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A Survey of Machine Learning for Indoor Positioning

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ABSTRACT Widespread proliferation of wireless coverage has enabled culmination of number of advanced location-based services (LBS). Continuous tracking of accurate physical location is the foundation of these services, which is a challenging task especially indoors. Multitude of techniques and algorithms have been proposed for indoor positioning systems (IPS's). However, accuracy, reliability, scalability and, adaptability to the environment still remain as challenges for widespread deployment. Especially, unpredictable radio propagation characteristics in vastly varying indoor environments plus access technology limitations contribute to these challenges. Machine learning (ML) approaches have been widely attempted recently to overcome these challenges with reasonable success. In this paper, we aim to provide a comprehensive survey of ML enabled localization techniques using most common wireless technologies. First, we provide a brief background on indoor localization techniques. Afterwards, we discuss various ML techniques (supervised and unsupervised) that could alleviate different challenges in indoor localization including Non-line-of-sight (NLOS) issue, device heterogeneity and environmental variations with reasonable complexity. The trade-offs among multitude of issues are discussed using numerous published results. We also discuss how the ML algorithms can be effectively used for fusing different technologies and algorithms to achieve a comprehensive IPS. In essence, this survey will serve as a reference material to acquire a detailed knowledge on recent development of machine learning for accurate indoor positioning.

INDEX TERMS Indoor positioning system (IPS), location-based services (LBS), machine learning (ML), non-line-of-sight (NLOS), wireless positioning, indoor tracking.

I. INTRODUCTION

Accurate real time positioning is the key to enable location-based services (LBS). Although the global positioning system (GPS) is widely used for localization in outdoors, the GPS usability is not satisfactory in the confined indoor environments. Unlike outdoor, indoor environments are very complex with varying shapes, sizes with the presence/absence of stationary and moving objects (e.g. furniture and people). These factors significantly alter both line-of sight (LOS) and non-line of sight (NLOS) radio signal propagation causing unpredictable attenuation, scattering, shadowing and blind spots that significantly degrade the accuracy of indoor positioning.

However, due to the high demand for LBS, significant attention has been made on the development of indoor positioning systems (IPS) recently. Typical ranging techniques based on received-signal-strength-indicator (RSSI) [1], time-of-arrival (ToA) [2], time-difference-of-arrival (TDoA) [3], angle-of-arrival (AoA) [4], and channel-state-information (CSI) [5] have been proposed using various access technologies such as Wi-Fi [6], Bluetooth [7], ultra wide band (UWB) [8], and radio-frequency identification tags (RFID) [9] for indoor positioning. Most ranging techniques require at least three known anchor nodes to calculate the location of the unknown target. Few range free techniques such as Centroid [10] method and DV hop [11] technique are also studied in the literature.

All these approaches suffer from multitude of challenges including poor accuracy, high computational complexity, and unreliability while, most positioning devices lack strong processing power. In addition, the ability to maintain big databases (for large scale IPS) while ensuring security and privacy, and supporting device heterogeneity at a reasonable cost are some other challenges in indoor localization [12].

In recent years, artificial intelligence (AI) and machine learning (ML) algorithms find good success in indoor local-

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TABLE 1. Selected Acronyms and their explanations.

Acronym	Explanation
AI	Artificial Intelligence
ANN	Artificial Neural Network
AoA	Angle of Arrival
AP	Access Point
BLE	Bluetooth Low Energy
BM	Boltzmann Machine
CIR	Channel Impulse Response
CNN	Convolutional Neural Networks
CSI	Channel State Information
CTF	Channel Transfer Function
DBL	Device Based Localization
DBN	Deep Belief Network
DL	Deep Learning
DNN	Deep Neural Network
EKF	Extended Kalman Filtering
ELM	Extreme Learning Machine
FCF	Frequency Coherence Function
KNN	K-Nearest Neighbour
KPCA	Kernel Principal Components Analysis
LDA	Linear Determinant Analysis
LOS	Line of Sight
LS	Least Squares
LSTM	Long Short Term Memory
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MLP	Multi-Layer Perceptron
NLOS	Non-Line of Sight
PDR	Pedestrian Dead Reckoning
PCA	Principal Component Analysis
RBM	Restricted Boltzmann Machine
RF	Radio Frequency
RFID	Radio Frequency Identification Device
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RSSI	Received Signal Strength Indicator
SVM	Support Vector Machine
SVR	Support Vector Regressor
TDoA	Time Difference of Arrival
ToA	Time of Arrival
UWB	Ultra Wide Band

ization [13]–[16]. The main advantage of AI/ML approaches is their ability to make decisions effectively using observed data without accurate mathematical formulation.

For example, the authors in [17]–[20] have applied supervised and unsupervised ML techniques for NLOS identification and mitigation while deep learning (DL) technique is applied for NLOS mitigation in [14]. A DL Recurrent neural network (RNN) has been used to cope with RSSI signal fluctuation by exploring its time domain correlation in [13]. Moreover, DL techniques have been used to extract the hidden features of the RSSI measurement to minimize the collection of fingerprint data in [21] and explore the unknown environment during robot navigation in [22]. In addition, supervised and unsupervised learning-based dimension reduction techniques have been used to reduce the complexity and storage space of fingerprint data in [23] and [24].

ML has also proven as an effective way to fuse multi-dimensional data collected from multiple positioning sensors, technologies and methods. For example, both supervised and unsupervised learning have been applied for fusion weight generation in [25]–[27]. However, unsupervised ML fusion technique is superior since it calculates the weights in real-time without offline training [28]. Furthermore, transfer learning has been applied in fingerprint-based localization to enhance system scalability without excessive site surveys and without sacrificing accuracy when there is a lack of labeled data [29].

While the literature contains a good number of articles on the application of ML for indoor localization, to the best of our knowledge no comprehensive survey has been conducted on this topic. Therefore, in this paper, we discuss existing techniques for indoor localization and establish a precedent for the need of ML techniques in the said domain. Moreover, our paper follows intuitive flow by pointing out the challenges and issues in indoor localization, listing the existing solutions, and afterwards identifying the gaps that lead us to ML- and DL-based solutions in indoor environments.

The rest of the paper is organized as follows: A basic discussion on the nuts and bolts of indoor localization is presented in Section II. A brief overview of ML techniques is presented in Section III followed by a deeper analysis of existing ML-based solutions for IPS in Section IV. Few potential applications are highlighted in Section V and finally in Section VI, we discuss the limitations in ML approached and future challenges.

II. REVIEW OF INDOOR LOCALIZATION BASICS

An Indoor Positioning System (IPS) is a GPS free system that estimates the position of the objects or people in a confined environment (e.g. buildings, tunnels) in a continuous manner. Typically, it has two phases: 1) the distance measurement phase and 2) the position estimation phase [30]. In the distance measurement phase, an IPS estimates the distance between the target and anchor nodes whose positions are known *apriori* using a suitable ranging technique. Then, the IPS uses these distance observations to estimate the location of the target by using different localization/positioning methods.

A. RANGING AND ENHANCED RANGING TECHNIQUES

The most common used localization techniques are given below:

Received-Signal-Strength-Indicator (RSSI): RSSI in general is the easiest parameter to measure, however it yields the most inaccurate distance measurement, especially in indoors due to fading, shadowing, refraction, scattering, and reflections. Therefore, the use of different filters, like the Extended Kalman Filter (EKF) [31] and other ML techniques have been used to mitigate the RSSI fluctuations.

Time-of-Arrival (ToA): ToA technique uses the signal propagation time to calculate the range (distance between the target and the anchor node). ToA is in general much more accurate than the RSSI approach.

However, processing time and synchronization time affect the distance measurement in ToA [32]. There are few techniques, such as the symmetric double sided two-way ToA ranging [33] are proposed to eliminate the time synchronization error. This approach averages out the error by considering

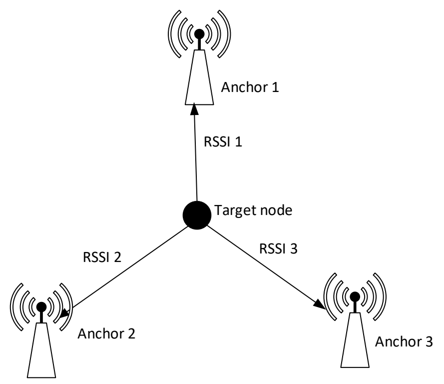

FIGURE 1. Schematic diagram of positioning using RSSI measurements.

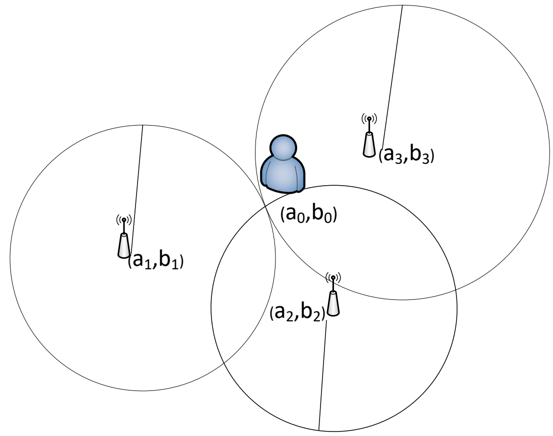

FIGURE 2. Schematic diagram of Trilateration-based positioning.

many back and forth rounds signal propagation between the nodes.

