Journal of Intelligent & Robotic Systems (2021) 101: 63
https://doi.org/10.1007/s10846-021-01327-z

A Survey of Machine Learning Techniques for Indoor Localization and Navigation Systems

Priya Roy[1] · **Chandreyee Chowdhury**[1]

Received: 25 December 2019 / Accepted: 25 January 2021 / Published online: 4 March 2021

Abstract

In the recent past, we have witnessed the adoption of different machine learning techniques for indoor positioning applications using WiFi, Bluetooth and other technologies. The techniques range from heuristically derived hand-crafted feature-based traditional machine learning algorithms, feature selection algorithms to the hierarchically self-evolving feature-based Deep Learning algorithms. The transient and chaotic nature of the WiFi/Bluetooth fingerprint data along with different signal sensitivity of different device configurations presents numerous challenges that influence the performance of the indoor localization system in the wild. This article is intended to offer a comprehensive state-of-the-art survey on machine learning techniques that have recently been adopted for localization purposes. Hence, we review the applicability of machine learning techniques in this domain along with basic localization principles, applications, and the underlying problems and challenges associated with the existing systems. We also articulate the recent advances and state-of-the-art machine learning techniques to visualize the possible future directions in the research field of indoor localization.

Keywords Indoor localization · Fingerprinting · Supervised learning · Transfer learning · Extreme learning machine · Deep learning · Mobile robot · SLAM

1 Introduction

Nowadays, indoor Location-Based Services (LBS) have become an essential part of people's daily life with the large-scale proliferation of smart devices. The prime objectives of LBS are locating a user in indoor spaces, helping the users to navigate in unfamiliar places such as shopping arcades, airports, railway stations, and so forth. Constantly monitoring the location of mentally challenged patients or aged persons is essential in hospitals or residence. Asset tracking services are required in warehouses to locate the goods and inventory in real-time. Hence, these types of services have been typically integrated into our social activities. GPS is not applied for localization in indoor spaces as the satellite signals cannot penetrate well in the complex indoor area. Additionally, line-of-sight measurement is required for traditional outdoors positioning techniques such as trilateration and triangulation. Hence, such techniques are not suitable in indoors with walls, obstacles, etc [158].

Consequently, several technologies, including Wireless Fidelity (WiFi), Ultra-Wide Band (UWB), Ultrasonic, Infrared, Radio-Frequency Identification (RFID), Bluetooth Low Energy (BLE), and Zigbee, have been applied for designing *Indoor Localization System (ILS)* to fulfill the growing demands of the same [42]. Realizing this growing demand, few indoor navigation systems have started to emerge. However, many building owners do not wish to share information about their indoor floor plan in public due to privacy reasons. Thus, despite of many research efforts, a ubiquitous solution of ILS is still out of reach.

Existing survey works mainly focus on various technologies used for ILS as in [158], the statistical/probabilistic techniques and the signal characteristics for solving indoor localization problems as in [42]. Localization techniques like Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA), Time of Flight (ToF), Return Time of Flight (RToF), Phase of Arrival (PoA) are also discussed in the literature [154, 158] however, these techniques

✉ Priya Roy
priyaroy.rs@jadavpuruniversity.in

Chandreyee Chowdhury
chandreyee.chowdhury@jadavpuruniversity.in

[1] Computer Science and Engineering, Jadavpur University, Kolkata, India

require the prior knowledge about the exact location of the Access Points (APs), distance and angle measurements. Unfortunately, in most of the cases, the location of APs are unknown. Among all the localization technologies wireless fingerprinting-based localization is very popular due to simplicity and easy deployment. It reduces the hardware deployment cost by using the existing wireless network infrastructure of a building like WiFi (e.g. IEEE 802.11). The collected radio frequency measurement of a location is known as fingerprint or signature through which every location can be uniquely identified. Usually, this radio frequency measurement is the Received Signal Strength (RSS) of WiFi, Bluetooth, etc.

In the recent past, we have witnessed the adoption of machine learning techniques in indoor positioning and the effectiveness of machine learning techniques in extracting knowledge, discovering, learning and improving localization accuracy can be observed in the literature. These approaches are very effective than traditional mathematical approaches for complex non-linear problems that are too complicated for handwritten rules and/or equations. Machine learning techniques can provide a scalable solution to the problem for large indoor spaces as the classifiers, can be easily tuned as the datasets are updated [1, 50, 169]. Moreover, unlike statistical approaches, machine learning techniques can be easily extended to provide a stable performance under various ambient conditions [1, 47, 168]. The online learning ability of classifiers allows to incrementally adapt to changing ambient scenario which is very difficult with traditional approaches [47, 168]. Even, the knowledge gained through training for one ambient condition or one experimental region can be transferred to learn a new but related ambient condition or region respectively through transfer learning mechanisms [62, 170].

Interestingly, similar to the usual indoor fingerprinting approaches, machine learning approaches also include an offline training phase and an online testing phase. In the training phase, a model is obtained based on the available data. Then, using this training model, the performance of a machine learning algorithm is validated through some set of controlled experiments when the ground truth is already known. Later, during the testing phase, the algorithm predicts an outcome in the real environment by exploiting the training model without having any knowledge about the actual outcome of the test data in advance. Thus, the fingerprint-based indoor localization problem is effectively solved by pattern matching techniques that are applied in machine learning algorithms.

Many researchers have employed machine learning techniques not only for wireless fingerprint-based localization but also for other types of localization based on RFID [14, 67, 68, 153, 167], BLE [20], Camera [48, 64, 90], Ultrasonic beacons [111], ZigBee [28], Inertial sensor [131], and so on. More importantly, in this domain, appropriate machine learning algorithms can be chosen on the basis of the application areas, challenges, technologies, etc. However, we could not find out any state-of-the-art survey works that discuss the applicability, mapping and comparison of various machine learning techniques in this field and suitability of a technique to design the ILS for some specific purpose. In this regard, the objectives of this survey are as follows:

– It provides a comprehensive discussion on the basis of ILS and the relevant algorithms conceived from the machine learning approaches which are used in recent works.
– It presents an in-depth discussion about the generic challenges and the corresponding machine learning approaches that are used to handle them in literature.
– It highlights open issues and future trends in this research direction.

This paper is further structured as follows. Section 2 briefly discusses the existing literature. The brief overview of ILS is presented in Section 3. The comprehensive overview of machine learning algorithms that are used in prior works is discussed in Section 4. Section 5 discusses open issues and future directions in this domain. Finally, Section 6 concludes this survey.

2 Literature Survey on Traditional Indoor Localization

This section summarizes the traditional approaches of user and robot localization along with a brief discussion about the existing survey articles.

2.1 Survey on User Localization and Navigation

One of the pioneer systems for user localization and tracking is RADAR [11] that uses RSS values from the user device to estimate their location. This system adopts the nearest neighbor(s) in the signal space approach that is very similar to kNN. Another well-known system, Horus [157] uses a joint clustering technique for estimating location and also reducing the computational complexity. To achieve high localization accuracy, this system also identifies the various causes which affect the wireless channel. Ni et al. [80] have proposed an RFID-based system, LANDMARC, for tracking the user location. Various RFID tags, served as reference nodes, are deployed in an indoor space. A tracking tag is equipped with the user device or the object to be tracked. Then, the reference node measures the signal strength of the tracking tag to predict the location of the device or object. Ward et al. [138] have designed

BAT based on ultrasonic signals and this system has been experimentally evaluated in [38]. The centralized system architecture has been employed in this system. The proprietary transmitters are equipped with the devices to be tracked. The receivers having known and fixed positions receive the transmitted signals that are used for location estimation. These receivers and transmitters need to be synchronized. BAT [138] gives significant accuracy i.e. 3 cm in the 3D spaces, however, its accuracy is very sensitive with the deployment of the ultrasonic receivers. Moreover, the use of many dedicated anchor nodes makes this system costly. Thus, large scale deployment of such a system is prohibitively expensive.

Combining both radio frequency (RF) signal and ultrasonic signal, Priyantha et al. [92] have designed Cricket that offers several advantages including user privacy, ease of deployment, stability, cost-effectiveness, etc. Unlike BAT [138], this system does not need any synchronization between the transmitter and receiver. Cricket [92] eliminates the need for any centralized control or information and explicit coordination between the transmitters. Using a randomized algorithm, the mounted transmitters on the ceiling emit ultrasonic signals in a distributed way. Moreover, Cricket [92] is not a conventional location tracking system, it is a location-support system used by location-dependent applications. It achieves an accuracy of 10 cm, however, its range is limited due to the use of ultrasonic signals. Usually, the ultrasonic signal can be able to propagate less than 5m distance and does not penetrate obstacles. Thus, the ultrasonic positioning systems like BAT [138] and Cricket [92] require a lot of precisely positioned reference nodes to locate an object in indoor spaces. Hence, the precise deployment of all the reference nodes becomes more labor-intensive in the case of a large indoor area. To address this problem, Savvides et al. [107] have introduced the concept of iterative multi-lateration. In this technique, a sensor node whose position is estimated using the reference nodes, itself becomes a new reference node and this process is repeated until all the sensor nodes are located. Based on the idea of iterative multi-lateration, a distributed positioning algorithm has been proposed in DOLPHIN [74] to reduce the deployment cost of the ultrasonic positioning system. DOLPHIN [74] has also employed several techniques to achieve high positioning accuracy. McCarthy et al. [71] have proposed two novel ultrasound positioning system synchronous BUZZ and asynchronous BUZZ that employ narrowband ultrasound. In their systems, the mobile devices to be located receive the short bursts of narrowband ultrasound signals generated by beacons deployed at some fixed position. Using the transmission pattern of these bursts, the mobile devices itself calculate their location. Compared to other systems, BUZZ [71] saves component costs and reduces power consumption.

In the recent past, the smartphone-based approaches have found a huge boost in this research field as it requires the existing infrastructure (e.g. WiFi and/or Bluetooth based) and in-built sensors of the hand-held devices. Thus, in this context, we have summarized some conventional smartphone-based approaches.

Kang et al. [49] have introduced SmartPDR, which is a smartphone-based Pedestrian Dead Reckoning (PDR) approach for tracking the user in indoor spaces. SmartPDR [49] is based on a typical dead reckoning approach that is widely employed to solve localization problems in anonymous indoor environments. The accelerometer, magnetometer, and gyroscope of a smartphone are used in their approach to observe the movement of pedestrians. Chen et al. [18] have proposed a sensor fusion framework for smartphone-based indoor localization by combining the WiFi-based Weighted Path Loss (WPL) algorithm, PDR and landmarks. Their framework has been able to achieve a mean localization accuracy of 1 m. In their proposed PDR approach, landmarks are introduced to overcome the error of initial estimation which accordingly improves the accuracy of estimating the directions of walking. Moreover, a Kalman filter has been applied to fuse the readings of the magnetometer and gyroscope. Since the RSS is very vulnerable to indoor environment dynamics, the RSS fingerprint map needs to be updated to provide long-term localization services. In this regard, Wu et al. [143] have designed an automatic and continuous radio map updating method by leveraging smartphones without additional hardware and extra participation of users. Researchers have also proposed smartphone-based indoor positioning schemes that require the support of additional infrastructure. Among them, Yang et al. [150] have presented a smartphone-based ILS which incorporates a Kalman filter to fuse an infrastructure oriented acoustic localization system and an inertial sensor-based dead reckoning approach. A fuzzy inference system is designed for a short-term high accuracy tracking by utilizing inertial sensors. Hence, their system is stable for the long-term, and also robust against the short-term noise of the acoustic system.

Furthermore, BLE-based infrastructure provides several advantages than WiFi, such as less power consumption, higher sample rate, etc. Considering those advantages of BLE, Zhuang et al. [165] have proposed an algorithm for smartphone-based ILS using WiFi and BLE beacon. Their proposed algorithm combines the channel-separate polynomial regression model with channel-separate fingerprinting (FP), outlier detection and Extended Kalman filtering (EKF). FP and PRM have been employed to predict the location of the target and measuring the distances between them. Thus, deterministic and probabilistic approaches for indoor localization of users mostly include techniques such as PDR and Kalman filters.

2.2 Survey on Robot Localization and Navigation

In the recent past, indoor navigation for autonomous mobile robots grabs the attention of the researchers. Indoor mobile robot navigation plays a vital role in personal assistant robots, self-driving cars, industrial applications like automated manufacture, assemble of large aerospace structures and many more. Indoor mobile robot localization and navigation denotes the robot's ability to determine its own location and orientation within its frame of reference and then, to search a relevant path towards its target location. In order to reach autonomy, the mobile robots need a mapping process in which a spatial layout of an environment is obtained through sensory information. Mobile robots generally use Simultaneous Localization and Mapping (SLAM) to infer an estimated map of an environment and concurrently deduce their location, activity and path using this map [27]. Different places in an indoor area (e.g., stairs, elevators, corners, doors) exhibit unique sensors signatures that can be used as landmarks. The robots collect information by sensing nearby landmarks and simultaneously measures its motion. SLAM gives a probabilistic framework to deduce the map (Θ) along with the location (x_t, y_t) and orientation of the robot (ϕ_t). So, the objective of SLAM is to find the estimated pose of the robot ($\hat{s_t}$) and the map ($\hat{\phi_t}$) by maximizing the probability density function given below:

$$p(s_t, \Theta | u^t, z^t, n^t) \tag{1}$$

Where, u_t denotes the motion update of robot at time t obtained from the sensor of robot, $z^t = \{z_1, \cdots, z_t\}$ represent the history of landmark observations which is relative to the position of the user. Moreover, $n^t = \{n_1, \cdots, n_t\}$ specifies the variables of data association and n^t is the identity of the observed landmark at time t.

The Extended Kalman Filter(EKF) is one of the traditional approaches which estimates this probability density function [2]. This approach represents the map and poses of a robot by a high-dimensional Gaussian Density function. One of the limitations of the EKF-SLAM approach is the computational complexity which is quadratic in the number of landmarks [75]. The other limitation is the data association problem i.e. how to identify landmarks that have a similar signature (e.g. two nearby turns, elevator, staircase). In the literature of EKF-SLAM, this problem is handled by restricting the inference to the most similar landmarks given in the robot's current map [23]. Other approaches have been also proposed to overcome this problem. Interleaving the decision of data association with the map building for revising the decision of past data association is one of them [8, 120]. Such approaches require a lot of time to execute and hence, cannot be executed in real-time. Hence, to overcome the limitations of the EKF-SLAM, the FastSLAM approach has been introduced [75, 76]. The FastSLAM algorithm is logarithmic in the number of landmarks unlike the quadratic time complexity of the EKF-SLAM approach. Additionally, the decision of data association in the FastSLAM is handled using a per-particle basis. So, this algorithm has to maintain posteriors over several data associations which is not the most similar one in the EKF-SLAM approach. Hence, the FastSLAM approach is more robust to the problem of data association [75, 76].

Apart from the landmark-based mapping process, occupancy grid mapping is also widely used in SLAM. The representation of an environment using the occupancy grid was initially proposed in 1985 [78] and formalized by Alberto Elfes in 1991 [24]. The basic concept of the occupancy grid is to represent a map of an environment as a grid of evenly shaped cells. The value of each cell denotes its state e.g. free, occupied, or not mapped. The occupancy values of the cells are determined and updated using a Bayesian probability approach. Basically, the occupancy grid map determines the occupancy probability of each cell by taking the information of sensors as inputs. The resulting model is then used by the indoor mobile robots as a map of an indoor region for navigation purposes like planning of path, avoiding the obstacles, estimating pose, etc. The key advantages of employing occupancy grid mapping are: it is easy to build and addresses the difficulties of constructing a map from noisy and uncertain sensor data. Most of the mapping algorithms are very efficient in small environments and poorly scale when mapped to a large environment. At the time of exploring a large unknown environment sometimes a loop is closed and thus, the conventional occupancy grid map has to be rebuilt. For real-time operation this rebuilding becomes very time-consuming. Besides, path planning becomes computationally too expensive for very large occupancy grid maps. To overcome both problems, Schmuck et al. [109] have introduced a large-scale 3D occupancy grid map for mobile robot-based on hybrid metric-topological maps. More importantly, the proposed technique of Elfes is mostly used for a static environment. An autonomous vehicle needs precise information about its surroundings that can be static or dynamic. Thus, Wessner et al. [139] have presented an approach that extends a static occupancy grid to a dynamic occupancy grid. They have proposed a derivation strategy of the prediction and an update rule for the dynamic occupancy grid and validated their approach using one-dimensional simulation. Furthermore, in order to overcome the need for initial pose estimation of a mobile robot, Xu et al. [147] have proposed a novel real-time locating system in which a new 2D mapping module has been used to construct and maintain an additional 2D occupancy grid map. Along with more intuitive pose estimation, their approach also provides continuous navigation, path planning and allows the users to interact with the system. Nikdel et al. [81] have constructed a 2D occupancy grid bitmap using the LiDAR scan data of an indoor mobile robot. Then, they have manually labeled this grid map with human-meaningful navigational features such as open corridor, closed door, intersection. A Convolutional Neural Network (CNN) has been trained to identify these features on the provided input bitmaps.

For an industrial application, the position and orientation of an indoor mobile robot must be obtained in real-time. Hence, the 2D coordinates positioning and heading angle estimation of an indoor robot are not enough for an industrial application. In order to employ a mobile robot for a large-scale space, Huang et al. [44] have presented a novel approach for reliable and flexible positioning and navigation of the indoor mobile robot in 3D coordinates and measuring its orientation. They have mounted a rotary-laser transmitter on the robot to measure the scanning angles and obtaining the robot's location in 3D. Accordingly, they have proposed an algorithm of multi-angle intersection to determine the transmitter's spatial position and orientation. The accuracy, cost, area of the experiment, type of the used signal, the maximum number of mobile robots which can be localized at the same time-instant, are some of the vital parameters for an indoor robot positioning system. Yayan et al. [155] have designed a cost-effective mobile robot positioning system for large indoor environments based on the ultrasonic signal. To show the effectiveness of their positioning system, they have conducted experiments in the various test environments. The main difference with other existing systems is that using only ultrasonic signal they have achieved centimeter-level accuracy.

In recent years, autonomous ground robots and quadrotors have become popular for various applications such as lawn mowers, vacuum cleaners, industrial warehouse robots and so on. Thus, researchers have proposed various methods that allow the quadrotors to fly in the indoor regions without human control. Li et al. [56] designed an air-ground multi-robot system whose quadrotor is able to take-off, fly and land on the ground robot by utilizing their proposed marker-based and optical-flow-based methods. The poses and motion of the quadrotor have been estimated by the two LED markers attached to the ground robot and the optical-flow-based methods respectively. Harik et al. [37] have introduced a cooperative two-robot system where the ground robot is localized and navigated using a dead-reckoning approach and detection of landmarks. The quadrotor has the ability to fly in an indoor area by tracking the ground robot using its onboard bottom camera. Still, the performance of their scheme is not significant enough because of the slipping between the robot wheels and the ground surface. Moreover, if the quadrotor has failed to track the ground robot it would fail to locate and navigate itself. In order to fly the quadrotor more efficiently and flexibly with an autonomous ground robot, Lin et al. [58] have proposed a 3D cooperative SLAM method. The quadrotor and the ground robot are able to localize each other in the indoor spaces, navigate around the surrounding and generate their own maps. In addition, the ground robot is able to track the quadrotor and evaluate its pose.

Sound Source Localization(SSL) has a significant role in building more powerful autonomous robots. Most of the research works have used interaural time difference (ITD), interaural level difference (ILD), and spectral cues for localizing sound source. Valin et al. [127] have presented a robust SSL method in a 3D space based on the TDoA method. Their proposed method has validated using a mobile robotic platform having an array of 8 microphones. Gala et al. [33] have proposed a 3D SSL technique to estimate the elevation and azimuth angles of a stationary sound source. In order to do these, their proposed technique uses the estimated amplitude and phase shift of the ITD signal, recorded by a two-microphone array. Their developed SSL algorithm has been validated using a binaural device and a ground robotic platform. For estimating the orientation and distance of a sound source in a 3D space, Gala et al. [34] have designed another novel robotic platform using a self-rotational bi-microphone array. In this platform, the unmanned ground robots effectively localize the source of the sound. Moreover, Gala et al. [32] have also proposed two novel approaches for small autonomous unmanned vehicles (SAUVs) to localize multi-sound sources in 3D space. These approaches have used two machine learning techniques such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Random Sample Consensus (RANSAC) algorithms.

