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Indoor Localization Using Wi-Fi Fingerprinting with the Internet of Things: A Review

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Abstract

Indoor localization has gained significant attention recently due to the growing demand for location-aware applications within indoor environments. Among various techniques, Wi-Fi fingerprinting combined with the Internet of Things (IoT) has emerged as a promising solution for accurate and cost-effective indoor localization. This paper surveys the existing research related to indoor localization using Wi-Fi fingerprinting with the IoT, aiming to provide a comprehensive understanding of the advancements, challenges, and potential applications in this field. The paper begins by introducing the fundamental concepts of indoor localization and the role of Wi-Fi fingerprinting in achieving accurate position estimation. In addition, this paper focuses on the contributions of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in improving localization accuracy, robustness, and scalability. The reviewed papers have been examined from various aspects, including system architecture, deployment strategies, fingerprint creation techniques, and localization algorithms, with a discussion about the advantages and limitations of each approach. In addition to discussing the state-of-the-art techniques, this paper identifies research gaps and open challenges in indoor localization using Wi-Fi fingerprinting with the IoT. The findings presented in this paper can guide future research efforts, leading to the development of intelligent and context-aware IoT applications within indoor environments.

Keywords- Artificial Intelligence (AI), Indoor Localization, Internet of Things (IoT), Received Signal Strength (RSS).

I. INTRODUCTION

Indoor localization refers to the process of determining the position or location of objects, individuals, or devices within an indoor environment. Unlike outdoor environments where the Global Positioning System (GPS) can be used for localization, indoor spaces often lack reliable GPS signals, making it necessary to rely on alternative techniques. Indoor localization is crucial in various domains, including retail, healthcare, manufacturing, logistics, and smart homes. It enables applications such as asset tracking, indoor navigation, proximity-based marketing, security monitoring, and resource optimization within indoor spaces [1]. Several techniques are commonly used for indoor localization, including:

1. Wi-Fi Fingerprinting: This technique utilizes the presence and signal strength of Wi-Fi access points (APs) within an indoor space. By creating a database of Wi-Fi signal strength fingerprints at known locations, the current signal strengths measured by a device can be compared to estimate its position [2].
2. Bluetooth Low Energy (BLE) Beacons: BLE beacons are small devices that emit Bluetooth signals and can be deployed throughout an indoor environment. The signal strength of these beacons can be used to determine proximity and estimate the position of devices equipped with Bluetooth receivers [3].
3. Inertial Measurement Units (IMUs): IMUs consist of sensors like accelerometers, gyroscopes, and magnetometers, which can be used to measure the device's acceleration, rotation, and magnetic field. By integrating these measurements over time, it is possible to estimate the position and orientation of the device [4].
4. Ultrasonic and Infrared (IR) Signals: Ultrasonic or infrared transmitters and receivers can be placed in indoor spaces to measure these signals' time-of-flight or signal strength. Triangulation or trilateration techniques can then be applied to estimate the position of devices based on the measurements [5].
5. Magnetic Field Mapping: Magnetic fields within a building can vary based on the structure and presence of metallic objects. By mapping the magnetic field of an indoor space, it is possible to estimate a device's location by analyzing the changes in the magnetic field strength [1].

6. Radio Frequency Identification (RFID): RFID tags can be attached to objects or worn by individuals to enable localization within an indoor environment. RFID readers can detect the presence and location of these tags, allowing for asset tracking or personnel monitoring [1].

The choice of indoor localization technique depends on factors such as accuracy requirements, cost, infrastructure availability, and the specific use case. A combination of techniques or hybrid approaches is often employed to achieve higher accuracy and robustness [6].

Indoor localization continues to evolve with advancements in sensor technologies, Machine Learning (ML) algorithms, and the Internet of Things (IoT) proliferation. These developments enable real-time tracking, predictive analytics, and seamless integration with other smart systems, enhancing indoor experiences and increasing operational efficiencies [7].

The IoT is a transformative technology that connects various physical devices and objects, enabling them to communicate, share data, and collaborate with each other over the Internet. It represents a paradigm shift in how we interact with and leverage the power of everyday objects, making our environments smarter, more efficient, and more interconnected [8].

The architecture of the IoT consists of multiple layers and components that work together to enable seamless connectivity, data exchange, and intelligent decision-making. Fig. 1 shows the high-level overview of the typical architecture of the IoT that comprised of the following [9]:

- Perception Layer: The perception layer is the physical layer of the IoT architecture, comprising sensors, actuators, and devices that gather data from the surrounding environment. These devices can include temperature sensors, motion detectors, cameras, wearables, and other IoT-enabled devices that perceive and capture real-world data.
- Network Layer: The network layer facilitates the communication and connectivity between the IoT devices. It encompasses various communication technologies like Wi-Fi, Bluetooth, ZigBee, RFID, cellular networks, or Low-Power Wide-Area Networks (LPWANs). This layer ensures reliable and secure data transmission between devices and gateways.
- Gateway Layer: The gateway layer acts as an intermediary between the devices in the network layer and the cloud or central infrastructure. Gateways aggregate data from multiple devices, perform data preprocessing or filtering and establish a secure connection to transmit the data to the cloud or central server. They also enable local processing and decision-making at the network edge, reducing latency and bandwidth requirements.
- Cloud/Server Layer: The cloud or server layer forms the backbone of the IoT architecture, providing storage, processing, and managing the vast amount of data generated by IoT devices. Cloud platforms offer scalable and flexible infrastructure, allowing for data storage, analytics, and ML capabilities. They enable data aggregation, real-time processing, and integration of various IoT applications and services.
- Application Layer: The application layer encompasses the end-user applications and services that utilize the data and insights generated by the IoT infrastructure. These applications can be web-based dashboards, mobile apps, or specialized software that enable users to monitor and control IoT devices, visualize data, and make informed decisions based on IoT-generated information. The application layer is where the value and benefits of the IoT are realized, driving innovation across industries.
- Security and Privacy Layer: The security and privacy layer is a crucial component of the IoT architecture, addressing the challenges of securing the IoT ecosystem. It includes measures such as authentication, encryption, access control, data privacy, and secure communication protocols to protect the integrity, confidentiality, and privacy of IoT data and interactions.