Time-Difference-of-Arrival (TDoA): This method utilizes the difference in signal propagation times between the target node and the number of anchor nodes to determine the position of the target node [34]. In this technique, at least three anchor nodes are needed to calculate the location of the target at the intersection of the hyperboloids.

TDoA can address the issue of synchronization error to some extent as it accounts for the synchronization of only the transmitters [35]. However, the NLOS propagation of the signal significantly degrades the performance of the ToA/TDoA-based systems. Hence, in the literature a number of NLOS identification and mitigation methods were proposed to improve the accuracy of ToA/TDoA-based localization [36].

Angle-of-Arrival (AoA): AoA technique uses the angle that signal makes with an antenna array for position estimation [37]. This is an enhanced ranging technique. Since both the angle and distance measurement are used, ideally two anchor nodes are enough for the position estimation [38]. However, one drawback of this method is the requirement of antenna arrays that makes it complex and expensive [39]. This method may also employ time difference of arrival of the signal at individual antenna elements but, even more complex hardware and accurate calibration are required for this.

Channel-State-Information (CSI): This is also an enhanced ranging technique. CSI can be used to get an accurate estimate of the received signal over the entire signal bandwidth. This is much better than RSSI where, only a single amplitude value for the received signal is obtained. CSI generally needs multiple antennas and the channel frequency response seen by each antenna has to be estimated. CSI can provide both magnitude and the phase of the channel response and it is suitable for both range-based and range free localization schemes [5].

The advantages and disadvantages of different distance measurement techniques are summarized in Table 2.

B. LOCALIZATION METHODS

The localization methods which are commonly used for indoor localization are listed below:

Multilateration and Trilateration: It is a technique for estimating the position of the unknown node with the help of the three or more known nodes and the corresponding associated distances [40]. Trilateration is a special case of multilateration where only three known nodes are used. In a two-dimensional space, the position of the target node is computed by the intersection of three imaginary circles as shown in Figure 2. However, in the practical indoor environment, these circles do not meet at a single point due to NLOS effect that causes huge errors in the positioning. Hence, there are two major issues in the trilateration algorithms:

1) Target node is not at the common intersecting point of the circles due to inaccuracy in ranging techniques.
2) The given known anchor nodes may be co-linear.

Different techniques and algorithms have been presented to address these issues. In [41], a hybrid technique of fingerprinting and trilateration has been used to overcome the first issue. In [42], authors proposed a least-square method to solve both the issues stated above. In the same spirit, authors in [43] propose a weighted least square method to solve the non ideal case of trilateration.

Triangulation: It can be used for positioning accuracy when the angle of arrival is available. It is less complex with moderate precision [44] requiring at least two anchor nodes. Location accuracy in this technique heavily depends on the precision of the AoA estimation. Increasing the number of anchor nodes can enhance the localization performance.

Fingerprinting: It is a widely used indoor positioning method using various wireless access technology such as Wi-Fi, BLE, and ZigBee [45]–[47]. Fingerprint-based localization method involves two phases:

1) Offline phase training.

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TABLE 2. Advantages and disadvantages of different distance measurement techniques.

Technique	Advantages	Disadvantages
RSSI	A simple technique for the distance measurement as typically there is no need for extra hardware. Cost effective and less complex.	Provides low precision due to NLOS propagation of signal. Strong optimization and positioning techniques are required for accurate results.
CSI	This has high granularity over RSSI due to both amplitude and phase information of channel frequency.	Complexity is higher than that in RSSI-based and most other IPS techniques.
ToA	ToA provides the highest precision of the measurement among most range-based methods with strict clock synchronization between the transmitter and the receiver.	Expensive due to extra devices and modules needed to lower synchronization error.
TDoA	TDoA can provide better precision than ToA (especially when ToA has notable synchronization error between the clocks).	It is expensive due to extra devices and modules added to lower synchronization error.
AoA	AoA provides more accuracy for the target node location estimation for short distance of signal propagation.	Requires antenna arrays and extra hardware. It is often hard to implement AoA due to multi path effects.

2) Online phase testing.

During the training phase, RSSI or CSI data is collected at access points (APs) for different known indoor positions called reference points (RPs) and a radio map is constructed with the measured data for each recorded position. During the online phase, the real-time position of the target node is estimated by comparing measured data at APs for the target node and the radio map created in the training phase.

This method provides high accuracy if more offline data is collected accurately to construct the radio map. However, constructing the radio map for large area deployment requires tremendous effort (e.g., manpower, time and cost). Moreover, for dynamic networks, when the positions of the nodes, even a single node, are changed or deleted unexpectedly, the offline database should be recreated.

ML algorithms are often used to enhance the accuracy of fingerprinting and help recreating radio maps. K-Nearest Neighbors (K-NN) is the simplest algorithm used for fingerprint-based localization methods. Here K represents the number of the nearest neighbors. In this algorithm a distance metric is calculated that computes the distances between the measurements in the training phase and the measurements of the target at different APs. The most commonly used distance metric is Euclidean distance. In this algorithm K nearest RPs of the target are selected from the radio map which have the lowest distances. Afterwards, the coordinates of these RPs are averaged to estimate the location of the target. However, other distance metrics such as Manhattan distance, Mahalanobis, and Minkowski distances are also used with K-NN algorithm [48].

The authors in [48], [49] have compared Mahalanobis, Manhattan, and Euclidean distances in fingerprint-based localization and found that Manhattan also known as City Block distance provides more accurate results than others. Different improvements to the K-NN algorithms have been found in the literature. For example, authors in [50] and [51] have used enhanced weighted K-NN algorithm and clustering-based K-NN algorithms, respectively for higher accuracy.

Centroid: In this method, a geometric relation is used to estimate the location of the unknown node rather than using the distance or angle measurement. The positions of the anchor nodes are determined when a stable communication link is established between each anchor node and the unknown target node. As the position of the anchor nodes connected to the target node form a definite geometric shape, the centroid of that geometric shape is considered as the location of the unknown nodes. Different algorithms have been employed in the literature that utilized the centroid method. A BLE beacon RSSI-based indoor positioning system using Weighted Centroid Localization (WCL) approach has been proposed in [52].

DV Hop: This method involves estimating the distance-vector in a multi-hop environment based on the hop count. The coordinates of the i^{th} node and the minimum hop count value from the anchor node to the i^{th} node are maintained in an information table. The anchor node broadcasts the location information to the neighbor nodes which then rebroadcast the information to others and so on. The important task for this method is to find the hop size for a particular hop. After getting the average hop size h, the distance of the node that is m hops away from the anchor node is simply calculated as $m \times h$. Based on the measured distance, target nodes locate themselves using a position estimation algorithm.

A Voronoi diagram is typically used to scale the DV hop algorithm so that the scope of the flooding in the DV hop localization system is limited [52]. Additional anchor nodes are created by promoting suitable localization nodes [11].

The advantages and disadvantages of different localization methods are presented in Table 3

C. WIRELESS TECHNOLOGIES USED FOR INDOOR LOCALIZATION

In this subsection, radio frequency wireless technologies that are most commonly used in indoor localization are briefly presented.

Wi-Fi: Wi-Fi is most widely used for IPS because of the ubiquitous availability of Wi-Fi systems [53]. It can provide fairly large coverage range however, the power consumption of WLAN systems are comparatively higher [54]. Typically, the Wi-Fi based localization methods are trilateration or fingerprint based. AoA, ToA and RSSI-based ranging techniques are used for trilateration-based methods [55]. RSSI and CSI

TABLE 3. Advantages and disadvantages of different localization methods.

Technique	Advantages	Disadvantages
Fingerprinting and K-NN	Provides higher accuracy and it is fairly easy to use as no hardware and other devices are needed.	It is time and cost inefficient due to off-line measurement requirements. Also, not robust against topography changes.
Trilateration	Provides very higher accuracy when applied with other optimization techniques with comparatively less complex.	Higher location error in case of non-ideal case. Demands additional positioning algorithms to be applied.
Triangulation	Provides high accuracy if the measured AoA has good precision. Accuracy increases by increasing the number of anchor nodes.	Location accuracy highly suffers from even a small error in the angle calculations.
DV Hop	Simple and gives better accuracy with more nodes deployed.	Provides very low accuracy for less nodes and used only to estimate some rough localization measurement.
Centroid	Does not need direct measurement values and position can be estimated using geometric calculations.	Additional algorithms are needed for better accuracy.

measurements are usually used to generate the fingerprint-map. RSSI is more attractive because RSSI information can be easily collected from a commodity access point (AP) without extra hardware [56]. However, the fluctuation of RSSI often leads to severe performance degradation. In the literature, many machine-learning methods have been found to mitigate the impact of RSSI fluctuations [47], [57], [58]. For pattern matching in online phase K-Nearest Neighbor (K-NN), Artificial Neural Network (ANN) [59], Support Vector Machine (SVM) [60] and K-means [61] and Random Forest [62] algorithms have been used. Advance network interface cards (NICs) are required to measure CSI that adds extra cost. However, CSI-based fingerprinting can obtain centimeter-level localization accuracy [63].

