoor localization systems help improve patient safety, optimize staff performance, and use equipment efficiently [51,52]. Implementation of tracking systems allows monitoring patient movements in real time, which is especially important for people with cognitive impairments, minimizing the likelihood of incidents [53,54]. In case of emergencies (e.g., accidents, fires), localization systems allow you to quickly determine the location of personnel and necessary resources, ensuring prompt provision of medical care [55].
2. Retail and shopping malls. In large retail spaces, indoor localization technologies provide a personalized approach to customer interaction and optimization of business processes [56]. The use of mobile applications with indoor navigation allows visitors to easily navigate the shopping center space and find the stores and products they need. Analysis of customer locations makes it possible to generate personalized offers and notifications, increasing engagement and stimulating sales. In retail and shopping malls, VLC-RSSI fingerprinting is attractive because it can reuse LED lighting infrastructure to provide high-accuracy indoor navigation [41].
3. Smart offices. In a corporate environment, indoor localization systems allow you to effectively manage space, increasing employee comfort and productivity [57]. In a hybrid work environment, employees can quickly find free desks, meeting rooms, and collaboration areas. Intelligent building management systems automatically adjust lighting and climate control depending on room occupancy, reducing energy costs. In emergency situations (e.g., fire, smoke), localization systems track personnel movements and direct them to the nearest emergency exits [55,58].
4. Logistics and warehouse complexes. At industrial facilities, internal localization systems help optimize logistics processes and improve safety. Product location tracking systems help minimize inventory errors and reduce product search time [59]. Monitoring employee movements in hazardous areas improves safety and reduces the risk

of industrial injuries. Localization technologies provide navigation for mobile robots and drones for automated cargo transportation [60,61].
5. Transport hubs. At airports, railway stations, and bus stations, internal localization technologies improve passenger convenience and flow management efficiency. Passengers can quickly locate boarding gates, check-in counters and other key areas, reducing the likelihood of delays. Integrating localization systems with airport logistics services improves the reliability of the baggage handling process [62,63]. LiDAL, the first indoor light-based object detection system based on radar principles and using VLC, is applied in various scenarios, the most notable example being car detection in airport parking lots [64,65].
6. Museums and cultural sites. In cultural institutions, localization enables the creation of personalized interactive routes and improved interaction with visitors. Visitors can easily find the exhibits and exhibition areas that interest them [66,67].
7. Educational institutions. On university campuses, indoor localization systems improve ease of movement and resource management [68]. First-year students and visitors to campus can navigate the campus more quickly. In emergency situations, technologies help control the movement of students and staff, speeding up the evacuation process [55]. Analysis of the occupancy of classrooms and study areas allows for their optimal use.
8. Sports and entertainment events. In large arenas and stadiums, localization plays a key role in organizing events and managing the flow of people. Visitors can quickly find their seats, reducing the likelihood of congestion. Localization systems help prevent crowds from congesting in narrow passages. Integration with mobile applications allows for the provision of event-related content to visitors [3].
9. Hotels and resorts. In the hospitality industry, indoor localization systems provide personalized services and convenience for guests. Guests can easily find restaurants, swimming pools, gyms, and conference rooms [69]. Localization systems help fulfill customer requests faster.
10. Smart cities. In the concept of "smart cities", localization technologies are integrated with IoT devices to improve the efficiency of urban infrastructure [70]. Citizens can find administrative offices, stores, and other important objects. In emergency situations, localization systems help direct people to safe zones.

Thus, indoor localization technologies have wide application possibilities, increasing efficiency and safety in various fields. Their further development in combination with IoT and AI opens up new prospects for process optimization and improving the quality of services.

6. Localization Technologies

This section provides an overview of the main wireless communication technologies commonly used for indoor localization: Wi-Fi, Bluetooth, ZigBee, LoRa and VLC.

The pie chart in Figure 7 illustrates the distribution of articles included in the review based on the types of wireless technologies used in RSSI fingerprint-based indoor localization tasks. The chart clearly shows the dominant position of Wi-Fi technology, which is utilized in 45% of the analyzed studies. This prevalence is due to the widespread availability of Wi-Fi infrastructure in buildings, ease of access to RSSI data, and high compatibility with existing devices.

Bluetooth ranks second, being employed in 18% of the studies. Its popularity is attributed to low energy consumption and the ability to integrate with mobile devices and BLE beacons. VLC accounts for 15% of the reviewed works, demonstrating its potential to achieve high positioning accuracy by leveraging existing LED lighting infrastructure, although its applicability is limited by line-of-sight requirements. LoRa technology appears in 7% of the publications, reflecting growing interest in large-scale localization with low power requirements. ZigBee is used in 7% of the studies, benefiting from its support for mesh networking and resistance to interference. The remaining 8% are categorized as other technologies, including UWB, RFID, and FM. Thus, the chart highlights that Wi-Fi remains the most commonly adopted solution for indoor positioning tasks, while alternative technologies are applied in more specialized scenarios. Below is a brief description of each of these technologies.

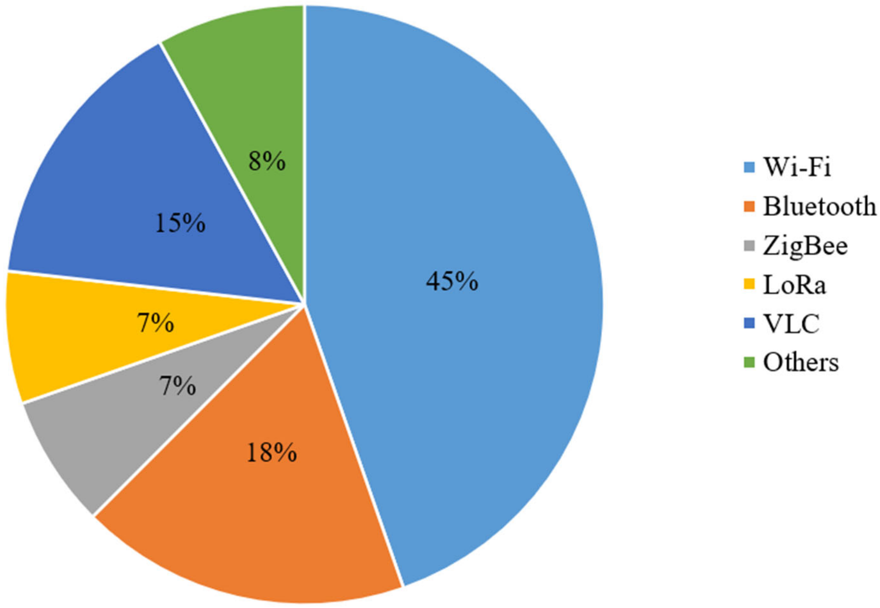

Figure 7. Distribution of reviewed articles by technology.

6.1. Wi-Fi

Wi-Fi is a wireless communication technology based on IEEE 802.11 standards. It provides data transmission in the 2.4 GHz, 5 GHz and 6 GHz bands, using Orthogonal Frequency-Division Multiplexing (OFDM) to ensure a stable signal and high speed. Wi-Fi networks operate on the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) protocol, which prevents collisions during data transmission [71].

In addition to traditional data transmission, Wi-Fi is widely used in indoor positioning systems. Wi-Fi-based positioning methods include measuring the RSSI and using phase and time characteristics [72]. Wi-Fi signals can pass through walls and other obstacles, making localization possible even in conditions where there is no direct line of sight [73].

6.2. Bluetooth

Bluetooth is a wireless communication technology that operates in the 2.4 GHz band and uses Frequency Hopping Spread Spectrum (FHSS) to reduce interference. Unlike Wi-Fi, Bluetooth is optimized for energy-efficient data transmission, making it popular in IoT systems [74].

BLE allows you to determine your location using beacons and signal analysis [75]. The RSSI fingerprint method allows you to create a database of RSSI fingerprint, which is then used to determine the location using ML algorithms. In addition, modern BLE solutions use AoA and Angle of Departure (AoD) technologies, which improve positioning accuracy [76].

6.3. ZigBee

ZigBee is a wireless communication protocol based on the IEEE 802.15.4 standard and designed for energy-efficient data networks. It operates in the 2.4 GHz, 915 MHz and 868 MHz bands, enabling self-organizing mesh networks [77].

In indoor positioning systems, ZigBee utilizes RSSI to estimate the distance between devices. Combined with ML algorithms, ZigBee can be employed for localization in low-power environments [78].

6.4. LoRa

LoRa is a wireless communication technology designed to transmit data over long distances with minimal power consumption. It uses a patented LoRa modulation method based on Chirp Spread Spectrum (CSS), which provides high immunity to noise. LoRa operates in unlicensed frequency bands (868 MHz in Europe, 915 MHz in North America and 433 MHz in Asia) [79].

Although LoRa is primarily aimed at wide area networks (LoRaWAN), it can also be used for indoor localization [80]. Basic localization methods include RSSI and Time Difference of Arrival (TDoA), which allows to estimate distance based on the difference in the time it takes for a signal to arrive at different receivers [81].

6.5. VLC

VLC is a wireless technology that uses the visible spectrum (400–800 THz) to transmit data, typically using LED lights as transmitters [82]. VLC systems work by modulating the intensity of light at high frequencies that are invisible to the human eye, and are received using photodiodes. Because light does not penetrate walls, VLC offers high spatial confinement and immunity to electromagnetic interference, making it an attractive alternative to traditional radio frequency-based methods [83].