Another major application of mobile robots is to search the source of gaseous compounds in the air. Most of the prior works have used a ground robot and performed a 2D search. However, the localization of the odor sources in the air is a 3D phenomenon. Rahbar et al. [94] have proposed a bio-inspired 3D algorithm to address the problem of odor source localization in a wind tunnel. Their method uses a ground robot as well as an aerial vehicle to robustly identify the source. In order to get a chemical gas concentration map of an unknown indoor environment, Turduev et al. [125] have implemented several bio-inspired algorithms. In their experiments, the robots send their collected sensor readings and calculated position information to a remote computer which combines, filters and interpolates the data to obtain a chemical concentration map of the experimental environment. In the recent past, Micro Air Vehicles (MAVs) and autonomous robo-fly have started to emerge. The researchers of the University of Washington have created a fully autonomous "RoboFly" after spending an extensive effort of more than 20 years [1]. This is basically a robotic insect that could easily fly into tiny spaces where human or even a drone can not enter to find the disaster survivors. It could also examine the growing crops in the field to detect pests and diseases. Scheper et al. [108] have presented the first flapping-wing MAV to autonomously explore multi-room in an indoor region. Their proposed DelFly explorer is equipped with a 4g stereo vision system and an on-board autopilot. This vehicle has been able to successfully navigate between two opposite side rooms that have separated by a corridor.

Mobile robots that are autonomously moving in the ground or flying in the air typically consume a lot of energy. Thus, navigating a battery-powered autonomous mobile robot arises several issues. First of all, the robot must be able to cover its region before completely finishing its battery power so that it can safely return for recharging. Secondly, the robot must be able to finish its assigned task as early as possible in order to require a minimum number of intermediate recharge sessions. The on-board battery of an indoor mobile robot allows a few hours of continuous operation. So, the major concern is the need to return for the recharge that requires consumption of high-power and finding the shortest path from the robots' current position to the charging point. Liu et al. [60] have designed an approach to predict and manage the voltages of the on-board battery for optimizing the mobile robot transportation in the laboratory. Their approach considers the forecasting results of the batteries and selects the appropriate mobile robot for transportation. Lo et al. [63] have also paid their attention to the problem of energy consumption of a battery-powered autonomous indoor mobile robot. They have designed a fuzzy logic velocity controller to reduce energy consumption. Shnaps et al. [112] have introduced a novel battery-powered coverage algorithm for mobile robot navigation. Using this algorithm, the robot properly utilized the maximum of the battery's life and breakdowns due to insufficient battery power are prevented. They have also described the online battery-powered coverage problem where an autonomous mobile robot having no prior knowledge of an environment, must be able to gather information about the nearby obstacles using local obstacle detection sensors.

2.3 Existing Surveys on Indoor Localization

The available survey articles of this field have highlighted the indoor localization problem, technologies, applications and mostly the deterministic methods that are applied to implement the same. Table 1 summarized a time-line of the literature survey articles.

Liu et al. [59] have presented an in-depth overview of the state-of-the-art wireless indoor positioning systems and solutions. The localization schemes like triangulation, scene analysis, and proximity have been analyzed and comparisons among the different techniques and systems is presented. Besides, Fischer et al. [31] have discussed the indoor localization techniques that are useful for assisting emergency responders in challenging ambience such as darkness, smokey, fire-outbreak, power outages and so on.

Smartphone-based indoor localization has been of huge interest in recent years due to its integration with multiple inertial sensors (e.g. accelerometer, gyroscope and magnetometer). Localization can be benefited with the help of mobility information along with wireless signals. Yang et al. [152] have presented their views on the need and importance of the mobility enhancing smartphone-based ILS. Built-in sensors can identify numerous types of mobility information such as acceleration, angular velocity, absolute direction. Certain important issues like increasing location accuracy, decreasing deployment cost and enrich location context can also be addressed by incorporating mobility. They have also discussed the main obstacles such as noisy sensor data, unconstrained phone placement and complicated human activities that prevent accurate measurement estimates. However, the significant challenge is the integration of complementary sensing modalities with the noisy nature of crowdsourced data.

Hossain et al. [42] have presented a survey on calibration-free indoor positioning systems to emphasize the associated challenges of traditional fingerprinting techniques, such as the cost of time and manpower, unforeseen environmental changes, device heterogeneity and so on. Apart from the traditional performance comparison criteria like accuracy, precision, various calibration-free performance metrics such as map requirement, need for additional sensors, addressing device heterogeneity have also been reviewed. Device heterogeneity may be addressed with the help of calibration-free techniques as users are expected to be using heterogeneous devices during the training phase. The authors have emphasized the security and privacy issues which are found to be a major drawback of the calibration-free techniques.

According to the various applications of indoor localization, Xiao et al. [145] have divided the existing approaches into two categories: device-based and device free. Several key demands of these two categories such as accuracy, real-time, cost, reliability, robustness, etc. and the associated challenges have been discussed. Device-based systems have been further categorized into smartphone-based and tag-based systems. They have also detailed out the state-of-the-art device-based and device-free techniques according

[1] https://www.cnbc.com/video/2018/11/02/university-of-washington-engineers-created-the-robofly-a-small-flying-robot-that-goes-where-humans-cant.html

Table 1 A brief comparison among the existing surveys of indoor localization

Exist.work, location service	Approaches	Sensor/ Technology reviewed	Metric/criteria of comparison	Application considered	Challenges/Future trend considered
[59] in 2007 for user	Triangulation, Scene analysis, Proximity	GPS, RFID, Cellular, UWB, WLAN, Bluetooth	Accuracy, precision, complexity, robustness, scalability, cost	Asset tracking, inventory management, robotics, emergency	Novel hybrid positioning algorithm, integration of various wireless positioning systems, integration of indoor and outdoor localization, how to use sensor for improving accuracy
[31] in 2010 for emergency responders	Triangulation, Fingerprinting, Proximity sensing, Dead reckoning, Ad Hoc relative positioning	Ultrasound, Inertial sensor, Laser range scanner, RFID	Accuracy, error rate	Localization for emergency responders	Benchmarks for evaluating different positioning systems, lack of accounting for uncertainties in localization
[152] in 2015 for user	Human mobility information i.e., displacement, direction, integrated information	Accelerometer, Gyroscope, Magnetometer	Error distance	Services and applications in personal, public, medical, commercial domain	Localization error, deployment cost, absence of location context
[42] in 2015 for user	Calibration free localization	WiFi, Inertial sensor, Radio frequency	Accuracy, precision, scalability, robustness, security, privacy, cost, complexity, map requirement, acquiring fix location, seamless user participation	Medical resource tracking, navigating fire-fighters, commercial LBS	More investigation on security, privacy, energy efficiency and deployment issues of calibration free techniques
[145] in 2016 for user	Wireless localization from device perspective	WiFi, Inertial sensor, Acoustic, Bluetooth, GSM, Light, Infrared, UWB, RFID, Ultrasonic	Accuracy, real-time, cost, energy efficiency, scalability, privacy, reliability robustness	Navigation, warehouse monitoring, asset tracking	Selection of technology, integration of device-free system, placement of infrastructure, map build, anomaly/ entity identification, enlarging location context
[158] in 2017 for user	Probabilistic, ANN, kNN, SVM, AoA, ToF, TDoA, RToF, PoA	WiFi, Bluetooth, Zigbee, RFID, UWB, Light, Acoustic, Ultrasound, SigFox, LoRA, IEEE 802.11ah	Availability, cost, energy efficiency, range of reception, accuracy, latency, scalability	Context aware marketing and customer service, medical, disaster management, security, asset management and tracking, IoT	Multipath effect and noise, indoor ambience, energy efficiency, privacy, security, cost, lack of Standardization, negative impact of used technology, handover
[154] in 2017 for user and mobile robot	ToA, AoA, TDoA, Fingerprinting, Hybrid techniques, SLAM	UWB, WLAN, Inertial sensor, Signals of Opportunities	Accuracy	Robotics, ambient assisted living, health applications, LBS, 5G networks	Generating radio map with less human interpretation, Integrating various non-radio techniques and wireless positioning solutions, security, privacy, scalability, complexity, accuracy, cost effectiveness
[87] in 2017 for mobile robot	Fuzzy logic, Neural Network, GA, ACO, PSO	Sensors like Ultrasonic range finder, Sharp infrared range, Camera	NA	Applications of mobile robot in different areas	Nature-inspired algorithm for mobile robot navigation and obstacle avoidance
[126] in 2018 for mobile robot	Mobile robot kinematics, Dynamics, Wheeled control	Sensors like Vision, Sonar, Laser range finder	Systematic, non-systematic error	Applications of mobile robot in industrial, service, medical, and social domain	Minimize the gap between the available technologies or approaches and the market demands of autonomous mobile robot

to different modalities, including WiFi, inertial sensors, visible lights, acoustic, FM, Bluetooth, camera, and the combination of various modalities.

Zafari et al. [158] have provided a discussion on several emerging technologies such as SigFox, Low Range Wide Area Network (LoRaWAN), WiFi Halow and Weightless which are actually designed for Internet of Things (IoT) communication but can be applied in ILS as well. These above-mentioned technologies are classified into the device and monitor-based localization. Their research also highlighted certain challenges that need to be addressed for developing a stable IoT-based indoor localization technique. Moreover, Yassin et al. [154] have focused on fusing the hybrid positioning systems and game theory to improve the accuracy and robustness of the overall system. They have also detailed out the applications of ILS such as robotics, ambient assisted living, health care applications, LBS, etc.

Furthermore, Pandey et al. [87] have studied various techniques that are used by the mobile robot for navigation and obstacle avoidance. They have classified the mobile robot navigation algorithm into three categories: Deterministic, Nondeterministic, and Evolutionary. Discussion about various soft computing-based mobile robot navigation techniques such as the Fuzzy logic technique, Genetic Algorithm (GA), Ant Colony Optimization (ACO) Particle Swarm Optimization (PSO), etc. have been provided in their survey. In addition, Tzafestas et al. [126] have also presented an in-depth discussion about the existing control and navigation methodologies of the mobile robot.

Thus, the existing literature mostly reviewed the indoor localization techniques based on the different technologies, sensing modalities and usage in different scenarios such as assisting responders, calibration-free localization, navigation of mobile robots. However, there is a need for an up-to-date and comprehensive review of the machine learning techniques that are increasingly being applied to this problem domain. In this regard, a brief overview of ILS is elaborated first (in Section 3) followed by a thorough discussion on the machine learning techniques applied to this problem.

3 Overview of Machine Learning-based ILS

In this section, an overview of indoor localization is presented along with the underlying framework of this system. The applications are categorized and their usefulness in this field are described. Common challenges are also discussed.

3.1 Framework of Machine Learning-based ILS

The phases of ILS are depicted in Fig. 1 and described below:

Data Collection In this step, the required data are collected from every possible training points or predefined pedestrians/landmarks. Considering the various technologies of ILS, different types of data can be acquired such as the RSS of Bluetooth, WiFi access points (APs), RFID, the measured values of the inertial sensor, etc. During the collection of data, various perspectives that may affect the data need to be kept in mind. A brief overview of existing data collection modes and respective localization services mentioned in Table 2. There are three types of data acquisition processes, dedicated user-based, crowdsourcing and automated device (e.g. robot, drone) based.

Dedicated User-Based Data Collection Only the dedicated users who are willing to collect data can participate. Users acquire data from reference points using their smart devices. In order to obtain the labeled data, users tag the location information or label to the collected fingerprints. In UJIIndoorLoc [121], 21 users have captured RSS data of 520 APs from 933 location points using 25 different mobile devices. They have covered 3 buildings of their university campus and each building has 4 or 5 floors. Considering the dynamics of indoor ambience, Roy et al. [100] presented a dataset, JUIndoorLoc, where the RSS data of different APs are collected for various perspectives including open and closed room, presence and absence of users in the vicinity.

Crowdsourcing-Based Data Collection One of the real-life examples of crowdsourcing is *Waze*. Using this crowdsourced application, the users can report about traffic jams and gives the directions for the best route to take. Waze also crowdsources the information by measuring the speed of vehicles to determine traffic jams and asks the user to report the blocked routes. In an indoor scenario, this method relies upon a crowd of people who have agreed to collect data explicitly or implicitly using their mobile devices. In order to obtain the tagged location information or label with the collected data, the crowdsourced data collection application relies on the feedback of the crowd. Hence, one of the biggest challenges of this approach is the labeling problem i.e, through the feedback of the crowd, one can intentionally or unintentionally feed the wrong locations or labels into the database. Rai et al. [95] have designed a crowdsourced application, Zee, for indoor localization that runs as a background process on the users' smartphones without requiring the active participation of the users. At the time of data collection, the users are walking and standing in different positions of experimental regions keeping their smartphone in different positions. RCILS[162] is another crowdsourced-based system for indoor localization, that uses in-built sensors of a smartphone to record WiFi fingerprints, air pressure and motion data including acceleration, heading angle and angular velocity.

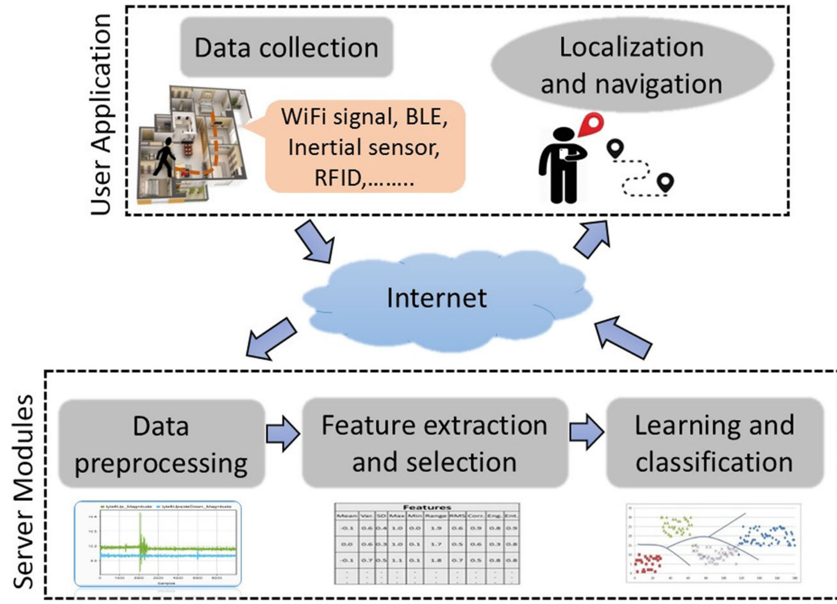

Fig. 1 The framework of machine learning-based ILS

Robot-Based Data Collection In a robot-based data collection, the measuring devices (e.g. smartphone) and the associated sensors (e.g. magnetometer, gyroscope, odometer, camera, etc.) equipped with the robot are used for robots' self-positioning and SLAM approaches. The major challenge of the automatic data collection using robots lies in its embedded SLAM method. In the literature, the SLAM-based approaches for acquiring WiFi data have already been studied [15, 51]. Moreover, the position of the robot may be incorrect at some time and hence, in the localization phase errors get accumulated by the robot. By the time the robot computes its correct position, the unreliable data are collected which requires manual filtering. Sometimes, the robot needs manual support in order to avoid collision with nearby obstacles or to reach a certain destination. According to Kong et al. [51] a 2D map of an indoor area is enough for a robots' self-localization. In Turtlebot robotic platform [79], two SLAM approaches are used to address the problem of automatic data acquisition. Recently, in the offline training, the mobile robot uses synchronized received signal software for collecting RSS of each AP from a known location [21].

Data Preprocessing A raw dataset may not always be cleaned and formatted. Generally, a raw dataset has missing values, noises and maybe in an undesirable format. So, a raw dataset cannot be directly used for constructing machine learning models. In the data preprocessing phase, the raw data is cleaned and processed for making it suitable for

Table 2 A brief overview of the data collection and respective localization service mentioned in the existing literature

Exist. work	Localization Service	Sensor used	Collection pattern	Dataset specifies
[121]	For user	WiFi RSS	Inside of each room and outside corridor (in front of door)	Publicly available; Dedicated user-based
[100]	For user	WiFi RSS	Grid based- grid size is $1 \times 1 sq.m.$	Publicly available; Dedicated user-based
[95]	For user	WiFi RSS, accelerometer, compass, gyroscope	Movement trail of pedestrian	Not publicly available; Crowdsourcing-based
[162]	For user	WiFi RSS, accelerometer, gyroscope, magnetometer, barometer	Movement trail of pedestrian	Not publicly available; Crowdsourcing-based
[15]	For mobile robot	WiFi RSS, onboard camera, odometer, laser scanner	Navigation trail of robot	videos of experiments and results are publicly available; Robot-based
[79]	For mobile robot	WiFi RSS	Reference point based	Not publicly available; Robot-based
[21]	For mobile robot	WiFi RSS	Reference point based- distance between 2 points is 1.2 m	Not publicly available; Robot-based

a machine learning model, so that, the performance of a machine learning model is improved. Thus, this is the most vital phase of any machine learning model.

Interpolating Missing Data Each instance of a raw-dataset may not contain data for all the attributes/ features. These, missing entries need to be filled with some values before generating a machine learning model. There are some strategies to fill these missing entries. Let us assume, an instance, x_i has a missing data for a particular feature say f_j and for the same feature, f_j, rest of the instances have data. Then, all the non-missing values of f_j are taken to compute the mean or median for replacing the missing data. Sometimes, the most frequent value among all the non-missing values of f_j is taken for replacement. Moreover, these strategies are also applied based on the class label. Instead of computing mean/ median for all the non-missing values of f_j, the mean/ median of f_j, for those instances whose class label is the same as of x_i, is taken to replace the missing data. In the same way, based on the class label, the most frequent value of f_j is considered for replacement. Furthermore, the missing data is also replaced by a dummy value that is not present in a raw dataset. In the publicly available datasets of this domain such as UJIIndoorLoc [121] and JUIndoorLoc [100] the missing data are replaced by the dummy values, like +100 and -110 respectively.

Filtering Filtering is a process to remove unwanted noise from the data. Sarshar et al. [106] have filtered out the noise from received WiFi signals with the help of the Wiener filter. This filter gives an estimation of the desired signal pattern from a corrupted signal pattern. The main objective of this filtering process is to minimize the mean square error between the estimated and the desired signal patterns. In this domain, Particle filter is also used as a particle smoother to remove noise [82] and fusing different sensory information. Kalman filter is another widely used filtering process that effectively deals with noisy sensor data. Kalman filter has many applications such as navigation and control of autonomous aerial and ground vehicles [12, 144], path planning of indoor mobile robot [2], etc. kalman filter is a most common technique for fusing sensor data [18, 67] as it is computationally light. Thus, Chen et al. [18] have fused inertial sensor data, WiFi signal strength and landmarks using Kalman filter for improving the performance of their proposed system.

Windowing Windowing is a technique in which the dataset is split into subsets based on very small time intervals of equal length based on the requirement. According to Wu et al. [142], the walking pattern of the user is random and hence, the collected fingerprints may be overlapped. So, in the preprocessing step, they merge two fingerprints if the RSS difference of those two fingerprints is lower than a predefined threshold. To avoid the effect of shadowing, fading and interference of WiFi RSS, Xue et al. [149] have removed the weakest RSS and computed the average RSS over a certain period of time. Roy et al. [102] have computed mean and variance of RSS fingerprints of every 2 s of time interval to add new features like mean of RSS and variance of RSS.