Radio Frequency Identification Device (RFID): RFID is a very inexpensive technology [64]. In general, RFID-based positioning technology is durable against environmental factors and can be used almost in any application. The fingerprinting position method based on RSSI measurement can be used for RFID-based indoor positioning systems [65]. Ni et al. have proposed a scheme named LANDMARC [66] where active RFIDs are used to track the user location. Although LANDMARC is a comparatively long-range energy efficient system, it suffers from tracking latency. Huang et al. [67] have proposed an active RFID-based real-time RFID indoor positioning system. They use Kalman filters for drift removal and Heron bilateration for location estimation. Siachalou et al. [68] have proposed a phased fingerprint-based positioning system for tracking in warehouses and large retail stores. Result shows that phase-based fingerprinting is more immune to multipath fading and coupling effects with the environment and outperforms the RSSI-based fingerprinting.

ZigBee: ZigBee is a low data rate wireless personal area network [69], [70]. The authors in [46], have proposed a fingerprint-based positioning system where the interference data is first filtered out in the training phase and then the weighted nearest algorithm and Bayesian algorithm were used to calculate pedestrian's location. The reported accuracy in their work is 81 cm. Gharghan et al. [71] have proposed a ZigBee-based positioning system where they have used log-normal shadowing model (LNSM) to estimate the distance and then applied adaptive neural fuzzy inference system (ANFIS) to improve the distance estimation accuracy. Simulation results show that the distance estimation accuracy has been improved by 84% and 99% for indoor and outdoor velodromes, respectively. Fang et al. [72] have proposed a ZigBee-based ensemble learning localization framework for indoor environments that takes the advantages of various algorithms, weights the estimation results, and combines them to improve accuracy.

Ultra Wide Band (UWB): Since UWB is a short-range radio technology that transmits short pulses (< 1 ns) over a large bandwidth, it is less sensitive to multipath effects and offers high precision. Localization systems based on UWB technology achieve an accuracy of centimeters (<30 cm) that is considerably better than BLE or Wi-Fi. The main challenge in UWB-based IPS is the NLOS effect. The NLOS signal significantly reduces the accuracy of localization. ML techniques have been gaining a lot of research attention in the literature to distinguish and mitigate the NLOS effect [73]. The authors in [74], have proposed an UWB system for positioning in harsh environment that does not require any $apriori$ knowledge. The root mean square (RMS) of absolute range errors after NLOS mitigation was reduced from the original 1.3 meter to 0.651 meter in their experiment in a real office environment.

Bluetooth Low Energy (BLE): Bluetooth has been considered as a competitor to Wi-Fi due to the wide adaptability of Bluetooth Low Energy (BLE) by most smart phones [45]. BLE can provide a coverage range of 70-100 meters with high energy efficiency [75]. In recent years BLE-based RSSI fingerprinting has gained a lot of attention in research community. To improve the accuracy in indoor localization, Yadav et al. [76] proposed Inertial Measurement Unit (IMU) sensors and BLE beacon-based positioning system that employs a probabilistic approach involving the fingerprint-technique and Pedestrian Dead Reckoning (PDR) [77]. These two methods are combined through a fuzzy-logic Kalman filter called Trusted K nearest Bayesian estimation (TKBE) algorithm. Result shows that the accuracy of their proposed algorithm

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TABLE 4. Comparison of distance measurement techniques and algorithms with appropriate wireless standards.

Measuring Techniques	Localization Methods & Algorithms	Technology	Complexity	Cost	Accuracy	Scalability
RSSI [79]	Fingerprinting	RFID	High	High	High	High
RSSI [80]	Lateration	Wi-Fi	Low	Medium	Medium	Medium
RSSI [81]	Min-max	Bluetooth	Medium	Medium	Low	Medium
RSSI [82]	K-NN	WLAN	Medium	Low	Low	High
RSSI [83]	SVM, MLP	WLAN	Medium	Low	High	High
ToA,ToF [84]	Fingerprinting	Wi-Fi	High	Medium	Medium	Medium
ToA,ToF [84]	Trilateration	UWB	Medium	Medium	Low	Medium
TDoA [85]	Trilateration	UWB	Medium	Medium	High	High
TDoA [86]	Fingerprinting	Bluetooth	High	High	High	Low
TDoA [87]	Fingerprinting	Wi-Fi	High	High	High	Medium
TDoA [51]	Least Square	UWB	Medium	Medium to High	High	High
TDoA+AoA [88]	Least Square	UWB	Medium	Medium to High	Very High	Medium to High
AoA [87]	Triangulation	Wi-Fi	High	High	Medium	Medium

is less than one meter in most of the experimental cases. The authors in [78], compared the performance of Wi-Fi, BLE and ZigBee with simple RSSI-based trilateration method and found the achieved accuracy of Wi-Fi, BLE and ZigBee are 48.6 cm, 84.4 cm and 91.1 cm respectively.

The localization perspective of different measuring techniques along with different localization algorithms and technologies with respect to accuracy, cost, complexity, and scalability is summarized in Table 4.

III. MACHINE LEARNING FOR IPS

Machine Learning algorithms can effectively solve many of the limitations of the conventional techniques used for localization in indoor environments. Conventional methods often lack scalability; therefore, cannot perform well in the large scale IPS such as airports, shopping malls and multi-storey buildings with large training data sets.

Furthermore, traditional IPS methods are not very flexible in adapting well to dynamically changing environments and in the presence of multi-dimensional and heterogeneous data applications.

A. MOTIVATION OF USING ML IN INDOOR LOCALIZATION

Fluctuation in RSSI is the most challenging problem in IPS and it effects the location accuracy adversely. The most significant advantage of ML is its ability to learn useful information from the input data with known or unknown statistics. For instance, recurrent neural networks could effectively exploit the sequential correlation of time-varying RSSI measurements and use the trajectory information to mitigate RSSI fluctuations [13].

One of the limiting factors in usage and accuracy of fingerprinting-based localization methods is the presence of high dimensional data and related computational complexity. Supervised and unsupervised dimension reduction techniques such as principal components analysis (PCA) [24] and Gaussian process manifold kernel dimension reduction (GPMKDR) [23] techniques can be applied to transform the high dimensional features to low dimension that significantly reduce the storage space and computational complexity of fingerprint-based localization.

Reinforcement learning is another promising ML technique, that can achieve fast network control based on defined learned policies. It is used in robot navigation that enables the robot to create an efficient adaptive control system for itself which learns from its own experience and behavior [89].

Scalability and adaptability of an IPS model to the changing environments is a desirable feature specially in dynamically changing indoor applications. In this spirit Transfer learning plays an important role as it enables machine learning to learn new things quickly in the new environment by comparing with the things learnt beforehand. Transfer learning can be applied in indoor positioning in the scenario when the amount of data in the source domain is sufficient, whereas the amount of data in the target domain is small. For instance, transfer learning mechanism can be applied into fingerprint-based localization to enhance system scalability without excessive site surveys and without sacrificing accuracy when there is lack of labeled data [29]. In addition to transfer learning, DL techniques have shown great potentials in enhancing localization, in complex environment scenarios. Specifically, in situations when it is difficult to extract and model the nonlinear correlated features [14].

Furthermore, various techniques such as, Bayesian estimation based concept including Kalman filters [90], [91]; unscented Kalman filters [92]; non Bayesian methods such as Least Squares (LS) [93]–[96]; subsample interpolation [97], [98] and deconvolution approximations [99] are proposed for improved localization by mitigating multipath propagation error. Bayesian methods show better performance than other conventional algorithms in positioning accuracy.

Amalgamation of sensor data is used for accurate location estimation in the indoor environment, and which is strongly dependent on efficient data fusion techniques. Conventional methods for data fusion include LS [93]–[95] and MMSE [96]

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TABLE 5. Summary of different machine-learning techniques.

