REAL TIME OBJECT LOCALIZATION IN COMPLEX INDOOR ENVIRONMENT USING HYBRID WIRLESS TECHNOLOGIES

By

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ABSTRACT

Title: Real Time Object Localization in Complex Indoor Environment Using Hybrid Wireless Technologies

Positioning refers to locating the actual position of an object with respect to some coordinates, i.e. two-dimensional (x, y), with reference to some existing known place. Positioning is further divided into two more categories, like indoor and outdoor positioning. For outdoor localization, the Global Positioning System (GPS) is already an existing solution that is not suitable for indoor environments due to different obstacles such as line of sight (LOS). In the case of indoor environments where the existing solutions are still not up to the mark. Indoor environments have complex and different obstacles like furniture, the presence of human objects, wireless equipment, light, and other physical obstacles that attenuate and degrade the received (RSS) signal strength, due to which position estimation accuracy is affected. To address this problem, different scholars used various technologies such as Bluetooth, wireless local area networks (WLAN), and ZigBee together with traditional and trigonometric methods as well as machine learning techniques to minimize the error and improve position estimation accuracy. In this research, we have proposed a real-time positioning system based on hybrid wireless technologies using existing machine learning models such as support vector machine (SVM), random forest (RF), and logistic regression (LR) that are applied to the Miskolc hybrid indoor localization dataset based on three wireless technologies: magnetometer, wireless local area networks (WLAN), and Bluetooth. Based on our simulation results using hybrid technologies, machine learning models give accuracies of 83.7%, 93.5%, and 98.7% with an error rate of 0.162m, 0.065 m, and 0.012m for logistic regression, support vector machine, and random forest, respectively. Experimental results and literature survey also validate that random forest (RF) achieved a high accuracy of 98.7% and a lower error rate of 0.012m as compared to the other machine learning models, showing a remarkable improvement compared to previous approaches.

Keywords: Positioning, Localization, Bluetooth, Wi-Fi, RSSI, Machine learning

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LIST OF ABBREVIATIONS

BLE	-	Bluetooth Low Energy
ML	-	Machine Learning
GPS	-	Global Positioning System
RFID	-	Radio-Frequency Identification
RSSI	-	Received Signal Strength Indicator
AOA	-	Angle of Arrival
TOA	-	Time of Arrival
IPS	-	Indoor Positioning System
RF	-	Radio Frequency
AI	-	Artificial Intelligence
ML	-	Machine Learning
DL	-	Deep Learning
SVM	-	Support Vector Machine
RF	-	Random Forest
LOS	-	Line of Sight
NumPy	-	Numerical Python
RSS	-	Received Signal Strength
LED	-	Light Emitting Diode
VLC	-	Visible Light Communication
ANN	-	Artificial neural networks

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I shall also acknowledge the extended assistance from the administration of the Department of Computer Sciences who supported me all through my research experience and simplified the challenges I faced. For all whom I did not mention but I shall not neglect their significant contribution, thanks for everything.

DEDICATION

This thesis work is dedicated to my parents, brothers, my teachers, all family members, and friends.

CHAPTER 1

INTRODUCTION

1.1 Overview

Object localization is the most crucial, prominent job that helps and allows to track the position of an object or maybe to reach a specific location by applying different localization techniques, technologies, and methods in an appropriate way for indoor and outdoor environments [1]. There are a lot of applications that are based on object localization for the purpose to track and locate objects [2]. Locating objects in complex surroundings is a very complicated, difficult task [3]. To prepare infrastructure for localization in large, as well as in complex environments (i.e., city, campus) today is a complicated job. As each technology has its plus and minus points such as GPS is not appropriate for indoor environments. GPS as well as GN satellite systems are the most important and mature locating methods for outdoor navigation, an outdoor positioning infrastructure is shown in figure 1.1, but can't give fair accuracy in indoor environments due to irregular signal, non-line of sight, and complex environments obstacles. Indoor positioning is nominated as the collection of technologies, techniques, and methods that trace, and track user and objects in indoor environments where GPS and satellite does not perform well [4].

Figure 1.1: Outdoor Positioning Environment [5]

1.2 Real Time Object Localization

Real-time localization, sometimes named dynamic positioning, refers to tracing, locating, and tracking the user or object in real-time by applying tags and allowing readers to gain an appropriate location by collecting active and passive location-related data. In the static positioning case, the required object is not moved and remains in a static position. These systems continuously trace the locality of an object to achieve better location estimation in complex real-time environments[6]. There are various indoor localization technologies that are in trend and in utilization these days. The wireless technologies that are applied for indoor localization are mostly categorized based on the frequencies they utilize. An indoor environment for positioning and localization purposes is shown in Figure 1.2. There are various technologies used currently for indoor localization such as Wi-Fi, Zig bee, Bluetooth, UWB (Ultra-wideband), and RFID (Radio Frequency Identification) etc. Wi-Fi is the most common and in trend technology for indoor localization in the current scenario. In the initial stages, the Wi-Fi range was up to 100m that now boosted up to approximately 1km. Most of the currently available mobile, laptops, and other portable devices are Wi-Fi supported, so for now Wi-Fi is the most appropriate candidate for indoor localization. Zig Bee is the most prominent due to its less power utilization, with a mesh layout of the network. In the current scenario, this is the most suitable and major technology alongside Wi-Fi networks. The most important key feature of this technology is its plus point of less energy consumption and low cost as well as long-distance coverage, but with all this, it also gives a low data rate. Here, Bluetooth is also a famous indoor localization technology that is basically a personal area network standard for communication between devices over a less distance such as earphones and mobile phones, requiring a greater number of devices for the localization of an environment. Its valuable key feature is its consumption of less power[7].

Figure 1.2: Indoor Positioning Environment [5]

Ultra-wide band (UWB) technology gain popularity in the field of radar systems goes back to twenty centuries, this technology has a great impact on communication, localization, and radar related fields in current era. This technology gives best accuracy as compared to Wi-Fi, Bluetooth and has a high bandwidth as well [8]. Along with these technologies there are also a number of techniques and algorithms are available for indoor localization with some machine learning techniques, one of them is proximity that is easy to implement but have accurateness with low level. Rather than that triangulation and trilateration are also available. But one main drawback of triangulation is that it is not feasible for localization as its requirements of more hardware, whereas trilateration required more access point [9]. Indoor positioning techniques are basically divided into two categories based on algorithms and signal characteristics such as triangulation, trilateration, proximity, fingerprinting, AOA (Angle of arrival), TOA (Time of Arrival), TDOA (Time difference of arrival) etc. From all of these, fingerprinting is most suitable and well known technique for real time object localization. It consists of two phases named as offline and online phase of fingerprinting. Its offline phase is for the purpose to collect data about area and prepare a database that is generally known as radio map. After that in online phase algorithms are applied at the collected dataset, location estimation is done [10]. Algorithms that are in practice in localization are mainly deterministic and probabilistic. In indoor localization the main focus is on the algorithm accuracy, easiness and it should be fast. Different machine learning algorithm are implemented, and each has its plus minus points. K-NN is a technique which is also known as most popular algorithm of ML (Machine learning) that is mainly focus on K value, but to locate the K value is very tough task in an optimize way [11]. Bayesian algorithm is also commonly applied in localization for classification purpose, used Bayes postulate, draw a conditional probability for every individual node of network. Decision tree is also most prominent and usually used classification algorithm of machine learning. This is just like hierarchal mechanism that is represent each attribute in form of node.