Feature Extraction This phase provides a piece of indicative information to identify patterns. If a raw dataset contains a large feature set and the features are suspected to be redundant, then the feature extraction technique is applied to generate a derived set of non-redundant and informative features from the original feature set. In image-based indoor mobile robot localization, the feature extraction is difficult as the activities of humans, the position change of objects make the indoor ambience dynamic. Thus, Xu et al. [146] have utilized the images of the ceiling captured by the camera mounted on the top of the robot and applied feature extraction on those images in order to obtain location and orientation of an indoor mobile robot. Hernández et al. [41] have proposed a novel approach for navigation of the indoor mobile robots where they have introduced two methods for feature extraction based on the geometric shape of the object and the bag of words. Moreover, Paolanti et al. [89] have used two Convolutional Neural Networks for extracting visual and textual features from the images that are captured by an indoor mobile robot. The feature extraction technique is also known as *dimensionality reduction*. In dimensionality reduction, high dimensional data is transformed into a low dimensional space in such a way that the transformed low dimensional data retains some relevant properties of the original data. *Principa000l Component Analysis (PCA)* is the most simplest and commonly used dimensionality reduction technique. PCA removes correlated features, reduces overfitting and improves the performance of a machine learning model. It is also used to visualize the high dimensional data in a low dimensional space. In this literature, PCA has been used to project the high dimensional RSS fingerprints into a low dimensional feature space without losing any meaningful information [26, 46, 104]. Despite of many advantages, PCA also has some issues. PCA turns the original features of a dataset into principal components that are less interpretable and readable as the original ones. Moreover, after implementing PCA some information may be lost if the number of principal components is not chosen carefully.

Feature Selection The important features that contribute most to learn a model are selected through feature selection techniques. This technique reduces overfitting, training time and complexity of the prediction model while improving the prediction accuracy. Feature selection techniques are generally classified into three categories such as Filter method, Wrapper method, and Embedded method.

Filter Method In order to select features, the filter method uses the feature ranking techniques. Feature ranking means how important each feature is to build a model. Ranks are assigned to the features based on their scores in various statistical testing. In those statistical tests, the correlation between each feature and the outcome variable is computed. There are various statistical tests including Pearson's correlation, Linear discriminant analysis (LDA), Analysis of variance (ANOVA), Chi-Square, Variance threshold, Information gain and so on. Roy et al. [98, 99] have selected a minimal set of stable APs as features by applying different feature selection approaches such as Correlation attribute evaluation, Information gain, etc.

Wrapper Method In this method, a subset of features is taken from the original feature set and used to train a model. Based on the inferences drawn from the previous model, a feature is added in the feature subset or removed from the feature subset. Some common examples of wrapper methods are given below:

- *Forward Feature Selection:* This is an iterative approach that starts with a model having no feature in it. In each iteration, one feature is added at a time and selects the feature set, that best improves the model, for the next iteration. This process is repeated until the addition of a new feature does not enhance the performance of the model.
- *Backward Feature Elimination:* This is also an iterative approach that starts with a model having all the features in it. In each iteration, one feature is removed at a time and selects the feature set, that best improves the model, for the next iteration. This process is repeated until the elimination of an existing feature does not enhance the performance of the model.

Embedded Method This method combines the efficiency of both filter and wrapper methods. Some common examples of this method include LASSO regression, RIDGE regression, Elastic Net. Moreover, the feature selection using the Random Forest algorithm is also very popular [164] and belongs to the category of embedded methods. Random Forest consists of a large number of decision trees. Every node of a decision tree has a condition on a feature and based on that condition the tree splits the dataset into two parts. This locally optimal condition is chosen by calculating impurity (such as Gini impurity, Information gain). In a forest, the impurity decreased by every feature is averaged and accordingly, all the features get ranks. However, in this impurity reduction-based feature selection, it is very hard to remove a feature that is correlated to the other selected feature.

Learning and Classification Machine learning techniques are applied to the extracted or selected feature set to construct the classification model. Supervised learning techniques are applied if the data are collected using the traditional fingerprinting method. Otherwise, for crowdsourced data, unsupervised or semi-supervised learning techniques could be the choice. These classification models are used for estimating the current location of a user or object based on the test datasets collected from them. Hernández et al. [41] have proposed an image-based indoor mobile robot navigation approach in which SVM is used as a classification algorithm for detecting objects in an indoor environment. Paolanti et al. [89] have introduced a novel system for surveying and monitoring in a retail store using a mobile robot platform. After feature extraction, they employed six state-of-the-art classifiers, such as SVM, kNN, Decision Tree, Naive Bayes, Random Forest and ANN to identify the content of the planogram image. Furthermore, Cui et al. [21] have designed a robust algorithm to locate indoor mobile robot by combining the well-known classifiers ELM and PCA. How these classifiers are applied to robot and user localization problem is presented in detail in Section 4.

3.2 Applications of ILS

The various application areas of indoor localization and certain real-time applications are discussed below. This corresponds to the discussion on machine learning techniques applied to these different application domains in Section 4.

Localization, Tracking and Navigation One of the primary objectives of the ILS is to locate the static position of an object, tracking the actual sequence of positions of any moving object and navigate with ease in the indoor environment [1, 103, 151]. In construction management, this technology has been used to keep track of labors, materials, machinery [140]. Other applications of ILS include keeping track of patients and other entities in hospital [14], localization in dark environment [66], indoor LBS [28, 169], geo-fencing and real-time occupancy distribution monitoring [169], navigation for visually impaired persons [91], tracking in autonomous systems [111] etc. Surveillance can be another paradigm where a suspect may be tracked indoors.

Asset Tracking and Warehouse Monitoring Nowadays, ILS has become very popular for asset management and tracking [25, 113, 115, 167]. In a warehouse, tracking assets like electronic equipment, manufacturing objects are in high demand [67, 153]. Tracking wares in the whole supply chain [64], autonomous system of tracking [68], theft protection and other security-related issues[167] are the main requirement of indoor asset tracking. *IndoorAtlas*[2] is an indoor asset tracking application that tracks the electronic assets including laptops, smartphones, IoT devices as well as industrial equipment, and medical appliances.

Autonomous Vehicle Navigation Autonomous vehicle navigation is one of the vital applications of indoor localization. In the indoor region, Unmanned Aerial Vehicles (UAV) and Unmanned Ground Vehicles (UGV) have gained huge popularity for providing aerial surveillance, finding a path for emergency evacuation, search and rescue operation and many more [105]. Recently, Autonomous Drone Racing has become one of the most popular e-sports in indoor [48]. The indoor navigation algorithm is required for a collision-free movement of UAV, UGV and drones due to the lack of GPS signals in indoor regions [84, 90]. In addition, autonomous navigation of the mobile robot plays a major role in warehouse robots, self-driving cars, smart wheelchairs, personal assistant robots and many more. However, the autonomous navigation of an indoor mobile robot in an unstructured and unknown indoor environment is a challenging task [128]. In the recent past, significant research works [37, 56, 58] are found that improves the indoor mobile robot navigation approach. Those robot requires SLAM approach for self-localization in an indoor region and deducing a path from its' current position to its' destination. Patel et al. [90] have fused the vision and depth measurements of camera and LiDAR to build an autonomous ground vehicle navigation policy which is robust to the possibility of sensor failure or corruption of data. Xia et al. [144] have introduced a SLAM approach for UGVs using Cubature Kalman Filter to minimize the computation complexity and to enhance the stability. Moreover, Aguilar et al. [3] have presented a real-time localization and mapping approach for on-board UGV using an RGBD camera. So, indoor positioning and navigation is very essential for the indoor mobile robots including UAV and UGV to safely navigate without any collision in an indoor area.

Moreover, indoor localization is used for business promotion. As an example, in the United Kingdom, *Intu* [3] developed a technology to provide opportunities for small retailers to explore and exploit interesting business models such as push notifications sending discount vouchers. Additionally, during disasters such as a fire outbreak in a building, indoor localization can be of immense help to the firefighters to save maximum lives.

[2] https://www.indooratlas.com/asset-tracking/

[3] https://www.telegraph.co.uk/finance/newsbysector/retailandconsumer/11858755/Trafford-Centre-owner-unveils-indoor-mapping-and-deals-app.html

3.3 Challenges of ILS

Indoor localization provides many scopes and new dimensions but still, there are some challenges which should be addressed upon so as to develop a better next-generation technology. Some of the significant challenges are discussed below. This corresponds to the discussion on machine learning techniques applied to mitigate these challenges in Section 4.

Error Accumulation in the Received Data In an indoor region, various factors affect the emitted signals and the sensor readings as depicted in Fig. 2. Signals of WiFi, BLE, RFID are mostly affected by attenuation, fading, shadowing, human movement, indoor ambient conditions, presence of interfering devices, obstacle and so forth (shown in Fig. 2a,b, c). Hence, noises are accumulated in those signals, so, erroneous signals are received at the receiver end. Besides, the measurements of inertial sensors are mostly influenced by temperature fluctuation and the presence of ferromagnetic objects in the indoor spaces as shown in Fig. 2d. Generally, the biases, bias stability, and thermo-mechanical noise are the most common errors that affect the inertial measurements [22, 152]. The systematic error, generated by biases, are integrated with the measurements of counting steps, estimating stride length, heading, orientation, etc. Filters like Noise Extended Kalman filter, Particle filter have been used in this literature to eliminate the drift and noises from the sensor data [57, 110].

Minimizing the Effort of Site Survey The fingerprint collection from a site is very time consuming and requires a lot of human effort. In most cases, it also requires overhead for labeling the fingerprints. Hence, this site survey is difficult to repeat for different indoor ambient conditions, rearrangement of furniture and so on. If the fingerprint dataset is not updated then there is a huge difference between train and test fingerprints of the same location. So, the accuracy of machine learning algorithms gets affected.

Selection of Important Feature Set Any real-time localization and navigation approach requires fast processing speed. Involving all the features in the training model generation not only wastes excessive memory space but also increases the computation overhead. Hence, the important features should be selected carefully, otherwise, the performance of the system may be degraded. Roy et al. [99] have selected important features that are less affected by the change of indoor ambience. They have experimentally shown that the important feature set has improved the localization accuracy than the original feature set.

Improving the Reliability of Localization Approaches Existing ILS may not meet all the demands of realistic applications

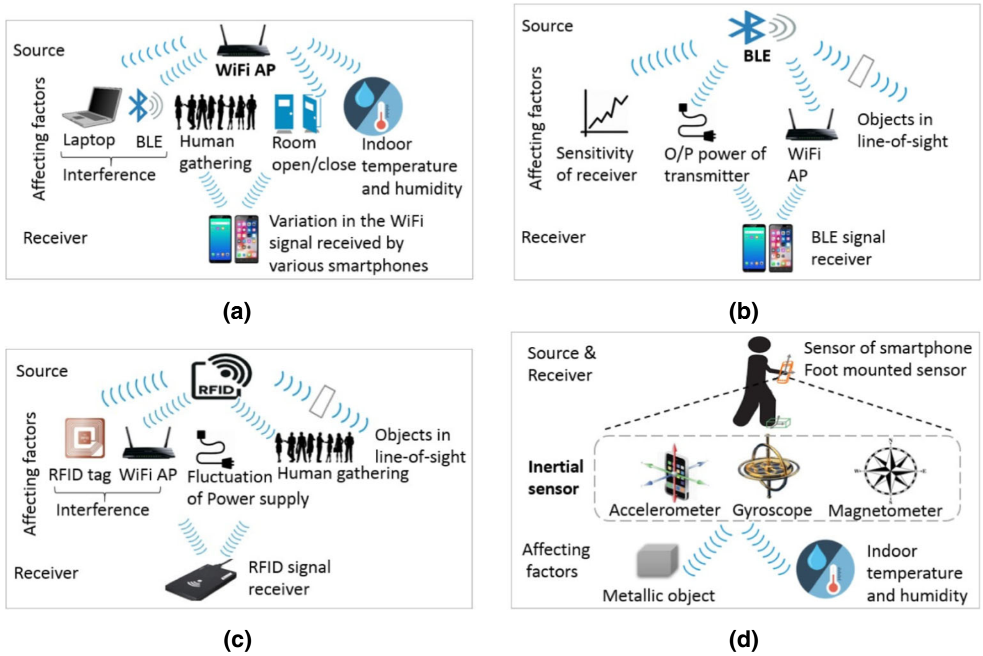

Fig. 2 Various factors that affect **a** WiFi signals **b** Bluetooth signals **c** RFID signals **d** Measured values of inertial sensor

due to some limitations such as huge computational complexity, an increase of location prediction time, inconsistent performance and many more. So, to increase reliability, these limitations need to be addressed carefully. In this literature, WiFi has been used alongside Bluetooth [20, 52], inertial sensors [131] and other technologies to increase localization accuracy. Besides, Wang et al. [134, 137] have also focused on improving reliability. So, they have used Channel State Information (CSI) instead of WiFi RSS as CSI is not that vulnerable as RSS.

Device Heterogeneity Multiple smartphones from the same place at the same time may record different signal strengths from the same source due to the different hardware configurations. Hence, identifying an unknown location becomes a difficult task for a machine learning algorithm when the train and test devices are different. However, in practice, during the training phase, it is not possible to collect fingerprints from all possible device configurations. One possible way is to update the training model using online learning algorithms [47, 168].

3.4 Parameters for Performance Evaluation

The parameters for performance evaluation are divided into two categories: performance metrics and performance issues.

3.4.1 Performance Metrics

The performance of ILS is evaluated on the basis of the following metrics:

Accuracy Accuracy is the one of the most vital performance metric of any positioning system. It measures how accurately a system can predict an unknown location. In terms of machine learning, accuracy is defined as N^c/N^t, where, N^c and N^t are the number of correctly classified instances and total instances respectively.

According to the prediction of positive and negative instances, accuracy is further defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where, TP and TN are the number of positive instances and negative instances that are correctly classified as positive and negative respectively. Besides, FP and FN are the number of negative instances and positive instances that are incorrectly classified as positive and negative respectively.

Precision The precision is used to measure how consistently the accuracy can be achieved. It is the proportion of positive instances which is correctly classified. So, the precision is defined by $TP/(TP + FP)$.

Recall The recall, also known as sensitivity, refers to the rate of true positive. So, the recall is defined by $TP/(TP+FN)$.

Average Localization Error The error rate, Er, of a localization system is defined as N^m/N^t, where N^m is the number of miss-classified or incorrectly classified instances. Moreover, the localization error is generally defined by the Euclidean distance between the actual location, (x, y), and the predicted location, $(\hat{x}, \hat{y})$.

Hence, the average localization error, Er^{av}, is as follows.

$$Er^{av} = \frac{\sum_{i=1}^{N^t} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N^t} \tag{3}$$

Mean Squared Error (MSE) The MSE refers to the mean of the squared difference between the actual location and the predicted location. Hence, the MSE is defined as follows.

$$MSE = \frac{\sum_{i=1}^{N^t} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}{N^t} \tag{4}$$

Root Mean Squared Error (RMSE) The RMSE refers to the square root of the MSE. Hence, the $RMSE$ is defined as follows.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N^t} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}{N^t}} \tag{5}$$

In the recent past, the performances of the existing machine learning-based indoor localization and navigation systems are mostly measured by accuracy [14, 66, 68, 84, 90, 101, 153], average localization error [28, 48, 67, 101, 111, 169], MSE [64], RMSE [90, 103, 111] and precision [48, 66, 67, 91, 111, 169]. Accuracy (in %) measures how many times a system correctly classifies a location i.e. the success rate of a system. So, the percentage of incorrect predictions is also obtained. However, in case of an incorrect prediction, how far is the predicted location from the actual location can not be obtained from the accuracy. Similarly, precision says nothing about the error between the actual and predicted locations. In this regard, for understanding the effectiveness of any indoor localization and navigation systems, the average localization error, MSE, RMSE are the most crucial metrics.

3.4.2 Performance Issues

ILS needs to meet the following performance issues in order to provide seamless services.

Scalability In literature, most of the existing works are found to perform experiments within a limited scope of experimental areas using a limited set of mobile devices. A system is termed as scalable when it is easily deployed in a large experimental area and offers its services to a variety of mobile devices with similar performance as with limited scope.

Robustness The robustness ensures that a localization system is able to provide its service in an unforeseen indoor ambience such as change of surrounding objects, presence of interfering devices, malfunctioning of active APs, etc. However, the system may perform with a coarse level of accuracy compared to the ideal situation.

In this context, the next section gives a brief overview of the applicability of machine learning techniques to this domain.

4 Overview of Machine Learning Techniques used in ILS

Machine learning approaches are preferred nowadays as compared to other techniques because of the fact that machine learning techniques learn from data heuristically and hence, can respond in spite of minor variations in features.

The main issue of ILS is the varying indoor contexts such as different times in a day, indoor ambience, different devices for recording data and many more. Hence, the ILS can be categorized into two different classes i.e. train-test under same context and train-test under different contexts. Each of these classes is further classified based on different machine learning approaches used in the prior works of ILS as shown in Fig. 3. These categorization is elaborated in the Sections 4.1, 4.2. A discussion about the existing works where meta-heuristics techniques have been used along with machine learning techniques is presented in Section 4.3 and a brief comparison among the existing works is elaborated in Section 4.4.

4.1 Train-test Under Same Context

Usually, supervised, semi-supervised and unsupervised learning are used when the train and test sets are collected from similar context. Supervised learning needs a properly labeled fingerprint dataset that requires intensive data collection effort. Semi-supervised learning mechanisms can deal with grossly labeled data while unsupervised learning mechanisms do not require any labeled dataset. The well known supervised learning classifiers, such as k-Nearest Neighbor (kNN) [5, 52], K* [70, 102], Support Vector Machine (SVM) [19, 29, 97], Bayesian Network [7, 69, 148], Naive Bayes [40, 160], Decision Tree [166], Random Forest [4, 14, 96, 136] and Neural Network [17, 73, 111] distinguish among the classes (locations in this case) accurately with a known decision boundary.

More importantly, the offline site survey or fingerprinting is a very hectic process as discussed earlier. Recently, the crowdsourcing approach is preferred to avoid the labor and time required for collecting data. In this approach, the users walk around the indoor spaces for their daily activities and the smart devices with them record data at some specific time intervals. Hence, proper labeling of the fingerprint is not guaranteed. Under these circumstances, semi-supervised and unsupervised learning approaches are used to estimate an unknown location. The semi-supervised

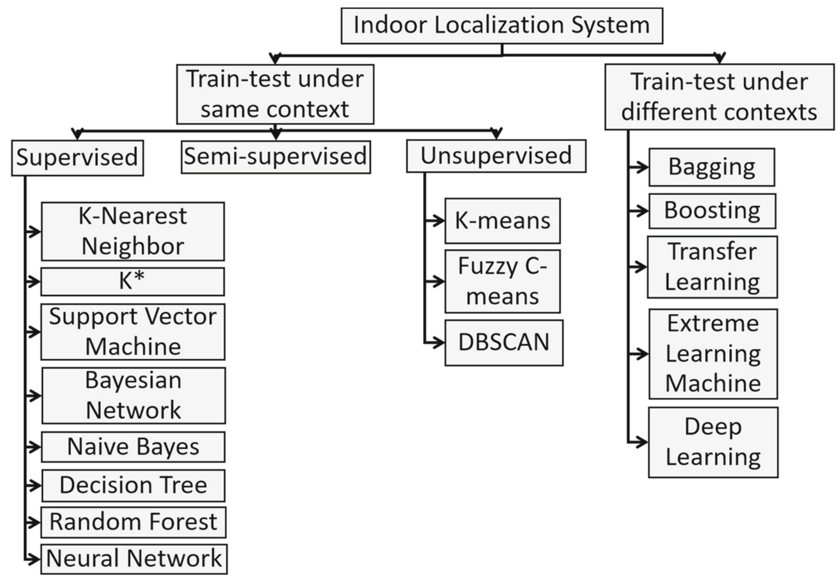

Fig. 3 The classification hierarchy of ILS according to the usage of machine learning algorithm

approach requires a combination of a few labeled data (of known location) and a number of unlabeled data (without mentioning the location). This approach is able to estimate the unknown locations based on few data with known locations. Besides, unsupervised learning finds out the hidden patterns in the data samples.

The different algorithms of supervised, semi-supervised and unsupervised learning which are used to solve the indoor localization problem are further discussed below.