Algorithms	Description
Supervised Learning: K-Nearest Neighbor (K-NN)	K-NN is a simple and effective ML algorithm. It classifies data in feature space according to distance [60]. This model predicts the value of new data points by comparing the similarity of this value with the training data and finds out K neighbors which have maximum closeness with the new data.
Supervised Learning: Support Vector Machine (SVM)	SVM is a low computational complexity enhanced supervised learning algorithm that is used for classification as well as regression problem. SVM works on the principle of margin calculation. It plots data items in n-dimensional space and draw $n-1$ hyper-plane to divide the training data-set into n classes in such a way that the distance between the class and the hyper-plane is maximized.
Supervised Learning: Decision Tree	Decision tree forms a learning tree structure to solve the classification or regression problems. This model split the training data into several labels based on certain rules. After creating a tree structure it predicts the labels of the new data by iterating the input data through a learning tree. The information flows in Decision Tree is very transparent and users can easily relate their hypothesis without any analytical background.
Supervised Learning: Random Forest	Random forest algorithm is a collection of number of Decision Trees and each tree in the forest gives a classification. The output is the mode of the classes (classification) of the individual trees or mean prediction (regression) of the individual trees. This algorithm overcomes the over-fitting problem that is one of the drawbacks of Decision tree.
Supervised Learning: Artificial Neural Network (ANN)	ANN is also known as back propagation learning algorithm. It is built based on the model of human brain that contains a hundred of billions of neurons. ANN networks consist of input and output layers, as well as a hidden layer consisting of units that transform the input into something that the output layer can use. ANN is used for indoor position for its robustness against noise and interference which are one of the major factors affecting the accuracy of IPS.
Unsupervised Learning: K-means	It is a most well-known clustering algorithm in unsupervised ML family [61]. It partitions the data set according to their features into K number of predefined non-overlapping distinct clusters or subgroups, where K is a positive integer.
Unsupervised Learning: Principal Components Analysis (PCA)	It is a multivariate technique for data compression that uses orthogonal transformation to identify principal components. Afterwards, the principal components are arranged in descending order of the variance. It is used to reduce the dimension of large data to facilitate the computation faster and easier [24] .
Reinforcement Learning (RL)	RL is based on learning by trial and error. RL is inspired by the learning behavior of human which uses previous experiences to react in new situations [106]. During RL, decisions are made on the basis of the obtained reward or punishment. The algorithm receives rewards by performing correctly and penalties for performing incorrectly.
Deep Learning (DL)	DL is a branch of ML techniques that is based on ANN concept. DL can be supervised and unsupervised using labeled and unlabeled data. The key aspect of DL is the $iterative\ weight\ adjusting$ among each pair of neurons. DL models are trained by using large sets of labeled data that learn features directly without the need for manual feature extractions [107]. Combination of RL and DL is known as Deep Reinforcement Learning (DRL) and inherits the benefits of both RL and DL [108], .
Transfer Learning	Transfer learning helps the system to learn subjects in new fields by comparing it to what the system already knows. The advantage of the transfer learning is that this model can be applied to similar problems and get good results by making minor adjustments to a trained model. Transfer learning can be applied into fingerprint-based localization to enhance system scalability without excessive site survey [29].

are not very promising. It requires the knowledge of probability distribution in localization measurements, which is often unavailable in real applications. Also, LS method is not perfect as the noise is amplified by squaring and also LS involves extra variables in the equation. Maximum a Posterior (MAP) estimator [100]- and MMSE [96]-based hybrid positioning algorithm show some performance improvement but on expense of computational complexity. ML algorithms are particularly good in handling multi-dimensional and multi-variety data under dynamic, uncertain environments. It can be effectively trained to fuse results obtained from multiple positioning sensors, technologies, and methods.

Bayesian methods integrate multi-modal location sensors and exploit historical data through a recursive tracking process [101]. Particularly, Kalman filters have been [102]–[104] used to estimate the most likely current location based on prior measurements, assuming Gaussian noise and linear motion dynamics. However unsupervised ML fusion technique is more realistic to use in practical scenario because it exploits the online measurements to calculate the weights typically in real-time and does not need to be trained during the offline phase [105].

In the following sections, we will discuss different ML techniques used in overcoming various indoor localization

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challenges, in detail. Also, summary of different ML techniques are presented in Table 5.

B. SPECIFICS OF ML TECHNIQUES IN LOCALIZATION

In localization, classifier algorithms are mainly used to extract core features of the signals. In fingerprint-method clustering is performed based on these extracted features. Feature extraction is also important for NLOS identification and mitigation. K-NN [109], Support-Vector Machine(SVM) [110], Random Forest, Decision Tree, Artificial Neural Networks (ANN) [111] are widely used classification algorithms.

Data mapping and over-fitting are the big challenges in fingerprint-based localization systems. K-NN is widely used for pattern matching in fingerprint-technique. However, K-NN does not work well with large data sets and with high dimensional data. In noisy irregular environments (such as underground mines and subway stations) due to the presence of time varying attenuation and noise factors, RSSI exhibits high dimensionality [112]. In such cases, SVM is more effective since it adopts kernels mechanism to find difference between two points of the two separate classes and models linear and nonlinear relations with better generalization performance [17]. However, SVM-based methods are time-consuming and require lots of memory when the number of support vectors (SVs) become large. The Decision Tree based indoor localization provides better performance in improving localization accuracy than other classification like K-NN, and Neural Network [113]. However, there is a possibility of information missing when the Decision Tree deals with continuous numerical data and performs categorization.

In practical fingerprinting scenarios, a fingerprint-map generated in the offline phase contains a large data set. So it is time consuming to compare the data acquired in the online phase with each data point of the fingerprint map. Therefore, the fingerprint-map is divided into a number of clusters and the data of the target node is compared only with the data point of the corresponding cluster center. Hence, the cluster with highest matching is selected. Then, the acquired data is compared only with the data within the matching cluster and the location estimation is carried out. If the number of reference points is still large in each group after clustering or the number of layers in the decision cannot be reduced, then the problem of overfitting is likely to occur. In this case Random Forest can be used to eliminate the over-fitting problem. A RF model is constructed based on the fingerprint-information of the reference points in the group after clustering [114].

Moreover, it is important in fingerprint-localization techniques that each reference point must exhibit at least one difference from other reference points in terms of extracted features. However, it is often seen that some features are not informative or repeat redundant information from other features. In such a case, dimensionality reduction is important to reduce the model's complexity, to shorten the training period and save the storage space. In case of high dimensional data, Principal Component Analysis (PCA) is beneficial as it simplifies the complexity of high dimensional data while retaining trends and patterns. PCA is mainly used for dimension reduction and shrinking the radio map for saving storage space [24].

However, in complex environment scenarios where features extraction is difficult and data has high dimensionality, DL is very promising to improve localization accuracy [21]. DL is well known for its distributed computing capability and analyzing of a huge volume of unlabeled and un-categorized data. The biggest advantage of DL algorithms is their ability to extract features from data directly without manual feature extraction [107]. This eliminates the need of domain expertise and extraction of hardcore features. Feature extraction and classification are carried out by a DL algorithm known as Convolutional Neural Network (CNN) [115].

Many of the indoor positioning approaches are vulnerable to global positioning error and kidnapped-robot problems. The global localization problem occurs when the initial position of the target is unknown to the IPS during initialization. While kidnapped-robot problem occurs when a well-located target moves to an unknown environment. In such a challenging situation, RL proves to be the best technique to use. As RL enables the agent to achieve a long-term objective by interacting with the environment (based on the reward and penalty process), and are able to solve problems caused by radio signal instability. Therefore, RL techniques are able to construct the map and optimize its action continuously [116].

The applications of ML techniques in solving various challenges in indoor localization are presented in Table 6.

IV. EXISTING ML BASED ENHANCEMENTS TO IPS

In this section, we survey the existing ML based solutions addressing different challenges in indoor localization.

A. ML FOR NLOS ERROR MINIMIZATION

One of the main challenges in indoor positioning is the large ranging error caused by NLOS/multipath propagation. Therefore, it is imperative to mitigate this effect. In the literature a significant amount of work has been found on NLOS problems. The existing literature typically deals with NLOS mitigation in two ways:

1) Identifying NLOS propagation and then suppressing the NLOS induced range error.
2) Mitigating NLOS effect directly without implementing NLOS identification.

In NLOS identification, the goal is to distinguish the NLOS signals and LOS signals between a transmitter and a receiver by analyzing the channel statistics, range estimates or the radio map [128].

In the literature different ML approaches have been applied to extract different features from the received signal/waveform and classify the NLOS/LOS components. To this end, in [17], Stefano et al. have developed least-square support vector machine based techniques for NLOS identification and mitigation that does not require any explicit statistical model. From

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TABLE 6. Research problems in localization and applied machine-learning techniques.