1.3 Motivation

An indoor positioning system (IPS) is a network of devices used to locate people or objects where GPS and other satellite technologies lack precision or fail entirely, such as inside multistory buildings, airports, alleys, parking garages, and underground locations. During the current era a large number of applications has been developed for this crucial purpose. Basically all these developments are based on the time and according to the needs, demand of the market and society. Such as these tracking systems demands raising in every field of life such as in different types of gaming systems, for kids tracking, in hospitals for patients monitoring, for real time labors and equipment monitoring in industrial spaces, and monitoring of defense systems as well. Real time tracking or localization can be indoor or may be outdoor to perform the localization for tracking the objects dynamically in current environments. If we take the outdoor localization scenario for tracking objects here the Global Positioning System (GPS) is most reliable ,appropriate, that is based on satellites and works with line of sight (LOS) mechanism that is feasible and reliable for outdoor detection systems and applications [12]. The main concern for GPS is that it’s signal not perfectly works in indoor environments, or may be unavailable, and normally we can say that the signal strength is week. To overcome such types of issues and obstacles now researchers main focus is on to brings and develop such systems for indoor tracking systems that gives perfect and accurate real time indoor location of an object. In localization the phrase “Navigation”, tracking or localization” is used differently for different scenario and aspects. Such as the word navigation relates to track the location of a known object, such as Shakar Parian Islamabad and Lake View Park Islamabad are famous places and geo tagged as well. As compare to this in indoor environments the scenario is comparatively change here such as the localization area may be Lab-1, or may be where the head Office-A. Rather than this the word “Navigation” and “Tracking” is also applied in different scenarios. For instance, to track the real time worker’s movements, or trace out a children location in indoor environment. So, in this research our main focus on accurate positioning by applying hybrid technologies and machine learning for real time detection of objects.

1.4 Applications

Indoor localization applications have become an integral and essential aspect of our everyday lives. Such as the most crucial one the applications at home like medical related support at home to monitor a patient, its emergency situations, also monitor and detected patients falls at home. At hospitals to monitor the medical staff in emergency wards through these types of systems is also gain popularity. To track the medical devices and equipment is also an important task as well. For measuring, monitoring the environment related parameters such as heat, pressure, air pollution and humidity is the burning question of today life, indoor localization systems have a great role for such purpose. Indoor positioning systems also brings a revolution in law, enforcement related jobs, rescues services and fire related rescues. Law enforcement agencies take a great benefit from positioning systems such as police utilize positioning techniques, technologies to locate the robbers, thieves to control these crimes, to find out such personnel and locate objects as well. For industrial Real time complex environments positioning techniques and systems has now become a life line. To locate, track and detect the various types of industrial equipment, tools and the workers is the most important task that are perform by the positioning systems. Positioning applications has also controlled the different services such as cargo management at airports to enhance the working capacity [13]. Positioning applications has also gain popularity in IOT (internet of things) based systems such as disaster management reliefs. The applications of indoor localization systems in different scenarios and fields are discussed below briefly.

1.4.1 Real Time Indoor Localization Dynamically

Localization environments are mainly divided into two important categories named as indoor and outdoor. This is already discussing that outdoor navigation as well as GPS is a standard localization system that work well in case of outdoor environments. But in term of indoor localization measure to locate objects, visitors or people in indoor scenarios in congested areas like airports, schools, homes etc. this is not applicable [13]. But the newest trend in localization is to locate the objects and people in real time dynamically that mean to locate them live for the purpose of navigation, tracking for complex indoor environments.

1.4.2 Tracking System for Disaster

Now a day's indoor localization plays a vital role during in case of some calamity such as earthquake, fire, accidents, and even in case of diseases such as Covid-19. In such scenario to track the objects and humans is a great challenge and here is indoor tracking system working as a great source of relief for the purpose of tracking because to tracking objects in indoor environments is so difficult due to different obstacles such as physical objects like furniture, electronic devices, noise and attenuation etc. A further challenge lies in the fact that indoor spaces are often dynamic environments with both the agents and obstacles moving and changing constantly and locate objects in such situation is so difficult due to congested space and places [14]. In such cases localization applications are a great source of relief for the purpose of guidance, post disaster analysis, situational awareness, resource management and emergency personnel evacuation.

1.4.3 Localization System for Tourism

Tourism industry is growing day by day not only in Pakistan but also in the world, so to locate the tourists and the tourist's objects like vehicles is very much important in this scenario. And a large number of application are available for locating tourists such as during the Hajj Days Mina Locator is mostly famous and commonly in practice application to locate Muslim pilgrims during Hajj days [15]. So here it is clear that indoor localization applications prove a great relief for the tourism industry.

1.4.4 Industrial Localization System

Industries now a days have a great dependence on localization system from different point of view and several types of robots based system are installed for monitoring, observation and working purpose. In such types of industrial systems to locate objects and workers is so difficult and challenging task due to different obstacles like multipath effects, noise, attenuation and different physical objects [16].

1.4.5 Medical Purpose Localization System

Indoor localization systems in the medical field contribute to enhanced patient care, operational efficiency, and safety, ultimately improving the healthcare experience for both patients and healthcare providers. In such scenarios tracking is becoming a very important and crucial task [17]. This type of indoor localization system can be particularly useful for monitoring patients with cognitive impairments, dementia, or those prone to wandering, ensuring their safety and preventing potential accidents.

1.4.6 Office Tracking System

To monitor and observe the employs during the working hour in offices is a great task for the authorities. So, for this purpose office localization systems are commonly in practice for big companies to monitor the working in real time environments. These systems can track the real-time location of employees within the office premises. This information can be useful for optimizing office layouts, facilitating collaboration, and improving employee safety during emergencies. And to design an accurate office tracking system with high accuracy and less error rate is gain so high popularity during these days.

