Journal of Computer Science

Research Article

Enhancing Indoor Asset Tracking: IoT Integration and Machine Learning Approaches for Optimized Performance

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Article history
Received: 21-12-2024
Revised: 31-12-2024
Accepted: 04-01-2025

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Abstract: Indoor asset tracking entails the surveillance and governance of the position and movement of tangible assets within enclosed spaces, including warehouses, hospitals, and workplaces. Indoor asset tracking systems employ technologies such as Radio Frequency Identification (RFID), Bluetooth Low Energy (BLE), Wi-Fi, and UWB (Ultra-Wideband) to deliver real-time visibility and precise placement of goods. This research introduces indoor asset tracking with IoT and machine learning. Indoor asset tracking has advanced significantly with the incorporation of Internet of Things (IoT) and machine learning technology. The Internet of Things facilitates the effortless acquisition of real-time data from diverse sensors and devices, while machine learning algorithms analyze this data to deliver precise tracking and predictive analytics. This combination enables the tracking of asset locations, conditions, and movements in indoor settings, including storage areas, hospitals and different industries. This study gathers data from the BLE tracker, which transmits information to the LoRa gateway. This research utilizes supervised learning methodologies, including Support Vector Machines (SVMs), K-Nearest Neighbors (KNNs), and Neural Networks (NN). The F-score, recall, precision, and accuracy are employed for evaluation purposes. The experimental results indicate that the KNN model achieves the best accuracy of 80.5%.

Keywords: Indoor Asset Tracking, Machine Learning, IoT, BLE

Introduction

The ubiquity and continuous improvement of smartphones and other personal electronic devices have resulted in significant growth and advancement in several Information and Communications Technology (ICT) industries. By utilizing the sensors and protocols built into mobile devices, indoor tracking technology has advanced to enable a wide range of services. Compared to approaches based on WiFi, the number of tries to detect position in interior situations using Bluetooth has grown because of the introduction of iBeacon (Kohne & Sieck, 2014) and Eddystone (David *et al.*, 2022). This is mostly because Bluetooth is designed to function with a minimum amount of power consumption (Sesyuk *et al.*, 2022; Song *et al.*, 2019; Ninh *et al.*, 2020; Zafari *et al.*, 2019).

Indoor tracking possesses numerous applications and has been the subject of investigation across various sectors. Location-based marketing is a prominent topic that has prompted extensive research on these systems. The objective of location-based marketing is to provide clients with a customized experience, pertinent information about products or services, and exclusive offers contingent upon the client's location. This sort of solution, in conjunction with the integration of payment capabilities through alerts or the monitoring of consumer behavior, offers information that has the potential to enhance the overall experience of the end customer (Shum *et al.*, 2022).

This project involved the development of an Internet of Things (IoT) system that utilized Machine Learning (ML) for the assessment of the positions of indoor assets, items, individuals, or animals. To deliver the optimal solution for this type of system, it is essential to analyze several methodologies, designs, and frameworks (Fortino *et al.*, 2020). This study investigates the fingerprinting method as a substitute for trilateration in indoor location estimation. The method employs an intelligent system that collects data from the RSSI levels of the object's wireless connection with many access points, subsequently correlating these data sets with a specific spatial location (Li *et al.*, 2019). Employing Bluetooth Low Energy (BLE) technology, Scanning Stations are placed in the study area at regular intervals to read periodic beacon messages sent by a tag connected to the item (Teran *et al.*, 2017). When all of the scanners have collected enough data, they upload it to a server. From

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there, an ML model that has been trained to use fingerprinting to predict the object's location is applied.

The principal objective of the IoT indoor positioning system is to facilitate asset identification and monitoring, hence generating alerts regarding their existence or absence. To do this, multiple elements of an IoT architecture were created. The components comprised: (i) Processing and storage layers; (ii) A Bluetooth communication layer linking the scanning stations and mobile TAGs; (iii) A local MQTT broker for data centralization; and (iv) Fully tailored electronic devices for hardware and firmware (Pu and You, 2018). A training phase of the research entailed the acquisition and labeling of a location dataset to serve as input for training the neural network. A subsequent deployment and operational phase ensued.

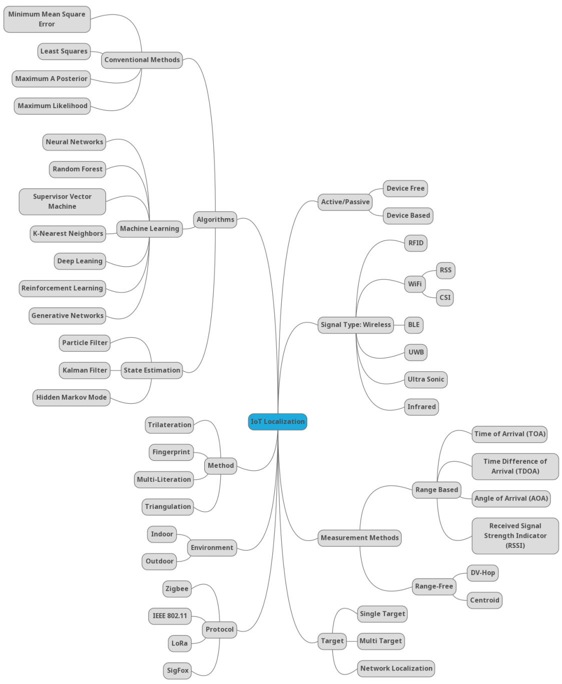


Fig. 1: A high-level overview of the IoT localization classification

Indoor positioning has undergone significant advancement; nonetheless, a definitive standard for the many methodologies has yet to materialize. To enhance data mining and machine learning applications, particularly at the edge, for efficient decision-making in dynamic and constrained IoT environments, considerable efforts have been devoted to proposing a general simulation-driven methodology for IoT systems (Savaglio & Fortino, 2021). Figure (1) presents a comprehensive overview of the classification of IoT localization.

Fundamental of Indoor Asset Tracking

Indoor asset monitoring employs diverse technologies and approaches to identify, monitor, and manage assets within enclosed locations such as warehouses, hospitals, offices, and retail areas. The primary objective is to improve operational efficiency, security, and asset utilization by offering real-time visibility into the location and status of assets.

Principal technologies in indoor asset tracking comprise Radio Frequency Identification (RFID), WiFi, Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), and infrared systems. RFID tags and readers provide the automatic identification and tracking of things affixed with RFID tags. WiFi and BLE utilize existing network infrastructure to deliver location data derived from signal strength and triangulation. UWB provides high-accuracy position tracking by quantifying the duration of signal transmission between devices.