Research Problems/ Objectives	ML Techniques
NLOS Classification & Mitigation	1. Random Forest [18] 2. Support Vector Machine Regressor [117] 3. Relevance Vector Machine (RVM) [118] 4. Least Squares SVM Classifier (LS-SVMC) [17] 5. Deep Learning [21] 6. Convolution Neural Network (CNN) [14]
Feature Extraction	1. Principal Component Analysis (PCA) [24] 2. K-Nearest Neighbor (K-NN) [27] 3. Deep Learning [21] 4. Recurrent Neural Network [13]
Dimension Reduction	1. Linear Discriminant Analysis (LDA) [119] 2. Principal Component Analysis (PCA) [119]
Avoiding RSSI Fluctuation	1. SVM [120] 2. Recurrent Neural Network [13] 3. Deep Auto Encoder [121], [122] 4. Convolutional Neural Network [115] 5. Multi-Layer Perceptron (MLP) [123]
Minimizing Computation Complexity	1. Gaussian Process Manifold Kernel Dimension Reduction (GPMKDR) [23] 2. Principal Component Analysis [24] 3. Kernel Principal Component Analysis [124] 4. K-Means [130]
Minimizing Training Time	1. Deep Belief Network (DBN) [21] 2. Online Independent SVM (OISVM) [125] 3. Extreme Learning Machine (ELM) [126] 4. Transfer Learning [29]
Robot Navigation	1. Deep Reinforcement Learning [127] 2. Deep Q-network (DQN) [22] 3. Double Deep Q network (D3QN) [89]
Trajectory Learning	1. Linear Discriminant Analysis (LDA) [119]. 2. Principal Component Analysis (PCA) [119]
Weight Learning in Fusion	1. Supervised Learning: K-NN [27] 2. Unsupervised Learning: Online Independent SVM (OISVM) [125]

the received waveform the authors have extracted different features such as energy of the received signal, rise time, maximum amplitude of the received signal, mean excess delay, root mean square (RMS) delay spread and kurtosis and constructed different length feature subsets. The authors have designed three localization strategies:

1) Identification that only considers LOS signals for localization.
2) Identification and mitigation that classifies the NLOS and LOS signals and then mitigates the range estimates error of NLOS signals.
3) Hybrid approach that discards mitigated NLOS range estimates in the presence of sufficient number of LOS signals.

Results show that the identification strategy classifies the NLOS/LOS successfully with 91% accuracy using a feature subset that includes energy of the received signal, rise time, kurtosis. The identification and mitigation strategy achieves outage probability (i.e. error is less than 2 m) around 10% without the presence of any LOS signals, while the hybrid approach further improves the performance, specially in presence of significant number of LOS signals. In [18], Ramadan et al. have proposed a Random Forest based method for NLOS identification in which Channel Impulse Response (CIR) is used for features extraction. Authors extracted many features including mean, standard deviation, skewness, and kurtosis from the received signal to train the Random Forest algorithm. In the experiment, the authors estimated CIR by placing a transmitter and receiver at different positions in a wide hall at a height of 1.6 m. The authors used two metrics: identification accuracy and algorithm running time to evaluate the performance of the Random Forest algorithm with least squares-support vector machine (LS-SVM) [19], and other state-of-the-art classification algorithms. Results show that Random Forest achieves NLOS and LOS identification accuracy of 97.3% and 95% respectively, with a reasonable computational complexity.

Henk et al. [117] have proposed two non-parametric regression techniques for ranging error mitigation on features extracted directly from the received waveform. The first technique employs regression with SVM, and the second technique employs regression with Gaussian Process (GP). The performances of the proposed techniques were evaluated in terms of outage. Results show that GP error mitigation has good performance, with outages remaining below 10% for all NLOS.

Nguyen et al. [118] have proposed Relevance Vector Machine (RVM) based method for UWB ToA localization. In their proposed model an RVM based classifier is used to identify the LOS and NLOS signals. Afterwards, a RVM regressor is adopted for ranging error prediction. The authors have compared the performance of RVM and SVM in NLOS identification and localization accuracy estimation. Results show that using three features, the mis-identification probability of SVM and RVM classifier are 0.1143 and 0.1084, respectively while the number of used relevance vectors and support vectors are 50 and 12, respectively. It is observed that in 63.37% cases, RVM achieves the positioning error less than 1 m while the corresponding percentages of SVM is 58.48%.

The current ongoing research of NLOS identification and mitigation techniques mainly developed for UWB radio signals [117], [118]. Due to the large bandwidth of UWB signals which means short time domain pulses, the LOS component can be readily identified. Therefore, these techniques cannot be readily applied to narrow band communication technologies such as Wi-Fi. In this spirit, Xiao et al. [129] proposed two ML and one hypothesis testing algorithms using RSSI measurements from received signals for NLOS identification and mitigation in Wi-Fi systems. Their proposed Least Squares Support Vector Machine Classifier (LS-SVMC), and Gaussian Processes Classifier (GPC) identify the NLOS signals while Least Square Support Vector Machine Regressor (LS-SVMR) plus Gaussian Processes Regressor (GPR) perform NLOS mitigation. Performing extensive experiments in various indoor environments, it has been found that their proposed techniques can distinguish between LOS/NLOS conditions with an accuracy of around 95%. Simulation results show that the performance of GPR is slightly better than LS-SVMR when the training data is low. The mean errors are .86 m and .82 m for LS-SVMR and GPR, respectively.

In the aforementioned works [17], [18], [117], [118], the authors defined and extracted various features by analysing the signal properties first, and then employed them as the input vector to the classifier (e.g., SVM, MLP). Kurtosis, peak to lead delay, mean excess delay, and RMS delay spread are the most commonly used features for NLOS/LOS identification. However, in the complex environment, it is hard to define the features manually. To overcome this problem, Jiang et al. [14] proposed a DL method for UWB NLOS detection and classification. The proposed method is based on the Convolution Neural Network (CNN) and Long-Short Term Memory Recurrent Neural Networks (LSTM-RNN) where CNN was used to extract the non-temporal features from the raw channel impulse response (CIR). Afterwards, the extracted features in CNN are fed into the LSTM for classifying LOS and NLOS signals. Results show that CNN-LSTM outperforms the LSTM in NLOS classification compared with single LSTM. Authors of [73] also used CNN for accurate location estimation in an UWB IPS with multiple anchor nodes.

Although supervised ML is widely used in the literature to identify NLOS signals, it is not quite feasible to use in the scenario where the environment often changes due to the movement of the furniture from one location to another location. To overcome this limitation, Fan et al. [20] proposed an unsupervised approach called Expectation Maximization for Gaussian Mixture Models (EM-GMM) that discriminates the LOS and NLOS components. Specially they applied EM over GMM to find the maximum likelihood of a received signal to determine whether it belongs to LOS or NLOS distribution. Moreover, the authors found that their proposed algorithm achieves almost the same NLOS detection accuracy as supervised learning algorithms while it takes only 44% of running time required by them. The main advantage of EM-GMM is that it does not require any rigorous and explicit labeling of the database at a certain location.

The performance of different ML approaches in NLOS classification and mitigation is shown in Table 7.

Lessons Learned: First, based on [118] and [17], [117], we observe that the performance of RVM classifier is better than SVM in NLOS identification and mitigation. Moreover, RVM uses fewer relevance vectors than the number of support vectors in the SVM. From these observations, it can be inferred that RVM [118] is preferred to the SVM in NLOS identification and mitigation. Second, according to [14], DL can be used to directly extract features for NLOS/LOS classification in a dynamic network environment with time-varying channel impulse response (CIR). Third, based on [20] unsupervised ML approaches are useful for classification NLOS and LOS signal classification in an unknown environment where there is no labelled data.

B. ML FOR ENHANCED FINGERPRINTING BASED LOCALIZATION

1) Reducing Computation Complexity and Save Storage

To reduce computation complexity and save storage space for fingerprint-based localization of a multi storey building, authors in [130] proposed a K-means based method to each floor. The observation vector is compared with the cluster head's (CH's) of each floor to decide the correct floor. In the second stage the comparisons are done with floor wise. In this model the server transmits only the cluster head info with their corresponding floor labels to the client that significantly reduces the complexity.

Mo et al. [124] proposed a Random Forest based space-division model where the entire radio map is first divided into multiple sub radio maps. Afterwards, maximum likelihood estimation (MLE) and Kernel Principal Components Analysis (KPCA) are applied for estimating the intrinsic dimensionality and extracting features of each sub radio map respectively. Results show that their proposed method cuts down radio map size by 74% along with noise suppression and achieves 98% coarse location accuracy.

Salamah et al. [24] proposed a Principal Component Analysis (PCA) method to improve the performance and to reduce the computational cost of the Wi-Fi indoor localization systems. Result shows that the proposed method in [24] can reduce the computational complexity by 70% using RF.

Jia et al. [23] proposed a supervised learning based Gaussian Process Manifold Kernel Dimension Reduction (GPMKDR) method. In the proposed method, raw RSSI

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TABLE 7. Machine learning based solutions for NLOS identification/mitigation.