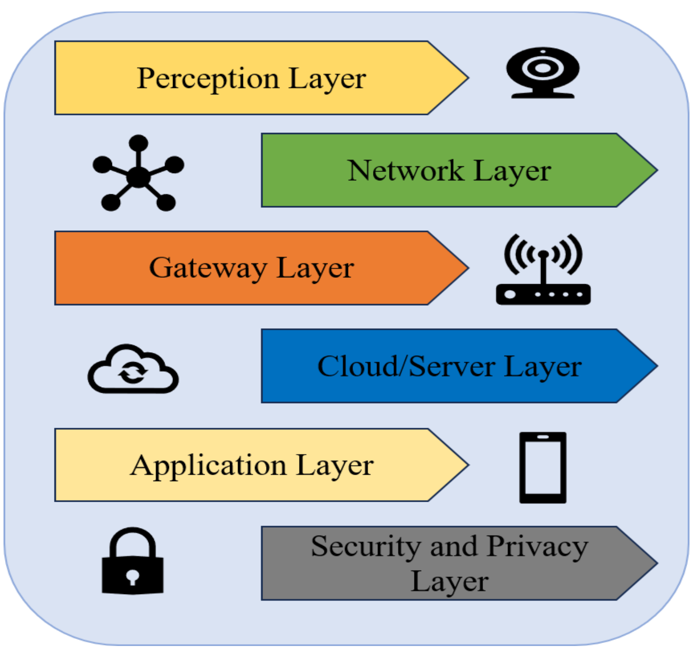

Fig. 1. The high-level overview of the typical IoT architecture

The architecture of the IoT is designed to enable seamless connectivity, data flow, and interoperability between the physical devices, the network, the cloud infrastructure, and the applications. It allows data collection, analysis, and utilization to drive intelligent decision-making, automation, and innovation in various domains, including smart homes, healthcare, agriculture, transportation, industrial automation, and more. As the IoT ecosystem evolves, the architecture will adapt to address new challenges and requirements, including edge computing, distributed processing, and integrating emerging technologies such as Artificial Intelligence (AI) and blockchain. The architecture will continue to shape the future of the IoT, enabling a connected and intelligent world with endless possibilities [10].

Wi-Fi fingerprinting, combined with the IoT, is a popular technique used for indoor localization. Wi-Fi fingerprinting relies on the presence of Wi-Fi APs and their signal strength to estimate a device's location. Each location within an indoor space has a unique set of Wi-Fi signal strength values from different APs, forming a "fingerprint" specific to that location. By comparing the current signal strengths of nearby APs with a pre-recorded database of fingerprints, it becomes possible to determine the device's approximate position. Combined with the IoT, Wi-Fi fingerprinting for indoor localization has become more powerful and versatile. The IoT refers to the interconnected network of physical devices embedded with sensors, software, and connectivity, enabling them to collect and exchange data. In the context of indoor localization, IoT devices can act as data collection points, transmitting Wi-Fi signal strength measurements to a central server or cloud platform [2].

The rest of the paper is organized as follows: Section II highlights the main applications that employ indoor localization in an IoT environment. While Section III provides a brief description of indoor localization techniques and algorithms. Section IV reviews the state-of-the-art research related to the utilization of Wi-Fi fingerprinting in indoor localization. On the other hand, Section V discusses the findings of the surveyed research and highlights the main tracks of future research directions. Finally, Section VI concludes the current work.

II. UTILIZING INDOOR LOCALIZATION IN IOT ENVIRONMENT

Indoor localization plays a crucial role in various IoT applications by enabling accurate tracking, monitoring, and automation within indoor environments. Below are some examples of how indoor localization is utilized in IoT applications [11-13]:

- Asset Tracking: IoT-enabled indoor localization allows real-time tracking and management of assets within buildings or warehouses. By attaching IoT devices or RFID tags to assets, their locations can be continuously monitored. This enables efficient asset utilization, reduces loss or theft, and streamlines inventory management.
- Smart Homes: Indoor localization in IoT-based smart homes allows for personalized automation and enhanced user experiences. By tracking the location of individuals within the home, various smart devices can respond accordingly. For example, lights can turn on/off automatically as someone enters or leaves a room, heating or cooling systems can adjust based on occupancy, and home appliances can operate based on the user's proximity.
- Indoor Navigation: IoT-based indoor navigation systems utilize indoor localization to guide individuals within complex buildings or venues. By integrating real-time location data with interactive maps and directions, users can easily navigate indoor spaces, find specific points of interest, and receive location-based information or promotions. This is particularly useful in airports, shopping malls, museums, or large office buildings.
- Industrial Automation: Indoor localization in industrial settings improves automation and safety. IoT devices with localization capabilities can track the location of goods, vehicles, or workers in warehouses or manufacturing plants. This enables efficient logistics, optimizes workflows, and enhances worker safety by alerting them to potential hazards or ensuring compliance with restricted zones.
- Healthcare: Indoor localization is valuable for asset tracking, patient monitoring, and workflow optimization in healthcare environments. IoT devices integrated with localization can track medical equipment, locate staff members, monitor patient movement, and automate patient flow management. This improves efficiency, reduces errors, and enhances patient care and safety.
- Retail and Marketing: Indoor localization combined with IoT devices enables personalized marketing and customer analytics in retail environments. By tracking the location and movement of customers, retailers can offer targeted promotions, optimize store layouts, and gain insights into customer behavior and preferences. This improves the shopping experience and increases customer engagement.
- Safety and Security: Indoor localization is utilized in IoT-based safety and security systems. By monitoring the location of individuals or assets, security systems can detect unauthorized access, track evacuations during emergencies, and provide real-time information to first responders. It enhances situational awareness and ensures timely responses to critical events.

III. INDOOR LOCALIZATION TECHNIQUES AND ALGORITHMS

In recent years, indoor localization has experienced notable progress due to the increasing need for location-aware applications in interior environments. In contrast to outdoor environments where GPS-based methods are frequently utilized, indoor localization poses distinct obstacles, including restricted GPS accessibility, multipath effects, and signal attenuation. Consequently, a multitude of methods and algorithms have been devised by researchers to specifically tackle these challenges and attain precise positioning within indoor environments [14]. The following is a summary of the many different methods and algorithms for indoor localization that have been proposed in the academic literature. The essential ideas underlying these methods and their benefits, drawbacks, and applicability to various indoor settings are discussed. This section seeks to provide a thorough overview of the developments in indoor localization by examining the state-of-the-art methodologies, and to direct future research in this rapidly growing topic.

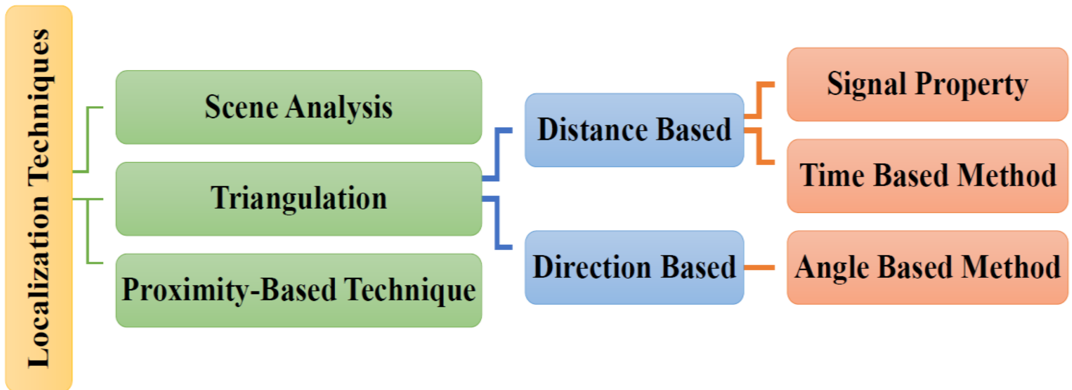

Fig. 2. Indoor localization techniques

The indoor localization techniques include the following, and Table I summarizes them from different perspectives [15]-[18]:

1. Scene Analysis

The primary principle underlying scene analysis methods, also called fingerprinting, involves leveraging distinctive characteristics of a given scene at a particular location to describe and subsequently recognize that location. Therefore, the determination of the coordinates of an unidentified point can be deduced by analyzing the resemblance of observed scene attributes. The accuracy and complexity of this positioning method are determined by the nature of these features and their respective representations.

2. Triangulation

Triangulation is a method that leverages the geometric attributes of triangles in order to ascertain the precise position of a given target. There are two derivations associated with it: lateration and angulation. The techniques that utilize the measurement of propagation time in a system, such as Time of Arrival (TOA), Round-Trip Time of Flight (RTOF), and Time Difference of Arrival (TDOA), as well as methods based on Received Signal Strength (RSS) and received signal phase, are collectively referred to as lateration techniques. The AOA estimation technique, alternatively referred to as an angulation technique, is a commonly employed method in various academic disciplines.

- Lateration

  The three terms, namely lateration, trilateration, and multi-lateration, pertain to determining a position based on distance measurements. Lateration or trilateration is a method employed to ascertain the precise location of an object by measuring the distances between said object and multiple reference points. This technique is alternatively referred to as range measurement. Trilateration is a geometric method requiring a minimum of three fixed points to ascertain a position accurately. The techniques that utilize the measurement of propagation-time system, such as Time of Arrival (TOA), Round-Trip Time of Flight (RTOF), and Time Difference of Arrival (TDOA), as well as methods based on Received Signal Strength (RSS) and received signal phase, are commonly referred to as lateration techniques.