1.5 Real Time Localization Detection Techniques and Technologies

Real time indoor localization mainly based on two prerequisites for locating objects. First, one is the sensing techniques and technologies. These technologies may be a hardware device that implant with different types of sensors for the purpose of signal transmission for making communication of hardware with software, to enhance and measure the transmitted signal strength for the objective of processing of signals to gain the distance estimate and when these distance estimate are estimated these are used for predict the real time location of an object in and indoor positioning system with respect to different types of estimated coordinate for localization [18]. Now a day with respect to sensor based technologies the most common in practice technologies is RF (Radio Frequency) to estimate the position of static and specific coordinate. Radio Frequency based most commonly technology examples are Bluetooth/BLE (Bluetooth low energy), Wi-Fi, and Zigbee. These are most common in practice due to their easily commercial accessibility and feasibility. Among different types of sensing based technologies that are available, our main focus on the hybrid technologies like Wi-Fi, Bluetooth and Magnetometer. We used these technologies in our research. The main focus on these technologies due to the availability, cost and due to provide good accuracy in terms of locating objects. Because these are easily available and less costly and provides high accuracy in terms of indoor localization. Our research dataset collect location related data by using these three hybrid technologies. According to the recent research the latest Bluetooth standard that is recently and currently realized by (BSIP) Bluetooth special interest group and its version is 5.1, this technology that ranges from 40 to 400m as the new specification [19]. Wi-Fi is also a medium localization wireless technology, its ranges between 20 to 40 meter and plus point is its less infrastructure cost. And it gives more best and reliable results when it applied in hybrid system.

Different literation based techniques are used for distance estimation. In these techniques the RS (Received Signals) are transformed to distance estimates by applying different models by using radio propagation. When the radio estimates are gained, these are available then with the help of these estimated distance some important mathematical models are applied to detect and navigate the object location with respect to some specific coordination. Some examples of these types of techniques are included trilateration, minimax, and multiliteration etc. Trilateration is a commonly used technique in indoor localization that involves determining the position of a target device by measuring the distances between the target device and multiple reference points in the environment. It is important to note that trilateration can be affected by factors such as signal quality, signal propagation characteristics, and environmental obstacles, which may introduce errors or uncertainties in the positioning accuracy.

Accuracy of Literation based techniques mainly depends on two things firstly distance estimation with correctness, accuracy, secondly position estimation techniques for modeling purpose to gain enhanced accuracy [20]. A detail description of these approaches and their working mechanism is discussed in chapter 2.

As for the finger printing techniques, these approaches contain two basic initial steps namely offline and online phases. The offline step is also termed as training phase or sometimes termed as calibration phase. And online phase is termed with many different terms like tacking, positioning or may be determination phase sometimes [21]. In step 1 of fingerprinting technique a radio map is created that consist a collection of signals of each grid location in which scenario or environment the system is fixed and operational for positioning and detection purpose. In fingerprinting technique, the main crucial and difficult task is this one to generate an offline map and collection of each fingerprint of every location that completely depends on the structures of the location related environment and here is minor change at any stage will distract the overall offline radio map. The second phase of fingerprinting approach is related to pattern matching. Pattern matching in fingerprinting-based indoor localization aims to find the best match or matches form the database based on the measured features at the target location. However, it's important to note that the accuracy of fingerprinting-based techniques mainly depends on the quality of the wireless signals in the environments that are collected in an indoor environment for localization.

1.6 Problem Background

Accurate position estimation in Indoor environment for tracking objects actual position in real time due to complex indoor setup is a challenging task. The word complex means, position estimation error due to indoor physical objects, presence of humans, frequent changes in the indoor environment may affect signals due to which distance estimation is difficult to predict. Other than this, various researchers focused on a single wireless technology with existing traditional position estimation techniques [22]. Accurate estimation is still a challenging task in case of industrial applications, guiding blind persons, accurate locations of child's, robotics for industrial and home use requires accurate estimation of the locality or any human object equipped with wireless gadgets. Moreover, in complex indoor environments signals are effected from noise, physical objects, light, multipath and other physical obstacles that radiate the wireless signals [23]. Different technologies, and techniques are used for localization and to locate objects in such scenarios.

1.7 Problem Formulation

Designing an accurate tracking and navigation solution especially in a complex indoor environment with furniture, radio signal, wireless equipment, light, and other physical obstacles which radiate and degrade wireless signal/attenuate that cause system complexity and indoor localization system lower performance [24]. Now results in distance estimation error, in case of industrial domain or specialized indoor plants and tracking solutions are [25] dependent on accurate signal reception and modeling of distance estimation, in order to estimate or navigate with high accuracy, optimal resource utilization and less complex solutions are still a challenging task [26]. And any sort of change in localization setup also effect the system performance and accuracy.

1.8 Research Objectives

- To design an accurate, optimize localization model using hybrid wireless technology.
- To minimize the localization error using hybrid wireless technologies and machine learning models which are flexible, and sustainable in case of frequent changes in the indoor setup, due to which indoor environments are considered as complex in terms of modeling position estimation and tracking models for real time deployments.

1.9 Research Questions

- How to locate the real time location of an object in complex indoor environment accurately using machine learning techniques?
- How to investigate hybrid wireless technologies for accurate navigation and tracking solutions using localization techniques?

1.10 Contribution and Signification

In this proposed indoor localization system, the main objective is to detect object in real time complex indoor environment by applying hybrid indoor localization technologies with machine learning classifier instead of using traditional techniques for locating object in complex indoor environment. Here a detailed review of various indoor localization technologies, techniques is also performed to select suitable technologies for designing a hybrid wireless technologies based indoor localization system with accurate results and minimum error rate with respect to machine learning models. To evaluate the performance of our proposed real time indoor localization system using machine learning classifiers, here we require real time RSSI samples of locations. For this purpose, we use a dataset that is collected on base of real time RSSI samples. Statistical parameters are collected and based on these samples, we further classified and extended these RSSI dataset of three technologies to 1539 samples. Based on three technologies real time hybrid dataset we have developed and performed machine learning classifiers to predict the position accuracy, error rate, the variations on base of time and distance. For the purpose of comparison among these machine learning models we measured their performance with the help of accuracy and error rate for comparative analysis.

1.11 Scope of the Study

Now a day's indoor localization become part and parcel in every field of life. Indoor positioning related to locate objects in indoor environments gain popularity in current era. Different techniques and technologies are used for this purpose. This proposed system will help to locate employees and even student's locations in a real time complex indoor environment like in a university multi story building by applying machine learning mode. This study will also help in hospitals and industrial environments for the purpose to locate patients, staff and even different equipment's.

1.12 Thesis Organization

This proposed research work has been divided into different chapters for the purpose of better understanding of the work. In chapter 1st of introduction there is a comprehensive overview, introduction of the topic is provided, after that discussion about background, motivation, and problem formulation, scope of the research study, research questions, research objective, the main scope, contribution and importance of the proposed work has discussed and explained. As for the 2nd chapter, here related work is discussed in detail with their main objective, limitations and contributions are discussed. And for comparative analysis of different positioning techniques and techniques are provided in tabular form for better comparison, at the end of the chapter the summary is also provided. Chapter 3 is related to methodology of the work that provides complete knowledge in detail about review of different indoor localization technologies, dataset, machine learning techniques, programing language, accuracy and classification and preprocessing of the work. In 4th chapter is discussed about technical background and experimental set, included positioning, localization technologies, machine learning classification, programming language, different libraries and function and experimental setup is explained in tabular form also. In fifth chapter different indoor localization and machine learning parameters are explained and comparison of this research work with previous study is also discussed. In last, chapter 6 of this research work conclusion, challenges and future work is discussed in detail for enhancement of this work.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

In this chapter overview of the most recent studies related to the indoor localization object detection that have been performed by different researchers with respect to several techniques, technologies and datasets is done. In literature review chapter several technologies, ML techniques and hybrid systems are also discussed. Literature review is performed by mainly focused on indoor localization technologies, ML techniques and hybrid technologies systems that related to real time scenarios. And all these techniques and technologies comparison is also given after each discussion for the purpose of appropriate selection of technologies and techniques for our hybrid real time indoor localization system.