7. Approaches to Radiomap Generation and Data Preprocessing

Accurate radiomap construction and effective preprocessing of RSSI data are essential for the success of fingerprint-based localization systems. This section provides a structured overview of the main strategies for generating radiomap, including manual, automated, simulated, and hybrid approaches. It also presents a detailed classification of preprocessing techniques aimed at addressing noise, missing values, outliers, and high dimensionality, thereby enhancing the reliability and robustness of ML/DL-based localization models.

7.1. Radiomap Generation Techniques

The basic principle of RSSI Fingerprint method is to create a radiomap, which is a database of RSSI values collected at reference points in the room. This data is used to subsequently determine the location of the device based on the analysis of the received signals. The generation of a radiomap is one of the key stages in the RSSI Fingerprint method, since the correctness of the device location directly depends on the quality and accuracy of this map. The radiomap serves as a basis for subsequent comparison of real RSSI measurements with reference values, and any error or insufficient detail at the stage of its formation can significantly reduce the accuracy of positioning. Therefore, the choice of the method for constructing a radiomap, as well as the density and reliability of the collected data, play a decisive role in the effectiveness of the entire localization system. There are various approaches to generating radiomap, which can be divided into five main groups (Figure 8).

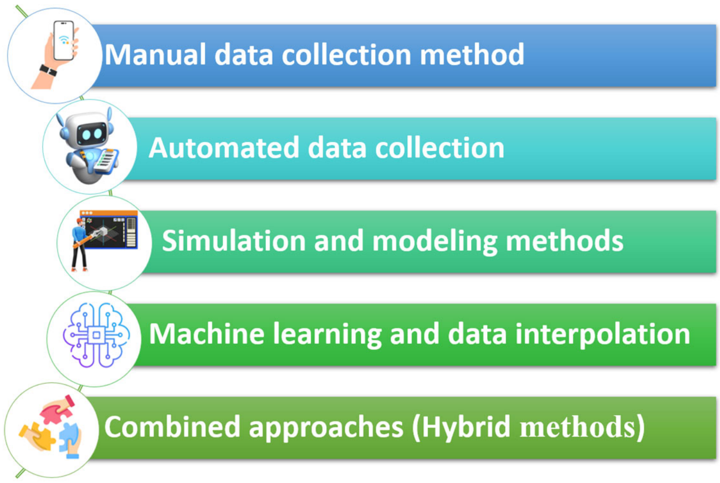

Figure 8. Radiomap generation techniques.

In addition to on-site collection radiomap, publicly available datasets are widely used in the indoor localization literature as standardized benchmark data for testing and validating algorithms. These datasets provide ready-made radiomap collected under controlled conditions, allowing researchers to objectively compare localization methods and evaluate their generalization capabilities. The most commonly used datasets are described below:

UJIIndoorLoc—one of the largest and most well-known Wi-Fi fingerprinting datasets. It was collected on the campus of Universitat Jaume I, Spain. It includes more than 21,000 records [84]. The UJIIndoorLoc database is flexible as it supports localization tasks based on building ID, floor and location classification, 3D coordinate regression or hybrid approaches due to its large-scale multi-floor structure.

The JUIndoorLoc dataset covers a five-floor building at Jadavpur University (India), RSSI measurements were collected on a fine 1 m^2 grid using a custom Android application [85]. It is specifically designed for evaluating machine learning and deep learning models.

The Tampere dataset is a crowdsourced Wi-Fi fingerprint database collected at Tampere University of Technology, Finland [86]. It includes 4648 fingerprints recorded from 21 Android devices in various orientations in the university's five-story, 22,570 m^2 building. The data was collected by freely moving volunteers, allowing for the capture of different signal propagation patterns across floors and conditions.

The IPIN2016 Tutorial dataset was collected in a 30×5 m^2 (150 m^2) corridor at the Faculty of Engineering, University of Alcala, Spain [87]. It contains 927 training fingerprints and 702 test samples, as well as signals recorded from 168 detected Wi-Fi access points (WAPs) on one floor.

The Wireless InSite dataset is a synthetic database created using Remcom's Wireless InSite 3.3.0 ray tracing software [88]. It simulates Wi-Fi signal propagation in challenging indoor environments and provides realistic channel characteristics such as path loss, delay spread, angle of arrival, and RSSI values.

The UTSIndoorLoc dataset was collected from the Faculty of Engineering and Information Technology (FEIT) building at the University of Technology Sydney (UTS), Australia [89]. It covers 16 publicly accessible floors with a total floor area of approximately 44,000 m^2. The dataset contains 9494 Wi-Fi fingerprints recorded at 1840 control points, including 9107 training samples and 387 testing samples.

7.1.1. Manual Data Collection Method

The manual data collection method is a traditional way of creating a radiomap, where RSSI measurements are taken manually at pre-defined reference points in the room. A person walks through the pre-defined positions, recording the coordinates of the reference points and recording the RSSI values from the available access points. An example of this approach is the study [90], which used traditional manual data collection methods to build a radiomap. The data were collected in the university library building on the 3rd and 5th floors for 15 months. Trained specialists took several consecutive Wi-Fi fingerprints (a total of 63,504 samples) at fixed 448 positions and in specified directions. Another example is the study [91], in which RSSI values were collected manually using ZigBee. Data collection was performed in a simple 5×5 m^2 lobby and four sensor nodes were used, arranged in a rectangular shape as an access point. The main disadvantages of this approach are its labor intensity and high time costs, especially for large or dynamically changing spaces.

7.1.2. Automated Data Collection

Automated data collection significantly reduces labor costs and time expenditures compared to traditional methods that require manual data collection. For this purpose, mobile robots equipped with SLAM (Simultaneous Localization and Mapping) technology are used. SLAM simultaneously solves two problems: determining the current location of the robot and building a map of the environment. This technique is especially effective in conditions where there is no pre-known map, and allows the robot to adjust its route in real time based on the data it receives. The work [92] describes the use of a robot to autonomously build a fingerprint without stopping, which significantly speeds up the process of creating a fingerprint. Using SLAM, the authors reduce the time to build a Wi-Fi fingerprint map by 64–71% and reduce energy consumption by 61–64%. The work [93] also uses a TurtleBot 2 mobile robot with LiDAR SLAM to automatically generate a radiomap.

Crowdsourcing offers an alternative automation method where data is collected by regular users using mobile devices. The use of crowdsourcing for automatic data collection is described in the study [94], where data is collected from users' mobile devices. Users select a route on a building plan via a mobile app and Wi-Fi RSS data is automatically collected as the user moves, with data locations calculated based on timestamps and movement speed. The study [95] presents a new method for automatically generating a radiomap for indoor Wi-Fi localization using crowdsourced data. The system significantly reduced the time required to generate the radiomap while maintaining high accuracy, showing an average positioning error of 2.34 m.

7.1.3. Simulation and Modeling Methods

Simulation and modeling techniques allow generating a radiomap without the need to conduct a full survey of the real environment. This is especially useful for complex or hard-to-reach areas where manual data collection may be difficult or impossible. The study [96] proposes a new method, semi-simulated Wi-Fi fingerprint construction, which allows generating a dense radiomap with less time and effort. The proposed semi-simulated RSS (SS-RSS) method generates dense fingerprints using only coarse real-world measurements by simulating data at intermediate positions. The fully simulated radiomap method proposed in the study [97] by Batoul Sulaiman et al. uses Wireless InSite software to generate a fully simulated radiomap. The authors simulated radio signal propagation taking into account building materials. The 3D Shoot and Bouncing Ray method was used to evaluate the influence of different materials (concrete, glass, wood, metal) on RSSI.

7.1.4. Machine Learning and Data Interpolation

ML and interpolation methods can generate a radiomap based on a limited number of measurements. Data interpolation is the process of estimating unknown values that lie between two known data points. In other words, interpolation allows the prediction of intermediate data values based on existing measurements or observations. An example is the work [98], which proposes the Access-Point Centered Window-Based Radio-Map Generation Network (APCW-RGN) method to automatically generate a Wi-Fi radiomap, reducing the time and cost of data collection. The method uses generative adversarial network (GAN) and an access point-centered data window, which allows taking into account obstacle materials and the distance to the AP. The study [99] uses Euclidean distance matrix recovery methods using deep neural networks and CNNs to improve the accuracy of indoor positioning based on RSSI. The proposed method restores missing data and remove noise in signal strength measurements, reducing the complexity of real-time computations by moving most of the processing to the offline stage. Zhang and Cai proposed a radiomap generation method based on multivariate polynomial interpolation, which enables the creation of high-density RSSI fingerprint databases from a limited number of reference points, significantly reducing calibration efforts [100]. The study proposes a method for improving the RSSI fingerprint database for indoor localization using spatial interpolation (IDW, quadratic and cubic spline, kriging), which allows creating synthetic data with an accuracy comparable to real measurements and a maximum prediction error of no more than 6 dBm [101]. In the paper [11], authors presented a new fingerprint database reconstruction method for visible light positioning. Instead of relying on dense offline measurements or complex signal propagation models, their approach synthesizes fingerprints based on known LED coordinates while taking into account the photodiode rotation angle. This method significantly reduces the inspection effort and achieves accuracy comparable to dense fingerprint databases, reducing the positioning error to 39.85% in simulations and 29.78% in experiments.