  – Round-Trip Time (RToF) and Round-Trip Time (RTT)

    It calculates the distance traveled by the signal pulse from the transmitting device to the measuring equipment and back. In TOA, the transmission and receiving times are recorded by two local clocks in each node, whereas in RTT, only one node is used. This benefit allows this technique to address the synchronization issue partially. These method's range measurements to various devices must be performed in succession, which might result in dangerous latencies for situations where devices move fast.

  – The Time of Arrival (ToA) and the Time of Flight (ToF)

    Systems for measuring the arrival time of signals emitted from mobile devices to several receiving beacons are known as Time of Arrival (ToA) systems. In ToA, the mobile device sends a signal with a time stamp to beacons that are receiving it. [17]The transmission time delay and accompanying signal speed are used to determine the distance across the mobile node and the receiving end of beacons at the moment of reception. The transmission start time(s) must be known with precision for the ToA approach to work. This allows for proper synchronization of mobile devices and receiving beacons with an accurate time source. ToA is the most precise method for removing multi-path effects in an indoor setting. The need for exact time synchronization across all devices is one of the drawbacks of the TOA technique. The system's cost will increase since a second server is required for time delay measurement. Along with this, a denser environment, one with more people, can also cause an increase in latency.

- Angle-Based Method

With the use of the Angle of Arrival (AoA) approach, it is possible to pinpoint the angle at which several base stations receive a mobile signal from a specific place. AoA technique only needs two beacons to estimate location in a 2D dimension plane. Location estimate (triangulation) is performed using three or more beacons to increase accuracy. It requires extremely directional antennas or antenna arrays for direction detection. The point of intersection of two Lines of Bearing (LoBs) can then be estimated from the known reference locations using geometric relationships. Techniques based on AoA have inherent limitations. The need for more antennas to measure angles increases the expense of developing an AoA system.

- Signal Property-Based Method
  Most wireless localization systems use time information or angle-based calculations to determine how far away the positioning device is. They are affected by the multipath effect in both cases. This may result in a reduction in predicted location accuracy. The alternative technique uses the attenuation of the outgoing signal intensity to calculate the distance between the unknown node and the reference node using various sets of measurement units. Only radio transmissions are compatible with this technique. The majority of wireless localization systems employ the received signal's attributes to determine where to place the positioning device, with the (RSSI) being the most popular signal-related aspect. Estimates of RSSI measurements are nonlinear and strongly reliant on environmental influence. These techniques utilize WiFi technology. Because a server is required to deploy this system, this technology can only be used with access points less expensive than Wi-Fi routers.

3. Proximity Detection

One of the easiest positioning techniques to use is proximity detection or connectivity-based. Information about the relative position is provided symbolically. The cell of origin (CoO) approach with a known position and constrained range is used to identify the position of mobile device clients[19]. When more than one beacon locates a moving target, it simply relays the location with the strongest signal. The deployment density of beacon points and signal range have an impact on CoO accuracy. Several wireless location methods are used to accomplish this technique, including the system operating IR, RFID, GSM (Cell-ID), Bluetooth, and bespoke radio devices.

Table I: summary of indoor localization techniques

Techniques	Measurement Type	Indoor Accuracy	Cost	Affected by Multipath	Line of Sight / Non-Line of Sight	Coverage	Details
Scene Analysis	Received Signal Strength	High	Medium	No	Both	Good	(1) Demands rigorous calibration. (2) The antenna's position.
ToA	Time of arrival	High	High	Yes	Los	Good	(1) The necessity for time synchronization. (2) The antenna's location must be provided.
AoA	Angle of Arrival	medium	high	yes	Los	good	(1) The angular characteristics of the antenna affect accuracy. (2) The antenna's location must be provided.
Proximity	Signal Type	Low to High	Low	No	both	good	(1) Adding an extra antenna can increase accuracy. However, the price will go up. (2) Accuracy is roughly equivalent to cell size.

IV. LITERATURE REVIEW

The rapid advancements in ML and Deep Learning (DL) techniques have revolutionized various fields, including the domain of indoor localization in the IoT using Wi-Fi fingerprinting. DL algorithms have demonstrated exceptional capabilities in capturing intricate patterns and relationships in complex data. This section presents a comprehensive literature review that surveys recent research on Wi-Fi fingerprinting for IoT indoor localization, focusing specifically on integrating DL techniques. In addition, this section examines the state-of-the-art approaches, methodologies, and advancements in this field, highlighting the contributions, limitations, and potential applications of DL in enhancing the accuracy and scalability of indoor localization. By exploring the recent literature, this section aims to provide a comprehensive overview of the research landscape and identify emerging trends and opportunities for future exploration and innovation in Wi-Fi fingerprinting for IoT indoor localization using deep learning techniques [19].

Hoang *et al.* in.[20] presented a Wi-Fi-based fingerprinting localization system that utilized Recurrent Neural Networks (RNNs). The authors suggested a trajectory positioning that considered the correlation among various RSSI values in the trajectory. Different RNN-based algorithms had been employed, including long short-term memory (LSTM), bidirectional LSTM (BiLSTM), vanilla RNN, gated recurrent unit (GRU), bidirectional GRU (BiGRU), and bidirectional RNN (BiRNN). The experimental results demonstrated that their introduced approach reached an average location error of 0.75m and outperformed other ML algorithms by 30%. The authors concluded that 80% of error was achieved under 1m for approximate location.