2.2 Literature Review

Accurate, reliable, and feasible indoor localization has become the crucial, most fundamental part of localization and navigation types of networks in real time complex environments. In the previous decade's indoor localization services mostly focus and based on sole technology like they focus on a Bluetooth, do all for its performance and preciseness. But now a day's hybrid localization technologies, techniques have become the part and parcel of Real Time object locating systems. Hybrid positioning use two or more technologies or utilize their different feature to gain better performance and accuracy. In this section our main focus is to identify the most recent indoor positioning models that are developed or designed for real time complex indoor environments. In the reference [27] the authors purposed a hybrid system by applying Wi-Fi and WSN methods for indoor localization to increase accuracy. For this purpose, the authors used the Received Signal Strength (RSS) that is obtained from several access points that are available in the marked space. In this purposed system the practical tessellation of the indoor environments surface is also performed. And an ANN approach for the purpose to estimate the location with respect to RSS and gained 0.625 m accuracy from the distance of tile to tile in indoor environment. purposed a system that works with seismic waves, have the ability to detect minor footsteps in the real time indoor environment. The authors remove the noise from the waves signal to detect the object footsteps in an accurate way, purposed a mathematical mechanism for the system named as SVIM that is not required training and achieved an accuracy of 97 percent at average. [28] Purposed a system for dense Bluetooth Real Time indoor localization to improve the accuracy by applying the integration methods of triangulation and dead reckoning. GPS is best for outdoor environments but not available for indoor so for this researchers focus on wireless technologies that are accurately perform in indoor environments combined, takes the advantage of the features of BLE, Wi-Fi with the RSS, both technologies are applied and performance shows that the combination of these two technologies in terms of accuracy is more reliable rather than use them solely. And the performance analysis is performed by the weighted KNN that is applied on these two technologies signals in real time. The achieved outcomes showed that estimation by applying fingerprinting location method is more accurate rather than BLE. The authors [29] developed a device free localization mechanism that is mainly based on Wi-Fi to detect user in indoor environment in real time. The purposed system based on available signal of Wi-Fi and some semi-supervised learning for the purpose to locate the objects that are not stationary state. The machine learning techniques have been applied to overcome the object annotation and the input signal uncertainties. For the purpose to denoise the input data, the low pass filter is used and in this way the system gained an accuracy of 98% $\pm$ at the initial phase of performing test. [30] Purposed a newly hybrid system that is based on the combination of two available localization techniques named as trilateration, fingerprinting for the purpose of cost-effective UWB-based localization in complex environments. In this purposed system the required location is detected by applying trilateration algorithms, for the creation of some extra distances the authors applied the fingerprinting algorithms. The auxiliary distances are created by a non-regression algorithm that is based on fingerprinting database, in this way achieved an accuracy level of 95% that is for room level. [31] Presents a localization mechanism that has high accuracy, have a good computational capability for positioning in indoor environments and based on dual-phase deep learning method. The first stage mainly contributed to identify the environment for localization by applying a convolutional neural network (CNN), based on a radio-frequency real dataset. At second stage do localization on account of the information that is gained from first stage by deploying another CNN method. Through numerical examination of this novel system it is known that the localization accuracy is enhanced at a rate of 51.3%, and the authors gained an overall 97.81% accuracy of locating objects. [32] Also utilize the advantages of presently available structure and technologies to enhance the localization. For the purpose to enhance the localization estimation here the authors utilize the hybrid techniques of technologies. Here a handover technique is applied for the technologies and algorithm to gain information that is saved in fingerprints. This given solution is highly recommendable in sense of to cut down large number of unnecessary computations, battery saving is the best solution here as well which gives reduced power usage. [33] Applied hybrid localization method in which combination in which BLE beacons, IMU (inertial measurement unit) sensor, and geomagnetic field with this smart phone camera is applied for three different categories of location base system applications. And gain an accuracy of 80% time for a distance of 2m, by this hybrid mechanism. With this [34] also present a hybrid method for the purpose to enhance accuracy of IPS, by applying the integration of Bluetooth low energy (BLE) fingerprinting, PDR by utilizing the kalman filter to enhance IPS accuracy. [35] utilize the benefits of integration of UWB and Wi-Fi, as Wi-Fi is applied without some specific structure, but it is not ensured high level of accuracy, to overcome the drawbacks of both these technologies they utilize the plus point of these technologies and provide an optimize solution with respect to accuracy and structure of system costs. When we take in view of taking data of location from multiple points [36] also purposed a system for indoor localization by applying different localization technologies simultaneous on commercial smart phone for real time localization. The authors applied different technologies like Wi-Fi, map matching, and inertial positioning. In this scenario the positioning engine working with the information that is obtained from smartphones sensors and not need to build a specific structure for the localization building. The positioning engine of this system gives good accuracy and reliability for real time indoor localization as well. this engine predict the initial location of the user, that is termed as TTFF and also have the ability to overcome the failures also with an accuracy of about 1-2 meter for real time indoor localization Another work is done by [37], and presents a hybrid HW fingerprint mechanism that works with a machine learning technique CNN. In this scenario the ratio fingerprint was achieved by the ratio of prominent RSSI access points. And, apply the machine learning method CNN to extract the characteristics of complex environment for indoor localization. The testing time span for this system was 15 days and gained an average improvement of accuracy for different methods like KNN 3.39%, SVM 8.03% and for CNN 9.03% respectively. But this system has also some limitation such as the experimental area was not so wider due to which the system error probability goes high and the accuracy improvements are bounded to a limit also. In indoor complex environments there are different types of obstacles that leads to, affect the accuracy of indoor localization systems such as Non Line of Sight (NLOS) and multipath effects that increased the probability of errors in measurements values and leads to system inaccuracy. To eradicate such obstacles [38] purposed a Wi-Fi based system that depends on received signal strength (RSS) and a number of interconnected access point's nodes which enhance indoor localization accuracy, for the purpose to remove the NLOS and time of flight error conditions the authors applied Kalman filter based on color noise. With all of this the authors also reduce the errors ranges from 9.1 m to 6.1 m, but this system has required more training due to the RSS data and only perform well in the limited environment. With respect to fingerprinting, [39] also presents an indoor localization algorithm that is related to NB-IOT systems. The authors build fingerprints with the help of CSI related information. Here the two algorithms are applied like KNN for tracking object estimation and multidimensional scaling (MDS) algorithm for CSI values evaluation. And reduce the location error with respect to triangular centroid algorithm, then added these results with MDS and KNN algorithms for the purpose to gain the final targeted object location and decreased the positioning error. With all of this, that system has also some limitations. With all of this, there are still this system has some limitations, like due to small quantity RPs it is not possible to achieved the CSI data in a best way that raise the issue of low precision. And the system is also confined for multi-target positioning, locating. [40] Purposed a mechanism that is based on fingerprint positioning and ZigBee technology. This method gives high accuracy by applying filtering algorithm to enhance the accuracy that is related to fingerprint database of ZigBee. The system experiment consists of two phases, at initial stage the fingerprint database data is filtered out and at second stage the nearest algorithm, the weighted nearest with collaboration of Bayesian algorithm are applied to estimate the object location. In this way an improved fingerprint database with a mean error close to or equal 0.81 m is gained. [41] Utilize the features smartphones sensing quality and presents a system for real time indoor localization without the expensive hardware. At first stage of this system preprocessing is performed at RSSI to eradicate the noise type's obstacles by signal and filtering layer. For the signal classification the machine learning techniques are used. Kalman filter, triangulation algorithm is applied for distance estimation between sender, receiver and gained an overall accuracy of 0.837 meter for the ideal environments and 0.985 meter for real time scenarios.