Compressed sensing has also been proposed as a promising technique for synthetic RSSI fingerprint generation. By exploiting the sparsity of RSSI measurements, compressed sensing enables the reconstruction of high-dimensional radio maps from a limited number of observations, thereby reducing the effort of site surveys while maintaining comparable localization accuracy [102]. In the paper [103], the authors proposed the RSSD-CS algorithm, in which RSS differences compensate for device heterogeneity, and CS reconstructs the complete fingerprint database from a limited number of samples. Their experiments showed that the RSSD-CS fusion method improves the positioning accuracy by 15–20% compared to traditional RSS- or SSD-based approaches, especially in scenarios with heterogeneous devices. The researchers in [104] propose a method to build indoor fingerprint databases using compressed data. They first use a super-complete dictionary-based sparse k-SVD coding method to ensure the sparsity of RSSI fingerprints, and then reconstruct a complete radio map from a limited number of measurements using compressed data. This approach significantly reduces the cost of site surveying, eliminating a critical bottleneck in the deployment of large-scale fingerprinting systems.

7.1.5. Combined Approaches (Hybrid Methods)

Hybrid approaches combine several methods to improve the accuracy and efficiency of radiomap generation. The study [105] combines subspace clustering methods with graph methods. The proposed method uses an RSSI data clustering algorithm using a signal subspace model and a sequential data segmentation algorithm. The system automatically matches data clusters to physical regions using a graph model and the Viterbi algorithm, which allows achieving a matching error of less than 1%. The work [106] combines SLAM and map management methods to create a hybrid radiomap. The study [93] combines automated robotic data collection and data generation using GAN. The work [97] presents a hybrid method that combines real measurements, interpolation and full modeling (Wireless InSite).

7.2. Data Preprocessing

Since RSSI data is susceptible to various sources of error, such as signal fluctuations, outliers, missing values, and high dimensionality, the data preprocessing stage is especially important. It is aimed at eliminating incorrect measurements and improving the quality of input information before feeding it to ML algorithms. Without adequate preprocessing, even the most advanced algorithms may yield unreliable results due to noisy or inconsistent input data. Therefore, the preprocessing stage is an important component in the development of an indoor localization system. There are various data preprocessing techniques, which can be divided into six main groups (Figure 9).

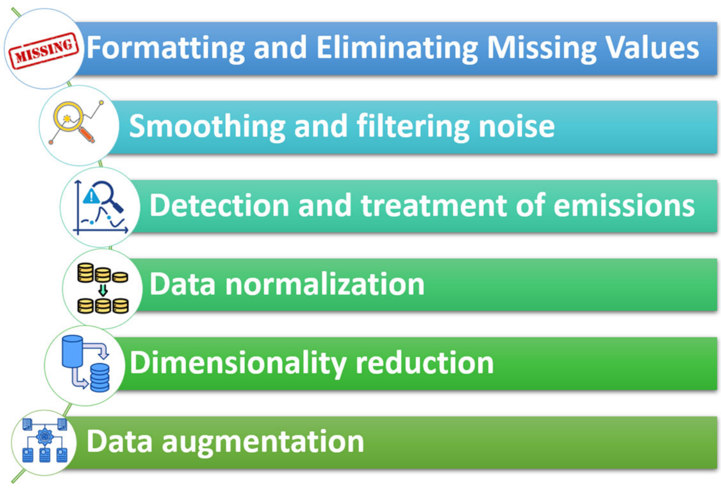

Figure 9. Data preprocessing techniques.

7.2.1. Formatting and Eliminating Missing Values

Handling missing values and anomalies in RSSI data is an important preprocessing step, since incomplete or corrupted data significantly reduces the accuracy of positioning algorithms. Various data cleaning and restoration methods are actively used to improve the reliability of the radiomap and the quality of the ML model. Below, an overview of the key approaches proposed in the literature is provided. The authors of [107] consider Wi-Fi data cleaning methods aimed at eliminating errors, anomalies, and missing values in RSSI measurements. The proposed algorithm utilizes the correlation between fingerprints based on RSS values and access point identifiers to compute the relationships among all samples and remove weakly correlated fingerprints from the dataset. The work [108] describes a radiomap reconstruction method that uses the extended Kalman filter (EKF) and Gaussian processes (GP) to fill in missing values. The authors show that the proposed method minimizes positioning errors by predicting missing RSSI values taking into account temporal and spatial correlation. The study [109] proposes a Neighbor Mean Filter algorithm for processing a fingerprint database to compensate for missing RSSI values. The technique reduces the level of positioning errors by filling in missing data with the average values of the nearest neighbors. The authors of [110] use an autoencoder and a GAN to automatically update the radiomap, minimizing the cost of collecting and labeling data. The method allows adapting the fingerprint database to changing environments, improving the stability of the positioning system. The work [111] presents an approach based on sparse data representation, which allows to significantly reduce the amount of required RSSI measurements. The authors use compressive sensing and SRSVD method to reconstruct missing values, achieving high accuracy with minimal resource overhead.

7.2.2. Smoothing and Filtering Noise

RSSI measurements are subject to significant fluctuations even under stationary conditions due to multipath reflections, signal absorption, and other environmental changes. These fluctuations have a negative impact on the stability of the radiomap and the accuracy of localization. Smoothing and filtering methods are actively used to improve the stability of the positioning system and suppress random noise. The authors of [112] apply the Kalman filter to reduce RSSI fluctuations when localizing Bluetooth devices, which improves the stability and accuracy of measurements. The work demonstrates that the proposed method effectively suppresses random signal fluctuations due to changes in the environment. The study [113] proposes a comprehensive approach combining wavelet transform, fuzzy clustering (Fuzzy C-Means), and Kalman filter to eliminate noise in RSSI data. Experiments show that the proposed method reduces the positioning error due to adaptive noise filtering. The authors of [114] combine the location fingerprint method with the unscented Kalman filter (UKF), providing improved filtering of RSSI data. The method demonstrates high resistance to noise and increased localization accuracy compared to traditional approaches. In [115], an autoencoder trained on noisy RSSI data to efficiently reconstruct efficient restoration of the original signal values. The authors show that the proposed method significantly reduces the impact of random RSSI fluctuations on positioning accuracy. In study [43], outlier noise filter in RSSI samples is mitigated using robust principal component analysis (RPCA). RPCA demonstrates a strong capability in effectively reducing noise.

7.2.3. Detection and Treatment of Emissions

RSSI measurements used in indoor localization tasks are often subject to outliers caused by multipath reflections, interference, hardware failures, and temporary signal fluctuations. Outliers can significantly distort the structure of the radiomap and lead to a decrease in positioning accuracy. Therefore, the key stage of preprocessing is the automatic detection and correct processing of anomalous values. The study in [116] presents an improved version of the weighted k-NN method to detect and eliminate outliers in RSSI data. The technique reduces the impact of anomalous values, increasing the positioning accuracy in a multipath environment. The authors of [117] apply a fast-clustering algorithm to identify anomalous RSSI values and their subsequent processing using the radial basis function (RBF). The method demonstrates high accuracy due to automatic detection of outliers in the data. The study [118] presents an outlier detection method based on autoencoders and CNN. The authors demonstrate that the proposed approach can automatically filter out anomalous RSSI values, improving localization accuracy. The study [119] proposes the use of GANs to detect anomalies in a radiomap. The authors show that GAN is effectively trained on normal data and can detect outliers that may reduce positioning accuracy.

7.2.4. Data Normalization

Data normalization allows to bring signal values to a common scale, eliminate the influence of scatter and make the data more homogeneous and suitable for training ML and DL models. Since RSSI values can vary significantly depending on the characteristics of access points, distance, transmitter power and signal propagation environment, using raw data without normalization leads to model instability and reduced positioning accuracy. The authors of [120] demonstrate that normalizing RSSI data before training a deep neural network (DNN) helps to minimize the influence of different access points on positioning results. The work [121] presents a method for RSSI normalization before feature extraction, which ensures data uniformity for subsequent training of ML models. The authors of [122] investigate the effect of normalizing RSSI values before processing them with ML and Kalman filter algorithms. The study shows that preliminary normalization helps to reduce positioning errors. The study [123] describes a method for normalizing RSSI data before converting them into images for processing with the Vision Transformer. The authors show that the proposed method improves localization accuracy by reducing the variability of RSSI values.

7.2.5. Dimensionality Reduction

In some cases, RSSI-based positioning systems may involve high-dimensional data due to a large number of access points and measurements. This can lead to feature redundancy, model overfitting, and high computational costs. Dimensionality reduction methods allow us to simplify the data structure, preserve the most significant information, and improve the efficiency of ML algorithms. There are many approaches to dimensionality reduction, including both linear and nonlinear methods. The authors of [124] propose using autoencoders to reduce the dimensionality of the radiomap, allowing us to extract the most significant features from the RSSI data. The method allows us to reduce the memory footprint and improve the efficiency of ML algorithms during localization. The study [125] provides a comparative analysis of various dimensionality reduction methods, including PCA, singular value decomposition (SVD), random projection, as applied to the problem of positioning in wireless networks. The authors demonstrate that the choice of the optimal method depends on the data structure and measurement conditions. The study [126] presents a stacked autoencoder method that reduces the dimensionality of data while preserving important spatial features of RSSI. The authors show that the proposed method improves the positioning accuracy due to a more compact data representation. The work [127] proposes a joint-norm robust principal component analysis (JRPCA) method for dimensionality reduction and denoising in the radiomap. The authors demonstrate that the JRPCA model outperforms traditional PCA methods in handling noisy data. The work [128] explores the application of kernel principal component analysis (KPCA) for the dimensionality reduction of a radiomap. Compared with traditional PCA, KPCA better preserves nonlinear dependencies in the data, which contributes to higher localization accuracy. The authors of [129] propose a cluster-based JRPCA algorithm for RSSI data dimensionality reduction and clustering. The method minimizes computational costs and improves model accuracy. The study [130] proposes a hybrid approach that combines an autoencoder and LSTM for simultaneous dimensionality reduction and temporal processing of RSSI data, aiming to enhance the system's robustness to signal fluctuations. The authors of [131] investigate the impact of KPCA on the performance of extreme ML for dimensionality reduction. Experiments show that the proposed method achieves better generalization ability of positioning models. The work [132] proposes various dimensionality reduction techniques that can improve classification accuracy in passive localization systems. The authors consider the use of t-SNE and PCA for improving the quality of the radiomap.