4.1.1 ILS based on Supervised Learning

These learning techniques deal with labeled data i.e during the data collection phase (training phase) of the indoor localization, meaningful tags are attached to the collected data. Some of the popularly used supervised learning algorithms for ILS are discussed as follows:

k-Nearest Neighbor (kNN) kNN is one kind of instance-based learning or lazy learning used to solve both classification and regression problems. In kNN classification, the unseen data is classified by the majority vote of its k nearest neighbors, i.e. the most common class among its k nearest neighbors is assigned to it. In the case of regression, an average value of k nearest neighbors is assigned to the unseen sample. Akre et al. [5] formed a training dataset from the collected RSS values corresponding to RFID tags. The class of the test data tag is determined using kNN, where the dominant class among the k nearest neighbors of the test data tag is found. In order to improve the accuracy of WiFi-based localization, Kriz et al. [52] have used BLE beacons along with WiFi RSS and considered weighted kNN for estimating unknown locations. In their proposed approach, BLE transmitters play an alternative role of WiFi APs, since, the battery-powered BLE transmitters are easily deployed in some areas where WiFi APs would not get power supply. Their proposed method determines k nearest fingerprints for an unknown fingerprint by applying Euclidean distance.

The kNN algorithm is easy to implement and requires only two parameters i.e. the value of k and the distance function (e.g. Euclidean or Minkowski or Manhattan etc.). As the dataset grows, more time is required to calculate the distance between a new data point and every existing data point. So, the performance of kNN reduces fast with the growth of the dataset. Moreover, data imbalance creates problems in kNN. For example, if the major training fingerprints are labeled as location l_i, then intuitively giving more preference to the same location, the label of an unknown fingerprint is predicted as location l_i.

K* In the instance-based classification problems, each new test instance is compared with the existing training instances using a distance metric, and the class of the closest training instance is assigned to the new test instance. The major difference of K* with the other instance-based algorithms is the application of the entropy for defining its distance metric. The entropy is determined by the probability of transforming an instance into another. The probabilities of transforming the new instance to all instances of a class are summed up. This process is followed for the rest of the classes and finally, the class with the highest probability is assigned to the new instance [119]. Along with several classifiers, Mascharka et al. [70] have used K* to analyze their collected indoor dataset. Roy et al. [102] have also used K* as a base learner to design a weighted ensemble classifier.

Like other datasets, indoor data also have missing values as the signal strengths of every APs are not usually heard from any particular location. K* tries to enhance its performance by handling the missing values as well as noisy features of a dataset.

Support Vector Machine (SVM) The objective of SVM is to find a hyperplane or a set of hyperplanes in the N-dimension (where N is the number of features) to distinctly classify the sample points. In the case of a two-class classification problem, the objective of SVM is to find an optimal hyperplane that has the maximum margin between the data points of both classes. Feng et al. [29] used the concept of SVM to identify the best hyperplane separating the training data points that are the nearest neighbors of a test data point. They have reduced the offline fingerprinting effort while retaining significant accuracies in the online phase. Moreover, estimating the proper location of a target becomes very difficult due to the variation of WiFi RSS in the dynamic indoor ambience as well as the shadowing, multipath propagation, attenuation of RSS. In order to overcome these difficulties, Chriki et al. [19] have used SVM to determine the zone of a target instead of estimating the proper geographic location of a target. They have selected SVM because of its ability to easily adapt to multi-class classification problems like indoor localization. In addition, to address the problem of device heterogeneity and fluctuation of WiFi fingerprints, Rezgui et al. [97] have proposed a novel normalized rank based SVM.

SVM relatively scales well with high dimensional data (i.e. the datasets having a large number of features). SVM also performs well with unstructured and semi-structured data such as images captured by a mobile robot [41]. SVM models are quite stable so, the small changes in the data due to the dynamic nature of indoor ambience do not affect the hyperplane(s) of SVM. Besides, these advantages, SVM also has some issues. Selecting an appropriate kernel function is a very tricky and complex task. A large number of support vectors are generated by using a high dimensional kernel which in-turn reduces the training time. With the increasing size of the training dataset, the memory requirement gets increased to store all the support vectors.

Bayesian Network This is a probabilistic graphical model based on Bayes theorem. The network is basically a directed acyclic graph (DAG) whose nodes are represented by the variables and every edge denotes the conditional dependencies among the two variables. Madigan et al. [69] have applied the hierarchical Bayesian model for indoor localization where only a minimal set of labeled fingerprints are required. The first layer of the model consists of the position variables. The second layer consists of distances of the variables from the base stations. The next two layers are composed of observed signal strengths and base station parameters. Alhammadi et al. [7] have proposed a robust 3D indoor positioning system, suitable for indoor IoT applications, using the Bayesian Network. Their proposed model is less computationally expensive and requires less number of reference points. In order to build a robust and accurate floor localization method, Xu et al. [148] have proposed a model using the Bayesian Network to accurately infer the floor level of a pedestrian in a multistoried building. They have fused inertial sensor and barometric measurements. Height change and landing number are measured by the barometer and using these measurements, the Bayesian Network infers the probability of floor change of a pedestrian.

Bayesian Network is easy to implement and efficiently generates a training model using less amount of training data. Thus, the cost of data acquisition in an indoor region is minimized. This algorithm works with an assumption that all the features are mutually independent, however, this is not possible in the real scenario.

Naive Bayes This is another type of probabilistic classifier based on Bayes theorem with a naive assumption i.e. independence among the features. So, the fundamental assumption of this algorithm is that each feature has an independent and equal contribution to the outcome. Zhang et al. [160] have investigated the performance of Bayes learning algorithms and have identified the common problem of zero probability caused by data incompleteness affect localization accuracy. So, they have proposed an improved Naive Base algorithm to overcome this problem. He et al. [40] have used voronoi diagram and Naive Bayes method to reduce computation complexity, time and human effort in RSS sample collection.

Like Bayesian Network, Naive Bayes algorithm is very easy to implement and requires a small amount of training samples. However, if the assumption of independence among the features does not hold then the performance of Naive Bayes is very poor.

Decision Tree This technique uses a tree structure to build the classification models. In the tree, each node signifies a test of a certain attribute of an instance. Each branch from that node connects to the next node or leaf node according to one of the possible outcomes of the test. The leaf nodes predict the outcomes or represent the class labels. Zia et al. [166] have investigated the performance of several machine learning techniques including Decision Tree in order to localize an object in indoor spaces. In this literature, Decision Tree algorithm is mainly used to form other techniques like Gradient Boosted Decision Tree, Random Forest, etc. which is mentioned later in this Section.

Decision Tree is very easy to understand and easily implemented. It automatically manages the missing values which often occurs during indoor data collection. This algorithm usually leads to overfitting of the data which is one of the major drawbacks. If the size of a dataset is very large, then a single tree may get complex and tends to overfit.

Random Forest As the name implies, Random Forest operates by constructing a large number of Decision Trees to form an ensemble learning model. Each Decision Tree of a Random Forest predicts a class and the most common class is considered as the final prediction result of the model. Calderoni et al. [14] proposed an ILS using the hierarchical Random Forest-based classifier to locate patients in a hospital environment. Their system has been specifically designed to work in an unfriendly environment where the signals of RFID transmitter could be disrupted by the nearby electronic devices and shielded walls. Besides Random Forest, two other classifiers namely macro-region classifier, and room classifier are also used to find confidence among different macro-regions. To address the problem of Non-line-of-sight (NLOS) identification, Ramadan et al. [96] have utilized the extracted features from the channel impulse response and employed a Random Forest algorithm. In the NLOS scenario, no recognizable radio signal directly travels between the AP and the user device. So, the NLOS travel time gets biased which incurs errors at the time of location estimation and degrades the location accuracy. Thus, NLOS identification is a major challenge to range-based indoor localization methods. Wang et al. [136] have presented a novel Random Forest fingerprinting localization technique using channel state information (CSI). Their proposed Random Forest model posses a good NLOS characteristic, economizes the memory space and also discovers the relevant feature of wireless channel data. In this domain, most of the existing works provide either room-level localization or coordinate location (x, y coordinates) of an unknown object. Akram et al. [4] have designed a novel infrastructure-less ILS, HybLoc, that utilizes a Gaussian Mixture Model and Random Forest-based ensemble model for room-level localization as well as precise localization (estimation of x, y coordinates).

Random Forest efficiently manages high dimensional data by judging the importance of the features. This algorithm is very stable and reduces variance and overfitting problems thus, the accuracy gets improved. Random Forest effectively handles missing values which are very common in indoor data. Moreover, this algorithm is robust to outliers and comparatively less impacted by the noisy data that is very common in indoor. Due to the changes in indoor ambience, some new samples are collected to update an existing training model. However, these samples may affect few trees, they have very little impact with respect to all the trees. Furthermore, to construct a lot of trees, Random Forest requires more resources and computational power.

Neural Network (NN) Neural Network consists of layers of interconnected nodes. It mainly contains an input layer, one or more hidden layer(s), and an output layer. During training, the actual output is compared with the predicted output of the network and accordingly the error is calculated. The error is then back-propagated through the network to modify each connection weight between the nodes. This back-propagation process is repeated multiple times until the network is tuned to give reasonable accuracy. In this literature, various types of Artificial Neural Network (ANN) have been used for notable progress [17, 73, 111]. Generalized Regression Neural Network (GRNN), a variant of the Radial Basis Function (RBF) Neural Network, has a much faster training process and hence, it is easy to implement than other variants of ANN. Considering the advantages of GRNN, Chen et al. [17] have designed a novel GRNN-based ILS which has flexibility, robustness without requiring extensive training samples. Their system has maintained a satisfactory trade-off between complexity and performance. Moreover, they have claimed significant performance improvement in both LOS and NLOS conditions through their simulation results. Shenoy et al. [111] have introduced a localization scheme based on ultrasonic beacons and wireless networks. In their proposed scheme, ANN takes ToA measurements to predict the 2D location coordinates of the mobile robots under LOS and NLOS conditions. They have claimed that their approach needs a lesser number of beacons for localization than the other existing ILS. Hence, their scheme is cost-effective and energy-efficient. Furthermore, aiming to build a stable fingerprint database by reducing the fluctuation of WiFi RSS, Meng et al. [73] have introduced an indoor positioning algorithm based on RBF Neural Network. In addition, their proposed approach has data fusion, nonlinear mapping and parallel processing capabilities.

Neural Network inherently detects non-linear, complex relationships between the dependent and independent features. Usually, the hidden layer has the ability to identify the interrelationship between the input variables. Neural Network-based model is computationally efficient and a small set of parameters needs to be tuned in order to maintain a low communication cost. Moreover, the Neural Network-based model is retrained easily when an indoor dataset is outdated or the new samples need to be collected to reflect the changes of indoor ambience. Besides all these advantages, one of the important issues is, this model is prone to overfitting.

Principal Component Analysis (PCA) In the studies on radio map calibration, the dimension reduction method improves the performance of a localization technique by extracting the key features from the original radio maps as well as reducing the computational complexities for localization.

In the prior solutions, the redundant APs are directly eliminated by evaluating the significance of various APs in terms of the maximum/average of RSS value, entropy, variance, etc. However, an inevitable loss of information occurred in such simple solutions, by the elimination of APs. Then, some advanced dimension reduction techniques, such as PCA have been reported in the literature of indoor localization to achieve better performance than the aforementioned solutions. PCA [26] projects a high-dimensional RSS fingerprint associated with a radio map into a low-dimensional space by linearly combining RSS values from various APs. Using the covariance matrix of the training data, PCA decorrelates the features and represents the data in the direction of the most significant variance. Thus, PCA has been used in prior works to select the most informative APs of an indoor region. In order to preserve the location information as much as possible, Jia et al. [46] proposed a supervised kernel PCA (SKPCA) for the dimension reduction of radio maps. They have used a nonlinear mapping to transform any high-dimensional fingerprint into a low-dimensional feature space. More importantly, the location information has been utilized sufficiently by maximizing the dependence between the corresponding location labels and the transformed features. Salamah et al. [104] used PCA to identify the redundancy caused by multivariate APs and to reduce those multivariate APs, duplicated fingerprints and noise between APs without losing much information.

PCA has some advantages, such as it eliminates the correlated features, reduces overfitting, enhances the performance of a machine learning model and improves the data visualization. Besides, PCA has some issues also. After implementing PCA on a dataset, the independent variables are turned into principal components which are less interpretable and readable. PCA chooses the features having maximum variance but, if the number of principal components is not selected carefully some information may be lost. Hence, PCA dimensionality reduction may degrade the positioning accuracy, which often goes against the objective of any positioning approach.

Hence, the supervised learning techniques require sufficiently labeled training samples. However, in some indoor spaces, the cost of obtaining enough training samples is very high or even impossible to obtain those samples. If the training samples are not enough, then supervised learning algorithms are unable to generate the proper mapping function through which data samples of unknown locations could be predicted.

4.1.2 ILS based on Semi-supervised Learning

Semi-supervised learning requires unlabeled data along with labeled data during the training phase. Obtaining all labeled data samples is very time-consuming as in the case of supervised learning. So, having a mix of labeled and unlabeled data is a good choice, since the labeled data would give a glimpse of the presence of possible classes. Unlabeled data can later be classified on the basis of those possible classes. Semi-supervised learning algorithms make use of assumptions such as continuity assumption, cluster assumption and manifold assumption.

Pulkkinen et al. [93] proposed a WiFi positioning approach in which a manifold learning method is used. The method helps in finding the important features of a high dimensional dataset, thereby reducing the dimensionality of the dataset into a more manageable one. The authors mapped points on the Isomap manifold to the geographical coordinate system by taking advantage of the small subset of precisely labelled fingerprints. Ouyang et al. [83] have applied a generative as well as a discriminative semi-supervised learning approach to enhance the radio map using a huge number of unlabeled fingerprints. Pan et al. [85] have combined the graph-based semi-supervised learning techniques and the collaborative filtering to reduce the fingerprinting effort and to predict the locations of the target as well as the APs. Different from the aforementioned works, Zhou et al. [163] have applied the Execution Characteristic Function (ECF) to minimize the required RSS sample collection from each RP. Meanwhile, they have employed a semi-supervised manifold alignment approach that uses the unlabeled samples with timestamps for constructing the radio map. Another graph-based semi-supervised learning technique has been proposed by Wang et al. [130]. Meanwhile, they have also proposed a Double Weighted kNN (DWkNN) algorithm due to the redundant RSS of different APs and varying location information of RSS. Moreover, Yoo et al. [156] have proposed a novel semi-supervised learning approach for smartphone-based mobile robot localization in the indoor region. Their proposed method is also robust with varying amount of training samples without compromising the computational speed.

Hence, semi-supervised learning algorithms are applicable when both labeled and unlabeled data are available. Moreover, the labeled data samples have to be obtained in such a way that those samples have to give a glimpse of all possible locations throughout the experimental region. Otherwise, the unlabeled data samples are not properly mapped with the possible data samples of known locations.

4.1.3 ILS based on Unsupervised Learning

This learning technique deals with unlabeled data and acts on the data without any guidance, hence the name unsupervised. Chen et al. [16] have combined smartphone sensors, iBeacons and WiFi RSS for designing a reliable unsupervised indoor localization scheme. Since the initial localization is vital for their proposed system, they have employed a weighted fusion algorithm combined with kNN to accurately predict the initial position. Trogh et al. [124] proposed a novel unsupervised learning approach that solely relies on the floor plan and unlabeled training fingerprints i.e. RSS of different APs with unknown ground truth locations. Their proposed unsupervised method automatically builds, maintains, and optimizes the unlabeled fingerprint datasets, without using any inertial sensor units and calibration effort. In addition, unsupervised learning techniques are found to efficiently estimate the depth and ego-motion for visual SLAMs. The CNN-based SLAM approaches for indoor mobile robot navigation require a large number of precisely labeled input data which is difficult to collect. So, Gao et al. [35] have applied unsupervised learning techniques to the unlabeled datasets for visual SLAM.

Unsupervised algorithms generally use clustering to group data points such that the clusters are dissimilar whereas the data points within the clusters are similar. Different clustering techniques are discussed below:

k-means The k-means clustering algorithm is one type of unsupervised learning in which the number of clusters, k, is decided a priori. At first, the k centroids are defined, one for each cluster. Then, the attachment of each data point of the given set to the nearest centroid takes place. The positions of the k centroids are again calculated until they no longer change their position. Wang et al. [131] used the k-means clustering approach in their unsupervised indoor localization scheme (UnLoc). In their scheme, the mobile devices sense the “landmarks” in indoor and on the basis of that, re-calibration of the mobile devices can be done. Their proposed technique eliminates the necessity of floor plans which are needed in the traditional fingerprinting method. Wu et al. [141] have designed an unsupervised approach for wireless indoor localization using k-means clustering and a logical floor plan mapping method that eliminated the effort of site surveys.

The main challenge with k-means is that the number of clusters (“k”) needs to be specified in order to use it. Most of the time, the reasonable k value can not be known a priori. In k-means, formation of the clusters depend upon the mean value of the data points of the clusters. Hence, a slight variation in the data points can affect the output of clustering.

Fuzzy C-means (FCM) In non-fuzzy clustering or hard clustering, all data points are divided into unique clusters such that each data point can belong to exactly one cluster. On contrary, in fuzzy clustering or soft clustering, any data point can belong to more than one cluster. Fuzzy C-means clustering (FCM) is one of the widely used fuzzy clustering algorithms. FCM clustering is quite similar to the k-means clustering technique. Suroso et al. [116] have designed an indoor localization model using FCM clustering to reduce the computational time and power consumption. Li et al. [55] have proposed a region-wise indoor localization approach in which they have applied an improved FCM clustering technique to divide the entire experimental area into multiple regions.

In the case of overlapped datasets, FCM clustering gives comparatively better results than the hard clustering algorithms. Like k-means, prior specification of the number of clusters is a major drawback of FCM clustering.

Density Based Spatial Clustering of Applications with Noise (DBSCAN) This is a density-based clustering algorithm that identifies distinctive groups or clusters from the unlabeled data based on the idea that the clusters of dense regions in the data space are separated by the clusters of lower dense regions. It can discover clusters having different shapes and sizes from a large amount of data, in presence of noise and outliers. In DBSCAN, the number of clusters need not be specified beforehand as opposed to k-means. It requires two parameters: eps and minPts. The “eps” signifies the neighborhood around a data point. Two data points are considered as neighbors if the distance between them is lower or equal to “eps”. Besides, “minPts” refers to the minimum number of data points within eps radius required to form a dense region. Wang et al. [132] have used DBSCAN to cluster the RSS fingerprint database and divided the entire region into several regions based on the clustering results. They have claimed that besides, improving the localization accuracy, the computational complexity and location prediction time reduces by clustering the fingerprint database. Li et al. [54] have also applied DBSCAN algorithm to distinguish uncorrelated WiFi RSS samples and cluster similar RSS samples. After clustering, they have applied regression approaches and designed their localization model with a finer pattern of the experimental environment.

DBSCAN has been used to effectively cluster the data samples in presence of the noisy samples. It is also robust to outliers. However, DBSCAN can not properly cluster the data samples having huge differences in densities. Moreover, the functionality of DBSCAN depends on the used distance metric.

Thus, unsupervised learning techniques are suitable for large and complex indoor environments where offline fingerprint collection is a very hectic process. In such a situation, crowdsourced unlabeled data without any location tagging will be a good choice as discussed earlier.

4.2 Train-test Under Different Contexts

Indoor context can change over time. Hence, it is difficult to ensure that test data could be captured in the same context in which the train data has been acquired. In a fixed location, signal strengths are heavily affected due to the variation of indoor ambient conditions. For example, RSS data taken by keeping the doors open can be much noisier than keeping the doors closed. These can affect the localization accuracy of individual classifiers [36]. In this scenario, the ensemble techniques such as Bagging and Boosting approaches are best suited as they better retain the generalization capability than the individual machine learning algorithms. Moreover, new WiFi APs or RFID tags can be deployed, replaced and/or even removed over time. These factors change the dimensions in collected data and hence result in modifying the feature space. This can be addressed by combining the Extreme Learning Machine (ELM) and Transfer Learning techniques as these techniques can dynamically update the classification model. Besides, Deep Learning has the capability to choose the appropriate feature for constructing an accurate model. All of the above-mentioned approaches are further detailed below.