Alitaleshi *et al.* in [21] introduced an Extreme Learning Machine (H-ELM) approach that was based on a Wi-Fi-fingerprinting technique for floor determination in an indoor environment. The authors employed UJIIndoorLoc dataset to validate their introduced approach, and the author argued that their approach achieved higher accuracy than other state-of-the-art solutions. The accuracy obtained from their experimental scenarios was 99.71% and 98.13% for both the training and testing phases.

Kim *et al.* in [22] introduced the Deep Neural Network (DNN) approach for scalable indoor localization techniques using Wi-Fi fingerprinting. Their proposed approach utilized a stacked autoencoder and feed-forward classifier to reduce the dimension of the feature space and multi-label classification, respectively. The UJIIndoorLoc dataset was employed to evaluate the presented approach by the authors, and they argued that their approach achieved a success rate of 91.18% with a positioning error of 9.29m.

Song *et al.* in [23] proposed a convolutional neural network-based indoor localization that adopted the fingerprint of W-Fi signal in multiple building with multiple floors. The authors utilized a One Dimensional-Convolutional Neural Network (1D-CNN) with stacked auto encoder. The UJIIndoorLoc dataset was utilized to evaluate their approach and the experimental results demonstrated that their approach achieved the highest success rates of 96.03% with position error of 11.78m.

González *et al.* in [24] combined the Wi-Fi fingerprinting approach with battery-saving techniques to determine the location of a user in an indoor environment. The users' mobile devices periodically scanned the available Wi-Fi networks by an application running in the background. While the location calculations were performed on a remote server. The authors considered the location accuracy and the device’s energy consumption while analyzing the obtained results. The authors argued that the mobile device consumed 0.8Wh while running on a 3.7V battery for a 24-hour cycle. On the other hand, the average localization error reached 4.51 meters.

Xue *et al.* in [25] presented a new approach for improving the RSSI observations by adopting an averaging technique that averaged the maximum RSSI values of selected networks. Also, the authors adopted the smoothness index employed for evaluating the RSSI quality and selecting the appropriate RSSI observations. The authors run their experiments in a building with four rooms and a corridor. The results obtained from their introduced approach showed a remarkable improvement in positioning accuracy when compared to other algorithms like the Kalman filtering algorithm, the particle filter algorithm, and the mean algorithm.

Zhang and Su in [26] proposed an indoor localization approach called the deep neural network method used for indoor positioning (DNNIP). The author employed the UJIIndoorLoc dataset, while their introduced model was based on auto-encoder and data stratification approaches. The authors argued that their developed approach eliminate the manual match of RSSI of the received Wi-Fi signal to determine the position of a user in an indoor environment, but rather, the process was done automatically. The results from their approach showed that the DNNIP approach achieved better classification accuracy when compared to other ML algorithms.

Nowicki *et al.* in [27] aimed to develop a DNN model to determine the location in an indoor environment that was characterized by lowering the location-determining system's computation burden. The authors argued that their approach still achieved satisfactory accuracy. The feature space in their approach was reduced using an autoencoder while achieving accurate classification. They validated their approach using the UJIIndoorLoc dataset, and their approach was compared to other solutions in the literature.

Apostolo *et al.* in [28] created a small dataset from the UJIIndoorLoc dataset to train their model that was based on the Deductive Separation for Indoor Positioning (DESIP) approach. The authors employed six ML algorithms to train and test their developed model. The authors declare that the accuracy for both the tailored and original datasets were similar when classifying the building and floor. Another finding from their obtained results showed that the region attribute achieved better accuracy when employing the original dataset than the tailored dataset.

Khatab *et al.* in [29] proposed a method that utilized an autoencoder approach to improve indoor localization performance during feature extraction and classification phases. The simulation results from their introduced approach showed that increasing the number of training datasets could significantly affect localization accuracy. The authors argued that their developed approach outperformed other ML models regarding localization success rate.

Bozkurt *et al.* in [30] compared several ML algorithms to study their effectiveness for indoor localization applications that employed the RSS of Wi-Fi radio. The authors adopted the UJIIndoorLoc dataset to train their developed model based on the Wi-Fi Fingerprinting approach. The authors argued that the K-Nearest Neighbor (KNN) algorithm outperformed other algorithms regarding computation time and model accuracy. In addition, the authors improved the Decision Tree (DT) classifier by utilizing AdaBoost and

Bagging ensembled algorithms that achieved an accuracy approximately similar to the KNN algorithm for indoor positioning applications when several experimental scenarios were conducted.

Adege *et al.* in [31] built a customized dataset comprising RSS of the Wi-Fi signal and the Basic Service Set Identifiers (BSSIDs). The generated dataset was preprocessed through two phases: missing value recovery of the RSS values using regression and reducing the dataset's features using Linear Discriminant Analysis (LDA). The authors utilized DNN to localize the user in an indoor environment based on Wi-Fi fingerprint. The simulation results from their developed approach showed significant improvements in classification accuracy, which is 99.15% compared to other ML algorithms.

Koike-Akino *et al.* in [32] built a customized dataset constructed using spatial beam Signal-To-Noise Ratios (SNRs) and mid-grained intermediate-level channel measurements obtained directly from IEEE 802.11ad/ay standards. The authors utilized DL algorithms to validate the developed approach using an in-house experimental platform comprising three millimeter-wave Wi-Fi routers. The authors achieved an accuracy of 99% for their introduced DL model.