Infrared systems use light waves to detect asset locations. These technologies can be integrated with software platforms that provide user interfaces, data analytics, and integration with other enterprise systems. Such platforms often include geofencing, which sets virtual boundaries to trigger alerts when an asset enters or leaves a designated area, and environmental monitoring, which tracks temperature and humidity.

The deployment of indoor asset tracking systems can significantly improve inventory management, reduce losses from theft or misplacement, enhance maintenance processes, and optimize space utilization. These systems support better decision-making and operational efficiencies across various industries by providing detailed insights into asset movements and usage patterns.

Comparison of Indoor and Outdoor Tracking

Indoor Positioning Systems (IPS) are engineered to monitor individuals or things within enclosed areas where conventional outdoor positioning technologies such as GPS or GNSS struggle due to obstacles like walls (Jia *et al.*, 2017). Table (1) shows the comparison between different tracking technologies. Here are some key points to consider.

Precision and Accuracy

Indoor: IPS technologies aim for high precision and accuracy within confined spaces, such as warehouses, hospitals, or shopping malls (Kunhoth *et al.*, 2019).

Outdoor: GPS provides global coverage but may have lower accuracy due to factors like signal interference or multipath effects.

Coverage and Resolution

Indoor: IPS focuses on smaller areas, providing detailed location information.

Outdoor: GPS covers vast regions but may lack fine-grained resolution.

DOI: 10.3844/jcssp.2025.1512.1525

Table 1: Key differences between a number of tracking technologies

Tracking Methods	Indoor/Outdoor	Pros	Cons
GPS (Thiagarajan *et al.*, 2010)	Outdoor Tracking	Extremely accurate placement Low-priced deployment	Participants are required Rarely perform work inside
Wi-Fi (Wu *et al.*, 2015)	Indoor Tracking	high accuracy of placement Inexpensive to implement	Participants are required Require specialized software
Camera (Thakoor *et al.*, 2015)	Indoor and Outdoor Tracking	Non-obtrusive High accuracy of placement No devices that individuals are carrying	LOS Difficult Implementation
RFID (Kim *et al.*, 2013)	Indoor Tracking	NLOS Adaptable Implementation High accuracy of placement	Obtrusive Personal technology that individuals carry
ZigBee (Choi and Zhou, 2012)	Indoor Tracking	NLOS Adaptable Implementation High accuracy of placement	Obtrusive Personal technology that individuals carry
Bluetooth (Cheng & Zhuang, 2010)	Indoor Tracking	NLOS Adaptable Implementation High accuracy of placement	Obtrusive Personal technology that individuals carry
Cellular signal (Gember *et al.*, 2012; Dalip & Kumar, 2014)	Outdoor Tracking	Non-Line of Sight (NLOS) Wide Coverage Area Frequently implemented infrastructures.	Invasive Inaccurate positioning Rigid implementation Common devices that individuals own

Update Frequency

Indoor: IPS can offer real-time updates for dynamic tracking (Wang *et al.*, 2017).

Outdoor: GPS updates less frequently due to satellite orbits.

Infrastructure Cost

Indoor: Setting up IPS infrastructure (such as beacons or reference nodes) can be costly.

Outdoor: GPS infrastructure is already in place globally.

Suitability for the Environment

Indoor: IPS works well in enclosed spaces with limited visibility to satellites.

Outdoor: GPS is optimal for unobstructed environments with a direct view of the sky (Asaad & Maghdid, 2022).

IoT Technologies for Indoor Asset Tracking

Indoor asset tracking employs diverse IoT technologies to identify and oversee assets within enclosed environments, such as warehouses, hospitals, or office buildings (Bencak *et al.*, 2022). This is a summary of the key IoT technologies employed for indoor asset tracking (Cantón Paterna *et al.*, 2017):

Radio Frequency Identification (RFID)

An Examination of the Significance of Asset Tracking Employing RFID technology for the automatic tracking of assets is a strategy that can enhance asset management efficiently and swiftly. An RFID asset-tracking system utilizes electromagnetic fields to transmit data from an RFID tag to a reader (Brindha *et al.*, 2020). The patient ID is a unique identity assigned to each physician. This ID enables entry into the application and the operational IoT Asset Tracking System through the use of an RFID tag and reader. The block architecture for this system is seen below in Figure (2).

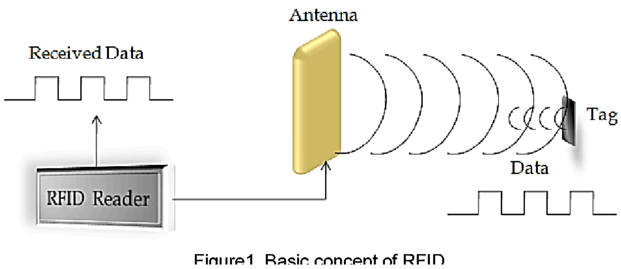


Fig. 2: Basic concept of RFID system (Evizal *et al.*, 2013)

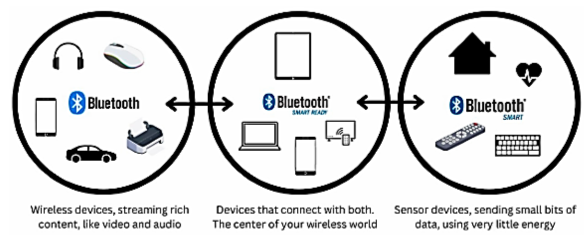


Fig. 3: BLE usage

Bluetooth Low Energy (BLE)

Bluetooth Low Energy, also referred to as BLE, is an innovative wireless communication technology that facilitates short-range communication while enhancing cost efficiency and reducing battery consumption. The radio architecture of BLE has experienced a substantial and essential alteration to facilitate short-range communication (Jia Liu *et al.*, 2012; Liu *et al.*, 2013). BLE provides a similar communication range while exhibiting markedly reduced power usage. Most BLE devices operate on coin-cell batteries, which can sustain functionality for months, if not years, with regular use. The capacity to transmit substantial data volumes is a fundamental characteristic of sensor technologies facilitated by BLE technology (Cho *et al.*, 2014). Upon re-entering proximity, BLE technology reinstates connections, facilitating a more advanced and resilient link. Wireless sensor networks gain advantages from BLE's enhanced short-range communication features,

DOI: 10.3844/jcssp.2025.1512.1525

which are attributed to its advanced data transfer capabilities (Cho *et al.*, 2014). Figure (3) illustrates the utilization of BLE.