Objective	Description	Features	Results	Remarks
NLOS identification	Supervised Learning: RF; UWB [18]	Mean, standard deviation, skewness and kurtosis.	NLOS and LOS identification accuracies are 97.3% and 95%, respectively.	It has less computational complexity than the LS-SVM [17].
NLOS error mitigation	Supervised Learning: SVM and GP; UWB [117]	Energy, maximum amplitude, rise time, mean excess delay, RMS delay, kurtosis and estimated distance.	GP outperforms SVM in NLOS error mitigation.	Directly mitigates the NLOS error without NLOS identification.
NLOS identification & mitigation	Supervised Learning: RVM; UWB [118]	Energy, maximum amplitude, rise time, mean excess delay, RMS delay, kurtosis and estimated distance.	RVM outperforms SVM in terms of outage.	RVM has lower computation complexity than SVM.
NLOS identification and mitigation	Supervised: LS-SVM and GP; Wi-Fi [129]	Mean and standard deviation, Kurtosis, Skewness, Rician K-factor, log mean, and goodness of mean.	NLOS identification and distance estimation accuracies are 95% and 60%, respectively.	Robust to dynamic environmental changes.
NLOS identification	Unsupervised: Gaussian mixture model; UWB [20]	Mean access delay, RMS delay.	LOS and NLOS signals can be classified with 86.50% accuracy.	It takes only 44% of running time required by LS-SVM.
NLOS classification	Deep Learning: CNN and LSTM; UWB [14]	CNN extracts the non temporal features from the CIR.	CNN+LSTM outperforms the LSTM and obtained NLOS classification accuracy is 81.56% .	High computation load and training time.

measurements and their location labels are first processed by GPMKDR in the offline phase. GPMKDR is used to train a nonlinear mapping that transforms any high dimensional RSSI vector to a low dimensional feature. Results show that GPMKDR significantly improves the localization performance in comparison with the PCA-based method.

2) Minimizing Training Time

Le et al. [21] proposed a machine-learning based indoor position model to reduce the workload of fingerprinting by applying Deep Belief Network (DBN) on the unlabeled RSSI measurements. DBN extracts the hidden features of the fingerprints, and thereby minimizes the collection of fingerprints. In this paper, a pre-training phase is employed to train an unsupervised deep feature learning model. Afterwards, the model is used to extract the deep features of the labeled fingerprints for localization estimation. The extracted features are used as inputs for conventional regression and classification techniques such as SVM and K-NN. Results show that the proposed method improves the localization accuracy by 1.9 m by using only 10% of labeled fingerprints while the baseline approach uses 100% of the labeled fingerprints.

Wu et al. [125] proposed an Online Independent Support Vector Machine (OISVM) classification-based localization method using RSSI from Wi-Fi signals. Compared to traditional SVM, OISVM is capable of learning online and works seamlessly with crowdsourcing. Moreover, the model size in OISVM is smaller than SVM and it can control the trade-off between accuracy and model size. These features make OISVM attractive to use in commercial mobile applications. In the offline phase, the proposed method develops a new kernel selection parameter to reduce the time cost. Therefore, the training time of the proposed method could be much faster than the traditional methods. In the online phase, location estimation is conducted for new RSSI samples, and meanwhile online learning is performed as new training data arrives, which can be collected via crowdsourcing. Results show that the proposed method in [125] significantly reduces the prediction time and training time and achieves the localization accuracy error by 0.8 m.

3) Minimizing Signal Fluctuation

In fingerprint-based localization RSSI is widely used. However RSSI measurement value is very unstable due to the channel NLOS/multipath propagation, and device heterogeneity.

To mitigate RSSI fluctuations and enhance the accuracy of the localization, authors in [120] proposed a normalized rank based SVM that achieves room level accuracy. In the same spirit, Hoang at el. [13] proposed a Recurrent Neural Network (RNN) based solutions for Wi-Fi fingerprinting that exploits the correlation of RSSI measurements from time-varying RSSI and the trajectory information. The authors used different types of RNN, including Vanilla RNN, LSTM, Gated Recurrent Unit (GRU), Bidirectional RNN (BiRNN), Bidirectional LSTM (BiLSTM), and Bidirectional GRU (BiGRU) and evaluated the performances of these algorithms. Result shows that LSTM structure achieves an average localization error of 0.75 m that outperforms feed-forward neural network, K-NN, Kalman filter, and other probabilistic methods.

To overcome the negative effect of RSSI fluctuations in fingerprint-based localization, researchers have proposed fingerprint based on channel-state-information (CSI) where the CSI level at different reference points are recorded in the offline phase. Authors in [121], [122] developed a deep learning based method called DeepFi to improve the accuracy of fingerprint-based localization that uses CSI amplitudes from all the sub-carriers. The DeepFi system architecture includes an offline training phase and an online localization phase. In the offline training phase, DL is utilized to train all the weights of a deep network as fingerprints. In the offline training phase, DeepFi adopted a greedy learning algorithm using a stack of Restricted Boltzmann Machines (RBMs) to train the deep network in a layer-by-layer manner. In the online localization phase, a probabilistic data fusion method based on the radial basis function (RBF) was developed to obtain the estimated location. Result shows that DeepFi outperforms several existing RSSI and CSI-based schemes in different network scenarios.

In [115], the authors propose CiFi based on Deep Convolutional Neural Network (DCNN) with commodity 5GHz Wi-Fi. CIFi collects CSI data and scans the phase information that is later used to estimate AoA. The estimated AoA are transformed to CSI images. These images are used to train DCNN in the offline phase. In the online phase, the location of the target is predicted based on the trained DCNN and new AoA. Using CSI and RSSI, Hsieh et al. [123] proposed a DL based method based on multi-layer perceptron (MLP) and one-dimensional Convolutional Neural Network(1D-CNN) to estimate the location of the object. Result shows that the 1-D CNN network achieves excellent localization performance with low network complexity. We summarize the solutions mentioned in this subsection in Table 8.

Lesson Learned First, based on [130], applying K-means algorithm in floor wise in fingerprint-based localization of a multi storey building, significantly reduces the computation complexity. Second according to [24], PCA and KPCA significantly reduce the size of radio map as well as the computational complexity. Third, based on [23] we can conclude, in the presence of labelled location-data, Gaussian Process Manifold Kernel Dimension Reduction (GPMKDR) is preferred to PCA for dimension reduction. Fourth, from [21], deep belief network (DBN) can be applied to extract hidden features of unlabelled data from crowdsourcing fingerprinting that eliminates the need of excessive collection of radio-map in fingerprint-based localization. It is also useful in the scenario where environment changes very frequently. Fifth, following [125], training time can be reduced significantly when the system works with crowdsourcing seamlessly and dynamically updates the training data. At last, according to [121], [122], autoencoder is able to extract useful and robust information from RSS data or CSI data, and improves the localization accuracy.

C. ML FOR TRAJECTORY LEARNING

Fingerprint-based indoor positioning approaches require a prior radio map. Therefore, when a prior map is not available, trajectory learning based localization approaches such as SLAM [131]–[133] and crowdsourcing [134], [135] have been devised. In trajectory learning based localization approaches, spatial context such as maps and landmarks are used for calibrating the localization error without additional hardware [119], [136].

In order to deal with the scenarios when radio maps are not available, Yoo et al. [119] proposed a ML-based map-less indoor localization model for Wi-Fi based systems where smartphones are used to collect RSSI. The proposed model combines Particle filter and Gaussian Process (GP) for the position estimation and works in two phases. In the first phase, the algorithm analyses the pattern of the Wi-Fi signals collected from crowds and detects the start and end points of any landmark. Afterwards, it applies Linear Discriminant Analysis (LDA) and PCA for dimension reduction and clustering data points obtained from different landmarks. In the second phase, authors applied dynamic wrapping with Kalman smoothing to match different lengths and to time synchronization of the samples. Finally, authors applied GP and Particle filters for position estimation. Result shows that the model achieves accurate localization results and the posture of the participants does not influence the performance. Afterwards, the authors also extended their work in [135] for landmark and floor detection.

D. ML FOR ROBOT NAVIGATION

Autonomous navigation of mobile robots in a complex environment is a daunting task. Recognition of obstacles and their locations information are required for safe and robust navigation of the intelligent robot system [138]. In practical scenarios, this information is not available beforehand. High-level perception capabilities are required to acquire this information. DL, RL and their combination called Deep Reinforcement learning (DRL) manifest great potential in solving many challenges in robotics [137].

To explore an unknown environment during robot navigation, Tai et al. [22] proposed a Deep Q-Network (DQN) based learning model where Convolutional Network was used to extract features from an RGB-D sensor. After training a certain number of times, the robot can travel in new environments autonomously. Wang et al. [127] proposed a DRL architecture using a two-stream Q-network for the navigation tasks in dynamic environments. The proposed architecture divides the main task into two sub-tasks: local obstacle avoidance and global navigation. It processes spatial and temporal information separately for obstacle avoidance and generates action values. The global navigation sub task is resolved by a conventional Q-network framework. An online learning network and an action scheduler are introduced to combine

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TABLE 8. ML solutions for enhanced fingerprinting.