Table II summarizes the state-of-the-art research that was reviewed in this paper.

Table II: The summary of the reviewed papers

Ref.	year	Dataset	AI Technique	Remarks and Accuracy
[20]	2019	UJIIndoorLoc, Customize Dataset	RNNs	Error =0.75 m, and the model accuracy was 30% better than KNN and probabilistic algorithms.
[21]	2020	UJIIndoorLoc	H-ELM	Simple, fast, and efficient
[22]	2018	UJIIndoorLoc	DNNs	Lower complexity and energy consumption on mobile devices
[23]	2019	UJIIndoorLoc, Tampere	SAE,1D CNN	Accuracy=96.03%
[24]	2019	Energy-Efficient Indoor Localization Wi-Fi Fingerprint System	Naive Bayes, KNN	Error = 4.51 meters, and the reduction in the consumed energy was 8%
[25]	2017	Customize Dataset	KNN	– The suggested technique outperforms mean, Kalman filtering, and particle filtering in positioning accuracy. – Computational simplicity and robustness
[26]	2021	UJIIndoorLoc	SAE, DNN	– Higher classification accuracy than UJIIndoorLoc-based ML methods. – Accuracy=88.9%
[27]	2017	UJIIndoorLoc	SAE, DNN	Develop reliable and accurate classification
[28]	2019	UJIIndoorLoc, Customize Dataset	J48, BayesNet, KNN, SMO, Adaboost J48, Bagging J48	– J48, using the AdaBoost iterative algorithm, performed best on both database subsets. – The decreased database subsets had shorter elapsed times for every classification.
[29]	2018	Customize Dataset	AE, ELM	Accuracy was 94.75%, and the developed model aimed to enhance localization while gradually increasing the training data.

[30]	2015	UJIIndoorLoc	k-NN, DT, Naive Bayes	The KNN technique is best for positioning, according to experiments.
[31]	2018	Customize Dataset	DNN	There is an improvement in the computational time complexity while the model accuracy is 99.15% and 100%
[32]	2020	Customize Dataset	DNN	Accuracy=100% and 99%

V. RESULTS AND DISCUSSIONS

This section thoroughly studies the conclusions and revelations drawn from the recently reviewed research on Wi-Fi fingerprinting for IoT indoor localization utilizing DL methods. The findings of the evaluated papers have been examined in this area, with a particular emphasis on the functionality, precision, and potency of DL-based methods for indoor localization.

Indoor localization by the use of RSSI fingerprinting is one of the methods that is usually considered to be one of the most precise methods, and it produces results that are quite accurate. The UJIIndoorLoc database has emerged as the publication that uses datasets most frequently, accounting for 61.538% of the total reviewed papers. This is due to the fact that the database offers a wide range of advantages and is quite practical. A significant number of different labels and features characterize the dataset. The authors used a dataset with over 21,000 samples collected in various ways, as well as 520 access points. They covered a surface area of 108703 separate meters with three buildings with 4 and 5 levels. The results of this dataset showed significant accuracy and just a little variance when compared to GPS results. In addition, the researchers utilized a different dataset that was adapted specifically to the experimental environment. This was done in conjunction with the inclusion of a publicly accessible energy-efficient dataset by the researchers. Each and every one of the revised articles makes use of machine learning and deep learning techniques. Both the procedures that are used to prepare databases and the architectural layouts that are used for the models may be approached in a number of different ways. During the preprocessing step, several researchers utilized various methods for their models. These methods included relational labeling, diverse labeling, relational labeling, and filtering approaches. The feature reduction process is the primary focus of exploiting the model architecture component contained inside the autoencoder. The deployment of a number of different neural network combinations accomplishes this. In deep learning, the deep neural network is the most common type of underlying architecture. A great number of researchers have centered their attention on analyzing energy consumption, the complexity of models, and the shortening of the time required for training. It was determined that the amount of accuracy seen in the assessed articles was 99%, indicating a high degree of precision in the presented findings. According to the vast majority of the reviewed research, localization was utilized to accomplish several objective classifications. These classifications included the identification of the building and floor. The subsequent investigations concentrated on positional regression, especially the estimation of longitude and latitude.

VI. CONCLUSIONS

This review paper surveyed the research on Wi-Fi fingerprinting indoor localization in IoT environments using ML techniques. The combination of Wi-Fi fingerprinting and ML has demonstrated significant potential for accurate and robust indoor positioning in the context of IoT applications. The discussion included the strengths and limitations of Wi-Fi fingerprinting with ML, highlighted the advancements in the field, and provided insights into its practical implementation.

Our review reveals that when combined with ML algorithms, Wi-Fi fingerprinting can effectively overcome indoor localization challenges, such as signal attenuation, multipath effects, and limited GPS availability. ML techniques enable the creation of models that can learn complex relationships between Wi-Fi signal fingerprints and locations, improving accuracy and adaptability in dynamic indoor environments.

Building on the research surveyed, several future trends and areas of development for Wi-Fi fingerprinting indoor localization in IoT environments using ML can be summarized as follows:

- Hybrid Localization Techniques: Integrating Wi-Fi fingerprinting with other localization techniques, such as sensor fusion or magnetic field-based localization, holds promise for achieving even higher accuracy and robustness in indoor positioning. Hybrid approaches that combine the strengths of multiple technologies can lead to more reliable localization results.
- Deep Learning Architectures: Deep learning architectures, such as deep neural networks, convolutional neural networks (CNNs), or recurrent neural networks (RNNs), have shown exceptional performance in various domains. Future research should explore the application of these architectures to Wi-Fi fingerprinting indoor localization, leveraging their ability to capture intricate spatial dependencies and temporal dynamics.