7.2.6. Data Augmentation

Data augmentation is an important step in building ML models, especially when the number of available RSSI measurements is limited. Indoor localization requires a large and detailed radiomap, which can be labor-intensive to assemble manually. Augmentation methods allow creating synthetic or augmented data based on existing measurements, expanding the training set without the need for additional field experiments. The work [133] discusses the use of generative models to synthesize new RSSI data, which allows expanding the training set without additional measurements. The authors show that synthetic data can be effectively used to improve positioning accuracy. The study [134] combines fuzzy clustering methods and DL to model and augment RSSI data. The authors demonstrate that proposed method allows compensating for data gaps, improving the quality of the radiomap. The study [135] proposes to use the multi-output Gaussian process (MOGP) to generate new RSSI fingerprints taking into account the spatial correlation between access points. The work [136] presents a strategy for augmenting a radiomap based on a limited data set. The authors show that the use of ML and interpolation algorithms can significantly improve the positioning accuracy with a minimum number of measurements. The authors of [81] use CNN to generate new RSSI fingerprints, which improves the quality of the radiomap in a changing environment. The work [137] presents a data augmentation method to improve the robustness and accuracy of ML algorithms in room-level localization tasks. Synthetic RSSI data generation is used to improve the performance of models, especially when training data is limited. The study [11] presents a new fingerprint database reconstruction method for VLPs that does not depend on channel propagation models and instead uses only known LED coordinates and photodiode orientation, making the approach more practical and efficient compared to existing reconstruction methods. In the paper [138], the authors also developed a new fingerprint regeneration method for scenarios with uneven point distribution, which allows to do without an exact signal propagation model and improve positioning almost to the level of a dense database.

8. Machine Learning and Deep Learning

ML and DL algorithms can account for nonlinear dependencies, spatial correlation of signals, and adapt to environmental changes in RSSI-based indoor localization tasks. This section reviews the main approaches, including classical ML, DL, transfer learning, and reinforcement learning, as well as the performance metrics used to evaluate the models.

8.1. Performance Metrics

To objectively assess the quality of localization methods based on ML and RSSI fingerprint, various performance metrics are used. In the reviewed literature, a wide variety of performance metrics are employed to evaluate RSSI fingerprint-based localization systems, including accuracy, precision, average localization error, RMSE, R^2, and CDF. Such diversity complicates direct comparison between studies, as results are often reported using different criteria and datasets. Nevertheless, in this review we attempt to provide a consistent comparative analysis by grouping the most commonly used metrics and systematically defining them. The key metrics used in the studies are shown below:

1. *Accuracy*—shows the proportion of correctly identified locations relative to the total number of forecasts. Calculated as (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

where TP is true positive, TN is true negative, FP is false positive, FN is false negative classifications.

2. *Precision*—characterizes the proportion of correctly classified objects among all objects that were classified by the algorithm into a given class (5):

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

where *TP* is true positive, *FP* is false positive classifications.

A high precision value indicates that the algorithm generates a small number of false positives.

3. *Average Localization Error* is one of the key metrics that measures the average deviation between the predicted and actual location of the device. It is calculated using Equation (6):

$$Average\ Localization\ Error = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} \tag{6}$$

where N is the number of test points, (x_i, y_i) are the true coordinates, $(\hat{x}_i,\ \hat{y}_i)$ are the estimated coordinates.

4. Mean-Squared Error (*MSE*)—characterizes the average value of squared deviations of estimated coordinates from real ones. The equation for *MSE* is as follows (7):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right] \tag{7}$$

where N is the number of test points, (x_i, y_i) are the true coordinates, $(\hat{x}_i,\ \hat{y}_i)$ are the estimated coordinates.

MSE is sensitive to large errors because they significantly increase the value of the metric.

5. Root-Mean-Squared Error (*RMSE*)—is the square root of the *MSE*, used to estimate the typical size of the forecast error (8):

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right]} \tag{8}$$

where N is the number of test points, (x_i, y_i) are the true coordinates, $(\hat{x}_i,\ \hat{y}_i)$ are the estimated coordinates.

The *RMSE* metric is expressed in the same units as the original measurements (e.g., meters), making it clear and easy to interpret.

6. R-Squared (R^2)—shows what proportion of the variance in the data can be explained by the model used (9):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y}_i)^2} \tag{9}$$

where y_i are actual values, $\hat{y}_i$ are the predicted values, $\overline{y}$ is the average of the actual values. The closer the R^2 value is to 1, the better the model describes the original data.

7. Cumulative Distribution Function (*CDF*) is used for visual and quantitative analysis of the distribution of localization errors. It expresses the probability that the localization error will not be greater than a given value ***e*** (10):

$$CDF(e) = P(Error \le e) \tag{10}$$

where P denotes the probability and e is a predefined error threshold.

CDF allows for a visual assessment of the probability of a device being within a given error and is conveniently used to compare different localization methods.

Thus, the use of these metrics allows for a comprehensive and objective assessment of the effectiveness of the proposed methods, accurately identifying their strengths and weaknesses, and selecting optimal solutions from the point of view of practical implementation.

8.2. Machine Learning

8.2.1. k-Nearest Neighbors and Weighted k-NN

The k-NN algorithm is one of the most popular and easy-to-implement ML methods used in classification and regression problems. In the context of indoor localization based on RSSI fingerprint, k-NN is used to determine the location of a mobile node by comparing the current RSSI vector with previously registered fingerprints in the training base. The principle of k-NN is as follows: for a new observation, the k closest points in the training set are determined. The class or coordinate is predicted based on the labels of these neighbors—by voting or averaging coordinates [139].

Table 2 contains a comparative analysis of scientific articles that use k-NN algorithms and their modifications (WkNN, MKNN, DML-KNN, etc.). Key characteristics of each work are presented: title, year of publication, method used, technology and quantitative localization results. In particular, in the article [140], the improved WkNN model with Gaussian regression achieved RMSE of 1.78 m on BLE data, and Kalman filter with k-NN achieved 1.9 m on FM signals [141]. In study [142], authors use DML-KNN in their research and achieves improved accuracy in floor and coordinate classification tasks. Study using RBIC showed up to 99% classification accuracy for Wi-Fi fingerprints through clustering and subsequent classification [143]. Overall, models with hybrid approaches achieved significant reduction in localization errors through filtering and prediction compared to classical k-NN. In study [144], authors used WkNN for VLC with multiple photodiodes, achieving a median error of 4.74 mm with four luminaires and 9.87 mm with two luminaires, demonstrating the effectiveness of multi-photodiode reception for improving accuracy. In the paper [145] a method based on Spearman distance-WkNN was proposed, which provided an average localization error of about 4.9 cm, which confirms the applicability of statistical similarity metrics in improving the accuracy of RSSI-fingerprint VLC systems.

Table 2. Works using k-NN for RSSI-based indoor localization.

Title	Year	Method	Technology	Performance Results
[140]	2021	Improved WkNN + GPR	BLE	RMSE = 1.78 m, improved accuracy compared to kNN and WkNN algorithms
[141]	2020	Kalman Filter + KNN (KF-KNN)	FM	Average error = 1.9 m, improved accuracy compared to kNN and WkNN algorithms
[142]	2024	Distance Metric Learning (DML-KNN)	Wi-Fi	7.14 m with 90% of the localization errors. DML improves KNN performance by 80%
[143]	2023	Rank-Based Iterative Clustering (RBIC) + ML classifiers	Wi-Fi	Localization accuracy ranges from 94% to 99%
[144]	2020	WkNN	VLC	Median error of 4.74 mm for four luminaires and median error of 9.87 mm with two luminaires
[145]	2020	Spearman distance-WkNN	VLC	Positioning error is 4.9 cm
[146]	2024	M-kNN	LoRa	The modified k-NN model showed high accuracy, scoring 86.85% accuracy during 5-fold cross-validation
[147]	2024	k-NN, WkNN	Wi-Fi	Fingerprinting achieved 76.50% overall accuracy
[148]	2022	k-NN	Wi-Fi, BLE	Wi-Fi Fingerprinting gave the best accuracy among BLE and Zigbee at 3–5 anchors

8.2.2. Bayesian Methods

Bayesian methods in the context of the localization problem are based on the probabilistic interpretation of the location determination process. They are built on Bayes' theorem, which allows calculating the probability of a hypothesis in the presence of new data [149]. The basic approach is to create a model that estimates the probability of a device being in a certain position based on previously collected information and current RSSI measurements. In the field of localization, Bayesian methods are represented by various algorithms, among which the most common are the Naive Bayes classifier, Hidden Markov Model (HMM) and GP. Study [150] proposes an adaptive Bayesian model for multi-story environments that improves localization accuracy compared to traditional methods. The presented approach reduced the average localization error to 1.2 m on individual floors and to 1.8 m in the multi-story mode. In work [151], a Bayesian model-based method is presented for detecting RSSI fingerprint variations using unlabeled data. Experimental results show that the proposed approach provides an improvement in localization accuracy of about 10–15%, achieving an average error of about 1.5 m even under significant environmental changes. The work [152] proposes to use hidden Markov models with preliminary feature extraction using the dynamic mode decomposition (DMD) method. The testing results showed an average localization error of about 1.75 m and an overall accuracy of 94.65%, which is 12–40% better than classical approaches based on WKNN, RF, and Naive Bayes classifier.