2.3 Existing Technologies

There are a number of indoor localization technologies are presently available to attain the benefit of each other for the purpose to track and locate objects in a best way. The suitable technology should be selected with great care to overcome the performance and accuracy related domains of IPS. Different localization technologies are classified by scholars in different ways [42]. Among all of these technologies the most prominent are RFID, UWB, and Infrared, Ultrasonic, and Zig bee, Bluetooth, WLAN, Dead Reckoning and Wi-Fi [43]. Here a cursory view about different technologies and techniques is given below.

2.3.1 RFID

Radio-Frequency Identification technology is mainly based on RFID tags, middleware, and readers [44]. RFID tags can be classified into active, passive or may be into hybrid type tag that take the qualities of both these tags and semi active OR Battery-Supported. RFID active tags are applied for long distance locating and tracking with a range of near to 100m. Passive tags have also plus point as these are tiny in size, inexpensive and easy assembling with a range near to 10m [45]. There are several indoor positioning algorithms are applied with RFID such as AOA, TOA, TDOA, RSS, proximity, and fingerprint as well. Here the AOA sometimes not a good candidate due to affected by different obstacles like NLOS, and not suitable for real time and complex environment. RFID technologies are in demand these because of their less cost. But with this have a disadvantage of low accuracy and high response time [46].

2.3.2 Bluetooth

This is a most prominent localization technology for a limited range of wireless communication. This is a type of wireless standard for personal networks. Just like Wi-Fi it works with radio waves and frequencies for the purpose of communication. Its frequency range is between 2.402 GHz and 2.480 GHz. This technology plus point includes less transmission power utilization, less cost, less power, more battery lifetime, and security as well. Bluetooth technology new design is also available named as BLE with a communication range lies 70 meters to 100 meters with more effective power consumption. Bluetooth main disadvantage is that it covers small area and not appropriate for large areas Bluetooth technology has been embedded with different kinds of devices like mobile phone, laptop, desktop, PDA, etc. [47].

2.3.3 ZigBee

ZigBee is the mostly prominent due to its less power utilization, with mesh layout of network. In current scenario this is the most suitable and prominent technology alongside Wi-Fi networks. The most important key feature of this technology is its plus point of less energy consumption and low cost as well with long distance. But it’s also giving low data rate as well. Here Bluetooth is also a famous indoor localization technology that is basically a personal area network standard for communication between devices over a less distance such as earphones and mobile phones, requires a greater number of devices for the localization of an environment. Its valuable key feature is its consumption of less power. There is different configuration of ZigBee are available for master to master and master to slave as well. And this can also be applied in multiple fashions, for this the outcome is in the form of battery long life. In ZigBee routers are also used for the purpose to expand the communication, locating systems and this helps in connecting the more access points for the purpose to construct a larger network.

2.3.4 UWB

Ultra-Wideband is one of the most prominent, high speed and appropriate technology that is mainly established on base of electromagnetic waves and applied for indoor positioning. A large number of applications and localization systems apply this technology as its unique quality of high data transfer rate with an accuracy of one meter as well [48]. This positioning system is mainly divided into active and passive. The passive system applied reflection of signal, but not an UWB tag for locating purpose. Instead of passive system the active system applied battery power-based tag and have UWB sensors that are fixed, while these tags are not fixed. There are several techniques are applied in the technology such as ToA, TDoA, RSS, AOA etc. but the most prominent one is time of arrival. To apply this technology in indoor positioning give advantages in the form of more battery timing, more data rate, reliable accuracy, less consumption of power and saved from multipath impacts as well. With all of these this technology has some drawbacks as well like this is not publicly regulated, more cost is required due to sensors for large area to enhance the performance [49].

2.3.5 Wi-Fi

This is the most well-known wireless technology for indoor localization. Here WLAN can also be applied for locating purpose in a network. WLAN sometimes also named as medium distance technology. This technology structure is most prominent and well-known in indoor positioning environments because of low infrastructure cost. This technology accuracy may be changed from 20 meter to 40 meter, but that can be gone better by applying some other technologies with it.[50] This technology covers more area as compared to Bluetooth. Here the main disadvantage of this technology is its higher power usage. Battery power consumption is the main limitation for this technology [51].

2.3.6 IR

Infrared (IR) technology mainly based on and used electromagnetic radiation along with wavelength. This type of systems is well known for line-of-sight mechanisms. This technology plus point is its simple structure, light weight, small size and free from multipath as well. The main drawbacks of these types of systems are affectedness from signal interference, high maintenance cost [52] and such limitations affect the system performance in different scenarios.

2.3.7 Inertial

This is the one of the oldest navigation technologies that works with some primarily known position, period and locate the current position of the object and not only used in indoor scenarios but also in outdoor widely as well. This technology is most reliable one and give positioning services in even such situation when radio based positioning systems failed, and adverse weather conditions as well. Now a day this positioning technology is also applied in indoor environments due to the inertial services are also present in different devices like smartphones etc. to predict the object location precisely and efficiently [53]. This technology has several advantages like inexpensive, predict location in real time scenarios and also easily works with hybrid positioning systems. One main drawback of this technology is that is affected with continuous error as the distance go long. This error can be determined and removed by some hybrid mechanism that leads to positioning system complexity [54].

2.3.8 VLC

This is the prominent less range positioning technology that takes advantage of the visible light for the purpose of transfer data from one place to another. Commonly different types of lamps are applied to transfer signal but the mostly in practical use are LED lamps. These lamps are worked for two different objectives such as for to create light and communication as well. The main advantage of these types system is in the form of good accuracy, reliable, not complicated, and saved from multipath effect. These types of systems are largely applied in hospitals, halls, museums and shopping places as well. But these systems lead to complexity as applied for a large positioning area and system expenses also go high as well due to complex infrastructure, specific devices [55].