- Transfer Learning: Transfer learning techniques can be leveraged to enhance the efficiency and effectiveness of Wi-Fi fingerprinting indoor localization. Pre-trained models or knowledge from similar environments can be used to accelerate the training process and improve localization performance, particularly in scenarios where collecting large amounts of training data is challenging.
- Real-Time and Edge Computing: Real-time localization is crucial for time-sensitive IoT applications. Future research should focus on developing ML-based algorithms that can provide fast and real-time localization results, enabling rapid decision-making and dynamic tracking of IoT devices. Moving the computation and localization models closer to the edge devices can improve localization efficiency, reduce network latency, and enhance privacy.
- Scalability and Resource Constraints: As IoT deployments scale up, there is a need for Wi-Fi fingerprinting techniques that can handle large numbers of devices and access points efficiently. Research should address the scalability challenges and resource constraints associated with Wi-Fi fingerprinting in IoT environments, including optimizing fingerprint creation, management, and localization algorithms for high-density deployments.
- Privacy and Security: Protecting user privacy and ensuring location data security are critical considerations in Wi-Fi fingerprinting indoor localization. Future research should explore privacy-preserving ML techniques, secure communication protocols, and encryption methods to safeguard sensitive location information and address potential vulnerabilities.

In summary, Wi-Fi fingerprinting indoor localization in IoT environments using ML is a promising area of research that has the potential to revolutionize indoor positioning applications. By addressing the identified future trends, researchers can further advance the field, making Wi-Fi fingerprinting with ML a cornerstone technology for accurate and scalable indoor localization in diverse IoT domains such as smart homes, healthcare, logistics, and industrial automation.

REFERENCES

[1] H. Obeidat, W. Shuaieb, O. Obeidat, and R. Abd-Alhameed, “A Review of Indoor Localization Techniques and Wireless Technologies,” in *Wireless Personal Communications*, vol. 119, no. 1, pp. 289–327, February, 2021.
[2] S. He and S.-H. G. Chan, "Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons," in *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 466-490, Firstquarter 2016.
[3] G. Fischer; J. Bordoy; D. J. Schott; W. Xiong; A. Gabbrielli; F. Höflinger; K. Fischer, C. Schindelhauer, and S. J. Rupitsch, "Multimodal Indoor Localization: Fusion Possibilities of Ultrasonic and Bluetooth Low-Energy Data," in *IEEE Sensors Journal*, vol. 22, no. 6, pp. 5857-5868, March, 2022.
[4] C. Chen, C. X. Lu, J. Wahlström, A. Markham and N. Trigoni, "Deep Neural Network Based Inertial Odometry Using Low-Cost Inertial Measurement Units," in *IEEE Transactions on Mobile Computing*, vol. 20, no. 4, pp. 1351-1364, April, 2021.
[5] H. Yucel, R. Edizkan, T. Ozkir and A. Yazici, "Development of indoor positioning system with ultrasonic and infrared signals," in *2012 International Symposium on Innovations in Intelligent Systems and Applications*, Turkey, 2012, pp. 1-4.
[6] C. Kammel, T. Kögel, M. Gareis and M. Vossiek, "A Cost-Efficient Hybrid UHF RFID and Odometry-Based Mobile Robot Self-Localization Technique With Centimeter Precision," in *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 467-480, 2022.
[7] A. B. M. M. Rahman, T. Li, and Y. Wang, “Recent Advances in Indoor Localization via Visible Lights: A Survey,” in *Sensors*, vol. 20, no. 5, p. 1382, March, 2020.
[8] D. T. Vo *et al.*, "SWIPT-Enabled Cooperative Wireless IoT Networks With Friendly Jammer and Eavesdropper: Outage and Intercept Probability Analysis," in *IEEE Access*, vol. 11, pp. 86165-86177, 2023.
[9] H. Kaur and R. Kumar, “A Survey on Internet of Things (IoT): Layer-Specific, Domain-Specific and Industry-Defined Architectures,” in *Advances in Intelligent Systems and Computing*, pp. 265–275, June, 2020.
[10] S. S. Gill, S. Tuli, M. Xu, I. Singh, K. V. Singh, D. Lindsay, S. Tuli, D. Smirnova, M. Singh, U. Jain, H. Pervaiz, B. Sehgal, S. S. Kaila, S. Misra, M. S. Aslanpour, H. Mehta, V. Stankovski, and P. Garraghan,, “Transformative Effects of IoT, Blockchain and Artificial Intelligence on Cloud Computing: Evolution, Vision, Trends and Open Challenges,” in *Internet of Things*, vol. 8, pp. 100118, December, 2019.
[11] V. Bianchi, P. Ciampolini and I. De Munari, "RSSI-Based Indoor Localization and Identification for ZigBee Wireless Sensor Networks in Smart Homes," in *IEEE Transactions on Instrumentation and Measurement*, vol. 68, no. 2, pp. 566-575, February, 2019.
[12] M. S. Al-kahtani, F. Khan, and W. Taekeun, “Application of Internet of Things and Sensors in Healthcare,” in *Sensors*, vol. 22, no. 15. pp. 5738, July, 2022.
[13] S. M. Asaad and H. S. Maghdid, “A Comprehensive Review of Indoor/Outdoor Localization Solutions in IoT Era: Research Challenges and Future Perspectives,” in *Computer Networks*, vol. 212, pp. 109041, July, 2022.
[14] A. Yassin, Y. Nasser, M. Awad, A. Al-Dubai, R. Liu, C. Yuen, R. Raulefs, and E. Aboutanios, "Recent Advances in Indoor Localization: A Survey on Theoretical Approaches and Applications," in *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 1327-1346, Secondquarter 2017.