4.2.1 ILS Based on Bagging

Bagging or Bootstrap aggregating [13] is an ensemble-based meta-algorithm developed to improve the accuracy and stability of the machine learning algorithms that are used in classification and regression. An ensemble method combines the predictions of several machine learning algorithms together and generates more accurate predictions than any of those individual algorithms. Bagging is one of the famous ensembling approach which reduces variance, avoids over-fitting and produces a more robust model than the individual models composing it. Although this method is usually applied to decision tree-based algorithms, it can be applied to other algorithms as well. It is one kind of model averaging approach. In this approach, bags are chosen in a random way with replacement from the original train set. The weak learners learn independently from the set of bags. Finally, the predictions of weak learners are averaged in order to obtain a model with a lower variance.

In this context, certain multi-classification-based systems are designed using bagging and those systems are found to outperform other fingerprint matching algorithms like the nearest neighbor. Menendez et al. [72] designed the final multi-classification system using bagging. Besides, J48G (decision tree) is also used to derive the component classifiers. Finally, the confidence degrees of all the instance for each classifier is aggregated by an appropriate algebraic function like mean, median, max, min. Another multi-classifier-based ILS is proposed by Trawinski et al. [123]. In this system, two standard approaches including bagging and bagging combined with random subspace [88] are found to be applied.

Bagging is computationally expensive. Some training samples may get repeatedly misclassified in every bag.

4.2.2 ILS Based on Boosting

Boosting technique is used to “boost” the performance of individual classifiers. In this type of ensemble method, a strong classifier is built up from a number of weak classifiers. This is done by creating a classification model in each iteration from the training samples. In each iteration, a new classification model is built by assigning more weights to those instances that are misclassified in the previous iteration. Thus, it attempts to improve the classification of those instances. These iterations are repeated until the instances of a training set are perfectly predicted or a maximum number of models are added. Finally, the outputs of all weak learners are combined to generate a strong learner which eventually enhances the prediction capability of the model. AdaBoost (Adaptive Boosting) is the first successful boosting algorithm which is developed for binary classification.

Cooper et al. [20] designed an AdaBoost classifier for each room which returns a probability of observing an RSS vector in that room. The weak learners and their relative weights of each per-room classifier are learned by a greedy iterative procedure to optimize errors in training data. The weights are repeatedly adjusted to give more importance to the misclassified samples. In order to obtain a strong classifier for making a successful prediction, WANG et al. [133] have proposed a Subspace gradient boost decision tree algorithm. Moreover, Feng et al. [30] have used AdaBoost to remove the unfocused nearest neighbor points present in the fingerprint space.

Boosting is also time and computation expensive. The effectiveness of boosting techniques depend on the fingerprint data. If a single classification model is over-fitting then boosting can not avoid the same.

4.2.3 ILS Based on Transfer Learning

In Transfer learning [86], the knowledge gained while solving a particular task is stored and applied to solve another related task. Hence, the performance of modeling the second task gets improved and requires less amount of data. The effectiveness of this process depends on the metric i.e if the metrics are suitable to both source and target domain rather than being specific only to the source domain. Transfer learning algorithms can solve the problem of collecting large datasets for the target domain as is required by supervised learning algorithms. For the WiFi-based indoor localization problem, the layout of hotspots and APs change from time to time, thus requiring continuous fingerprinting which is infeasible. Hence, an effective Transfer learning algorithm would find the feature layout of the source domain that remains invariant (to an extent) to changes in the layout of APs and hotspots.

Liu et al. [62] proposed a Transfer learning-based framework for enhancing the scalability of fingerprint-based localization by reducing the effort of offline fingerprint collection for the target indoor regions. This framework reshapes the logical distances among the points in the target domain based on the knowledge transferred from the related source domain. The reshaping in the target domain is performed in such a manner that the logical distance would be minimized between online and offline points if they belong to the same cluster. Otherwise, the distance would be maximized such that the decision boundaries between each cluster will be far apart. In order to reduce the distribution discrepancy across the source and target domain and to select the shared characteristics, Zou et al. [170] have introduced a Transfer Kernel learning-based robust and adaptive indoor localization method.

Hence, Transfer learning can be an option for a stable and scalable solution for WiFi-based indoor localization by reducing the overhead of the offline site surveys for new indoor spaces. Moreover, sufficient fingerprint data must be obtained from the source region. Some similarity is required in the spatial layouts of the source and target regions. Otherwise, the transferred model is not effective for the target area and obviously, the positioning accuracy gets decreased.

4.2.4 ILS Based on Extreme Learning Machine (ELM)

A major drawback of the Feed-forward Neural Network is the slower learning speed than required. The two main reasons behind may be: the Neural Networks are trained by slow gradient-based learning algorithms, and such learning algorithms are used to iteratively tune all the parameters of the networks. These problems are overcome by introducing a learning algorithm called Extreme Learning Machine (ELM). In single-hidden layer Feed-Forward Neural Networks (SLFNs), ELM randomly selects hidden nodes and the parameters of hidden nodes need not be tuned. The output weights of the hidden nodes are analytically determined by ELM. In general, these weights are usually learned in a single step. Hence, this algorithm achieves a better generalization performance with an extremely fast learning speed than the networks trained using back-propagation [43]. Online sequential learning mechanisms are often applied to ELM which is especially useful to incorporate incremental learning.

Online Sequential ELMs (OS-ELM) has been used in this field [168] to eliminate two major drawbacks of traditional fingerprinting: the intensive cost of manpower/time for fingerprint collection and the dynamic nature of fingerprints in various ambient conditions. The first drawback is eliminated by the fast learning speed of OS-ELM while, the second one is addressed by the online sequential learning ability. In the online phase, to reflect the dynamics of ambience, new fingerprints are collected and integrated with the initial model for generating a revised model of OS-ELM. Yang et al. [153] OS-ELM based RFID positioning framework, for monitoring various manufacturing objects in a dynamic shop floor. They have applied OS-ELM for its extremely fast learning speed and high generalization capability to overcome the lack of an accurate and reliable real-time approach for handling massive signal data.

Jiang et al. [47] proposed a Feature Adaptive-OSELM method that not only relies upon the original features but also fits with the change of features. Thus, it is an ELM based Transfer Learning approach. They applied the algorithm in the WiFi-based indoor localization where a constant set of APs is not always available but old APs may be replaced/augmented by new APs. Accordingly, the dimension of feature vectors consisting of RSS values of the available APs may grow or shrink. Hence, the algorithm attempts to adjust the changing dimension of the feature sets depending on the availability of APs and hotspots. To generate a new feature set from the old feature set and new fingerprints, the authors introduced two data structures- (i) input-weight transfer matrix to adjust dimensionality change and (ii) input-weight supplement vector to adjust the feature matrix to reflect the new distribution found in the new data samples.

Zhang et al. [159] have presented a novel PDR-based indoor localization technique using OS-ELM to address certain drawbacks of the existing PDR approaches such as the accumulation of errors at the time of localization due to the usage of low-cost noisy sensors, complicated movements of human beings and so on. In their work, the process of PDR localization is first formulated as an approximation function. A sliding-window-based scheme has been introduced by them to preprocess the gathered inertial sensor data and to generate meaningful features.

Thus, OS-ELM can be used to address the difficulties regarding the offline site surveys and change of fingerprints in various indoor ambience.

4.2.5 ILS Based on Deep Learning

Deep learning is based on ANN and in some circumstances, it is even comparable to human expertise [53]. The word "deep" refers to the number of layers through which the data is transformed. More precisely, the Deep learning algorithms have a stacked hierarchical structure of increasing abstraction and complexity. One of the advantages of using Deep learning is that it is capable enough to build the feature set by itself. Deep learning algorithms require a large amount of labeled training data and processing power to achieve a significant level of accuracy. Moreover, a Deep learning model can be used to analyze unlabeled data once it has been trained with sufficient labeled data and achieved an acceptable level of accuracy. However, unlabeled data are not used to train a Deep learning model. Generally, most of the Deep learning methods use the architecture of the Neural Network. Hence, these models are often known as Deep Neural Network.

The two most popular types of Deep Neural Networks are Convolutional Neural Networks (CNN) and Recursive Neural Network (RNN). The input of CNN is passed through a consecutive number of convolution and pooling layers in the feature learning phase. Next, in the classification phase, the inputs of the feature learning phase are passed through a series of fully connected layer and finally, a softmax function is applied to classify an object. CNN's have been widely used in domains like image classification, image recognition and object detection especially for its ability to extract meaningful features that are subjectively understood by humans but difficult to define explicitly.

Wang et al. [134, 137] designed PhaseFi in which a Deep Neural Network with three hidden layers is used for training the phase data of Channel State Information (CSI). Feature-based fingerprints are created by the authors for incorporating the Deep Learning mechanism. Their approach is different from the traditional methods that consider the measured data as fingerprints. These fingerprints are easily affected by the indoor ambience. In the Deep Network, a large number of weights, used as feature-based fingerprints, represent the characteristics of the phase data for every location. The fingerprint dataset is created by training the different weights of the deep networks with the calibrated phase data of various locations. This training procedure includes pretraining, unrolling and fine-tuning. In order to reduce the computational complexity, they have also developed a greedy algorithm that is used to train the weights of the Deep Network in a layer-by-layer fashion. According to their reported experimental results, the performance of PhaseFi is better than other existing systems.

Besides, the WiFi signal strength, the ubiquitous magnetic field information collected from the inside regions of a building is also suitable for indoor localization. The magnetic field information inside a building can be unstable like the Earth's impulsive magnetic field. Hence, in this literature, the geomagnetic field has been utilized due to its global availability and stability. Zhang et al. [161] have proposed an indoor fingerprinting scheme, DeepPositioning, using Deep Neural Network and Deep Belief Network that fuses WiFi RSS and magnetic field to improve the accuracy. Although the training phase of this scheme requires much computational overhead, the testing phase is suitable and fast for real-time indoor localization. However, the performance is closely related to the numbers of APs, RPs, and labeled fingerprints in training sets. Moreover, the dynamic indoor environments caused by various factors significantly affect its performance.

The accuracy of indoor localization approaches relying only on WiFi infrastructure often gets degraded. Furthermore, it is not robust to the changes in indoor ambience due to the instability and inherent noises of the WiFi signals. In order to overcome those challenges, Abbas et al. [1] have presented a Deep Learning-based ILS, WiDeep, which provides a robust and fine-grained accuracy in the presence of noise. More importantly, WiDeep has a stack of denoising auto-encoders and a probabilistic framework to manage the noises of RSS. It also has a number of modules to avoid over-training and manage device heterogeneity. According to their results, WiDeep has achieved an average localization accuracy of 2.64m and 1.21m for the two testbeds.

Recently, for visual SLAM approaches, to estimate the depth and ego-motion of input images, Deep Learning techniques, such as CNN [118] are applied. These techniques yield better precision even for low-textured regions as they automatically learn high-level features from the input dataset. Patel et al. [90] applied CNNs to extract effective feature vectors from LiDAR and camera inputs that are later fused through the dropout regularization technique for precise indoor navigation of automated vehicles. Eight convolution layers are used with a max-pooling operation performed between every two layers to keep the size of the feature maps tractable. Rectification non-linearity is applied here rather than a sigmoid function.

Deep learning techniques require a large number of labeled training samples. Hence, taking into account the dynamic nature of the indoor spaces, the Deep Learning techniques continuously need new data samples to make the system more accurate and more stable.

4.3 ILS Based on Meta-heuristics Techniques and Machine Learning Techniques

Meta-heuristics techniques find a near-optimal solution to a problem through exploring and exploiting a larger search space. Such techniques can be applied for feature selection and parameter tuning of machine learning classifiers. On the contrary, machine learning classifiers can also be applied to fine-tune the parameters of complex meta-heuristics approaches.

Genetic Algorithm (GA) GA is a meta-heuristic search technique inspired by natural selection and genetic rules. This algorithm continuously improves the results and finds near-optimal solution(s) in a manner similar to natural selection. In order to conduct this, the fitness functions are selected to specify the effectiveness of each chromosome and operations such as cross-over and mutation are performed to produce off-springs. If the fitness of a new off-spring dominates an old off-spring, the new off-spring is added to the population discarding the old one. In this domain, the researchers have their own problem space on which they have applied GA to search for the optimal solution(s). Among them, Song et al. [114] designed a GA based solution to search for the optimal combination of candidate fingerprints of each device and further, proposed an analytical model to increase the probability of the best location estimation of indoor devices. Basak et al. [10] applied GA as an indoor fingerprinting algorithm where the optimal solution has been considered as the maximum correlation between the referenced grid and the received values. In each iteration, the possible location points have been compared with the offline radio map and according to maximum correlation, the most compatible grid has been selected. Suwannawach et al. [117] proposed a method to reduce the variance of RSS measurements. In order to perform this, they have applied GA to search the optimal weights of every AP and later, those weights have been used by the Weighted Distance Fingerprint algorithm (aka WDF which is a modified version of kNN) for measuring the variance of RSS. Izidio et al. [45]have designed a methodology for a WLAN-based indoor positioning system by using GA and NN. The fitness function has been defined as the generalization capabilities of the network of the test points which have not been included in the training set. They have achieved significant results with few parameters and their proposed method has shown to be less prone to overfitting than other state-of-the-art approaches.

Ant Colony Optimization (ACO) ACO is a population-based meta-heuristic technique which considers the foraging behavior of an ant for searching a path between their nest and the source of food. In ACO, the optimization problem becomes the problem of searching the best path on a weighted graph. The artificial ants construct solutions by moving on the graph. The process of solution construction depends on pheromone model, in which sets of parameters are associated to the graph components whose values are updated according to the movements of the ants. Liu et al. [61] have proposed an indoor navigation system to guide people in an unfamiliar place by using the technologies that do not require any infrastructure. They have used ACO for searching optimized path from a source point towards a destination.

Particle Swarm Optimization (PSO) PSO belongs to the class of Swarm Intelligence techniques. This technique is used to solve continuous and discrete optimization problems. PSO is inspired by the behavior of the flock of birds. So, in PSO, a set of particles, known as swarm, traverses in the search space of an optimization problem. The objective of each particle is to search better positions in the search space by modifying its velocity. The position of a particle denotes a candidate solution of the considered optimization problem. Like other domain, PSO has been used in this domain to find near-optimal solution of the considered optimization problem. To optimize the localization cost and performance, wang et al. [129] have designed an improved PSO-based Feed-forward Neural Network. Their proposed improved PSO technique has been used to optimize the connecting weights and structural parameters of the Neural Network in order to develop an optimal location prediction model.

4.4 Brief Comparison Among the Existing Works

In the previous two subsections, machine learning techniques and how these are applied to indoor localization are discussed. In this section, a brief comparison among the publicly available datasets for indoor localization is presented. Next, the representative works in this domain are compared on the basis of applications summarized in Section 3.2 and then on the basis of the challenges mentioned in Section 3.3.

4.4.1 Comparison of the Publicly Available Datasets of ILS

Some characteristics of the representative publicly available datasets of this domain are presented in Table 3. Montoliu et al. [77] have mentioned about a public repository of several indoor localization datasets named *IndoorLoc Platform* [4]. It is also a web platform for comparing and evaluating the performances of the available datasets as well as users' own dataset using two fingerprint-based indoor localization techniques including deterministic and probabilistic method. This platform has four different WiFi fingerprint-based indoor localization datasets as mentioned in Table 3. Among them, *UJIIndoorLoc* [121] is the first multi-floor, multi-building dataset available in this domain. Besides, *UJIIndoorLoc-Mag* [122] is the first magnetic field-based dataset of this domain. On the contrary, the dataset, presented by Lohan et al. [65], has been collected using crowdsourcing approach. Unless all the machine learning algorithms are compared for benchmark data collected under sufficiently varied ambient conditions, it is hardly possible to identify which machine learning algorithm provides significant accuracy in which kind of context, or which machine learning algorithms can provide stable localization accuracy. *JUIndoorLoc* [100] dataset contains some WiFi fingerprints collected for different perspectives such as temporal, indoor ambience and device heterogeneity. Localization error of around 1 to 3 meter is acceptable for user

[4] http://indoorlocplatform.uji.es/

Table 3 A brief comparison among the publicly available datasets of indoor localization along with the results of applying kNN (k=1)

Dataset	Repository	Fingerprints	#Attribute	#Samples	Results of 1NN
IPIN2016 Tutorial[a] [77]	IndoorLoc Platform	WiFi RSS	177	Train: 927 Validation: 702	Median error: 3.50m Mean error: 4.34m
IPIN2017 Tutorial[a] [77]	IndoorLoc Platform	WiFi RSS	162	Train: 1511 Validation: 405	Median error: 3m Mean error: 5.48m
Tampere University[a] [77]	IndoorLoc Platform	WiFi RSS	312, 357	Train: 2061 Test: 664	Mean error: 10.86m
UJIIndoorLoc[a] [121]	IndoorLoc Platform	WiFi RSS	529	Train: 19937 Validation: 1111	Mean error: 7.18m Success rate: 89.92%
UJIIndoorLoc-Mag[b] [122]	UCI machine learning	Values of x, y, z axis of M_g, A_c, O_r	13	Train: 270 Test: 11	Continuous method Mean error: 6.05±0.43m
WiFi crowdsourced[c] [65]	Zenodo	WiFi RSS	991	Train: 697 Test: 3951	Mean 2D error: 8.45m Floor detection: 92.26%
JUIndoorLoc[d] [100]	Private	WiFi RSS	177	Train: 23904 Test: 1460	Avg. error: 1.24m Success rate: 91.67%

M_g- Magnetometer, A_c- Accelerometer, O_r- Orientation sensor

[a] http://indoorlocplatform.uji.es/

[b] http://archive.ics.uci.edu/ml/datasets/UJIIndoorLoc-Mag

[c] 10.5281/zenodo.889798

[d] https://drive.google.com/open?id=1_z1qhoRIcpineP9AHkfVGCfB2Fd_e-fD

localization in indoor environments as from such close distance, a user can easily spot the target location through environmental cues, such as room nos, floor pattern, etc. The regularity of the building structure and the familiarity of the users to that environment decide how much localization error can be easily tolerated. Currently, there is a need for benchmarking platforms to compare different solutions using standardized evaluation metrics. This is necessary for the quality assurance of commercial localization solutions. So, an indoor localization test-bed is the need of the hour for quality assurance and commercial success of this technology. For a wide-scale RF-based indoor localization test-bed, EVARILOS Benchmarking Platform [39] has been developed that also includes localization datasets for comparison.

4.4.2 Comparison of the Existing Works of ILS in Application Perspective

Some emerging applications of existing ILS where various machine learning techniques have been used for localization are highlighted in Table 4. According to the table, a variety of supervised learning techniques like kNN, SVM, Decision Tree, Random Forest and ensemble learning technique like Gradient Boosting have been applied in the existing literature for user localization, tracking and navigation. Besides, the emerging techniques like ELM, ANN and Transfer learning are also found to be used in the recent works for the same application area. Considering RFID technology, a variety of machine learning techniques such as ELM, kNN and SVM are found to be applied for asset tracking. Moreover, from Table 4, it can be observed that a Deep learning method like CNN is recently incorporated for the camera and LiDAR-based vehicle navigation which is an emerging application of ILS. In addition, CNN is also found to be used as a camera-based technique for user localization as well as tracking goods in warehouses. The outcome of both image and radio signal based indoor localization yields the nearest reference point for the test data instances.

The actual cost of the localization systems (mentioned in Table 4) literally varies from \$10K to \$100K. It depends on the list of features provided, the infrastructure needed, indoor area measurement and most importantly the accuracy demanded by the specific application in terms of localization error in meter. Thus, only subjective costs are considered in Table 4. For a WiFi-based solution for smartphone users, the cost would only incur that due to software development and licensing. Thus, in Table 4, such solutions are considered as low cost. However, the system will most likely be moderately precise. For more precision, RFID, ZigBee and Ultrasonic beacon-based systems are mentioned that also adds infrastructure cost in addition to software development and licensing. Furthermore, the UAV, UGV, stereo camera, monocular camera, RGBD camera, thermal camera are expensive. Thus, the costs of the ILS, where these devices are used, are considered to be high cost.