8.2.3. Support Vector Machine

SVM is a powerful ML tool that has been successfully applied to the indoor localization problem based on fingerprinting technique. SVM effectively copes with nonlinear data dependencies by using various kernel functions and demonstrates high robustness to noise and variations in RSSI signals [153]. An analysis of six studies that applied the SVM method is presented in Table 3.

Table 3. Works using SVM for RSSI-based indoor localization.

Title	Year	Method	Technology	Performance Results
[154]	2020	One-vs-All SVM	ZigBee	Training accuracy: 84.92% Testing accuracy: 74.39% in area: 8 m × 12.5 m.
[155]	2023	Willmott's index of agreement (WIA) based on the SVM	Wi-Fi	Average localization accuracy 0.466 m, improvement 84.96%
[156]	2023	Kernel Adaptive Filtering, SVM based on reproducing kernel Hilbert space (RKHS)	Wi-Fi	Improved accuracy by at least 7%
[157]	2024	SVM and Transfer Learning	Wi-Fi	CSI is significantly more accurate than RSSI, especially for time series
[158]	2022	Back Propagation–Support Vector Regression (BP-SVR)	RFID	Average localization error 9.5 cm in a 6×8 m^2 room
[159]	2020	Hybrid approach (trilateration + fingerprinting with SVR)	UWB	Localization accuracy of over 95%
[160]	2021	A one-against-all multi-SVM classifier	VLC	The average positioning error declined by 73.28%

The highest localization results among the analyzed studies were achieved using hybrid approaches combining SVM with other modern ML algorithms and various data sources. Mo et al. proposed an approach based on a combination of back propagation neural network and support vector regression (BP-SVR), which achieved an average positioning error of only 9.5 cm in a 6×8 m^2 room [158]. High performance was also achieved by the method using UWB technology with a hybrid approach combining trilateration and SVR, where the average positioning error was less than 10 cm in complex multi-factorial environments [159]. The authors of [155] achieved an average localization accuracy of 0.466 m, which is 84.96% better than the results obtained using legacy radiomap, by using SVM regression with Wilmott Index of Agreement and automatic fingerprint database updating. The paper [160] proposes a method using a one-against-all multi-SVM classifier, which made it possible to compensate for the influence of random reception angles and reduce the average positioning error by 73.28% compared to traditional approaches.

8.2.4. Ensemble Methods

Random Forest is an ensemble ML method based on constructing multiple decision trees and aggregating their predictions to improve the overall accuracy of the model [161]. Many studies use RF as a standalone classifier or as part of ensemble methods—along with other algorithms (e.g., KNN, SVM, MLP).

Chen et al. proposed a gradient-based random forest (GBRF) localization method where RSSI features are transformed using a trained nonlinear mapping function [162]. Using RF as a regression model achieved a localization error of less than 1.5 m and significantly improved the nearest neighbor ranking compared to traditional k-NN approaches. Roy et al. presented a weighted ensemble classifier based on Dempster-Shafer belief theory, which used RF, SVM, KNN, and MLP algorithms as base models [163]. The method was tested on two widely used datasets, JUIndoorLoc and UJIIndoorLoc, where it demonstrated up to 98.26% classification accuracy and an average positioning error of 0.79 m. In study [146], Kamal et al. an experiment on indoor localization was implemented in a real environment—a multi-story round building, where LoRa technology was applied and RSSI + SNR fingerprinting was used. In a comparative analysis of various algorithms (RF, MKNN, SVM, Decision Tree), RF showed high positioning accuracy with an average error of about 2.2–2.5 m. In the paper [164], authors developed an autonomous VLP (Visible light positioning) fingerprinting system and evaluated multiple ML and model-based algorithms. Ridge regression achieved the best results with a mean error of 84.4 mm and a 90th percentile error of 144 mm, outperforming SVR, RF, k-NN, and MLP.

8.3. Deep Learning

With the development of computing power and the availability of large RSSI fingerprint datasets, deep neural networks (DNNs) have become popular. They are better at handling complex nonlinear dependencies in the signal space. The most popular approaches are listed below.

8.3.1. Fully Connected Networks (FCN)

FCNs, also known as multilayer perceptrons (MLPs), are a basic architecture of artificial neural networks in which each neuron in one layer is connected to every neuron in the neighbor layers [165]. Such networks are widely used in regression and classification problems, including indoor location tasks based on RSSI. In the context of positioning, MLPs are used to map an RSSI pattern to coordinates, extracting complex nonlinear relationships between the input features (RSSI) and the output (x, y coordinates). The network architecture can be optimized by choosing the number of hidden neurons, the activation function, and the learning strategy. In study [166], Puckdeevongs applied a 4-4-2 MLP architecture (four inputs from Wi-Fi stations, one hidden layer with four neurons, and two outputs—x, y coordinates). The network was trained and tested in the lab and hallway areas using data collected from ESP8266 modules. In the lab, the accuracy was higher: with an error less than 0.5 m as 20.93%, and an error from 0.5 to one meter as 34.88%. In work [77], Fahama et al. applied MLP, RNN, and k-NN algorithms for RSSI localization based on real and synthetic fingerprints collected in a ZigBee network. MLP trained on real data showed the best results in all scenarios with an error from 0.9280 to 1.0990 m.

8.3.2. Convolutional Neural Networks

CNNs are a type of deep neural networks originally developed for processing 2D images but have been successfully adapted to RSSI-based indoor localization tasks [167]. CNN have the ability to automatically extract spatial and temporal features from the input data. For example, Zhang et al. proposed a Wavelet-CNN architecture that uses the Haar wavelet transform before applying 1D convolution [168]. Below, Table 4 presents a summary of studies that use CNN for RSSI-based indoor localization.

Table 4. Works using CNN for RSSI-based indoor localization.

Title	Year	Method	Technology	Performance Results
[12]	2023	CNN	Wi-Fi	A verification accuracy up to 99.09%
[42]	2022	CNN	Wi-Fi	Accuracy is up to 91%
[81]	2024	CNN + SE (Squeeze and excitation)	LoRa	A localization error is 284.57 m on the test area, accuracy is 8.39% higher than analogues.
[168]	2023	Wavelet-CNN	Wi-Fi	The MAE is 1.54 m and RMSE is 1.84 m
[169]	2023	Radio robust image fingerprint localization RRIFLoc, ResNet	Wi-Fi	Reduces the average location estimation error by 56.87%
[170]	2023	CNN	Bluetooth	An accuracy is about 94%
[171]	2023	Extreme learning machine autoencoder (ELM-AE)-CNN	Wi-Fi	Localization improves up to 68.36% in Tampere and 67.56% in the UJIIndoorLoc dataset
[172]	2020	CNN	mmWave Wi-Fi	RMSE 11.1 cm; accuracy 99%, an average median error of 9.5 cm for direct coordinate estimate.

Deng et al. developed the RRIFLoc algorithm, which uses RSSI-to-image transformation followed by deep residual networks, achieving an error reduction of 56.87% compared with existing methods [169]. Zhu et al. proposed a Wi-Fi localization model based on a CNN including two fully connected layers, trained on RSSI heat maps [12]. To speed up data collection, 3D ray-tracing simulation was used. Verification accuracy of up to 99.09% was achieved on the UJIIndoorLoc and Wireless InSite datasets. Lutakamale et al. proposed a CNN-based approach with squeeze and excitation (SE) modules to enhance the attention to the most significant features, achieving an error of 284.57 m, which is 8.39% better than previous methods on the same dataset [81].

8.3.3. Recurrent Neural Networks

RNNs are a type of neural network architectures that can process sequential data due to the presence of feedback loops that allow them to remember information about previous inputs [173]. However, standard RNNs suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies. In response to this, modifications were developed—LSTM and GRU, which have improved memory management mechanisms [174]. LSTM includes memory cells and three control elements: input, output and forget gates, which allows for efficient storage and retrieval of information in long time sequences. GRU simplifies the structure by combining forget and input gates, providing similar performance at lower computational costs [175].

Table 5 presents the key studies using RNNs and their modifications LSTM. The article titles, year of publication, methods used, wireless technology applied and brief numerical results are provided. In study [176], using a dual-layer Bi-LSTM and attention mechanism, an error of 0.95 m was achieved, with 100% of the errors being less than 2.5 m, indicating high stability even under signal fluctuations. In the Bluetooth scenario [177], Bi-LSTM also achieved an error of 1.3 m, outperforming both LSTM and MLP, especially under unstable signal conditions.

Table 5. RNN in indoor localization tasks.

Title	Year	Method	Technology	Performance Results
[176]	2024	DL-BiLSTM	Wi-Fi	Average error is 0.95 m with 100% of the errors under 2.5 m; 37% improvement over DLSTM.
[177]	2022	Bi-LSTM	Bluetooth	Distance error is 1.3 m with probability of 95% in area 8 m × 12 m,
[178]	2022	LSTM	Wi-Fi	Improved the precision of indoor localization compared to state-of-the-art methods.
[179]	2023	Bi-LSTM	Wi-Fi	Improved coverage and accuracy in real-world conditions.