WiFi

WiFi is a radio signal employed to connect many devices. Devices in proximity to a connected router receive signals. The WiFi standard utilizes the 2.4 GHz and 5 GHz frequency bands for signal transmission. One can modify the frequency of their WiFi network utilizing dual-band equipment. Wireless local area networks, often known as WiFi, are delineated by the 802.11 standards established by the Institute of Electrical and Electronics Engineers (IEEE) (Sakib *et al.*, 2012; Rasool Jader, & Sadegh Aminifar, 2023). This resulted in the creation of multiple variants of the WiFi protocol, including 802.11a, 802.11b, 802.11g, 802.11n, 802.11ac and 802.11ax. Numerous channels exist for data transmission and reception inside each WiFi frequency band (Maduraga & Abeysekara, 2021). The numerous benefits of Wi-Fi-based indoor tracking solutions include their low cost, the provision of real-time location updates, and the widespread accessibility of equipment. Accurate indoor localization remains feasible despite the lack of a direct line of sight, as WiFi signals can penetrate walls and other barriers.

Long-Range Radio (LoRa)

This is a method to wirelessly modulate signals. LoRa devices are characterized by their long-range capabilities, cost-effectiveness, and ease of integration into networks, owing to their minimal infrastructure prerequisites. It facilitates chirp spread spectrum communication over extensive distances. It employs specialized radios, rarely used in consumer electronics, to mitigate interference from other devices. You can achieve a 20% cost reduction relative to alternative network technologies. LoRa employs an unlicensed RF spectrum. LoRa employs Forward Error Correction (FEC) to significantly diminish signal noise (Ingabire *et al.*, 2021).

LoRa is a superior choice for indoor localization owing to its affordability, extensive range, and low power requirements. Indoor localization systems utilizing LoRa technology are straightforward to implement and function effectively in various situations. The imprecision of LoRa complicates the identification of an exact location, which constitutes its primary disadvantage relative to other technologies. Moreover, LoRa may experience signal attenuation and interference from other wireless devices, thereby restricting its application in regions with little signal strength (Kim *et al.*, 2021).

Wireless Indoor Tracking Techniques

In this part, they study wireless indoor tracking techniques such as triangulation and trilateration.

Triangulation

This method is employed to ascertain the target's location by applying the geometric principles of triangles. The target location can be estimated or calculated using the positions of three or more access points. The distances between the target and the access points will be estimated using TOA, AOA, and RSS of the signals when the target devices receive signals from one or more access points (Bangash *et al.*, 2014). This will transpire anytime the target devices detect the signals. The angle delineates the projected position of the target, as depicted in Figure (4) below.

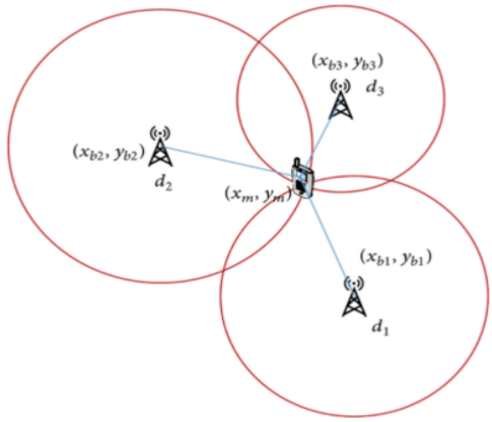


Fig. 4: A sample of triangulation positioning (Aminifar and Marzuki, 2013a-b)

An equation for the value of the figure's unidentified nodes could be articulated as follows:

$$\alpha = \angle AO_1C = 2\pi - 2\angle ADC \begin{cases} \sqrt{(x_{01} - x_a)^2 + (y_{01} - y_a)^2} = r_1 \\ \sqrt{(x_{01} - x_c)^2 + (y_{01} - y_c)^2} = r_1 \\ (x_a - x_c)^2 + (y_a - y_c)^2 = 2r_1 - 2r_1 \cos\alpha \end{cases} \quad (1)$$

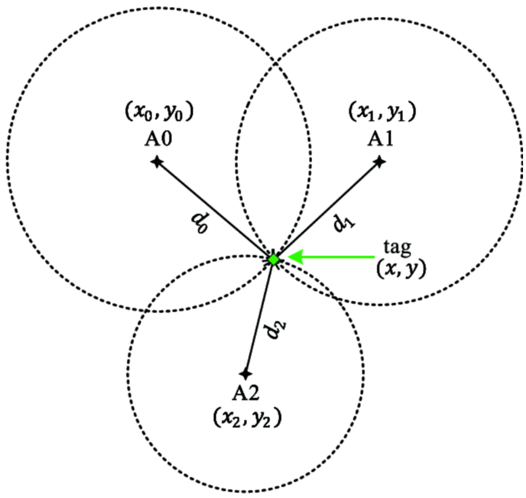


Fig. 5: 2D localization using trilateration (Aminifar, 2020)

Trilateration

This method uses distance measurements from several reference locations to pinpoint the target's position. A technique based on radio frequency signals is

DOI: 10.3844/jcssp.2025.1512.1525

developed to pinpoint the item in the field. RSS, which stands for radio frequency signal strength, is monitored by field readers regarding the tagged item. Subsequently, the trilateration system will convert the signal intensity into a distance utilizing the distance formula specified in Equation (2). Using this method, we can extract the tagged object's coordinates from two-dimensional (2D) alteration data as well as two-dimensional (2D) alteration data (Figure 5).

The following are 2D trilateration equations (Abd and Aminifar, 2022a-b):

$$\begin{cases} (x_0 - x)^2 + (y_0 - y)2 = d_0^2 \\ (x_1 - x)^2 + (y_1 - y)2 = d_1^2 \\ \vdots \\ (x_n - x)^2 + (y_n - y)2 = d_n^2 \end{cases} \quad (2)$$

The variation in UWB signal intensity adds to the positioning mistakes, making it difficult to detect the actual tag location given distances $(d_0, d_1, \ldots, d_n)$ in an inaccurate positioning situation.