Objective	Ref.	ML Mechanism	Contribution	Evaluation
Reducing size of the radio map	[124]	Unsupervised: RF+MLE+KPCA	RF is used for space division then MLE and KPCA are applied for estimating intrinsic dimensionality and feature extraction to reduce the radio map.	Size of the radio map is reduced by 74% and positioning accuracy is 2 m.
	[24]	Unsupervised: PCA+K-NN+RF	PCA is used for feature extraction from the pre-defined radio map which reduces the multivariate data matrix without losing important information.	Computational complexity is reduced by 70% in static mode and by 33% in the dynamic mode.
	[23]	Supervised: GPMKDR.	GPMKDR is used to train a non-linear mapping that transforms any high dimensional RSSI vector to a low dimensional feature.	Achieved mean error is 1.13 m.
Minimizing training time	[125]	Unsupervised: OISVM	OISVM is smaller than SVM and it can control the trade-off between accuracy and model size that makes it attractive to use in commercial mobile applications.	Using online learning, the estimation error is decreased by 80cm.
	[21]	Unsupervised Learning: Deep Belief Network (DBN)	DBN is used to extract the hidden features of the unlabeled fingerprints from crowdsourcing that reduces the time for fingerprint collection.	Localization accuracy is 1.9 m by using only 10% of labeled fingerprints.
Avoiding RSSI instability	[13]	Deep Learning: RNN, LSTM, GRU, BiRNN, BiLSTM, BiGRU	Utilize the correlation of RSSI measurements and the trajectory information to mitigate RSSI fluctuations.	Average localization error is 75 cm.
	[121]	Deep Learning: Restricted Boltzmann Machines	Uses a stack of RBMs to train the deep autoencoder in a layer by layer manner to reduce complexity.	Reported mean error is 94.25 cm.
	[115]	Deep Learning: CNN	This scheme transforms the AoA data into CSI image and utilizes 2-D CNN to improve localization performance as well.	Reported mean error is 2.3863 m.

two pre-trained policies and then continue exploring and optimizing until a stable policy is obtained.

E. ML FOR FUSING TECHNOLOGIES, FEATURES AND ALGORITHMS

Innovation and satisfying consumer expectations rely a lot on correct matching of the technology with the appropriate application. Two points need to be considered before choosing to design a suitable IPS platform: a) the most suitable technology for the IPS; b) compromising IPS metrics (i.e., Accuracy, precision, complexity, scalability, robustness, and cost) to achieve desired level of outcome. It is worth noting that IPS platform is application dependent and might require different technologies and performance metrics. For example, some applications may require moderate levels of accuracy while some applications such as industrial process tracking and indoor navigation systems for blind require high accuracy.

Each positioning technique and technology has certain advantages than others. Sometimes multiple technologies and techniques are combined together to achieve a satisfactory solution in a specific application [139], [140]. Fusing the information of different technologies, techniques and algorithms can improve the accuracy and robustness of the overall system. ML techniques can be applied to amalgamate this information in an effective way to improve the positioning accuracy, system robustness, and reduce the overall investment in LBS system solutions. The question is how the information obtained from different technologies and techniques are to be used and how to weight the results obtained from different algorithms to make a final decision.

In the literature, we found that the weight can be generated by averaging the output of multiple algorithms [25] or taking the weight of the best algorithm [25], [141]. The former approach of weight selection is often negatively biased by the output of the worst algorithm. And the latter one can be adopted only when trained data is available. Without training the algorithm in the offline phase, it may not be possible to determine the best algorithm. Therefore, there are two strategies to acquire weights: supervised weight learning and unsupervised weight learning. Supervised learning attempts to learn the weights by using the labeled data in the offline phase [25]. On the other hand, unsupervised learning learns the weights by using online data directly [26].

To improve the localization accuracy, authors in [27],

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proposed a cascaded two stage ML approach for precise localization in indoor environment that adaptively combined different radio frequency (RF) features such as Received Signal Strength Indicator (RSSI), Channel Transfer Function (CTF), and Frequency Coherence Function (FCF). In the first stage the proposed method used ML to identify the type of the surrounding indoor environment. Afterwards, authors applied the K-NN algorithm to identify the most appropriate selection and combination of RF features. Result demonstrates that the localization error, RMSE in the laboratory environment using this proposed framework is 39.68 cm.

A single fingerprint-based on RSSI or CIR cannot achieve the desired performance under dynamic environment changes. Therefore a group of fingerprints are used to improve the accuracy. To this end, Gu et al. [141] have proposed a Wi-Fi based localization method called Wi-Fi-FAGOT by developing Global Fusion Profile (GFP). In the offline phase, Wi-Fi-FAGOT first constructs a group of fingerprints called GOOF which consists of RSSI, Signal Strength Difference (SSD), and Hyperbolic Location Fingerprint (HLF). The GFP has been constructed by minimizing the average positioning error over the space of all GOOF classifiers. Therefore, the constructed GFP is available to fully exploit the complementarity among different kinds of fingerprints. GFP improves the accuracy of localization by fully leveraging all fingerprints without modifying any hardware, and thus very promising for indoor localization in the Wi-Fi environment. Result shows that WiFi-FAGOT performs better than other systems in real complex indoor environments.

In [142], the authors have constructed GOOF based on RSS Fingerprints (RSSFs), Covariance Matrix Fingerprints (CMFs), Fourth-order Cumulant Fingerprints (FoCFs), Fractional Low Order Moment Fingerprints (FLOMFs), and Signal Subspace Fingerprints (SSFs), which can be obtained by different transformations of the received signals at multiple antennas. Afterwards, the authors designed a parallel GOOF multiple classifier based on AdaBoost (GOOF-AdaBoost) to train multiple strong classifiers and proposed an efficient fusion algorithm called MUCUS (Multiple Classifiers Multiple Samples) to improve the accuracy of localization. MUCUS combines the predictions of multiple classifiers with different samples. Result shows that the localization error of MUCUS is 31.64 cm.

Later on, by using GFP, the authors in [25] proposed a supervised weight learning based Knowledge Aided Adaptive Localization (KAAL) approach. The authors developed two KAAL algorithms, GFP based Multiple Function Averaging (GFS-MFA) and GFP based Optimal Function Selection (GFS+OFS) to achieve highly accurate localization results. GFS-MFA chooses the weights according to the average of the outputs of multiple fingerprint functions, while GFS+OFS tries to obtain weights based on the output of the best fingerprint function in the offline phase. They test the performance of these algorithms using four typical fingerprint-fusions: neural-network (NN), K-NN, ELM and Random Forest. Result shows that GFS+OFS performs better than GFP+MFA and other conventional algorithms.

The above mentioned supervised fusion approaches cannot perform well in multipath and changing environments [25]. To overcome this drawback Guo et al. [28] proposed an unsupervised fusion localization method based on extended candidate location set (UFL-ECLS). In this method, in the offline phase multiple classifiers are trained using RSSI fingerprints. Afterwards, an extended candidate location set is constructed in the online phase by finding the location with prediction probability greater than a certain threshold from each classifier. UFL-ECLS iteratively updates the weights and location of the target by minimizing the positioning errors. Experimental results showed that UFL-ECLS can reduce 67th percentile RMSE(root mean square error) by 16.5% as compared with KAAL [25].

To minimize the high energy consumption of Wi-Fi enabled devices due to frequent AP scanning Niu et al. proposed ZIL [143], an energy-efficient indoor localization system where ZigBee interfaces are used to collect Wi-Fi signals. To identify Wi-Fi APs from ZigBee interfaces they developed RSSI Quantification and RSSI Normalization. To improve the localization accuracy, three K-NN based localization approaches adopting different distance metrics are evaluated including weighted Euclidean distance, weighted Manhattan distance and relative entropy. Result shows that ZIL can achieve the localization accuracy of 87%, which is competitive compared to state-of-the-art Wi-Fi fingerprint-based approaches, and it can save energy by 68% on average compared to the approach based purely on Wi-Fi interface.

Utilizing Wi-Fi signals and motion sensors comprehensively is an effective way to improve position estimates. To improve the positioning accuracy authors in [126] proposed a fusion location framework where an Extreme Learning Machine (ELM) regression algorithm is used to predict the position based on motion sensors. Afterwards, Wi-Fi fingerprint-location result is used to solve the error accumulation of motion sensors with Particle filter. We summarize the solutions mentioned in this subsection in Table 9.

Lesson Learned Fusing the information from different technologies and techniques with appropriate weights is another area we looked into. Here, the overall fused weights can be the average of the weights obtained from multiple algorithms or, they can be the weights of the best algorithm. However, the average weights could be severely impacted by the worst algorithm and it is not easy to find out the best algorithm to select the best weights. Also, it is generally impossible to obtain labeled data in advance. In addition, weights need periodic updates to handle environmental changes. Therefore, unsupervised learning approaches [28] are more attractive than the supervised learning approaches [25] to obtain the optimum fused weights in indoor localization.