2.3.9 Magnetic Positioning

As for magnetic positioning system this an ancient mechanism for tracking, locating objects, depends on magnetic field and also utilize the compass. But now in currently era there are indoor positioning systems that takes the advantages of artificially created fields to trace objects in localization environments. The authors [56] also applied the machine learning techniques in practical and achieved an accuracy of 0.8m. The main pros of this technology this is not affected from NLOS related issues and also provides best accuracy. To enhance the accuracy there is also some other techniques are applied with like [57] used a combination of magnetic technology, Camera and achieved an accuracy of 91%. But with all of this the main drawback of these types system is of limited range for positioning. For the purpose to enhance the range there is need to add a greater number of sensors that leads to complexity and higher cost.

2.3.10 Computer Vision

A computer vision indoor positioning system applied computer vision with cameras, some image related methods to gain information for the purpose to estimate the location of an object in indoor environments. These types of systems are classified into two types with respect to cameras such as moveable cameras and non-moveable cameras, this technology works with ML and Ego motion techniques. A non-moveable camera types system is purposed by to overcome the location errors and applied four different types of cameras to trace the location of an object and achieve an error margin 0.10 m. These types of systems main contribution is its low cost and privacy in case of cell phone cameras are applied, but these systems are also effected by light related issues [58].

2.3.11 Hybrid Technologies

Now a day the most recent advancement in the positioning field is in the form of hybrid positioning systems where the researchers take the plus points of one technology and combine it with another technology to overcome different issues, to enhance the performance and accuracy. The fusion of two or more technology leads to achieve the high accuracy, usability, less cost and enhance performance [59]. The most prominent and well known instance of hybrid system is Cricket positioning system that takes the features of two technologies named as Ultrasound and RF. And the researches done by [60] combines the three different technologies (BLE, RFID, Wi-Fi) as well and reduced the error margin at a point of 1.20 m. The authors [61] applied a hybrid mechanism also, and combines the computer vision, inertial technology for indoor positioning with DKF algorithm and gained an accuracy of 0.5m. As the hybrid positioning systems gives enhanced accuracy, good performance and usability, but with all of this, there are some challenges that are faced by these systems such as the complicated infrastructure, that leads to complexity and sometimes increase systems charges as well.

On the base of knowledge discussed and studied above the analysis of different positioning technologies is cited below in the form of Table 2.1.

Table 2.1 Comparative Analysis of Localization Technologies

Technology	**Year**	**Techniques**	**Pros**	**Cons**
RFID [44], [46] [59]	2015, 2018, 2020	AOA, ToA, TDoA, RSS, Proximity, Fingerprinting	• Small size tags • Easy assembling • inexpensive	• Low accuracy of passive tags • High response time
Zig Bee [40][60]	2017, 2019	RSSI, Fingerprinting	• Less energy consumption • Low cost as well with long distance.	• Low date transfer rate
Wi-Fi [50]	2015	RSS, TOA, TDOA, AOA, Proximity, Fingerprinting	• Covers more area as compared to Bluetooth • Low infrastructure cost	• Higher power usage
IR [45], [52]	2017 2020	TOA, AOA	• simple structure, light weight, • free from multipath • small size	• Affectedness from signal interference • High maintenance cost
UWB [48][49]	2013, 2019	ToA, TDoA, RSS, AOA	• high data transfer rate • more battery timing • saved from multipath impacts • good accuracy	• Not publicly regulated • More cost is required due to sensors for large area to enhance the performance
Bluetooth [47][61]	2020, 2021	RSS, Fingerprinting Proximity, TOA	• less cost, less power, • more battery life timing • secure and reliable	• Covers small area • Low bandwidth as Wi-Fi
Inertial [53][44]	2020, 2021	AOA, RSS, TOA, TDOA	• Inexpensive • predict location in real time scenarios • Suitable with Hybrid	• Effected with error as the distance go long. • Hybrid mechanism leads system complexity.
VLC [55],[56]	2020	AOA, RSS, TOA, TDOA	• Saved from Multipath • Good Accuracy, reliable	• Leads to complexity as applied for large area • This leads to high cost
Magnetic Positioning [56][57]	2021, 2021	ToA, TDoA RSS, AOA	• Saved from NLOS related issues • Good accuracy	• limited range • complexity and higher cost in case of large area
Computer Vision[58][59]	2019	ML, RSS, RSSI, Ego motion	• low cost • And privacy in case of cell phone cameras	• Affected by light related issues

Hybrid [59] [60] [61] [32]	2019, 2019, 2015, 2018	ToA, TDoA, RSS, AOA, ML, Fingerprint Proximity	• enhanced accuracy • good performance and usability	• Complicated infrastructure • Complexity

2.4 Localization Techniques

Localization techniques are applied for the purpose to obtain and estimate the nodes position with respect to enhance accuracy. These position techniques are classified on the base of signal properties and algorithm. Here we discuss traditional, machine learning techniques and give a comparative analysis of these techniques with respect to position estimation.

2.4.1 AOA

Angle of arrival is used to gain the required signal angle for the purpose to obtain the object location. The signal and its angle can be achieved in optimized, easy way if the device of user and beacons station applied the directional antenna technology. Through angle of arrival the required location can be traced with a smaller number of sensors, means it needs minimum number of access points, gives a best accuracy at room level and not good for larger area to positioning. But as it is known that this technique mainly focus on the phase information, that is not provides by few currently available technologies like Wi-Fi and Bluetooth etc. receivers, with all of this a main challenging task is to calculate the antenna array because of synchronization related issues [62].

2.4.2 TOA

As discussed above AOA is related to with angle, here times of arrival is basically depending on the distance. Sometimes this is also termed as time of flight as well. Mainly this is the time that required a signal to reach from a sender to receiver. Mainly TOA gives best accuracy, but it's hardware cost is also high as well, has a complicated hardware structure. But as for the ranging accuracy this technique require an ideal and best clock synchronization among all nodes that is a tough task as well so ranging accuracy is also limited [63].

2.4.3 RSS

Along the time, the Received Signal Strength is also a vital and crucial method to determine the distance. This method can only be applied with radio signal. RSS maintain a 1-to-1 corresponding among the required target and RSS. There is an inverse relation between RSS level and distance of sender, receive. The system that works based on RSS does not depend on timing that is the plus point that makes it more robust for multipath. As related to accuracy of RSS, this performs well in less distance as compared to long distance, require more training, complex algorithm are required for positioning in this technique [64]. As for the RSSI , this is the capacity that is defined as to measure the distance by applying various types of signal propagation model, [65] the distance between sender(TX) and receiver (RX) is measured by the given equation (1).

$$\boldsymbol{RSSI = -10\, n \log 10\ (d) + A} \qquad \textbf{(1)}$$

In this equation that is given above the "n" is related to path loss exponent and "A" provide the reference range that is taken from the receiver side.