8.3.4. Hybrid Architectures

Hybrid architectures in indoor localization tasks are a combination of different DL models and traditional ML methods to achieve high accuracy and robustness to noise and changing environments. Such architectures combine, for example, CNNs, autoencoders, transformers, and deep metric learning, providing both feature extraction and efficient coordinate classification or regression.

Table 6 provides an overview of the current studies using hybrid architectures. The work [180] proposes a hybrid architecture combining a CNN and a transformer encoder. First, the CNN extracts spatial features from RSSI fingerprints, and then the transformer processes the resulting vectors, taking into account global dependencies between APs. The authors of [181] combined a CNN and a convolutional autoencoder for positioning in a computationally constrained environment. The Convolutional Auto-Encoder is used for pre-training to extract the most significant features, and then the CNN classifies the position based on these features. The architecture is optimized to run on edge devices, achieving about 99% building accuracy, over 90% floor accuracy, and 9.5 m positioning mean error on UJIIndoorLoc. In the paper [182] a hybrid algorithm based on LSTM and FCN is proposed to solve the problem of positioning in visible light systems. Experimental results showed that the hybrid model provides an average positioning error of 0.92 cm and a maximum positioning error of less than 5 cm.

Table 6. Hybrid architectures in indoor localization tasks.

Title	Year	Method	Technology	Performance Results
[180]	2024	CNN + Transformer encoder	LoRa	Localization mean error is 290.71 m
[181]	2024	CNN + Convolutional Auto-Encoder	Wi-Fi	About 99% building accuracy, over 90% floor accuracy, and 9.5 m positioning mean error
[182]	2021	LSTM-FCN	VLC	An average positioning error of 0.92 cm and a maximum positioning error of less than 5 cm
[183]	2023	CNN + SAE (Stacking auto-encoders)	Wi-Fi	The floor accuracy is 96.73%, the building accuracy 100%, the position accuracy is 11.56 m
[184]	2024	Deep Gaussian Process Regression (DGPR) + Temporal Weighted RSSI Averaging + Kalman Filter	LoRa	Average error 1.94 m, 90% error of 3.28 m
[185]	2024	CNN + LSTM	Wi-Fi	The proposed architecture outperforms baseline DL methods by achieving higher accuracy across all evaluated datasets

8.4. Transfer Learning

Transfer Learning is an approach in ML and DL where a model trained on one task (or dataset) is reused or fine-tuned to solve another, related task or for a different environment [186]. In the context of RSSI fingerprint localization indoors, this method is especially relevant, since the propagation conditions of radio signals indoors often change. Instead of retraining the network from scratch for each new scenario, it is possible to use the already "accumulated" weights from a similar task and only slightly fine-tune them on data from a new environment [187].

In study [188], a TL-ILC scheme with weight freezing is proposed, where the autoencoder trained in the original environment is reused and fine-tuned using a small set of new data collected by another device in the same environment. Three transfer variants (decoder freezing, no freezing, random initialization) gave excellent results: the best average localization error was 0.82 m using TL-ILC Type-2. In work [189], the authors reformulate the indoor-localization problem as a regression problem and apply few-shot learning, which allows the model to adapt to new rooms using a limited amount of labeled RSSI data. In the experiment, the model showed a 57.9% improvement over few-shot classification, a 13% improvement over KNN and a 11.1% improvement over SAE-CNN. The authors of [190] apply an attention-based auxiliary network and a model transfer strategy between two different buildings. By leveraging the transfer learning mechanism and the attention-based auxiliary network (AAN), the positioning error was significantly reduced: the 75% and 90% CDF values and the average localization error of the AAN model decreased by 6.2%, 2.2%, and 4.6%, respectively, compared to the baseline.

8.5. Reinforcement Learning

Reinforcement learning is an ML paradigm in which an agent interacts with the environment through trial and error and receives a reward for successful actions. The agent's goal is to maximize the total reward by learning the optimal behavior strategy [191]. In indoor localization tasks using RSSI fingerprint, RL can be used to improve the data collection process, adapt to a dynamic environment, and optimize the trajectory of a mobile robot or user.

In study [87], the authors propose a hierarchical algorithm based on deep Q-learning that allows sequentially dividing the search space into octants, thereby exponentially reducing the search area with a time complexity. The method demonstrated high robustness to RSSI fluctuations and achieved a high accuracy and efficiency under single-plane and multi-plane localization conditions using the IPIN2016, UJIIndoorLoc, and UTSIndoorLoc datasets. In the study [192], the authors propose a continuous localization framework based on Deep Reinforcement Learning by formulating the localization task as a Markov Decision Process (MDP) and introducing a novel reward-setting mechanism grounded on the detection of stable radio beacons. Experimental validation using Bluetooth 5 devices demonstrated that the proposed method achieved a 59% reduction in root mean square localization error compared to the classical unsupervised multilateration approach. Hajiakhondi-Meybodi et al. proposed a reinforcement learning-based framework (JUNO) for dynamically selecting anchor nodes in ultra-wideband indoor localization systems to mitigate the effects of NLoS conditions [193]. Unlike conventional RL approaches, JUNO significantly improves convergence speed and location accuracy without requiring complex preprocessing, as demonstrated through simulations in ultra-dense indoor environments.

Despite the emergence of several promising reinforcement learning-based approaches for indoor localization, this area remains relatively underdeveloped. Significant research efforts are still required to refine RL architectures, optimize training processes, and enhance model resilience in environments with noisy and highly variable signal conditions.

9. Open Challenges and Future Directions

Despite significant progress in the development of indoor positioning systems based on RSSI fingerprint and ML methods, there are a number of unresolved issues that prevent the large-scale implementation of these solutions in real-world environments. The process of creating a radiomap using the RSSI fingerprint method is a complex task that is associated with many obstacles due to physical, technological and organizational factors. The main challenges of RSSI fingerprint based indoor localization are shown in Figure 10.

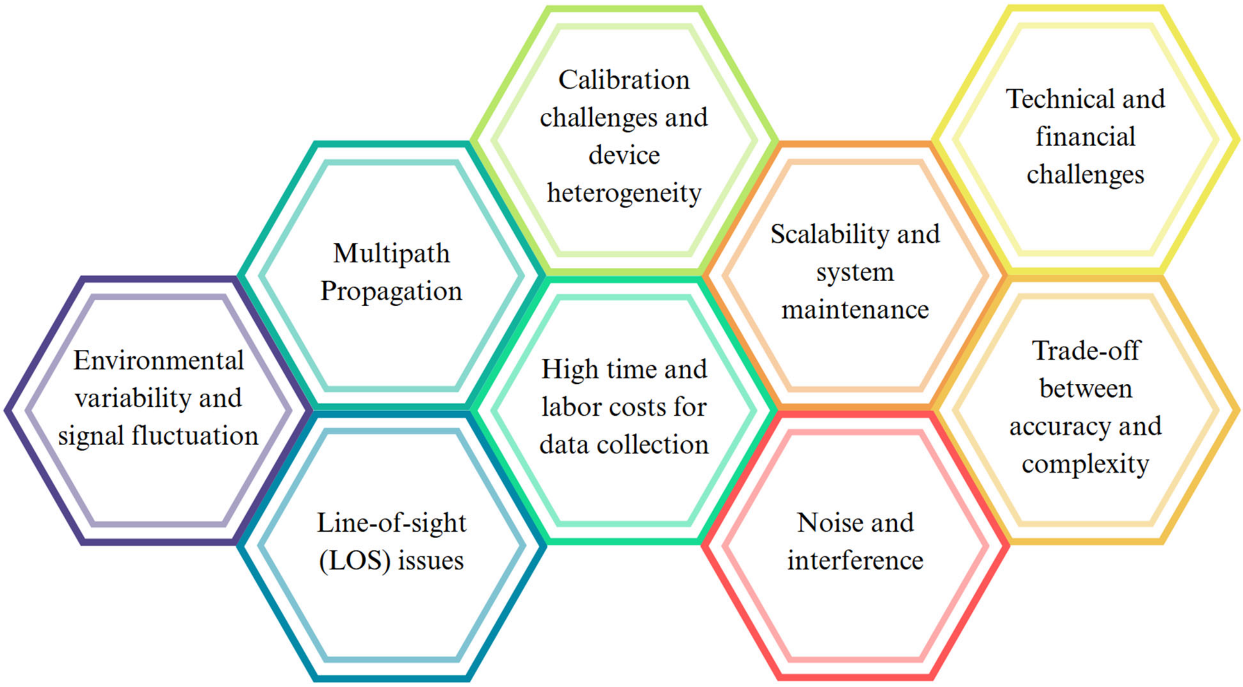

Figure 10. Challenges of RSSI fingerprint-based indoor localization.

One of the key challenges is environmental variability and signal variability. Indoor spaces often contain many reflective surfaces such as walls, ceilings, and furniture, which causes multipath propagation of the signal [194]. As a result, the receiver not only records the direct signal, but also its reflected versions, causing interference and significant variations in RSSI, even at fixed locations. This makes it difficult to create a predictable radiomap, as the slightest changes in the position of the receiver or objects in the room can cause significant changes in signal strength. Additionally, LoS issues arise in situations where radio waves pass through obstacles such as walls or furniture, which creates unpredictable changes in RSSI [195]. Environmental dynamics, such as people moving or furniture changing positions, also cause the radiomap to become outdated, as real conditions begin to diverge from previously recorded RSSI data [184]. To improve the stability of localization in a changing environment, it is recommended to use reinforcement learning methods that allow dynamically adapting the model and updating the radiomap based on the accumulated experience of interaction with the environment.