Table 4 Summary of the state-of-the-art ILS that have considered different applications mentioned in Section 3.2

Area	Exist. work, year	Application	Machine learning approach	Technology/Hardware	Major outcome/Performance	Cost
Localization, tracking and navigation	[14], 2015	Location tracking in hospital	Hierarchical Random Forest	RFID transmitters, receivers	Location in testbed *Accuracy:* 98% correct prediction	Moderate
	[66], 2015	Localization in dark environments	Active Transfer Learning, SVM	Long wave infrared thermal camera	Reference image *Accuracy:* 93.84%-99.17% *Precision:* 85%.	High
	[169], 2016	Indoor LBS, geo-fencing, real-time occupancy distribution monitoring	Weighted ELM (WELM)	WiFi, smartphone	Location in testbed *Precision:* increased by 39.89% over RSS-ELM *Avg.loc.error:* 2.715m	Low
	[103], 2016	Indoor positioning	PCA, kNN, SVM, Decision Tree, Random Forest	WiFi, smartphone	Location in testbed *RMSE:* 1m - 3.2m (static), 3.2m - 12.21m (dynamic)	Low
	[91], 2016	Navigation for visually impaired persons	Deep learning, CNN	RGBD camera, micro-motors, battery, bone-conductive headset, smartphone	Reference image *Precision:* 97.93% *Recall:* 95.34%	High
	[28], 2016	Indoor LBS	ANN-based gradient descent	WiFi, ZigBee sensor, coordinate node	Location in testbed *Loc.error:* 1.36m(WSN), 1.22m(WiFi), 1.05m(hybrid)	Moderate
	[1], 2018	Indoor positioning	Deep learning	WiFi, smartphone	Location in testbed *Avg. accuracy:* 2.64m, 1.21m	Low
	[151], 2019	Indoor positioning	Gradient Boosting, Weighted kNN	WiFi, smartphone	Location in testbed *Avg. accuracy:* 2.6m	Low
	[111], 2019	Location tracking in autonomous systems	Multilayer feed-forward ANN	Ultrasonic beacons	Loc. of target node *Mean error:* 11.44cm *RMSE:* 11.55cm *Precision:*92.64%	Moderate
Asset tracking & warehouse monitoring	[167], 2013	Asset tracking	ELM	RFID transmitters, receivers	Location in testbed *Accuracy:* 1.476m	Moderate
	[153], 2016	Monitor various manufacturing objects	OS-ELM (Sigmoid activation, RBF function)	RFID transmitters, receivers	Location in testbed *Cumulative accuracy:* enhances 6% over ELM	Moderate
	[67], 2017	Tracking in warehouses	ELM, kNN	RFID transmitters, receivers	Location in testbed *Avg.loc.error:* 0.059m *Precision:* increased 62.9%	Moderate
	[68], 2017	Automatically identify/track goods	Logistic Regression (LR), SVM, Decision Tree (DT)	RFID transmitters, receivers	Location in testbed *Accuracy:* 92.75% (LR), 95.3% (SVM), 92.85% (DT)	Moderate
	[64], 2018	Tracking goods in warehouses	CNN	Optical laser-based camera	Reference image *Mean absolute error:* 1.08m-6.76m	High
Vehicle navigation	[48], 2018	UAV racing in indoor, guidance, navigation	Deep learning	NVIDIA-TX2 computer, UAV with stereo camera	Reference image *Loc.error:* converges to 0 & $\leq$ 0.1m *Precision:* 0.755	High
	[84], 2018	Navigation of UAV in indoor	Deep learning, CNN	UAV with monocular camera	Reference image *Avg.#success:* 0.773 & 0.847	High
	[90], 2019	Autonomous navigation of UGV in indoor	Deep learning, CNN	UGV with monocular camera, LiDAR	Reference image *Accuracy:* 93.65% *RMSE:* 4.40m	High

4.4.3 Comparison of the Existing Works of ILS in Terms of the Various Research Challenges

A brief timeline of existing works is presented in Table 5 that summarizes the challenges addressed by the works along with the considered technologies and the applied machine learning techniques to handle the data collected through various technologies. Interestingly, kNN and its variants have been found in this literature to deal with a number of research challenges as shown in the Table 5. In order to improve the reliability of location measurements, ensemble techniques and Deep learning techniques have been used while ELM and Transfer learning techniques have been applied to design localization models with minimal training data. On the other hand, the unsupervised techniques have been found to be useful while dealing with inertial sensor data.

5 Open Issues and Future Directions

Despite of the existing research efforts, some open challenges still exist. Those are:

Unified Labeling Granularity The granularity of localization is not uniform in the literature. Some systems have been designed to provide room-level accuracy while others aim to provide accuracy with a granularity level of 2×2 sq. meter, 1×1 sq. meter, etc. Inertial sensor-based ILS systems mostly predicts the path trails rather than precise locations. Thus, a localization approach needs to be tuned separately for every granularity. The challenges are also vary depending on the level of granularity demanded by an application.

Selection and Extraction of Meaningful Features to Avoid Negative Transfer It is necessary to select meaningful features and transfer objects when the data samples of the source region are transferred to a new unmeasured target region. Improper selection of feature space and transfer mode due to the differences in the spatial layout and AP distribution of both regions may arise a serious negative transfer effect. Thus, the resulting localization accuracy may get decreased. So, effective mechanisms are needed to discover negative transfer in real-time. Correlation between the source and target regions should be carefully assessed.

Cost, Complexity and Ease of Use Many existing localization systems need the support of additional infrastructure like receivers, tags, expensive sensors, cameras, emitters, etc. A system will be cost-effective if it requires existing infrastructure only. If a positioning system is less complex, it will be computationally fast and capable enough to serve location queries from multiple clients in real-time. Different applications require different levels of precision. Thus, the demand for accuracy should determine the design of the specific ILS. For instance, an automated vehicle navigation service should be more precise than the localization of smartphone users. On the contrary, ease of use is an important factor especially for elder adults and differently-abled users. Usability guidelines for user interface development should be strictly adhered to so that the system could be equally accessible across all members of our society. For user navigation, system ubiquity should be an important concern.

Security and Privacy A secure localization system is less vulnerable to be attacked by an intruder. An insecure system would take more time to converge. User navigation could become a challenging task if many of the fingerprints have tampered. Privacy ensures the confidentiality of the localization data. Hence, security and privacy should be maintained while designing a system. Especially for crowd-sourced fingerprints, privacy issues are the major concern.

Appearance of New Sensors or Devices In the future, certain new types of sensors or devices will appear. How the existing localization systems will incorporate such new type of data into their localization framework is a research challenge. So, the localization frameworks should be flexible and inter-operable with respect to the different kinds of sensor combinations. For example, Albuquerque et al. [6] have used millimeter-wave radar that is equipped with the indoor mobile robot to estimate the location of the robot. Their proposed approach does not require extra hardware support as it takes the advantage of the AoA technique of each radar interference to obtain the robot position. So, plugging the new sensors to the existing localization system is an important research challenge.

Localization and Navigation in Emergency Conditions It is infeasible to collect data during emergency conditions. Even, the familiar users may not have the right perception of navigation during emergency conditions as the perceived map may change. However, localization during emergencies is essential and even critical during low visibility conditions. Deep Reinforcement learning mechanisms could be explored for navigating in such environments. Emergency data can be synthesized following real-life data distribution of past events for validation and performance tuning of such systems.

Table 5 Summary of representative works that have applied machine learning approaches to mitigate the challenges of ILS mentioned in Section 3.3 along with performance issues

Exist. work, year	Challenges considered	Machine Learning approach	Technology	Remarks
Surround- Sense [9], 2009	*Improving reliability:* Acquire fingerprints of ambient sound, light, color, WiFi	k-means, SVM	WiFi, A_c	Combines optical, acoustic, motion data to create fingerprints for logical localization. Achieved 87% localization accuracy considering all sensing modalities.
UnLoc [131], 2012	*Error accumulation in received data:* Erroneous location prediction in Dead-reckoning	Un-supervised clustering	A_c, G_y, M_g, WiFi	Combination of 3 methods: dead-reckoning, urban sensing, WiFi-based fingerprinting. Deals with several challenges of dead-reckoning, optimized energy level, robust to ambient changes. Median localization errors are 0.89m (offline), 1.69m (online).
FA-OSELM [47], 2014	*Selection of important features & minimizing site survey:* Change in feature space with adding, removing, moving of APs, save overhead of manual labeling	Feature Adaptive Online Sequential ELM (FA-OSELM)	WiFi	Requires less amount of data to transfer original model into a new model. Localization accuracies are less than 5m & 15m considering office & lounge area respectively.
[168], 2015	*Minimizing site survey:* Reducing time, manpower for offline site survey	Online Sequential ELM (OS-ELM)	WiFi	Requires less amount of training data. Accuracy is less than 1.973m considering 38 offline and 2 online calibration points. In presence of human, accuracy is 2.197m.
LoCo [20], 2016	*Improving reliability:* BLE & WiFi-based ILS for reducing computation complexity & increasing reliability	Adaptive Boosting	WiFi, BLE	Applied Boosting to a set of room-specific classifiers for room-level localization. Decision stumps of RSS are obtained by a greedy iterative procedure to differentiate each room. Accuracies are 0.966 & 0.991 for two datasets considering WiFi & BLE.
[52], 2016	*Improving reliability:* Integration of BLE to improve accuracy of WiFi-based ILS	Weighted kNN	WiFi, BLE	Illustrated how to combine signals of WiFi and BLE within one signal space. Median accuracy is 0.77m using WiFi & 17 BLE.
DeepFi [135], 2017	*Improving reliability:* Use CSI to overcome vulnerable nature of WiFi signal	Deep Learning	WiFi	Validated with parameters (number of antennas, test packets, packet per batch) & different indoor ambience (obstacles, human mobility, grid size of training). Achieved a minimum error of 1.829m.
[99], 2018	*Selection of important features:* Selecting minimal set of stable APs	kNN, Naive Bayes, Bayesian network	WiFi	ML-based feature selection techniques identify stable APs in various ambiance and device. Accuracy is 90.13% & avg. error is 1.3m considering minimal set of stable APs.
[62], 2018	*Device heterogeneity & minimizing site survey:* Enhancing scalability by reducing offline training	Transfer Learning	WiFi	Most appropriate metric learned from environment with sufficiently labeled fingerprints could be further referred for localization in a new environment. Moving objects affect the localization accuracy, still able to hold 85% accuracy.
[73], 2019	*Improving reliability:* Inconsistent accuracy of WiFi-based ILS	RBF-NN, fast clustering algorithm	WiFi	Used RBF NN for training optimization. Improved training speed of NN for more robust results. Mean square error is 1.459m using 25 neurons.

A_c- Accelerometer, G_y- Gyroscope, M_g- Magnetometer

6 Conclusion

This paper provides an overview of the machine learning techniques that are considered in the emerging field of indoor localization. A variety of machine learning techniques are found to be used here to address the challenges of ILS. Along with challenges, the major application domains of ILS are also detailed. However, benchmarking, standardization of techniques and datasets for ILS development are yet to come, though these are essential for quality assurance of localization services. Given sufficient fingerprint data, learning techniques such as semi-supervised learning and Deep Learning are found to provide effective localization accuracy. Transfer Learning is found to be applied for reducing the overhead of collecting a sufficient amount of fingerprints. Transfer Learning is also applied for designing a scalable and adaptive ILS. Neural Network sometimes suffers from slow learning speed as it adjusts the hidden layer parameters through an iterative approach. On the other hand, ELM overcomes this issue by randomly generating the parameters of the hidden layer and hence, it has an extremely fast learning speed. As a result, the training and testing time can be reduced by using ELM or its variants. Deep Neural Networks, CNN, RNN have efficiently solved the indoor localization problem especially with respect to image data with significant performance. However, Deep Learning techniques require more memory spaces than other machine learning algorithms. As an emerging trend, Transfer Learning, ELM, and Deep Learning techniques are found to be used in this domain irrespective of the sensor technologies like RFID, WiFi, Bluetooth, Camera, inertial sensor and so on. In this regard, the open issues and future trends of this field are also discussed in this study.

Acknowledgment This research work is supported by the State Government Fellowship Scheme of Jadavpur University funded by the Government of West Bengal, India and the project entitled-“Developing Framework for Indoor Location Based Services with Seamless Indoor Outdoor Navigation by expanding Spatial Data Infrastructure”, funded by the Ministry of Science and Technology, Department of Science and Technology, NGP Division, Government of India, ref no. NRDMS/UG/NetworkingProject/e-13/2019(G). We would like to thank the anonymous reviewers and the editor for considering our manuscript and providing valuable reviews which has greatly enhanced the quality of the paper.

Author Contributions Priya Roy conceived the study, performed the literature search, participated in the sequence alignment, drafted the manuscript and revised it critically for important intellectual content. Chandreyee Chowdhury conceived the study, revised it critically for important intellectual content and given final approval of the version to be published. All authors read and approved the final manuscript.

Funding This research work is partially supported by the State Government Fellowship Scheme of Jadavpur University funded by the Government of West Bengal, India and the project entitled-“Developing Framework for Indoor Location Based Services with Seamless Indoor Outdoor Navigation by expanding Spatial Data Infrastructure”, funded by the Ministry of Science and Technology, Department of Science and Technology, NGP Division, Government of India, ref no. NRDMS/UG/NetworkingProject/e-13/2019(G).

Declarations

Ethics Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Competing interests The authors declare that they have no competing interests.

References

1. Abbas, M., Elhamshary, M., Rizk, H., Torki, M., Youssef, M.: WiDeep: WiFi-based accurate and robust indoor localization system using deep learning. In: 2019 IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 1–10 (2019). https://doi.org/10.1109/PERCOM.2019.8767421
2. Abdelnasser, H., Mohamed, R., Elgohary, A., Alzantot, M.F., Wang, H., Sen, S., Choudhury, R.R., Youssef, M.: SemanticSLAM: Using environment landmarks for unsupervised indoor localization. IEEE Trans. Mob. Comput. **15**(7), 1770–1782 (2016). https://doi.org/10.1109/TMC.2015.2478451
3. Aguilar, W.G., Rodríguez, G.A., Álvarez, L., Sandoval, S., Quisaguano, F., Limaico, A.: On-board visual SLAM on a UGV using a RGB-D camera. In: International Conference on Intelligent Robotics and Applications, pp. 298–308. Springer (2017). https://doi.org/10.1007/978-3-319-65298-6_28
4. Akram, B.A., Akbar, A.H., Shafiq, O.: Hybloc: Hybrid indoor Wi-Fi localization using soft clustering-based random decision forest ensembles. IEEE Access **6**, 38251–38272 (2018). https://doi.org/10.1109/ACCESS.2018.2852658
5. Akré, J.M., Zhang, X., Baey, S., Kervella, B., Fladenmuller, A., Zancanaro, M.A., Fonseca, M.: Accurate 2-D localization of RFID tags using antenna transmission power control. In: Wireless Days (WD), vol. 2014, pp. 1–6. IEEE, IFIP (2014). https://doi.org/10.1109/WD.2014.7020802
6. Albuquerque, D.F., Gonçalves, E.S., Pedrosa, E.F., Teixeira, F.C., Vieira, J.N.: Robot self position based on asynchronous millimetre wave radar interference. In: 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–6 (2019). https://doi.org/10.1109/IPIN.2019.8911809
7. Alhammadi, A., Alraih, S., Hashim, F., Rasid, M.F.A.: Robust 3D indoor positioning system based on radio map using Bayesian network. In: 2019 IEEE 5th World Forum on Internet of Things (WF-IoT), pp. 107–110 (2019). https://doi.org/10.1109/WF-IoT.2019.8767318
8. Araneda, A., Soto, A. In: Ibero-American Conference on Artificial Intelligence, pp. 545–554. Springer (2004). https://doi.org/10.1007/978-3-540-30498-2_54
9. Azizyan, M., Constandache, I., Roy Choudhury, R.: SurroundSense: Mobile phone localization via ambience fingerprinting. In: Proceedings of the 15th Annual International Conference on Mobile Computing and Networking, Association for Computing Machinery, pp. 261–272. MobiCom ’09, New York (2009). https://doi.org/10.1145/1614320.1614350
10. Başak, A.A., Sazli, M.H.: Accurate indoor localization with optimized fingerprinting algorithm. In: 2017 5th International Istanbul Smart Grid and Cities Congress and Fair (ICSG), pp. 149–152 (2017). https://doi.org/10.1109/SGCF.2017.7947621
11. Bahl, P., Padmanabhan, V.N.: RADAR: An In-building RF-based user location and tracking system. In: Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064), vol. 2, pp. 775–784 (2000). https://doi.org/10.1109/INFCOM.2000.832252
12. Benini, A., Mancini, A., Longhi, S.: An IMU/UWB/vision-based Extended Kalman Filter for mini-UAV Localization in Indoor Environment using 802.15.4a Wireless Sensor Network. J. Intell. Robot. Syst. **70**(1-4), 461–476 (2013). https://doi.org/10.1007/s10846-012-9742-1
13. Breiman, L.: Bagging predictors. Machine Learn. **24**(2), 123–140 (1996). https://doi.org/10.1007/BF00058655
14. Calderoni, L., Ferrara, M., Franco, A., Maio, D.: Indoor Localization in a Hospital Environment using Random Forest