2.4.4 Proximity

This technique related to range free localization, is also sometimes termed as connectivity positioning or relative that is inexpensive and a method to predict the limit among the access point and the mobile. LED that is related with location base system circulate its ID that are mainly related with a specific field of interest. After taking the ID from the LED, the destination receiver guesses its position by comparing it with saved database positions. This technique accuracy is mainly depends on different parameters like a count of LED, the gap between sender and receiver [66]. This technique is mainly applied when the focus is on cost rather than the accuracy. Proximity measurement is estimated with respect to signal measurements that is denoted as S (i, j). This S is predicted on the base of RSS (i, j) that range value is between 0 and 1. Here I and j are the devices, and the threshold relation is shown as follows in the equation (2).

$$\boldsymbol{S_{i,j} = \begin{cases} 1, & RSS_{i,j} \geq RSS_T \\ 0, & RSS_{i,j} < RSS_T \end{cases}} \qquad \textbf{(2)}$$

Proximity only gives position related information and require a wide collection of readers to achieve a wider positioning area, this quality leads to more expensiveness and complexity as well. Hence this method no longer appears in recent literatures.

2.4.5 Fingerprinting Technique

Now a days fingerprinting (previously Scene Analysis) base technique has become a crucial and focusing research topic for the scholars. Systems that are based on this technique, utilize the features related to signal propagation to predict the positions of devices on the base of training process and survey of site that is main challenging task. In general, this technique consists of two stages named as training phase and testing (positioning) phase. In training phase, a database is built, maintained while at the testing stage a comparison is done to predict the location accurately. These types of system require a new radio map or fingerprint in situation of minor changes in infrastructure. This system accuracy goes high as the number of locations go high means require a large dataset. Means such types of system needs high searching overhead that is main challenge with such types of systems. To overcome such issues the researcher's main focus is on clustering methods to distribute the large training data set into smaller clusters like subsets[67]. Often several machine learning techniques, algorithms are applied in in real time indoor localization with fingerprint and other techniques to enhance the accuracy and computational power and some of them are as follows.

2.5 Machine Learning Techniques

2.5.1 KNN

The most crucial, prominent algorithm that is mainly applied with fingerprinting and mostly for pattern matching related jobs. But with all of this it is not perform well with huge data sets in real time, complex noisy environments. Mainly this algorithm takes data and classified it with respect to distance in the positioning space. And compare the data that is provided to it with the training data and predict the K neighbors that are maximally near to the new data [68].

2.5.2 CNN

There are different deep learning techniques that are applied for complex real time environments that do not need to extract space feature manually form one of them is CNN, this is the most commonly used class of neural networks which perform well with topology like structures that required data processing, maintains several layers. These layers mainly help the algorithm to learn the more complex attributes perfectly [69].

2.5.3 SVM

It is the most prominent and crucial algorithm to resolve the classification related issues on real time data in indoor localization scenarios. And have the feature to gain the multi class structure in an accurate way for the purpose to solve the regression related problems and through this algorithm optimal accuracy is also gained as well. It's important to note that the performance of SVM for indoor positioning depends on various factors, such as the quality and representativeness of the training data, feature engineering, and the selection of appropriate kernel functions and hyper parameters. Additionally, the choice of other algorithms, such as random forests or neural networks, may also be suitable for indoor positioning tasks based on the specific requirements and characteristics of the dataset and application. [70].

2.5.4 Decision Tree

Decision tree also one of the prominent machine learning techniques that are applied for indoor localization that are applied for indoor localization. It is just like a hierarchal structure that consist several nodes like base or parent nodes and child or non-parent nodes. This is one of the efficient methods that is applied with fingerprinting technique to estimate location [71]. Decision tree models are used in indoor localization due to their ability to handle complex decision-making processes and classify different locations accurately.

2.5.5 Linear Discriminant Analysis (LDA)

This is also the most crucial, prominent machine learning technique that is recently applied in indoor positioning environments, mostly applied with independent variable for huge amount of positioning data. It’s not common in practice with non-linear type of data for positioning estimation[71]. It is also important to note that LDA reduces the dimensionality of the input data while maximizing the separation between classes, making it a useful model for distinguishing between different indoor positions based on relevant features.

2.5.6 Random Forest

Commonly used in indoor localization to predict the location of objects or devices within indoor environments. In this context, the model leverages sensor data collected from various sources such as Wi-Fi signals, Bluetooth beacons, accelerometer readings, and magnetic field measurements. By training on a labeled dataset that includes examples of indoor locations along with corresponding sensor data, the random forest algorithm learns patterns and relationships between the sensor inputs and the actual locations. The algorithm combines multiple decision trees, each trained on a random subset of features and examples, to make predictions. This ensemble approach provides robustness against noise and overfitting. The random forest model is trained on a portion of the data, and the rest is used for evaluation to assess the model's accuracy and performance. Once trained, the model can take sensor data from new, unseen instances and predict the corresponding indoor location. By leveraging the power of random forest, indoor localization systems can provide accurate and reliable position estimations, enabling a wide range of applications such as asset tracking, navigation, and context-aware services within indoor environments.

2.5.7 Logistic Regression

A machine learning model used in indoor localization to classify whether a location is inside or outside a specific area? It works by modeling the relationship between input features, such as signal strengths or distance measurements, and the probability of a location belonging to a particular class. The model is trained on labeled data, where features and corresponding location labels are provided. After training, the logistic regression model can be used to predict the class of new locations based on their features. Logistic regression is a simple and interpretable model, but its effectiveness may be limited in complex indoor localization tasks that require more advanced models.

2.6 Hybrid Techniques

In real time indoor localization there are also some hybrid techniques available that takes the benefit of different distance related localization methods and combine these with scene analysis (fingerprint) technique to enhance the accuracy of the system. But these types of system are also may not be good in some scenarios like with Bluetooth it is not an easy way to achieve the optimized accuracy. To overcome such situations, the authors [62] proposed a system that works with LDA and BLE to trace the moving object in real time scenarios. After do studies and analysis of different localization techniques a comparative view is given below in the form of table 2.2.

Table 2.2 Analysis of Localization Techniques.

Techniques	**Accuracy**	**Issues/Challenges**
AOA[62]	Medium	This technique not best for larger area because accuracy go low at wide are.
TOA [63]	High	Require clock synchronization among overall access points that is a strenuous task and have complicated hardware.
RSS[64][65]	Medium	This technique main challenge is related to distance because this performs well in limited distance but not for long distance and require more training for good accuracy.
Proximity[66],[67],[68],[69]	Medium	Proximity only gives position related information and require a wide collection of readers to achieve a wider positioning area, this quality leads to more expensiveness and complexity as well. Hence this method no longer appears in recent literatures.

Fingerprinting[67]	High	The main challenge is to construct the radio map again in case of a minor change in the positioning space and system complexity goes high. This also increase the cost as well.
ML[43],[44]	High	These techniques needs a large amount of training data, computational power, and training time.
Hybrid[68]	High	These techniques are not applicable in some systems and give low accuracy like with Bluetooth.