They solved (2) using the famous least squares (LS) algorithm for practical location. Following these steps, the LS technique approximates the point where three circles cross by using the form of a linear equation of $a\xi = b$

$$a = \begin{bmatrix} x_1 - x_0 & y_1 - y_0 \\ x_2 - x_0 & y_2 - y_0 \\ \vdots & \vdots \\ x_n - x_0 & y_n - y_0 \end{bmatrix} \xi = \begin{bmatrix} x \\ y \end{bmatrix} \quad (3)$$

$$b = \frac{1}{2} \begin{bmatrix} x_1^2 + y_1^2 - d_1^2 - (x_0^2 + y_0^2 - d_0^2) \\ x_2^2 + y_2^2 - d_2^2 - (x_0^2 + y_0^2 - d_0^2) \\ \vdots \\ x_n^2 + y_n^2 - d_n^2 - (x_0^2 + y_0^2 - d_0^2) \end{bmatrix} \quad (4)$$

Now, the tag location is estimated as follows:

$$\xi = (a^T a)^{-1} a^T b \quad (5)$$

Background Study

The Internet of Things (IoT) enables the intelligent interconnection of millions of devices to provide smart services. This presents a significant challenge for smart cities, the Internet of Things, and wireless sensor networks, especially in indoor localization contexts. WiFi is one of the numerous technologies employed for indoor localization, utilizing received signal strengths (RSSs). Several factors can affect the signal strength of a WiFi RSS, including reflection, refraction, interference, and channel noise. No unknown node's position can be accurately defined using the abnormal and erratic RSS data employed in a WiFi indoor localization context. As a result, by combining supervised and unsupervised machine learning techniques with ensemble learning, this research has created an outlier identification strategy called iF-Ensemble for WiFi localization for enclosed areas. The system analyzes RSSs. This study employs the unsupervised learning technique of isolation forest (iForest). Support vector machines (SVMs), K-nearest neighbors (KNNs), and random forests (RFs) employing stacking, an ensemble learning method, are classified as supervised learning techniques. The ROC-AUC curve, F-score, recall, precision, and accuracy are employed for evaluation purposes. Upon the exclusion of outliers, the precision of the localization procedure in an indoor environment is enhanced by more than 2%, as per the assessment of the employed machine learning technique, which attains a notable accuracy of 97.8% utilizing the specified outlier detection methods (Khorsheed & Aminifar, 2023).

Materials and Methods

In this part, the author makes available a study approach that is founded on the concept of indoor asset localization.

Data Collection

The Process begins with data collection by a BLE and LoRa tracker, which is designed to scan for BLE beacons within a designated area, such as a room. The tracker continuously monitors its surroundings for any nearby BLE beacons, capturing essential information such as the unique identities (typically the MAC addresses or other identifiers) and the signal strengths of each beacon it detects. This data is crucial for various applications, including asset tracking, environmental monitoring, and presence detection.

Once the BLE + LoRa tracker gathers the beacon information, it packages this data into a structured message. This message includes the identities of all detected beacons and their respective signal strengths, providing a snapshot of the BLE environment within the room. The structured data ensures that the information is organized and ready for transmission to a central system for further analysis or action. To facilitate communication between the tracker and the central system, the LoRaWAN (Long Range Wide Area Network) protocol is employed. The BLE + LoRa tracker converts the collected beacon data into LoRaWAN-compatible messages. These messages adhere to the LoRaWAN protocol standards, ensuring that they can be efficiently and reliably transmitted over long distances. The protocol is designed for low-power, wide-area networks, making it ideal for scenarios where devices need to send data over long ranges with minimal power consumption.

Data Transmission

The transmission process involves sending the LoRaWAN messages using the LoRa modulation technique. LoRa modulation enables the messages to travel significant distances, even in environments with obstacles or interference. The BLE + LoRa tracker

DOI: 10.3844/jcssp.2025.1512.1525

transmits these messages to a nearby LoRa + GSM (Global System for Mobile Communications) gateway. This gateway serves as a bridge, receiving the LoRaWAN messages from the tracker. Upon receiving the messages, the LoRa + GSM gateway processes them and forwards the data to a central server or cloud-based system using GSM or Ethernet connectivity. This step is essential as it guarantees the data gathered by the BLE + LoRa tracker is accessible for real-time monitoring, analysis, and decision-making. The entire process, from data collection by the BLE + LoRa tracker to data transmission via the LoRaWAN protocol and the LoRa + GSM gateway, enables efficient and effective tracking and monitoring solutions in various environments.

Data Pre-Processing

The network server forwards the processed data to the appropriate application server or cloud service. This communication typically occurs over secure communication protocols such as MQTT, HTTPS, or other APIs. The LoRa + GSM gateway communicates with the cloud server using a suitable protocol like MQTT, HTTP/HTTPS, or custom APIs. During data forwarding, the gateway transmits the LoRaWAN messages, which include the BLE beacon data, to the cloud server using the chosen communication protocol. Once received by the cloud server, the messages are processed and the data is stored for further analysis or use.

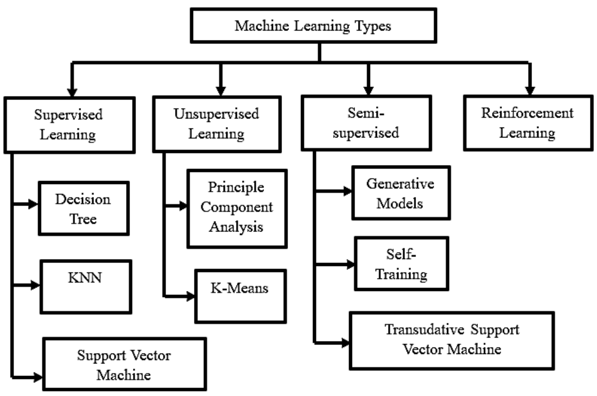


Fig. 6: Various types of ML techniques (Sarker, 2021; Dutta *et al.*, 2018; Bre *et al.*, 2018)

ML Algorithms for Indoor Localization

Machine learning methods comprise a series of statistical techniques that classify attitudes according to specific attributes and allocate them to distinct categories. The procedures are trained on multiple examples and serve as a framework for determining the categorization of those examples. The optimal match is utilized in this method to select the ideal combination that can yield new data. This machine learning method was initially used with certain classifications and subsequently modified to accommodate incoming data according to the training data's categorization (Taha & Aminifar, 2022; Jader & Aminifar, 2022a-b). Figure (6) represents the machine learning techniques.