Classifiers. Expert Syst. Appl. **42**(1), 125–134 (2015). https://doi.org/10.1016/j.eswa.2014.07.042
15. Chang, C., Wang, S., Wang, C.: Exploiting moving objects: Multi-Robot simultaneous localization and tracking. IEEE Trans. Autom. Sci. Eng. **13**(2), 810–827 (2016). https://doi.org/10.1109/TASE.2015.2426203
16. Chen, J., Zhang, Y., Xue, W.: Unsupervised Indoor localization based on smartphone sensors, iBeacon and Wi-Fi. Sensors **18**(5), 1378 (2018). https://doi.org/10.3390/s18051378
17. Chen, Z., Wang, J.: GROF: Indoor localization using a multiple-bandwidth general regression neural network and outlier filter. Sensors **18**(11), 3723 (2018). https://doi.org/10.3390/s18113723
18. Chen, Z., Zou, H., Jiang, H., Zhu, Q., Soh, Y.C., Xie, L.: Fusion of WiFi, smartphone sensors and landmarks using the Kalman filter for indoor localization. Sensors **15**(1), 715–732 (2015). https://doi.org/10.3390/s150100715
19. Chriki, A., Touati, H., Snoussi, H.: SVM-based indoor localization in wireless sensor networks. In: 2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 1144–1149 (2017). https://doi.org/10.1109/IWCMC.2017.7986446
20. Cooper, M., Biehl, J., Filby, G., Kratz, S.: Loco: Boosting for Indoor Location Classification Combining Wi-Fi and BLE. Pers. Ubiquit. Comput. **20**(1), 83–96 (2016). https://doi.org/10.1007/s00779-015-0899-z
21. Cui, W., Liu, Q., Zhang, L., Wang, H., Lu, X., Li, J.: A robust mobile robot indoor positioning system based on Wi-Fi. Int. J. Adv. Robot. Syst. **17**(1), 1729881419896660 (2020). https://doi.org/10.1177/1729881419896660
22. Diaz, E.M., Ahmed, D.B., Kaiser, S.: A review of indoor localization methods based on inertial sensors. In: Geographical and Fingerprinting Data to Create Systems for Indoor Positioning and Indoor/Outdoor Navigation, pp. 311–333. Elsevier, Amsterdam (2019). https://doi.org/10.1016/B978-0-12-813189-3.00016-2
23. Dissanayake, M.W.M.G., Newman, P., Clark, S., Durrant-Whyte, H.F., Csorba, M.: A solution to the simultaneous localization and map building (SLAM) problem. IEEE Trans. Robot. Autom. **17**(3), 229–241 (2001). https://doi.org/10.1109/70.938381
24. Elfes, A.: Occupancy grids: A probabilistic framework for robot perception and navigation (1991)
25. Emanuel, D.C., Mahan, L.G., Ungerbuehler, R.H.: Apparatus and method for asset tracking. US Patent 8,565,913 (2013)
26. Fang, S., Lin, T.: Principal component localization in indoor WLAN environments. IEEE Trans. Mob. Comput. **11**(1), 100–110 (2012). https://doi.org/10.1109/TMC.2011.30
27. Faragher, R., Harle, R.: SmartSLAM-An efficient smartphone indoor positioning system exploiting machine learning and opportunistic sensing. In: ION GNSS, vol. 13, pp. 1–14 (2013)
28. Farid, Z., Nordin, R., Ismail, M., Abdullah, N.F.: Hybrid Indoor-based WLAN-WSN localization scheme for improving accuracy based on artificial neural network. Mob. Inf. Syst. **2016**, 1–11 (2016). https://doi.org/10.1155/2016/6923931
29. Feng, Y., Minghua, J., Jing, L., Xiao, Q., Ming, H., Tao, P., Xinrong, H.: An improved indoor localization of WiFi based on support vector machines. Int. J. Future Generat. Commun. Netw **7**(5), 191–206 (2014)
30. Feng, Y., Minghua, J., Jing, L., Xiao, Q., Ming, H., Tao, P., Xinrong, H.: Improved AdaBoost-based Fingerprint Algorithm for WiFi Indoor Localization. In: 2014 IEEE 7th Joint International Information Technology and Artificial Intelligence Conference, pp. 16–19 (2014). https://doi.org/10.1109/ITAIC.2014.7064997
31. Fischer, C., Gellersen, H.: Location and navigation support for emergency responders: a survey. IEEE Pervas. Comput. **9**(1), 38–47 (2010). https://doi.org/10.1109/MPRV.2009.91
32. Gala, D., Lindsay, N., Sun, L.: Multi-sound-source localization for small autonomous unmanned vehicles with a self-rotating Bi-Microphone Array. arXiv:180405111 (2018a)
33. Gala, D., Lindsay, N., Sun, L.: Three-dimensional sound source localization for unmanned ground vehicles with a self-rotational two-microphone array. In: Proceedings of the 5th International Conference of Control, Dynamic Systems and Robotics, Niagara Falls, ON, Canada, pp. 7–9 (2018b). https://doi.org/10.11159/cdsr18.104
34. Gala, D., Lindsay, N., Sun, L.: Realtime active sound source localization for unmanned ground robots using a Self-Rotational Bi-Microphone array. J. Intell. Robot. Syst. **95**(3-4), 935–954 (2019). https://doi.org/10.1007/s10846-018-0908-3
35. Gao, X., Zhang, T.: Unsupervised learning to detect loops using deep neural networks for visual SLAM system. Autonomous Robots **41**(1), 1–18 (2017). https://doi.org/10.1007/s10514-015-95016-2
36. Ghosh, D., Roy, P., Chowdhury, C., Bandyopadhyay, S.: An Ensemble of Condition based Classifiers for Indoor Localization. In: 2016 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), pp. 1–6 (2016). https://doi.org/10.1109/ANTS.2016.7947872
37. Harik, E.H.C., Guérin, F., Guinand, F., Brethé, J., Pelvillain, H.: Towards an autonomous warehouse inventory scheme. In: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–8 (2016). https://doi.org/10.1109/SSCI.2016.7850056
38. Harle, R.K., Hopper, A.: Deploying and evaluating a location-aware system. In: Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, Association for Computing Machinery, New York, NY, USA, MobiSys '05, pp. 219–232 (2005). https://doi.org/10.1145/1067170.1067194
39. Haute, T.V., Poorter, E.D., Lemic, F., Handziski, V., Wirström, N., Voigt, T., Wolisz, A., Moerman, I.: Platform for Benchmarking of RF-Based indoor localization solutions. IEEE Commun. Magazine **53**(9), 126–133 (2015)
40. He, C., Guo, S., Wu, Y., Yang, Y.: A novel radio map construction method to reduce collection effort for indoor localization. Measurement **94**, 423–431 (2016). https://doi.org/10.1016/j.measurement.2016.08.021
41. Hernández, A.C., Gómez, C., Crespo, J., Barber, R.: Object detection applied to indoor environments for mobile robot navigation. Sensors **16**(8), 1180 (2016). https://doi.org/10.3390/s16081180
42. Hossain, A.M., Soh, W.S.: A survey of calibration-free indoor positioning systems. Comput. Commun. **66**, 1–13 (2015). https://doi.org/10.1016/j.comcom.2015.03.001
43. Huang, G.B., Zhu, Q.Y., Siew, C.K.: Extreme learning machine: theory and applications. Neurocomputing **70**(1-3), 489–501 (2006). https://doi.org/10.1016/j.neucom.2005.12.126
44. Huang, Z., Zhu, J., Yang, L., Xue, B., Wu, J., Zhao, Z.: Accurate 3-D position and orientation method for indoor mobile robot navigation based on photoelectric scanning. IEEE Trans. Instrum. Meas. **64**(9), 2518–2529 (2015). https://doi.org/10.1109/TIM.2015.2415031
45. Izidio, D.M.F., Ferreira, A.P.d.A., Barros, E.N.d.S.: Towards better generalization in WLAN positioning systems with genetic algorithms and neural networks. in: proceedings of the genetic and evolutionary computation conference, In: Association for Computing Machinery, New York, NY, USA, GECCO '19, pp. 1206–1213 (2019). https://doi.org/10.1145/3321707.3321712
46. Jia, B., Huang, B., Gao, H., Li, W.: Dimension Rreduction in Radio maps based on the Supervised Kernel Principal

Component Analysis. Soft. Comput. **22**(23), 7697–7703 (2018). https://doi.org/10.1007/s00500-018-3228-4
47. Jiang, X., Liu, J., Chen, Y., Liu, D., Gu, Y., Chen, Z.: Feature adaptive online sequential extreme learning machine for lifelong indoor localization. Neural Comput. Applic. **27**(1), 215–225 (2014). https://doi.org/10.1007/s00521-014-1714-x
48. Jung, S., Hwang, S., Shin, H., Shim, D.H.: Perception, guidance, and navigation for indoor autonomous drone racing using deep learning. IEEE Robot. Autom. Lett. **3**(3), 2539–2544 (2018). https://doi.org/10.1109/LRA.2018.2808368
49. Kang, W., Han, Y.: SmartPDR: Smartphone-Based pedestrian dead reckoning for indoor localization. IEEE Sensors J. **15**(5), 2906–2916 (2015). https://doi.org/10.1109/JSEN.2014.2382568
50. Kim, K.S., Lee, S., Huang, K.: A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on Wi-Fi fingerprinting. Big Data Analytics **3**(1), 4 (2018). https://doi.org/10.1186/s41044-018-0031-2
51. Kong, Z., Lu, Q.: A brief review of simultaneous localization and mapping. In: IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society, pp. 5517–5522 (2017). https://doi.org/10.1109/IECON.2017.8216955
52. Kriz, P., Maly, F., Kozel, T.: Improving indoor localization using bluetooth low energy beacons. Mob. Inf. Syst. 11 https://doi.org/10.1155/2016/2083094 (2016)
53. LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature **521**(7553), 436 (2015). https://doi.org/10.1038/nature14539
54. Li, H., Ng, J.K., Liu, K.: Handling fingerprint sparsity for Wi-Fi based indoor localization in complex environments. In: 2019 IEEE Smartworld, Ubiquitous Intelligence Computing, Advanced Trusted Computing, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), pp. 1109–1116 (2019). https://doi.org/10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00210
55. Li, J., Gao, X., Hu, Z., Wang, H., Cao, T., Yu, L.: Indoor localization method based on regional division with IFCM. Electronics **8**(5), 559 (2019). https://doi.org/10.3390/electronics8050559
56. Li, W., Zhang, T., Kühnlenz, K.: A Vision-guided Autonomous Quadrotor in an Air-ground Multi-robot System. In: 2011 IEEE International Conference on Robotics and Automation, pp. 2980–2985 (2011). https://doi.org/10.1109/ICRA.2011.5979579
57. Li, X., Wang, J., Liu, C., Zhang, L., Li, Z.: Integrated wifi/PDR/smartphone using an adaptive system noise extended Kalman filter algorithm for indoor localization. ISPRS Int. J. Geo-Inform. **5**(2), 8 (2016). https://doi.org/10.3390/ijgi5020008
58. Lin, X., Tsai, C., Tai, F.: Cooperative SLAM of an autonomous indoor Quadrotor Flying together with an autonomous ground robot. In: 2019 12th Asian Control Conference (ASCC), pp. 885–889 (2019)
59. Liu, H., Darabi, H., Banerjee, P., Liu, J.: Survey of wireless indoor positioning techniques and systems. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) **37**(6), 1067–1080 (2007). https://doi.org/10.1109/TSMCC.2007.905750
60. Liu, H., Stoll, N., Junginger, S., Thurow, K.: A new approach to battery power tracking and predicting for mobile robot transportation using wavelet decomposition and ANFIS networks. In: 2014 IEEE International Conference on Robotics and Biomimetics (ROBIO, vol. 2014, pp. 253–258 (2014). https://doi.org/10.1109/ROBIO.2014.7090339
61. Liu, K., Motta, G., Ma, T., Guo, T.: Multi-floor indoor navigation with geomagnetic field positioning and ant colony optimization algorithm. In: 2016 IEEE Symposium on Service-Oriented System Engineering (SOSE), pp. 314–323 (2016). https://doi.org/10.1109/SOSE.2016.18
62. Liu, K., Zhang, H., Ng, J.K.Y., Xia, Y., Feng, L., Lee, V.C.S., Son, S.H.: Toward Low-Overhead Fingerprint-Based indoor localization via transfer learning: design, implementation, and evaluation. IEEE Trans. Industrial Informatics. **14**(3), 898–908 (2018). https://doi.org/10.1109/TII.2017.2750240
63. Lo, C., Wu, K., Liu, J.: Wall following and human detection for mobile robot surveillance in indoor environment. In: 2014 IEEE International Conference on Mechatronics and Automation, pp. 1696–1702 (2014). https://doi.org/10.1109/ICMA.2014.6885956
64. Löffler, C., Riechel, S., Fischer, J., Mutschler, C.: Evaluation criteria for inside-out indoor positioning systems based on machine learning. In: 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1-8. IEEE (2018). https://doi.org/10.1109/IPIN.2018.8533862
65. Lohan, E.S., Torres-Sospedra, J., Leppakoski, H., Richter, P., Peng, Z., Huerta, J.: Wi-Fi Crowdsourced fingerprinting dataset for indoor positioning. Data 2(4) (2017)
66. Lu, G., Yan, Y., Ren, L., Saponaro, P., Sebe, N., Kambhamettu, C.: Where am I in the dark: Exploring active transfer learning on the use of indoor localization based on thermal imaging. Neurocomputing **173**, 83–92 (2016). https://doi.org/10.1016/j.neucom.2015.07.106
67. Ma, H., Wang, K.: Fusion of RSS and Phase Shift using the Kalman Filter for RFID Tracking. IEEE Sensors J. **17**(11), 3551–3558 (2017). https://doi.org/10.1109/JSEN.2017.2696054
68. Ma, H., Wang, Y., Wang, K.: Automatic detection of false positive RFID readings using machine learning algorithms. Expert Syst. Appl. **91**, 442–451 (2018). https://doi.org/10.1016/j.eswa.2017.09.021
69. Madigan, D., Einahrawy, E., Martin, R.P., Ju, W.H., Krishnan, P., Krishnakumar, A.: Bayesian indoor positioning systems. In: INFOCOM 2005. 24th Annual Joint Conf of the IEEE Computer and Communications Societies. Proc. IEEE, vol. 2, pp. 1217–1227 (2005). https://doi.org/10.1109/INFCOM.2005.1498348
70. Mascharka, D., Manley, E.: Machine learning for indoor localization using mobile phone-based sensors. arXiv:150506125 (2015)
71. McCarthy, M.R.: The BUZZ: Narrowband ultrasonic positioning for wearable computers. PhD thesis, Citeseer (2007). https://doi.org/10.1.1.153.671
72. Menéndez, P., Campomanes, C., Trawiński, K., Alonso, J.M.: Topology-based indoor localization by means of WiFi fingerprinting with a computational intelligent classifier. In: Intelligent Systems Design and Applications (ISDA), 2011 11th International Conference on, pp. 1020–1025. IEEE (2011). https://doi.org/10.1109/ISDA.2011.6121792
73. Meng, H., Yuan, F., Yan, T., Zeng, M.: Indoor positioning of RBF neural network based on improved fast clustering algorithm combined with LM algorithm. IEEE Access **7**, 5932–5945 (2019). https://doi.org/10.1109/ACCESS.2018.2888616
74. Minami, M., Fukuju, Y., Hirasawa, K., Yokoyama, S., Mizumachi, M., Morikawa, H., Aoyama, T.: Dolphin: A practical approach for implementing a fully distributed indoor ultrasonic positioning system. In: UbiComp 2004: Ubiquitous Computing, pp. 347–365. Springer, Berlin (2004). https://doi.org/10.1007/978-3-540-30119-6_21
75. Montemerlo, M., Thrun, S., Koller, D., Wegbreit, B.: FastSLAM: A factored solution to the simultaneous localization and mapping problem. Aaai/iaai 593–598 (2002)

76. Montemerlo, M., Thrun, S., Koller, D., Wegbreit, B., et al.: FastSLAM 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. In: IJCAI, pp. 1151–1156 (2003)
77. Montoliu, R., Sansano, E., Torres-Sospedra, J., Belmonte, O.: IndoorLoc Platform: A public repository for comparing and evaluating indoor positioning systems. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8 (2017). https://doi.org/10.1109/IPIN.2017.8115940
78. Moravec, H., Elfes, A.: High resolution maps from wide angle sonar. In: Proceedings. 1985 IEEE International Conference on Robotics and Automation, vol. 2, pp. 116–121 (1985). https://doi.org/10.1109/ROBOT.1985.1087316
79. Nastac, D., Lehan, E., Iftimie, F.A., Arsene, O., Cramariuc, B.: Automatic data acquisition with robots for indoor fingerprinting. In: 2018 International Conference on Communications (COMM), pp. 321–326 (2018). https://doi.org/10.1109/ICComm.2018.8484796
80. Ni, L.M., Yunhao, L., Yiu Cho, L., Patil, A.P.: LANDMARC: Indoor Location Sensing using Active RFID. In: Proceedings of the First IEEE International Conference on Pervasive Computing and Communications, 2003. (PerCom 2003), pp. 407–415 (2003). https://doi.org/10.1109/PERCOM.2003.1192765
81. Nikdel, P., Chen, M., Vaughan, R.: Recognizing and Tracking High-Level, Human-Meaningful Navigation Features of Occupancy Grid Maps. In: 2020 17Th Conference on Computer and Robot Vision (CRV), pp. 62–69. IEEE (2020). https://doi.org/10.1109/CRV50864.2020.00017
82. Nurminen, H., Ristimäki, A., Ali-Löytty, S., Piché, R.: Particle filter and smoother for indoor localization. In: International Conference on Indoor Positioning and Indoor Navigation, pp. 1–10 (2013). https://doi.org/10.1109/IPIN.2013.6817903
83. Ouyang, R.W., Wong, A.K., Lea, C., Chiang, M.: Indoor location estimation with reduced calibration exploiting unlabeled data via hybrid Generative/Discriminative learning. IEEE Trans. Mob. Comput. **11**(11), 1613–1626 (2012). https://doi.org/10.1109/TMC.2011.193
84. Padhy, R.P., Verma, S., Ahmad, S., Choudhury, S.K., Sa, P.K.: Deep neural network for autonomous UAV navigation in indoor corridor environments. Procedia computer science **133**, 643–650 (2018). https://doi.org/10.1016/j.procs.2018.07.099
85. Pan, J.J., Pan, S.J., Yin, J., Ni, L.M., Yang, Q.: Tracking mobile users in wireless networks via Semi-Supervised colocalization. IEEE Trans. Pattern Anal. Mach. Intell. **34**(3), 587–600 (2012). https://doi.org/10.1109/TPAMI.2011.165
86. Pan, S.J., Yang, Q.: A survey on transfer learning. IEEE Trans. Knowl. Data Eng. **22**(10), 1345–1359 (2010). https://doi.org/10.1109/TKDE.2009.191
87. Pandey, A., Pandey, S., Parhi, D.: Mobile robot navigation and obstacle avoidance techniques: A review. Int. Robot. Autom. J. **2**(3), 00022 (2017)
88. Panov, P., Džeroski, S.: Combining bagging and random subspaces to create better ensembles. In: International Symposium on Intelligent Data Analysis, pp. 118–129. Springer (2007). https://doi.org/10.1007/978-3-540-74825-0_11
89. Paolanti, M., Sturari, M., Mancini, A., Zingaretti, P., Frontoni, E.: Mobile robot for retail surveying and inventory using visual and textual analysis of monocular pictures based on deep learning. In: 2017 European Conference on Mobile Robots (ECMR), pp. 1–6 (2017). https://doi.org/10.1109/ECMR.2017.8098666
90. Patel, N., Choromanska, A., Krishnamurthy, P., Khorrami, F.: A deep learning gated architecture for UGV navigation robust to sensor failures. Robot. Autonom. Syst. **116**, 80–97 (2019). https://doi.org/10.1016/j.robot.2019.03.001
91. Poggi, M., Mattoccia, S.: A wearable mobility aid for the visually impaired based on embedded 3d vision and deep learning. In: 2016 IEEE Symposium on Computers and Communication (ISCC), pp. 208–213. IEEE (2016). https://doi.org/10.1109/ISCC.2016.7543741
92. Priyantha, N.B., Chakraborty, A., Balakrishnan, H.: The cricket location-support system. In: Proceedings of the 6th Annual International Conference on Mobile Computing and Networking, Association for Computing Machinery, New York, NY, USA, MobiCom '00, pp. 32–43 (2000). https://doi.org/10.1145/345910.345917
93. Pulkkinen, T., Roos, T., Myllymäki, P.: Semi-supervised Learning for WLAN Positioning. In: Intl Conf on Art. Neural Net., pp. 355–362 (2011). https://doi.org/10.1007/978-3-642-21735-7_44
94. Rahbar, F., Marjovi, A., Kibleur, P., Martinoli, A.: A 3-D Bio-inspired odor source localization and its validation in realistic environmental conditions. In: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 3983–3989 (2017). https://doi.org/10.1109/IROS.2017.8206252
95. Rai, A., Chintalapudi, K.K., Padmanabhan, V.N., Sen, R.: Zee: Zero-Effort Crowdsourcing for Indoor Localization. In: Proc. of the 18th annual Intl Conf on Mobile computing and networking, pp. 293–304. ACM (2012). https://doi.org/10.1145/2348543.2348580
96. Ramadan, M., Sark, V., Gutierrez, J., Grass, E.: NLOS Identification for Indoor Localization using Random Forest Algorithm. In: WSA 2018; 22nd International ITG Workshop on Smart Antennas, pp. 1–5 (2018)
97. Rezgui, Y., Pei, L., Chen, X., Wen, F., Han, C.: An efficient normalized rank based SVM for room level indoor WiFi localization with diverse devices. Mob. Inf. Syst. 2017 https://doi.org/10.1155/2017/6268797 (2017)
98. Roy, P., Chowdhury, C.: Indoor localization for Smart-handhelds with stable set of wireless access points. In: 2018 Fifth International Conference on Emerging Applications of Information Technology (EAIT), pp. 1–4 (2018). https://doi.org/10.1109/EAIT.2018.8470401
99. Roy, P., Chowdhury, C.: Smartphone based indoor localization using stable access points. In: Proc. of the Workshop Program of the 19th Intl Conf on Distributed Computing and Networking, ACM, Workshops ICDCN '18, pp. 17:1–17:6 (2018). https://doi.org/10.1145/3170521.3170538
100. Roy, P., Chowdhury, C., Ghosh, D., Bandyopadhyay, S.: JUIndoorLoc: A Ubiquitous Framework for Smartphone-Based Indoor Localization Subject to Context and Device Heterogeneity. Wireless Personal Communications https://doi.org/10.1007/s11277-019-06188-2 (2019)
101. Roy, P., Kundu, M., Chowdhury, C.: Indoor localization using stable set of wireless access points subject to varying granularity levels. In: 2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), pp. 491–496 (2019). https://doi.org/10.1109/WiSPNET45539.2019.9032859
102. Roy, P., Chowdhury, C., Kundu, M., Ghosh, D., Bandyopadhyay, S.: Novel weighted ensemble classifier for Smartphone based indoor localization. Expert Syst. Appl. **164**, 113758 (2021). https://doi.org/10.1016/j.eswa.2020.113758. http://www.sciencedirect.com/science/article/pii/S0957417420305820
103. Salamah, A.H., Tamazin, M., Sharkas, M.A., Khedr, M.: An Enhanced WiFi Indoor Localization System Based on Machine Learning. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8. IEEE (2016). https://doi.org/10.1109/IPIN.2016.7743586