[15] A. Papapostolou and H. Chaouchi, “Scene Analysis Indoor Positioning Enhancements,” in *Annals of Telecommunications - Annales des Télécommunications*, vol. 66, no. 9–10, pp. 519–533, November, 2010.
[16] E. Teoman and T. Ovatman, "Trilateration in Indoor Positioning with an Uncertain Reference Point," *2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC)*, Canada, 2019, pp. 397-402.
[17] Y. Hu, M. Z. Ozturk, B. Wang, C. Wu, F. Zhang and K. J. R. Liu, "Robust Passive Proximity Detection Using Wi-Fi," in *IEEE Internet of Things Journal*, vol. 10, no. 7, pp. 6221-6234, 1 April1, 2023.
[18] F. Zafari, A. Gkelias and K. K. Leung, "A Survey of Indoor Localization Systems and Technologies," in *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2568-2599, Thirdquarter 2019.
[19] S. Tiku and S. Pasricha, Machine Learning for Indoor Localization and Navigation. Springer International Publishing, 2023.
[20] M. T. Hoang, B. Yuen, X. Dong, T. Lu, R. Westendorp and K. Reddy, "Recurrent Neural Networks for Accurate RSSI Indoor Localization," in *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 10639-10651, December, 2019.
[21] A. Alitaleshi, H. Jazayeriy and S. J. Kazemitabar, "WiFi Fingerprinting based Floor Detection with Hierarchical Extreme Learning Machine," in *2020 10th International Conference on Computer and Knowledge Engineering (ICCKE)*, Iran, 2020, pp. 113-117.
[22] K. S. Kim, S. Lee, and K. Huang, “A Scalable Deep Neural Network Architecture for Multi-Building and Multi-Floor Indoor Localization Based On Wi-Fi Fingerprinting,” in *Big Data Analytics*, vol. 3, no. 1, April, 2018.
[23] X. Song, X. Fan, C. Xiang, Q. Ye, L. Liu, Z. Wang, X. He, N. Yang, and G. Fang, "A Novel Convolutional Neural Network Based Indoor Localization Framework With WiFi Fingerprinting," in *IEEE Access*, vol. 7, pp. 110698-110709, 2019.
[24] J. L. Salazar González, L. M. Soria Morillo, J. A. Álvarez-García, F. Enríquez De Salamanca Ros and A. R. Jiménez Ruiz, "Energy-Efficient Indoor Localization WiFi-Fingerprint System: An Experimental Study," in *IEEE Access*, vol. 7, pp. 162664-162682, 2019.
[25] W. Xue, W. Qiu, X. Hua and K. Yu, "Improved Wi-Fi RSSI Measurement for Indoor Localization," in *IEEE Sensors Journal*, vol. 17, no. 7, pp. 2224-2230, 1 April1, 2017.
[26] J. Zhang and Y. Su, “A Deep Neural Network Based on Stacked Auto-encoder and Dataset Stratification in Indoor Location,” in *Computational Science – ICCS 2021*, pp. 33–46, 2021.
[27] M. Nowicki and J. Wietrzykowski, “Low-Effort Place Recognition with WiFi Fingerprints Using Deep Learning,” in *Automation 2017*, pp. 575–584, 2017.
[28] G. H. Apostolo, I. G. B. Sampaio, and J. Viterbo, “Feature Selection on Database Optimization for Wi-Fi Fingerprint Indoor Positioning,” in *Procedia Computer Science*, vol. 159, pp. 251–260, 2019.
[29] Z. E. Khatab, A. Hajihoseini and S. A. Ghorashi, "A Fingerprint Method for Indoor Localization Using Autoencoder Based Deep Extreme Learning Machine," in *IEEE Sensors Letters*, vol. 2, no. 1, pp. 1-4, March 2018.
[30] S. Bozkurt, G. Elibol, S. Gunal and U. Yayan, "A comparative study on machine learning algorithms for indoor positioning," in *2015 International Symposium on Innovations in Intelligent SysTems and Applications (INISTA)*, Spain, 2015, pp. 1-8.
[31] A. Adege, H.-P. Lin, G. Tarekegn, and S.-S. Jeng, “Applying Deep Neural Network (DNN) for Robust Indoor Localization in Multi-Building Environment,” in *Applied Sciences*, vol. 8, no. 7, p. 1062, June, 2018.
[32] T. Koike-Akino, P. Wang, M. Pajovic, H. Sun and P. V. Orlik, "Fingerprinting-Based Indoor Localization with Commercial MMWave WiFi: A Deep Learning Approach," in *IEEE Access*, vol. 8, pp. 84879-84892, 2020.