Supervised Learning (SL)

Over the past two decades, extensive research has explored the application of fuzzy logic and machine learning to enhance system performance in control and diagnostic domains. Early work by Aminifar *et al.* (2002, 2006) paved the way with innovative CMOS fuzzy logic controller chips and novel membership function generators that utilize novel fuzzifiers and min-max circuit designs. Building on these fundamental studies, subsequent research has extended fuzzy inference techniques to biomedical applications, with investigations into Sugeno- and Mamdani-type systems for heart rate detection and other signal-processing tasks (Aminifar *et al.*, 2013a-b). In parallel, ensemble approaches combining clustering and classification algorithms, as well as fast and accurate neural network models, have been proposed for medical diagnostics, particularly in the diagnosis of gestational diabetes and diabetes diagnosis (Marzuki *et al.*, 2022). Additional contributions address uncertainty management in big data and demodulator selection for communication signals, further demonstrating the versatility of these techniques (Sharee *et al.*, 2021). Collectively, these studies highlight the significant potential of integrating fuzzy logic with machine learning—not only to drive innovations in in-house asset tracking and IoT applications but also to enhance predictive analytics in a variety of contexts.

A function that converts an input into an output is frequently learned using machine learning from sample pairs of inputs and outputs (Nguyen *et al.*, 2021). It deduces a function using annotated training data and a collection of training instances. SL is executed in a task-oriented context, wherein specific outputs are desired from a defined set of inputs (Esmaeili Kelishomi *et al.*, 2019). Common supervised tasks encompass "classification," which entails categorizing data, and "regression," which requires the transformation of data. One use of supervised learning is text classification, which entails identifying the probable category or sentiment of a text, such as a tweet or a product review. Figure (7) illustrates the diagram of supervised learning.

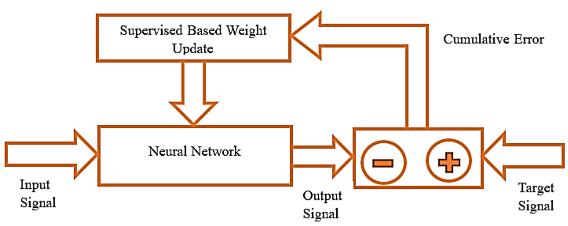


Fig. 7: Supervised Learning (Yusof *et al.*, 2017)

Support Vector Machine (SVM)

The SVM is a prominent and advanced machine learning methodology. Its primary function is to organize data. The SVM algorithm is fundamentally based on the concept of margin calculation. It establishes artificial barriers between various segments of economic distribution. To minimize potential classification mistakes during the Process, classes are separated from the margin to the maximum extent possible (Mahesh, 2020). Figure (8) illustrates the SVM visualization.

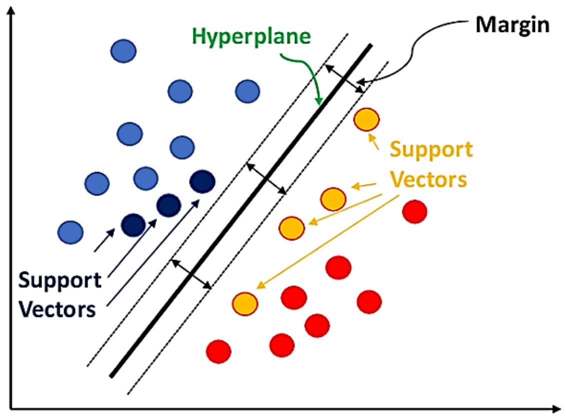


Fig. 8: SVM visualization (Manjrekar & Dudukovic, 2019)

KNN

KNN is a nonparametric technique employed for predictive tasks, including regression and classification. The input comprises the k nearest training instances, whereas the output is contingent upon whether the algorithm is employed for classification or regression. KNN is a fundamental technique in machine learning that classifies datasets by calculating the distance between two locations (Bahl & Padmanabhan, 2000). KNN is frequently employed because of its interpretability and little computational time. The values of k factors are essential in this procedure. To enhance prediction accuracy, the k values must be determined to minimize the validation error (Sandamini *et al.*, 2023). The location Loc is calculated by averaging the location values of k coordinates as follows:

$$Loc = \frac{1}{k}\sum_{x=-1}^{k} Loc_x$$

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs), a subtype of machine learning and the cornerstone of deep learning methodologies are predicated on neural networks. A neural network is a collection of algorithms designed to identify concealed relationships within a data set by emulating the functioning of the human brain. The network has numerous intricately linked processing units known as neurons that operate concurrently to resolve a particular problem. Neural networks possess the ability to learn from exemplars (You *et al.*, 2022). They cannot be compelled to execute a designated task. To avoid inefficiency or, more critically, suboptimal network performance, the instances must be meticulously selected. An artificial neural network (ANN) has one or more hidden layers, an output layer, and an input layer, as illustrated in Figure 9 (Valizadeh *et al.*, 2017). The weight and threshold of each node, or artificial neuron, are interconnected with other nodes. For machine learning systems, like artificial neural networks, to be effective in practical applications, they must be trained on and assimilate a substantial volume of data. Neural networks and traditional computers employ different methodologies for problem-solving.

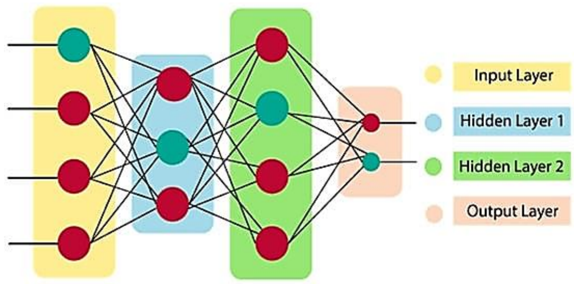


Fig. 9: Neural Network Structure (Bre *et al.*, 2018)

Decision Making

Decision-making is an essential process that entails assessing multiple inputs and identifying a suitable answer. An action decision is the outcome of this process, where a specific action is identified as necessary based on the analyzed data. When the system detects a significant event or condition, it triggers an alert, prompting the need for immediate attention and potential action. Conversely, if the evaluation indicates that the situation is normal or does not require intervention, the system concludes that no alert is needed. In this case, no action is taken. The alert system serves as the infrastructure that supports this entire Process, continuously monitoring conditions, evaluating data, and facilitating the decision-making process to ensure timely and appropriate responses to any identified issues.

Performance Metrics

There is more than one manner in which localization systems might be built using various technologies. The structural comparison of various technologies becomes more challenging due to these variations. As a result, several metrics, such as recall, precision, F1-score, and accuracy, are established for assessing the efficacy of localization systems (Nguyen *et al.*, 2021). Utilizing these parameters, researchers can evaluate the effectiveness of several localization systems that are architecturally distinct (Esmaeili Kelishomi *et al.*, 2019).