104. Salamah, A.H., Tamazin, M., Sharkas, M.A., Khedr, M., Mahmoud, M.: Comprehensive investigation on principle component Large-Scale Wi-Fi indoor localization. Sensors **19**(7), 1678 (2019). https://doi.org/10.3390/s19071678
105. Sampedro, C., Rodriguez-Ramos, A., Bavle, H., Carrio, A., de la Puente, P., Campoy, P.: A fully-autonomous aerial robot for search and rescue applications in indoor environments using learning-based techniques. J. Intell. Robotic Syst. **95**(2), 601–627 (2019). https://doi.org/10.1007/s10846-018-0898-1
106. Sarshar, H., Matwin, S.: Using Classification in the Preprocessing Step on Wi-Fi Data as an Enabler of Physical Analytics. IEEE, ICMLA. https://doi.org/10.1109/ICMLA.2016.0170 (2016)
107. Savvides, A., Han, C.C., Strivastava, M.B.: Dynamic fine-grained localization in ad-hoc networks of sensors. In: Proceedings of the 7th annual international conference on Mobile computing and networking, pp. 166–179 (2001). https://doi.org/10.1145/381677.381693
108. Scheper, K.Y.W., Karásek, M., De Wagter, C., Remes, B.D.W., De Croon, G.C.H.E.: First autonomous multi-room exploration with an insect-inspired flapping wing vehicle. In: 2018 IEEE International Conference on Robotics and Automation (ICRA), pp. 5546–5552 (2018). https://doi.org/10.1109/ICRA.2018.8460702
109. Schmuck, P., Scherer, S.A., Zell, A.: Hybrid Metric-Topological 3D Occupancy Grid Maps for Large-scale Mapping, vol. 49, pp. 230–235 (2016). https://doi.org/10.1016/j.ifacol.2016.07.738, 9th IFAC Symposium on Intelligent Autonomous Vehicles IAV 2016
110. Shang, J., Gu, F., Hu, X., Kealy, A.: APFIloc: An Infrastructure-free Indoor Localization Method Fusing Smartphone Inertial Sensors, Landmarks and Map Information. Sensors **15**(10), 27251–27272 (2015). https://doi.org/10.3390/s151027251
111. Shenoy, M.V., Karuppiah, A., Manjarekar, N.: A Lightweight ANN based Robust Localization Technique for Rapid Deployment of Autonomous Systems. J. Ambient. Intell. Humaniz. Comput. 1–16. https://doi.org/10.1007/s12652-019-01331-0 (2019)
112. Shnaps, I., Rimon, E.: Online coverage of planar environments by a battery powered autonomous mobile robot. IEEE Trans. Autom. Sci. Eng. **13**(2), 425–436 (2016). https://doi.org/10.1109/TASE.2016.2515165
113. Slavin, A.J., Martin, J.P., Ramos, D.J.: Fixed property monitoring with moving asset location tracking. US Patent App. **15**, 606,922 (2017)
114. Song, Z., Du, H., Huang, H., Liu, C.: Indoor localization via candidate fingerprints and genetic algorithm. In: Combinatorial Optimization and Applications, pp. 319–333. Springer (2015). https://doi.org/10.1007/978-3-319-26626-8_24
115. Stevens, T.D.: Wireless tracking and monitoring electronic seal. US Patent 8,456,302 (2013)
116. Suroso, D.J., Cherntanomwong, P., Sooraksa, P., Takada, J.: Location fingerprint technique using fuzzy c-means clustering algorithm for indoor localization. In: TENCON 2011 - 2011 IEEE Region 10 Conference, pp. 88–92 (2011). https://doi.org/10.1109/TENCON.2011.6129069
117. Suwannawach, P., Chivapreecha, S.: Reduce RSSI variance for indoor localization system using frequency analysis. Int. J. Future Comput. Commun. **8**(2), 1–5 (2019). https://doi.org/10.18178/ijfcc.2019.8.2.536
118. Tateno, K., Tombari, F., Laina, I., Navab, N.: CNN-SLAM: Real-Time Dense Monocular SLAM with Learned Depth Prediction. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6565–6574 (2017). https://doi.org/10.1109/CVPR.2017.695
119. Tejera Hernández, D.C.: An experimental study of k* algorithm. International Journal of Information Engineering & Electronic Business 7(2). https://doi.org/10.5815/ijieeb.2015.02.03 (2015)
120. Thrun, S., Burgard, W., Fox, D.: A probabilistic approach to concurrent mapping and localization for mobile robots, vol. 5, pp. 253–271 (1998). https://doi.org/10.1023/A:1008806205438
121. Torres-Sospedra, J., Montoliu, R., Martínez-Usó, A., Avariento, J.P., Arnau, T.J., Benedito-Bordonau, M., Huerta, J.: UJIIndoorLoc: A New multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems. In: Indoor Positioning and Indoor Navigation (IPIN), 2014 Intl Conf on, pp. 261–270. IEEE (2014). https://doi.org/10.1109/IPIN.2014.7275492
122. Torres-Sospedra, J., Rambla, D., Montoliu, R., Belmonte, O., Huerta, J.: UJIIndoorLoc-Mag: A new database for magnetic field-based localization problems. In: 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–10 (2015). https://doi.org/10.1109/IPIN.2015.7346763
123. Trawiński, K., Alonso, J.M., Hernández, N.: A multiclassifier approach for topology-based WiFi indoor localization. Soft. Comput. **17**(10), 1817–1831 (2013). https://doi.org/10.1007/s00500-013-1019-5
124. Trogh, J., Joseph, W., Martens, L., Plets, D.: An unsupervised learning technique to optimize radio maps for indoor localization. Sensors **19**(4), 752 (2019). https://doi.org/10.3390/s19040752
125. Turduev, M., Cabrita, G., Kırtay, M., Gazi, V., Marques, L.: Experimental studies on chemical concentration map building by a multi-robot system using bio-inspired algorithms. Autonom. Agents Multi-Agent Syst. **28**(1), 72–100 (2014). https://doi.org/10.1007/s10458-012-9213-x
126. Tzafestas, S.G.: Mobile robot control and navigation: A global overview. J. Intell. Robot. Syst. **91**(1), 35–58 (2018). https://doi.org/10.1007/s10846-018-0805-9
127. Valin, J., Michaud, F., Rouat, J., Letourneau, D.: Robust sound source localization using a microphone array on a mobile robot. In: Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453), vol. 2, pp. 1228–1233 (2003). https://doi.org/10.1109/IROS.2003.1248813
128. Wang, C., Meng, L., She, S., Mitchell, I.M., Li, T., Tung, F., Wan, W., Meng, M.Q., de Silva, C.W.: Autonomous mobile robot navigation in uneven and unstructured indoor environments. In: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 109–116 (2017). https://doi.org/10.1109/IROS.2017.8202145
129. Wang, C., Shi, Z., Wu, F.: An improved particle swarm optimization-based feed-forward neural network combined with RFID Sensors to Indoor Localization. Information **8**(1), 9 (2017a)
130. Wang, D., Wang, T., Zhao, F., Zhang, X.: Improved graph-based semi-supervised learning for fingerprint-based indoor localization. In: 2018 IEEE Global Communications Conference (GLOBECOM), pp. 1–6 (2018). https://doi.org/10.1109/GLOCOM.2018.8647621
131. Wang, H., Sen, S., Elgohary, A., Farid, M., Youssef, M., Choudhury, R.R.: No Need to War-drive: Unsupervised Indoor Localization. In: Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services, Association for Computing Machinery, New York, NY, USA, MobiSys '12, pp. 197–210 (2012). https://doi.org/10.1145/2307636.2307655
132. Wang, K., Yu, X., Xiong, Q., Zhu, Q., Lu, W., Huang, Y., Zhao, L.: Learning to improve WLAN indoor positioning accuracy based on DBSCAN-KRF algorithm from

RSS fingerprint data. IEEE Access **7**, 72308–72315 (2019a). https://doi.org/10.1109/ACCESS.2019.2919329
133. Wang, W., Li, T., Wang, W., Tu, Z.: Multiple fingerprints-based indoor localization via gbdt: Subspace and rssi. IEEE Access **7**, 80519–80529 (2019b). https://doi.org/10.1109/ACCESS.2019.2922995
134. Wang, X., Gao, L., Mao, S.: CSI Phase fingerprinting for indoor localization with a deep learning approach. IEEE Int. Things J. **3**(6), 1113–1123 (2016). https://doi.org/10.1109/JIOT.2016.2558659
135. Wang, X., Gao, L., Mao, S., Pandey, S.: CSI-Based Fingerprinting for Indoor localization: A Deep Learning Approach. IEEE Trans. Veh. Technol. **66**(1), 763–776 (2017b). https://doi.org/10.1109/TVT.2016.2545523
136. Wang, Y., Xiu, C., Zhang, X., Yang, D.: Wifi Indoor Localization with CSI Fingerprinting-based Random Forest. Sensors **18**(9), 2869 (2018). https://doi.org/10.3390/s18092869
137. Xuyu, W., Lingjun, G., Shiwen, M.: Phasefi: Phase Fingerprinting for Indoor Localization with a Deep Learning Approach. In: 2015 IEEE Global Communications Conference (GLOBECOM), pp. 1–6. IEEE (2015). https://doi.org/10.1109/GLOCOM.2015.7417517
138. Ward, A., Jones, A., Hopper, A.: A new location technique for the active office. IEEE Pers. Commun. **4**(5), 42–47 (1997). https://doi.org/10.1109/98.626982
139. Wessner, J., Utschick, W.: Extending Occupancy Grid Mapping for Dynamic Environments. In: 2018 IEEE Intelligent Vehicles Symposium, vol. IV, pp. 701–707 (2018). https://doi.org/10.1109/IVS.2018.8500362
140. Woo, S., Jeong, S., Mok, E., Xia, L., Choi, C., Pyeon, M., Heo, J.: Application of WiFi-based Indoor Positioning System for Labor Tracking at Construction sites: A Case Study in Guangzhou MTR. Autom. Constr. **20**(1), 3–13 (2011). https://doi.org/10.1016/j.autcon.2010.07.009
141. Wu, C., Yang, Z., Liu, Y., Xi, W.: WILL: Wireless indoor localization without site survey. IEEE Trans. Parallel Distribut. Syst. **24**(4), 839–848 (2013). https://doi.org/10.1109/TPDS.2012.179
142. Wu, C., Yang, Z., Liu, Y.: Smartphones based crowdsourcing for indoor localization. IEEE Trans. Mob. Comput. **14**(2), 444–457 (2015). https://doi.org/10.1109/TMC.2014.2320254
143. Wu, C., Yang, Z., Xiao, C.: Automatic radio map adaptation for indoor localization using smartphones. IEEE Trans. Mob. Comput. **17**(3), 517–528 (2018). https://doi.org/10.1109/TMC.2017.2737004
144. Xia, J., Iqbal, U., Noureldin, A., Atia, M.M., Sun, F.: Adaptive Square-root CKF based SLAM Algorithm for Indoor UGVs. In: 2017 IEEE International Conference on Mechatronics and Automation (ICMA), pp. 1942–1946 (2017). https://doi.org/10.1109/ICMA.2017.8016115
145. Xiao, J., Zhou, Z., Yi, Y., Ni, L.M.: A survey on wireless indoor localization from the device perspective. ACM Computing Surveys (CSUR) **49**(2), 25 (2016). https://doi.org/10.1145/2933232
146. Xu, D., Han, L., Tan, M., Li, Y.F.: Ceiling-Based Visual positioning for an indoor mobile robot with monocular vision. IEEE Trans. Ind. Electron. **56**(5), 1617–1628 (2009). https://doi.org/10.1109/TIE.2009.2012457
147. Xu, L., Feng, C., Kamat, V.R., Menassa, C.C.: An occupancy grid mapping enhanced visual SLAM for real-time locating applications in indoor GPS-denied environments. Autom. Constr. **104**, 230–245 (2019). https://doi.org/10.1016/j.autcon.2019.04.011
148. Xu, Z., Wei, J., Zhu, J., Yang, W.: A robust floor localization method using inertial and barometer measurements. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8 (2017). https://doi.org/10.1109/IPIN.2017.8115952
149. Xue, W., Qiu, W., Hua, X., Yu, K.: Improved Wi-Fi RSSI measurement for indoor localization. IEEE Sensors J. **17**(7), 2224–2230 (2017). https://doi.org/10.1109/JSEN.2017.2660522
150. Yang, H., Zhang, R., Bordoy, J., Höflinger, F., Li, W., Schindelhauer, C., Reindl, L.: Smartphone-Based Indoor localization system using inertial sensor and acoustic Transmitter/Receiver. IEEE Sensors J. **16**(22), 8051–8061 (2016). https://doi.org/10.1109/JSEN.2016.2604424
151. Yang, J., Zhao, X., Li, Z.: Crowdsourcing indoor positioning by Light-Weight automatic fingerprint updating via ensemble learning. IEEE Access **7**, 26255–26267 (2019). https://doi.org/10.1109/ACCESS.2019.2901736
152. Yang, Z., Wu, C., Zhou, Z., Zhang, X., Wang, X., Liu, Y.: Mobility Increases localizability: A Survey on Wireless Indoor Localization using Inertial Sensors. ACM Computing Surveys (CSUR) **47**(3), 54 (2015). https://doi.org/10.1145/2676430
153. Yang, Z., Zhang, P., Chen, L.: RFID-Enabled Indoor Positioning Method for a Real-time Manufacturing Execution System using OS-ELM. Neurocomputing **174**, 121–133 (2016). https://doi.org/10.1016/j.neucom.2015.05.120
154. Yassin, A., Nasser, Y., Awad, M., Al-Dubai, A., Liu, R., Yuen, C., Raulefs, R., Aboutanios, E.: Recent advances in indoor localization: a survey on theoretical approaches and applications. IEEE Commun. Surveys Tutor. **19**(2), 1327–1346 (2017). https://doi.org/10.1109/COMST.2016.2632427
155. Yayan, U., Yucel, H.: A low cost ultrasonic based positioning system for the indoor navigation of mobile robots. J. Intell. Robot. Syst. **78**(3-4), 541–552 (2015). https://doi.org/10.1007/s10846-014-0060-7
156. Yoo, J., Johansson, K.H.: Semi-supervised learning for mobile robot localization using wireless signal strengths. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–8 (2017). https://doi.org/10.1109/IPIN.2017.8115921
157. Youssef, M., Agrawala, A.: The Horus WLAN location determination system. In: Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, Association for Computing Machinery, New York, NY, USA, MobiSys '05, pp. 205–218 (2005). https://doi.org/10.1145/1067170.1067193
158. Zafari, F., Gkelias, A., Leung, K.: A survey of indoor localization systems and technologies. IEEE Commun. Surveys Tutor. **21**(3), 2568–2599 (2017). https://doi.org/10.1109/COMST.2019.2911558
159. Zhang, M., Wen, Y., Chen, J., Yang, X., Gao, R., Zhao, H.: Pedestrian Dead-Reckoning indoor localization based on OS-ELM. IEEE Access **6**, 6116–6129 (2018). https://doi.org/10.1109/ACCESS.2018.2791579
160. Zhang, W., Wang, L., Qin, Z., Zheng, X., Sun, L., Jin, N., Shu, L.: INBS: An Improved Naive Bayes Simple learning approach for accurate indoor localization. In: 2014 IEEE International Conference on Communications (ICC), pp. 148–153 (2014). https://doi.org/10.1109/ICC.2014.6883310
161. Zhang, W., Sengupta, R., Fodero, J., Li, X.: DeepPositioning: Intelligent fusion of pervasive magnetic field and WiFi fingerprinting for smartphone indoor localization via deep learning. In: 16th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 7–13 (2017). https://doi.org/10.1109/ICMLA.2017.0-185
162. Zhou, B., Li, Q., Mao, Q., Tu, W.: A Robust Crowdsourcing-based Indoor Localization System. Sensors **17**(4), 864 (2017). https://doi.org/10.3390/s17040864
163. Zhou, M., Tang, Y., Tian, Z., Geng, X.: Semi-Supervised Learning for indoor hybrid fingerprint database calibration with

low effort. IEEE Access **5**, 4388–4400 (2017). https://doi.org/10.1109/ACCESS.2017.2678603
164. Zhou, Q., Zhou, H., Li, T.: Cost-sensitive feature selection using random forest: Selecting low-cost subsets of informative features. Knowl.-Based Syst. **95**, 1–11 (2016). DOI10.1016/j.knosys.2015.11.010. http://www.sciencedirect.com/science/article/pii/S0950705115004372
165. Zhuang, Y., Yang, J., Li, Y., Qi, L., El-Sheimy, N.: Smartphone-based Indoor Localization with Bluetooth Low Energy Beacons. Sensors **16**(5), 596 (2016). https://doi.org/10.3390/s16050596
166. Zia, K., Iram, H., Aziz-ul-Haq, M., Zia, A.: Comparative study of classification techniques for indoor localization of mobile devices. In: 2018 28th International Telecommunication Networks and Applications Conference (ITNAC), pp. 1–5 (2018). https://doi.org/10.1109/ATNAC.2018.8615220
167. Zou, H., Wang, H., Xie, L., Jia, Q.S.: An RFID Indoor positioning system by using weighted path loss and extreme learning machine. In: 2013 IEEE 1St International Conference on Cyber-Physical Systems, Networks, and Applications (CPSNA), pp. 66–71. IEEE (2013). https://doi.org/10.1109/CPSNA.2013.6614248
168. Zou, H., Lu, X., Jiang, H., Xie, L.: A fast and precise indoor localization algorithm based on an online sequential extreme learning machine. Sensors **15**(1), 1804–1824 (2015). https://doi.org/10.3390/s150101804
169. Zou, H., Huang, B., Lu, X., Jiang, H., Xie, L.: A robust indoor positioning system based on the procrustes analysis and weighted extreme learning machine. IEEE Trans. Wireless Commun. **15**(2), 1252–1266 (2016). https://doi.org/10.1109/TWC.2015.2487963
170. Zou, H., Zhou, Y., Jiang, H., Huang, B., Xie, L., Spanos, C.: Adaptive localization in dynamic indoor environments by transfer kernel learning. In: 2017 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6 (2017). https://doi.org/10.1109/WCNC.2017.7925444

Priya Roy is currently pursuing her Ph.D. degree in Computer Science and Engineering Department at Jadavpur University, India under the supervision of Dr. Chandreyee Chowdhury. Her research interests include indoor localization and machine learning. She received her B.Tech. degree in Computer Science and Engineering from Dream Institute of Technology, India in 2012 and M.Tech. deree in Computer Technology from Jadavpur University, India, in 2016.

Chandreyee Chowdhury is a faculty in the Department of Computer Science and Engineering at Jadavpur University, India. She received Ph.D. in Engineering from Jadavpur University in 2013 and M.E. in Computer Science and Engineering from Jadavpur University in 2005. She has published several research articles in international journals and conferences. Her research interests include routing issues of Wireless Body Area Networks, mobile crowd-sensing, and applications of smartphone sensing. She is a member of IEEE and IEEE Computer Society.