The process of creating a radiomap requires significant time and labor resources [97]. In most cases, researchers have to physically walk around all points in the space and collect data from all available signal sources, which is especially problematic in large buildings or multi-story complexes. Even small changes in the physical structure of the room may require a complete or partial rewrite of the radiomap, which increases the workload of the researcher and reduces the efficiency of the system [196]. The development of automatic radiomap updating systems, such as autonomous robots or drones capable of recalculating

RSSI in real time, partially solves this problem, but significantly increases the cost and complexity of the system [92].

The heterogeneity of devices and the need for calibration are another serious problem [197]. Different devices, including smartphones, tablets and specialized sensors, have different characteristics of radio signal receivers, which leads to different RSSI values at the same point in WI-FI systems [198]. BLE-based localization systems are also affected by device heterogeneity: In the paper [199], authors empirically demonstrated that RSSI values can vary up to 6 dB between smartphone models in the same positions and orientations due to hardware variability. To address this issue, they propose using RSSI ranking, which improves interoperability between devices based on the relative order. The heterogeneity of devices creates a problem of data incompatibility and requires complex calibration procedures to ensure the same accuracy on all devices. To overcome this problem, it is advisable to use transfer learning methods that allow adapting trained models to new devices, as well as normalizing and calibrating RSSI data at the preprocessing stage.

Another significant challenge is noise and interference, which are inevitable in electromagnetically saturated indoor spaces. Wi-Fi networks, Bluetooth devices, microwave ovens, and other electronic equipment can create interference, distorting the RSSI [26]. To combat this, data filtering and noise reduction algorithms are used, but such methods increase the computational complexity of the system and can reduce the positioning accuracy [113,114]. To improve the reliability of the data, it is recommended to use filtering methods such as Kalman filter, wavelet transform and autoencoders, which can effectively remove noise components and restore the original signals.

Scalability and maintenance of the system also require significant effort. Large spaces require a large database of RSSI values for each point, which complicates data storage and management. Frequent recalibration of the radiomap and data updates lead to high operational costs. The complexity of integrating ML methods adds another layer of complexity [2]. Although such methods can improve the accuracy of the system, they require large amounts of data to train the models and powerful computing resources [3]. Moreover, ML models trained on data from one environment may not work correctly in another environment without additional training or adaptation, which requires constant data updates [200]. To improve generality, it is recommended to use few-shot learning, meta-learning, and adaptive tuning of models with a minimum amount of data collected in a new environment.

RSSI-based localization systems also face a trade-off between accuracy and complexity [201]. The fingerprinting method requires complex data matching algorithms, which can slow down the system in real time, especially in applications where data processing speed is critical, such as security systems or emergency navigation. Technical and financial challenges in implementing the system include the high cost of installing a large number of access points to provide coverage of the entire room and the difficulty of integrating the localization system with existing IoT or building management systems [202]. As a solution, it is proposed to use lightweight architectures (e.g., MobileNet [203], TinyML [204]) and knowledge distillation methods to create simplified versions of models without significant loss of accuracy.

Another important point to mention is that in smart cities, the compatibility of different localization systems installed in buildings is of particular importance. This requires unified data format standards, as well as reliable protection of location information during its transmission and storage. An important condition is the integration of localization solutions with city monitoring platforms. At the same time, the system must be scalable not only within a single facility, but also cover a network of interconnected positioning points throughout the city, which requires the use of cloud-edge architectures and modern methods of data integration and processing.

In addition to the challenges faced by RF-RSSI methods, RSSI fingerprinting in VLC has its own limitations. Firstly, VLC localization requires strict line-of-sight between the LEDs and receivers; shadowing or occlusion can significantly reduce performance, and high spatial confinement reduces the coverage area [205]. Secondly, ambient light variations and dynamic lighting conditions can lead to instability of fingerprint databases [34]. Finally, although centimeter-level accuracy can be achieved under controlled conditions, performance is significantly reduced by uneven or sparse fingerprint distributions, affecting reliability and scalability [44]. VLC-RSSI challenges such as line-of-sight dependence, shadowing, and ambient light variations can be mitigated using hybrid RF-VLC systems, multi-sensor data fusion, adaptive filtering, and relative RSSI normalization. Scalability and non-uniform LED placement can be addressed using crowdsourcing, synthetic fingerprint generation and integration with smart lighting infrastructure.

Together, these factors create significant barriers to creating an accurate and reliable radiomap, requiring an integrated approach to the development and optimization of RSSI-based indoor localization systems. These difficulties are addressed through automation, crowdsourcing, interpolation, adaptive models, and generative approaches. Modern methods allow the creation of more accurate, adaptive, and scalable radiomaps while minimizing time and resource costs.

10. Discussion on the Development of an Indoor Localization System Based on RSSI Fingerprint

This review provides detailed recommendations for creating an indoor localization system based on the RSSI fingerprint method, covering all key stages—from technology selection to building a machine learning model. Creating an indoor localization system based on the RSSI fingerprint method requires a comprehensive approach, covering technology selection, radio map construction, data preprocessing, and machine learning algorithm selection. The diagram shown in Figure 11 reflects the main stages of the RSSI-based localization system design process.

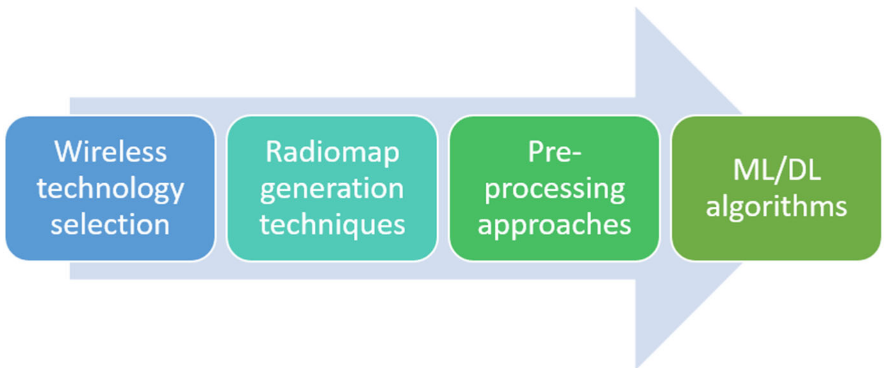

Figure 11. Key stages in designing an indoor localization system based on the RSSI fingerprint method.

Firstly, the choice of wireless technology plays a crucial role in the design of an RSSI fingerprint-based indoor localization system and should be based on a thorough analysis of its advantages and limitations. Based on the analysis of the articles included in this review, the findings presented in Table 7 summarize the main characteristics of wireless technologies commonly used in RSSI fingerprint-based indoor localization systems.

Table 7. Comparison of wireless technologies for RSSI Fingerprint-based indoor localization.

Technology	Frequency Band	Advantages	Disadvantages
Wi-Fi	2.4/5 GHz	Widely available infrastructure, easy access to RSSI data, relatively high data throughput	High RSSI fluctuation, multipath effects, interference from other devices
Bluetooth (BLE)	2.4 GHz	Low energy consumption, widely supported on mobile devices, suitable for beacon-based positioning	Short range, RSSI is noisy and less stable, affected by human body blocking
ZigBee	2.4 GHz	Low power, mesh networking capability, good for dense networks	Low data rate, less RSSI resolution, fewer compatible consumer devices
LoRa	433/868/915 MHz	Long range, excellent penetration through walls, ultra-low power	Very coarse RSSI resolution, low data rate, limited indoor accuracy
VLC	400–800 THz	Centimeter-level accuracy, immunity to RF interference, high spatial confinement, uses existing LED lighting infrastructure	Requires line-of-sight, sensitive to shadowing and ambient light variations, limited coverage beyond walls

Based on Table 7, we can draw the following conclusions regarding the choice of technology for building an indoor localization system based on RSSI fingerprint. Each technology has its own advantages and limitations that need to be considered depending on the requirements of a specific application scenario. Wi-Fi provides ease of implementation due to the existing infrastructure and high availability of RSSI data, but suffers from signal instability and interference, which can reduce accuracy. Bluetooth demonstrates low power consumption and good support on mobile devices, making it convenient for personalized and portable solutions, albeit with limited range and signal stability. ZigBee is beneficial for building dense networks within smart buildings due to its support for mesh networks, but is limited by low data rates and low prevalence among consumer devices. LoRa has a long range and excellent signal penetration, making it suitable for large-scale systems with low accuracy requirements, but its low RSSI resolution limits its applicability to high-precision localization tasks. VLC technology offers centimeter-level accuracy, immunity to electromagnetic interference, and the ability to reuse existing LED lighting infrastructure, but it requires line-of-sight, is very sensitive to shadowing, and cannot provide coverage through walls.

Thus, the choice of technology depends on the specific requirements of the system: if accuracy is important and the infrastructure already exists, it makes sense to use Wi-Fi; for mobile and energy-saving solutions, BLE is better; if the priority is network stability and scalability, it is worth considering ZigBee; and for large-scale coverage with minimal accuracy requirements, LoRa; when centimeter-level accuracy is required in controlled spaces with installed LED lighting, VLC becomes a promising complementary solution to RF-based approaches.