Confusion Matrix

When testing a classifier's efficacy on a known-good data set, a confusion matrix is a useful tool in machine

DOI: 10.3844/jcssp.2025.1512.1525

learning. Python has been used to build the outlier identification method. Python has a module named metrics, which includes two classes: Confusion_matrix() and classification report(). These Python classes accept the actual labels of the problem and the predicted outcomes of the classifier as input, producing a matrix as output. Accuracy, recall, precision, F-score, and specificity are supplementary performance metrics derived from the confusion matrix.

Implementation

The suggested method for identifying outliers has been executed in Python utilizing JetBrains PyCharm and Jupyter Notebook tools. Python is the preeminent programming language utilized in data science due to its extensive libraries, built-in classes, and functions for data processing and visualization. The subsequent stages were executed via a Python program to identify outliers in the RSS data from the indoor localization environment:

- BLE+ LoRa trackers collect data and send it to a LoRa gateway
- The data can be transmitted using three different protocols: MQTT, HTTP/HTTPS, or APIs
- The LoRa gateway receives the data from the trackers. The data is then processed using machine learning algorithms like SVM, KNN, or NN
- A decision is made on the activation of an alert based on the outcomes of the machine learning analysis
- If an alert is triggered, it is sent to the alert system. If no alert is triggered, then no further action is taken

Overall, this system appears to be designed to collect data from trackers, process the data using machine learning, and then make decisions about whether or not to trigger an alert (Figure 10). The specific actions taken by the alert system would depend on the specific application.

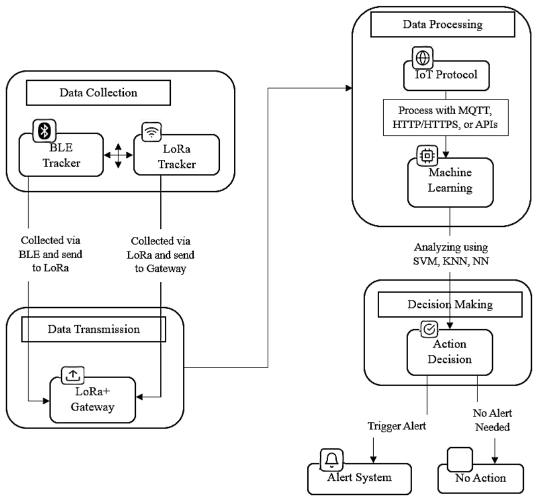


Fig. 10: Flowchart of Proposed work

Results and Discussion

This part presents the calculation of outcomes and the assessment of the suggested approach utilizing the test dataset gathered in an indoor environment. A Python script was executed for this objective.

Original Dataset

Figure 11 displays the column from the original dataset. The Process begins with data collection by a BLE and LoRa tracker, which is designed to scan for BLE beacons within a designated area, such as a room. It has 13 locations, including b3001, b3002, b3003 and so on.

```
Index(['location', 'date', 'b3001', 'b3002', 'b3003', 'b3004', 'b3005',
       'b3006', 'b3007', 'b3008', 'b3009', 'b3010', 'b3011', 'b3012', 'b3013'],
      dtype='object')
```

Fig. 11: Display column from the original dataset

Pre-Processing Dataset

Figure 12 shows the calculation of each location date based on mean, max, min, and std. After that, it split the data into training and testing (Figure 13).

	b3001	b3002	b3003	b3012	b3013
count	1420.000000	1420.000000	1420.000000	1420.000000	1420.000000
mean	-197.825352	-156.623944	-175.533099	-197.233803	-196.065493
std	16.259105	60.217747	49.452958	18.541088	22.053924
min	-200.000000	-200.000000	-200.000000	-200.000000	-200.000000
25%	-200.000000	-200.000000	-200.000000	-200.000000	-200.000000
50%	-200.000000	-200.000000	-200.000000	-200.000000	-200.000000
75%	-200.000000	-78.000000	-200.000000	-200.000000	-200.000000
max	-67.000000	-59.000000	-56.000000	-60.000000	-59.000000

Fig. 12: Calculate basic statics

```
Training set size: (1136, 13)
Test set size: (284, 13)
```

Fig. 13: Split dataset

Data Visualization

Figure 14 shows the visualization of each location data.

Plotting correlation coefficients vs i-beacons

Figure 15 illustrates the relationship between the quantity of beacons and their cumulative frequency. In simpler terms, the y-axis shows how many beacons have a certain number of beacons or less. For instance, according to the graph, nearly all the beacons (around 95%) have 3008 beacons or less. There seems to be a very small number of beacons (around 5%) that have more than 3008 beacons.

DOI: 10.3844/jcssp.2025.1512.1525

The correlation between the number of beacons and the cumulative frequency of beacons appears to be positive. As the quantity of beacons escalates, the cumulative frequency correspondingly rises.