V. APPLICATIONS OF INDOOR LOCALIZATION

The advancement of indoor localization and the proliferation of smart portable devices in recent years have facilitated a wide range of location based services (LBS).

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TABLE 9. ML based solutions for fusion based localization.

Ref.	Learning Mech.	Fused			Localization Accuracy	Remarks
		Tech.	Features	Algorithm		
[25]	Supervised Learning	Wi-Fi	RSSI	K-NN, RF	2.6 m.	Works only when training data is available.
[141]	Supervised Learning	Wi-Fi	RSSI, SSD, HLF	K-NN	3.4 m.	Sensitive to signal fluctuations.
[27]	Supervised Learning	-	RSSI, CTF, FCF	K-NN	39.68 cm.	Computation burden is heavy.
[143]	Supervised Learning	Wi-Fi, ZigBee	RSSI	K-NN	87%.	Intrinsic meaning of the data cannot be given.
[142]	Unsupervised Learning	Wi-Fi	RSSI, RSSIF, CMF, FoCF, FLOMF, SSF	Multiple Classifiers Multiple Samples (MUCUS) fusion algorithm	31.64 cm.	Algorithms are tested only on the present of Gaussian and impulsive noise.
[28]	Unsupervised Learning	Wi-Fi	RSSI	K-NN, SVM, logistic regression	2.6 m.	Works well without labelled data.

Contextual-aware Location based Marketing:

Contextual-aware location based marketing is a revolutionary idea in e-commerce, that has the potential to improve sales and profits. This type of marketing helps the seller to reach consumers in real time and enhance their shopping experience. This is relevant especially at this time of technological advances, when nearly everyone owns smart mobile devices. Widespread access to personalized mobile devices allow customized marketing approaches based on the location, social profile, spending pattern, navigation history, online behavior, browsing patterns and inclination (subjects they 'like' and 'follow' on social media). The aim of this marketing strategy is to draw an inference from the personal interests, past shopping history, requested feedback, email reminders, and then send them relevant advertisements and coupons from stores close to the location of the consumer.

Indoor positioning systems are an integral component of location-based marketing as well as other LBS. Positioning systems allow geographically localizing the mobile device both outdoor and indoor. The most commonly used technologies in location based marketing applications include geofencing with GPS positioning, Bluetooth beacon RFID, and Wi-Fi.

Tracking Mining Workers: Due to large number of disasters with many fatalities in underground mines, currently there is a legal requirement to continuously track all the coal miners. This is mandated by the Mine Improvement and New Emergency Response (MINER) act of 2006. Therefore, the mining industry is actively pursuing developing various solutions to track miners in underground mines [144]. Although zone based RFID localization [145] is prevalent in mines, several new technologies including directional antennas [146], beam forming leaky feeders [147] and ML algorithms [112] are researched to improve the reliability and accuracy.

Inventory Tracking: LBS is not just about people. There are cases when automatic tracking of numerous items in huge warehouses and factories are needed [148]. In this case, not only localization and identification but also managing the localities of these items in real time is needed. Therefore, in addition to localization techniques and data base management, new Medium Access Control layer protocols also needed to ensure all these items are properly identified without collisions and blockage [149]. Often deep learning techniques are needed here to handle the huge data [73].

Ambient Assisted Living: Accurate indoor positioning is the ground of ambient assisted living platforms. These systems provide assistance to elderly, infirm or disabled individuals to live comfortably in their homes, neighborhood and public places. The elderly people affected by neurodegenerative conditions need behavioral tracking including monitoring daily activities, detection of daily movement patterns, recording vital signs and detection of endangering events (fall, injury) etc. [150]. Many IPS technologies including Wi-Fi and Bluetooth can be used in this application.

Disaster Recovery: In cases of indoor trapping of individuals in the wake of fire and earthquake, indoor localization techniques could identify the specific location of individuals in danger and rescue them from the building within the shortest possible time. Since the indoor environment is usually unknown to the rescuer, accounting for the exact number of people that are trapped and rescuing them safely could be difficult. A positioning system free from prior measurement, calibration, configuration and deployment could be the best tool for a rescue force. In extreme cases the in-built communication facility might also collapse due to the disaster. Context-aware positioning can be a game-changer in this type of scenario [151].

Public Safety and Law Enforcement: Efficient indoor positioning could pinpoint the location and origin of the danger within a building/facility [152], so that a disaster can

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be mitigated and managed at inception. For example, the police have been using indoor positioning technology based on Bluetooth Beacon installed throughout campus buildings and open places to help pinpoint emergencies, so that police can respond timely avoiding unnecessary hindrance and delay. Indoor positioning technology could be taken to the next level by developing applications that detect location of explosives, stolen items inside buildings in order to assist trained police dogs, bomb squad or for an endangered individual to locate the nearest emergency exit in a smoky environment.

Health Services: Indoor localization has huge potential to improve the service quality in the health care sector in multiple ways. IPS can help front end workers to find the patient in time in a crowded hospital [153]. Patients can also find therapy rooms on their own with indoor navigation. Doctors could track the mobility and safety of patients. Visitors could find their patients in the medical facility without hassle. Even wheelchairs and specialized surgery equipment can be found inside surgery rooms easily.

VI. FUTURE CHALLENGES AND LIMITATION OF ML

Numerous ML based indoor positioning methods have been proposed in the past few years [154]. However, adaptation of ML-based solutions in indoor localization is still in its infancy. A number of issues need further investigation.

Mainly, ML based models are very much application specific. For example, a well-trained DL model developed on RSSI based fingerprinting can provide excellent results for the same, but it cannot be applied for CSI based fingerprinting.

Availability and Standardization of Training Data: The success of ML is data dependent. Most DL algorithms need adequate data. Even in reinforcement learning, the agent learns an action based on the reward/penalty feedback which can also be considered as the training data. The amount and quality of the available data significantly influences the performances of ML algorithms and determining the appropriate amount of the data is a tough task. That means, a realistic estimate of the required data-set size is needed for setting the performance bounds of different learning algorithms.

Both in supervised and unsupervised learning the training data sets are collected using different techniques and the collected data may vastly vary due to many factors including device heterogeneity [120]. For example, in radio fingerprinting, if the devices used to construct the radio map and the one used during the positioning phase are different, a significant pattern mismatch will occur. To solve this problem, it is crucial to develop a standard framework for training and predicting data that is independent on the hardware of the devices.

Cost of Training and Estimation Time: Two time metrics, training time and response time, are indispensable parts of a ML model. During the training timing, the algorithm trains itself to predict the output of future test data. During the response timing, the model predicts the output for a given input. Few approaches such as the RL based approaches can take a long training time since, RL learns through interacting with the environment by trial-and-error process. Also many deep learning algorithms can take a long time for training.

Therefore, selecting the most appropriate model for a given IPS environment is crucial to get the required accuracy while having minimal training and response times. Unnecessarily complex ML models shall not be used although, they might give us slightly better accuracy. This is essentially an optimization problem among complexity, timings (or delay) and accuracy.

Challenges of Deep Learning: Most indoor localization systems are device based where, the user devices, with limited storage capacity and computational capability, perform the location estimation [12]. Therefore, although, it is well known deep learning models are very promising, it is challenging to implement DL model in devised based IPS [21]. This is because, DL based models need computational and storage overhead for extracting complex features automatically from large volumes of unlabelled data.

In addition, DL models are very much application specific. A model can accurately predict the outcome when the model is trained well on that specific problem. Sufficient amount of data and time are required for training a DL model. A well-trained model may require retraining when the definition, state and the nature of the problem have been changed. Therefore, for real-time localization in complex environments, it is difficult to retrain the DL model timely for the frequently changing input information.

Lack of Variability: Machine-learning approach lacks variability, in cases where historical data is unavailable. Therefore, it is difficult to ascertain that predictions made by ML systems are suitable in all scenarios. For instance, even versatile ML algorithms like Transfer learning, that enables transferring the knowledge learned from one task to another similar task may not reliably transfer knowledge from a known domain to a new target domain with satisfactory level of accuracy.

However, the world is moving towards being a huge cyber physical system. The exponential growth in edge and distributed computing systems and omnipresent wireless access and cloud facilities have been the backbone of this transformation. Upcoming 5G (and beyond) wireless networks that integrate multitude of access technologies with seamless truly broadband coverage and ultra low-latency communication fuel this transformation.

Hence, due to the availability of advanced communication and computing infrastructure, the above mentioned challenges in indoor localization are expected to be handled successfully in future, providing numerous location based services both indoors and outdoors.

VII. CONCLUSIONS

This paper discusses various challenges in indoor localization, along with research efforts in this regard. We found machine-learning approaches have great potential to overcome these challenges effectively while conventional localization algorithms have limited success. We have surveyed the state-of-the-

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art ML based research efforts in solving various challenges associated with indoor localization. Furthermore, we have identified challenges related to successful deployment of ML-based localization techniques and have listed future research directions in this regard.

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