Secondly, the choice of the radiomap generation method also plays a key role in the accuracy, scalability and cost of the RSSI fingerprint-based localization system. In this review, was proposed a classification of methods into five main categories: manual collection, automated, simulation, ML/interpolation-based and hybrid.

Analyzing the articles presented in the review devoted to the radiomap generation methods, we can draw appropriate conclusions about the applicability of various approaches depending on the conditions. For small and static premises, manual RSSI fingerprint collection can be used, since it provides high control over the process, but it requires significant time. In conditions where it is necessary to cover large areas or ensure regular updates of the radio map (for example, in campuses, shopping centers or industrial facilities), preference should be given to automated methods using mobile robots or crowdsourcing, which can significantly reduce labor costs. If access to the premises is limited or rapid generation of a map for a prototype is required, simulation methods and fingerprint generation based on signal propagation models will be effective. With a limited number of measurements, it is advisable to use machine learning and interpolation methods to restore missing data and increase the density of the radio map. Hybrid methods that combine real measurements, simulations and generative approaches that provide a balance between accuracy, costs and adaptability of the system are considered the most universal.

However, it should be emphasized that each localization system is unique and should be designed taking into account the specifics of the environment, available infrastructure, accuracy requirements, update frequency and computing resources. Therefore, the final choice of radio map generation method remains with the researcher and should be based on a thorough analysis of the task and operating conditions.

The RSS reconstruction performance differs significantly between RF and VLC-based systems, highlighting both their unique advantages and inherent limitations. RF-based systems face challenges such as multipath fading and interference, but they benefit from high signal penetration, wide coverage, and well-established propagation models. Using advanced techniques such as compressed sensing, Gaussian processes, and generative machine learning, synthetic radio map reconstruction in RF can achieve accuracy close to that of dense surveys while leveraging the ubiquity of Wi-Fi, BLE, ZigBee, and LoRa infrastructures. In contrast, VLC-based systems benefit from the spatial limitation of visible light, resulting in more consistent RSS fingerprints and improved reconstruction accuracy under line-of-sight conditions. However, VLC-based reconstruction remains sensitive to shadowing and illumination variations. These differences indicate that while synthetic RF fingerprints can reduce survey effort in noisy environments, in VLC they can further exploit the inherent stability of the visible communication signal to achieve centimeter-level positioning accuracy.

Thirdly, the analysis of the RSSI data preprocessing methods presented in the review shows that since RSSI signals are subject to noise, outliers, missing values and high variability, the choice of an adequate processing strategy directly affects the final performance of the machine learning model. This review provides a detailed classification of data preprocessing methods, which allows researchers to navigate the selection of effective approaches at different stages of system construction and make informed decisions in future studies on indoor localization.

To eliminate missing values and anomalies in RSSI data, it is recommended to use fingerprint correlation-based restoration methods, neighbor filtering, extended Kalman filter, autoencoders and GAN, which allow effective gap filling and adaptation of the radio map to changing conditions. To improve the stability of RSSI data, filtering methods such as Kalman filter, wavelet transform, autoencoders and RPCA are used, which effectively suppress random signal fluctuations. To remove outliers caused by interference or multipath propagation, clustering algorithms, RBFs, autoencoders, and GANs are used to automatically detect and correct outliers without distorting the overall structure of the data. Normalization of RSSI values ensures that the data is scaled to a single scale, reduces the impact of differences between access points, and improves the stability and convergence of machine learning models. Dimensionality reduction methods such as PCA, KPCA, autoencoder, t-SNE, and JRPCA eliminate redundant features, reduce the computational load, and improve the efficiency of algorithms without losing significant information. To expand the training set and improve the robustness of models to noise, synthetic fingerprint generation methods are used, including GANs, multivariate Gaussian processes, and modeling the spatial correlation between access points.

Thus, the choice of specific preprocessing methods should be based on the characteristics of the source data and the type of model used. Ideally, a localization system should include a combined pipeline that combines cleaning, filtering, normalization, and dimensionality reduction, tailored to the specifics of the environment. As with radio map generation, the choice of data preprocessing strategy is a researcher's responsibility and should be determined by the environment, available computing resources, and positioning accuracy requirements.

Fourthly, the selection of machine and deep learning algorithms is a key step in building a localization system, since the accuracy, speed, and adaptability of the entire system depend on the characteristics of the model.

Table 8 provides a structured comparison of ML, DL, TL, and RL algorithms for indoor locations based on RSSI fingerprints in terms of their advantages, disadvantages, positioning accuracy, power consumption, and reliability. It can serve as a practical reference for researchers to select appropriate algorithms for their systems. Ideally, an indoor localization algorithm should demonstrate very high positioning accuracy, achieving a consistently low error rate. At the same time, it should provide low power consumption and high reliability, maintaining stable operation in different conditions. Classical machine learning algorithms such as k-NN, Bayesian, SVM, and ensemble methods have proven themselves well with limited data and low computing resources, demonstrating high interpretability and ease of implementation. Deep learning algorithms, including MLP, CNN, RNN, LSTM, GRU, and their hybrid combinations (e.g., CNN + LSTM, CNN + AE), provide high accuracy due to the ability to model nonlinear dependencies and take into account the spatiotemporal features of the signal. However, such models require large amounts of data and increased computing resources. Of particular interest are hybrid architectures and transfer learning, which allow models to be adapted to new conditions with minimal fine-tuning. Thus, the choice of a specific algorithm should be based on data characteristics, resource constraints, accuracy and robustness requirements, and the ability of the model to adapt to a changing environment. The review provides researchers with a structured comparison of models and their metrics (MAE, RMSE, accuracy, CDF), allowing them to make an informed decision when designing a localization system.

Table 8. Comparative analysis of ML/DL/TL/RL algorithms for RSSI fingerprint-based indoor localization.

Algorithm	Advantages	Disadvantages	Positioning Accuracy	Power Consumption	Robustness
k-NN (ML)	Simple, easy to implement; interpretable	High inference cost with large datasets; sensitive to noise and radio map density	Medium	Medium	Medium
Bayesian methods (ML)	Very lightweight; efficient on low-power devices	Strong independence assumption; reduced accuracy in multipath environments	Medium	Low	Medium
SVM (ML)	High accuracy on small datasets; strong generalization	Poor scalability to large datasets; sensitive to kernel choice	Medium	Medium	Medium
Ensemble Methods (ML)	Robust to noise/outliers; good generalization; interpretable	Risk of overfitting with small datasets	High	Medium	High
FCN (DL)	Learns nonlinear relationships; flexible architecture	Requires large labeled datasets; prone to overfitting	High	Medium	Medium

Table 8. *Cont.*

Algorithm	Advantages	Disadvantages	Positioning Accuracy	Power Consumption	Robustness
CNN (DL)	Extracts spatial patterns effectively; strong performance on RSSI maps	High training cost; requires structured input	High	High	High
RNN (DL)	Captures temporal dependencies; useful for trajectory data	Long training time; High training cost	High	High	High
Autoencoder (DL)	Dimensionality reduction; denoising; improves generalization	Indirect metric optimization; tuning complexity	High	Medium	High
CNN + LSTM (Hybrid DL)	Combines spatial and temporal features; very strong in dynamic cases	Highly data- and compute-intensive	High	High	High
CNN + AE (Hybrid DL)	Robust to noise; learns latent features; combines denoising and spatial feature extraction	Training complexity; tuning complexity	High	High	High
TL	Reduces calibration effort; enables cross-building and cross-device adaptation	Highly data-intensive	High	Medium	High
RL	Enables online adaptation; learns calibration and navigation policies	Sample inefficiency; complex reward design	High	High	Medium

In addition, if difficulties arise in the development or implementation of localization systems, researchers can refer to Section 9, which discusses in detail the main problems faced by modern RSSI-based approaches.

11. Conclusions

This review provides a comprehensive overview of modern indoor positioning solutions based on the RSSI fingerprint method and ML algorithms. The principles of constructing a radiomap, data preprocessing stages, and various approaches to model training are considered—from classical algorithms to deep neural networks and hybrid architectures. Special attention is given to radiomap generation and adaptation methods, as well as the challenges of transferring models across different devices and environments.

The analysis showed that ML and DL can effectively process unstable RSSI signals, take into account nonlinear dependencies and adapt to environmental changes, which significantly improves positioning accuracy. However, several key challenges remain, including signal variability, multipath propagation, lack of line-of-sight, manual data collection requirements, device heterogeneity, noise, scalability, and high maintenance costs. These issues significantly hinder the creation of accurate and reliable radiomap. To address these limitations, promising directions include automated data collection (e.g., SLAM, crowdsourcing), applying generative models and data augmentation techniques, and implementing adaptive and domain-independent algorithms such as transfer learning and few-shot learning. Particular interest lies in the application of reinforcement learning for dynamic adaptation of localization in changing environments.

In addition to the analytical data, the review provides recommendations for the design of indoor localization systems based on RSSI fingerprint, covering all key components: selection of wireless technologies, radio mapping methods, data pre-processing strategies, and ML/DL model selection. These structured guidelines are intended to assist researchers and practitioners in future research and development of effective, sustainable and scalable localization solutions. Thus, future research in this field should focus on developing intelligent, robust, and scalable indoor localization systems suitable for real-world applications—from smart buildings and logistics to healthcare and industrial automation.

In a broader context, the findings and structured recommendations presented in the review can significantly contribute to the development of smart city initiatives. The integration of indoor localization systems into municipal IoT platforms will improve citizen mobility, optimize energy consumption, improve emergency response, and create a more responsive, data-driven urban environment.

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