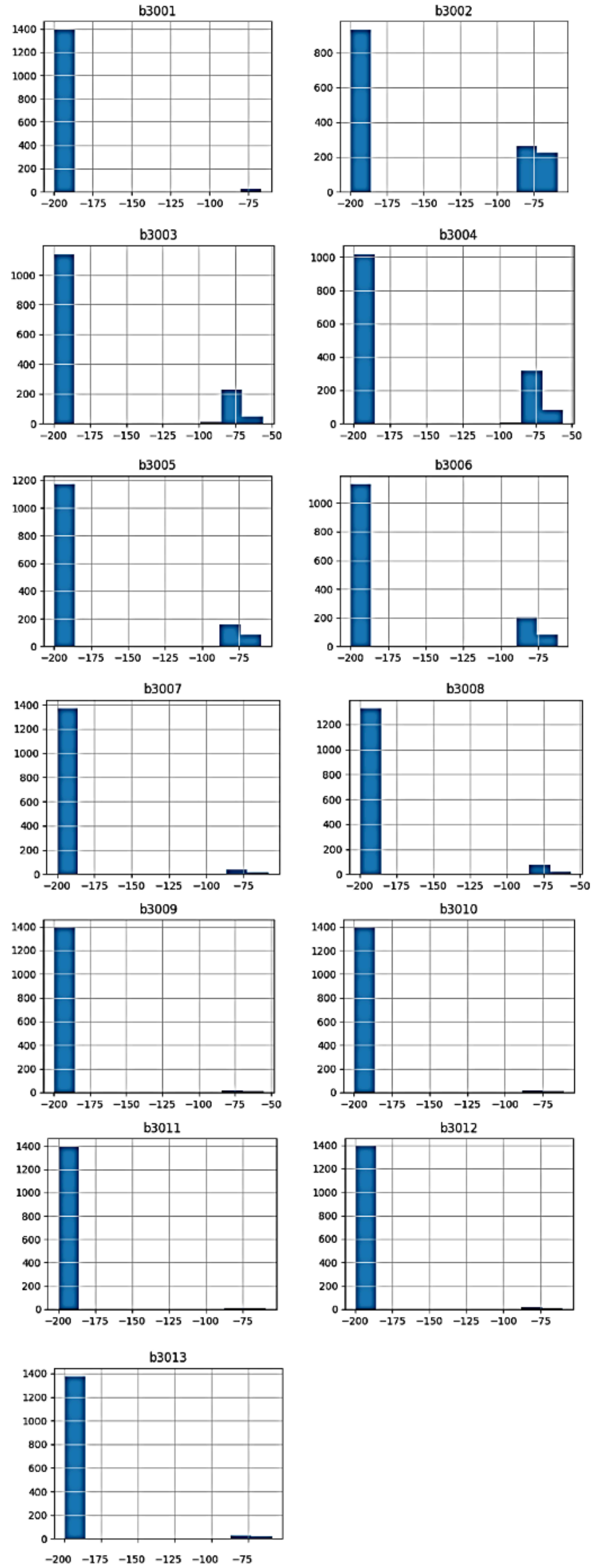


Fig. 14: Data Visualization

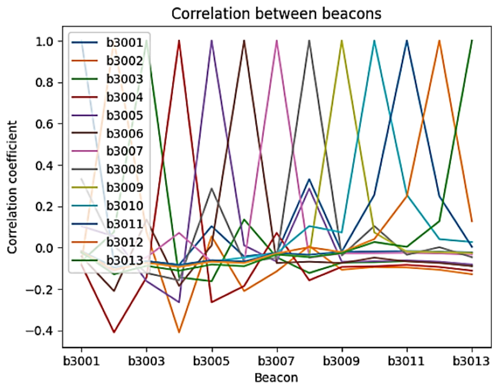


Fig. 15: Correlation between beacons

ML Classifier and Models

In this section, they find the accuracy of the proposed models, such as SVM, KNN, and NN.

SVM Classifier Matrix, Accuracy, and Classification Report

The outcome presents the classification report as well as the matrix of confusion for the SVM model; as shown in Figure 16, the SVM model has an accuracy of 79.08%.

```
Confusion Matrix:
[[1 0 0 ... 0 0 0]
 [0 3 0 ... 0 0 0]
 [0 0 1 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 1]
 [0 0 0 ... 0 4 0]
 [0 0 0 ... 0 0 4]]
```

(a)

```
    accuracy                        0.78      284
   macro avg       0.77      0.76   0.80      284
weighted avg       0.75      0.78   0.79      284


Accuracy Score:
0.79084507042253522
```

(b)

Fig. 16: (a) Confusion matrix (b) Classification report

KNN Model's Matrix, Accuracy and Classification Report

The result shows the confusion matrix and classification report of the KNN model (Figure 17). The accuracy of the KNN model is 80.05%.

```
[[0 0 1 ... 0 0 0]
 [0 3 0 ... 0 0 0]
 [0 1 0 ... 0 0 0]
 ...
 [0 0 0 ... 1 0 0]
 [0 0 0 ... 0 1 2]
 [0 0 0 ... 0 0 4]]
```

(a)

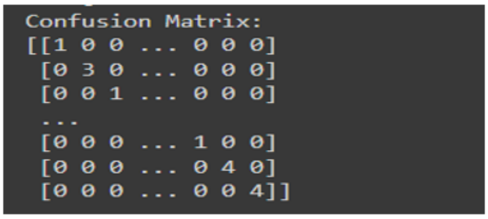
```
    accuracy                        0.80      284
   macro avg       0.77      0.78   0.79      284
weighted avg       0.78      0.79   0.80      284
```

(b)

Fig. 17: (a) confusion matrix (b) Classification report

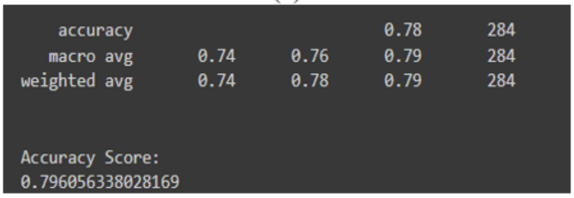
NN Model's Matrix

The result shows the confusion matrix and classification report of the NN model (Figure 18). The accuracy of the NN model is 79.6%.



```
Confusion Matrix:
[[1 0 0 ... 0 0 0]
 [0 3 0 ... 0 0 0]
 [0 0 1 ... 0 0 0]
 ...
 [0 0 0 ... 1 0 0]
 [0 0 0 ... 0 4 0]
 [0 0 0 ... 0 0 4]]
```

(a)



accuracy			0.78	284
macro avg	0.74	0.76	0.79	284
weighted avg	0.74	0.78	0.79	284

Accuracy Score:
0.796056338028169

(b)

Fig. 18: (a) Confusion matrix (b) Classification report

Decision-Making Using LoRa Gateway Action Visualization

Decision-making using LoRa Gateway Action Visualization involves leveraging real-time data from connected devices to inform and optimize choices, enhancing efficiency and responsiveness in various applications, such as smart cities, agriculture, and industrial monitoring. Figure 19 shows the gateway packet statistics and packet distribution among two nodes.

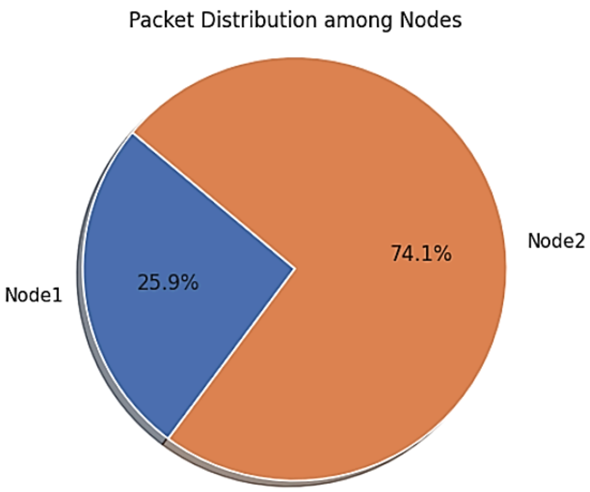


Fig. 19: Packet Distribution among nodes

Figure 20 shows the graph of number of packets counted per gateway. In the graph, the x-axis is labeled "Gateways" and the y-axis is labeled "Packets". The graph shows that Gateway 1 has the highest number of packets with a count of around 1.5, while Gateway 2 has the lowest number of packets at around 0.5.

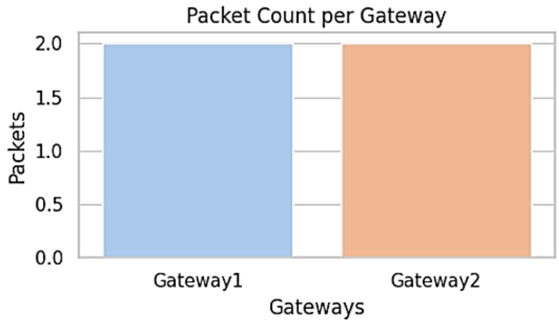


Fig. 20: Packet count per gateway

The graph shown in Figure (21), illustrates the distribution of nodes by the number of packets. For instance, according to the graph, there are close to 2 nodes that have 2 packets each. There seems to be a Node 1 that has 17 packets and Node 2 has 7 packets.

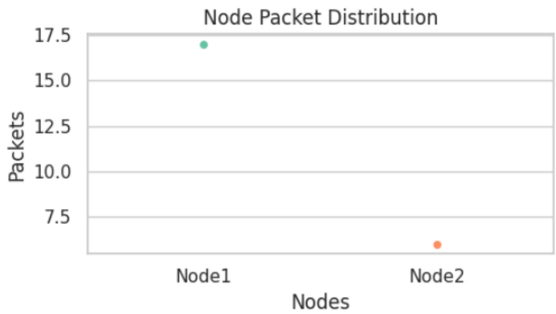


Fig. 21: Node packet distribution

Figure (22) shows a bar graph of the number of packets received by ten different gateways. Here, Node 1 has 40 packets, Node 2 has 30 packets, Node 3 has 20 packets, and so on. We can see that Node 10 received the most packets (50) while Node 5 received the least (0). Overall, the number of packets received varies across the gateways.

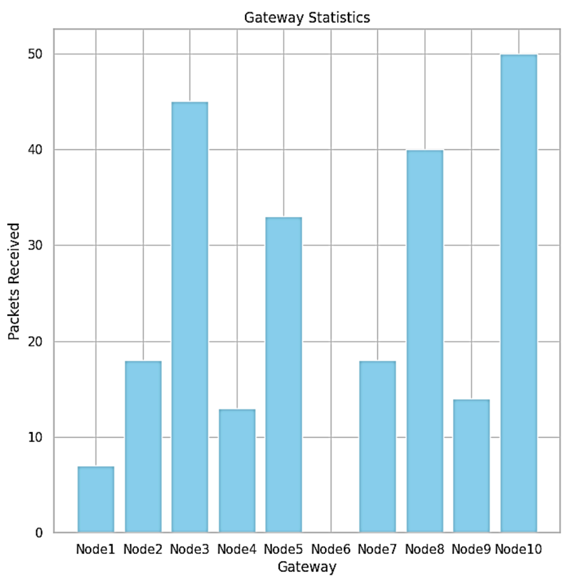


Fig. 22: Gateway statistics

Figure (23) shows the number of packets in various stages of processing for ten different nodes (Node1, Node2, Node3, etc.).

There are five bars for each node representing the following stages:

- Sent: The quantity of packets transmitted by the node
- In Process: The quantity of packets presently undergoing processing by the node
- Discard: The number of packets that were discarded by the node
- Received: The number of received packets by the node
- Packet Counts: This appears to represent the aggregate amount of packets for the node (Sent + Received + In Process + Discarded)

Here's a breakdown of the packet counts for Node1 as an example:

- Sent: 20 packets
- In Process: 10 packets
- Discard: 10 packets
- Received: 40 packets
- Packet Counts: 80 packets (which is the sum of the other four values)

It appears that Node 10 has the most packets overall (around 80), while Node 5 has the least (around 20). There exists considerable variance in the quantity of packets received by different nodes. For example, Node 1 received 40 packets, while Node 5 only received 10.

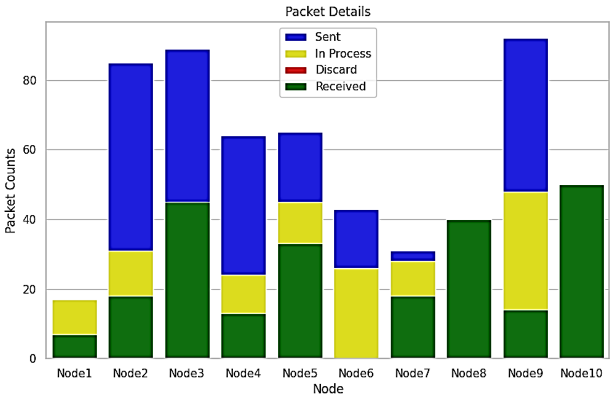


Fig. 23: Packet details

Conclusion

Indoor asset tracking plays a critical role in modern facility management by enabling the efficient monitoring and management of assets in confined spaces. A combination of IoT technologies and machine learning (ML) algorithms offers a powerful approach to improving the accuracy and reliability of these tracking systems. IoT devices, including sensors and lights, continuously collect real-time data about asset locations and conditions. This data is then analyzed using ML techniques to predict asset movements, increase utilization, and discover patterns that contribute to greater operational efficiency. By integrating IoT and ML, organizations can significantly improve asset tracking performance, including recall, F1 score, precision, and accuracy. This study explores the methodologies, technologies, and benefits of implementing indoor asset-tracking solutions based on IoT and ML.

Acknowledgment

We would like to express our sincere gratitude to the Department of Computer Science for their continuous support, resources, and guidance throughout the course of this study.

Funding Information

The authors declare no financial support or funding to disclose.

Author’s Contributions

Rafiq H. Maulud: Conceptualization, research, data analysis, simulation, modeling, and evaluation.

Sadegh Aminifar: Supervise, consult, and critically review results and discussion.

Ethics

This article is an original work and includes unpublished content. The corresponding author affirms that all co-authors have reviewed and approved the manuscript and there are no ethical concerns associated with it.

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