2.7 Summary

In this chapter of research work a complete and comprehensive detailed of different indoor localization technologies that are implemented by the researchers in their work is given. Some scholars mainly focus on sole technology according to the reviews of the different scholar works. While now a day a new trend of hybrid technologies is also common in practice. Here also a comprehensive detail of hybrid work of different researchers is given. After technologies and hybrid technologies in this chapter a brief discussion about ML techniques is also provided. With all of these techniques, technologies there is a research gap in terms of real time object localization and machine learning application is also identified.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Overview

This chapter provides a detail overview, complete introduction of the methodology that is carried out for performing the analysis and implementation of this research work. From the dataset description, the preprocessing techniques that have been performed on dataset to eliminate irrelevant information from the dataset to enhance the dataset performance, different machine learning classifier with a complete architecture, technologies, dataset collection and model training are the part of this section.

3.2 Methodology

To address the problem of real time accurate positioning in complex indoor environment, I have proposed a hybrid wireless technologies based system by applying machine learning models. In this research study, hybrid technology mechanism is opted to overcome the limitations and drawbacks of sole technology. To accurately detect the position of an object in indoor environment, I have use hybrid dataset of three different technologies named as magnetometer, Wi-Fi and Bluetooth for the purpose of experimental setup in real time indoor localization. An overview of the proposed architecture is given below in Figure. 3.1.

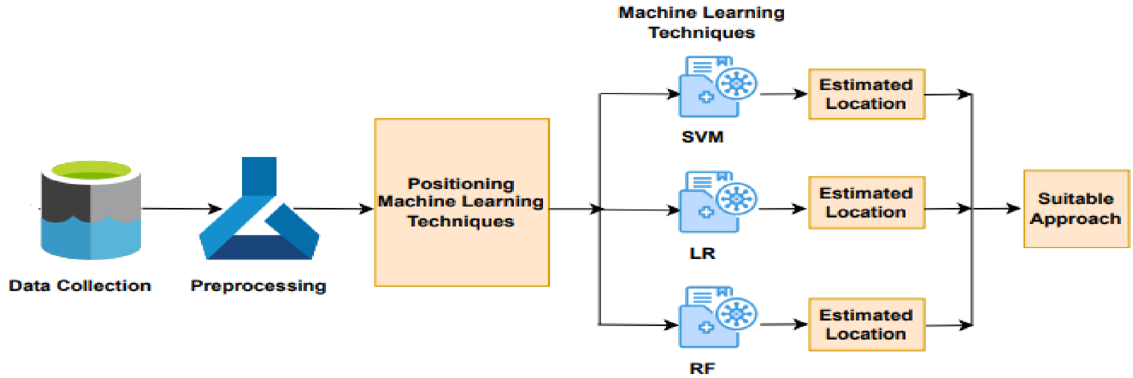

Figure 3.1: Proposed Architecture

From the above image, one can get an idea that how this research is being carried out? In this work, Miskolc dataset is used that is available in UCI machine learning repository and measurements are collected in a 3-story building. And for recording purpose ILONA system was applied to store and record these collection of indoor environment reference point measurements. For the purpose of applying machine learning models and preprocessing this dataset is converted into CSV format. Miskolc dataset contains 22 symbolic reference position points known as zones related to a 3-story building. This dataset contains 1539 measurements, and three different technologies access points such as 32 Wi-Fi access points and 20 Bluetooth devices access points as well. Figure 3.1a, 3.1b, 3.1c, 3.1d indicate ground floor, 1st floor and 2nd floor and floor plan positions respectively. All these measurements are changed into CSV Schema and these are represented below in table 3.1.

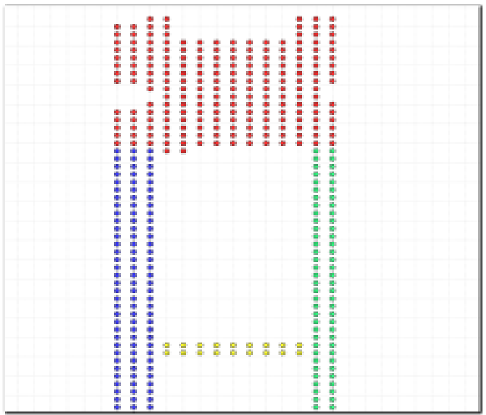

Figure 3.1a: Ground Floor

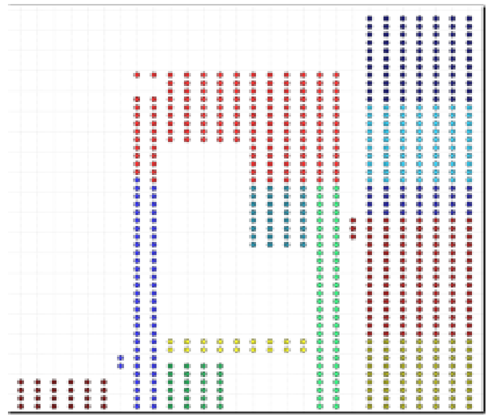

Figure 3.1b: 1st Floor

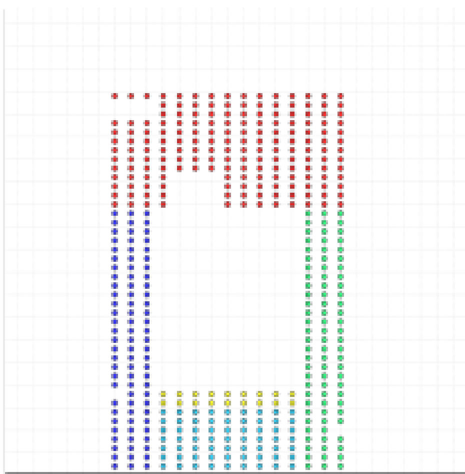

Figure 3.1c: 2nd Floor

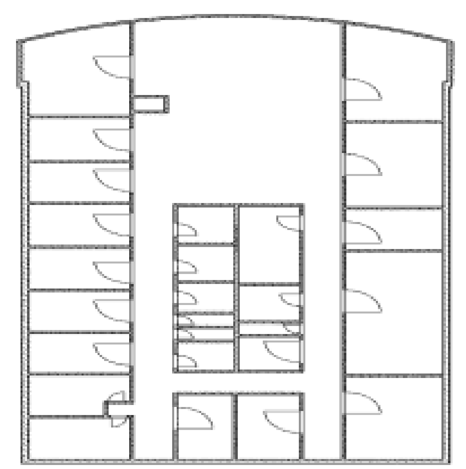

Figure 3.1d: Floor Plan

Table 3.1: CSV Schema of Measurement Points

Measurement Information		**Position Information**		**Measurement Information**		
ID	Timestamp	Absolute	Symbolic	Magnetometer	Wi-Fi RSSI	Bluetooth
1	2	3-5	6-7	8-10	11-42	43-65

In the measurement of the Wi-Fi technology is fixed in list indexed ranges from 11-42 that shows RSSI of related access point and this RSSI showed in negative format. If RSSI is near to Zero, the signal is in stronger form mean high RSSI. If in CSV format the accessed points are not observed, then there are showed with a null value. With respect to Bluetooth it measurement sensed the device address in this value 1 is assigned otherwise '0' is assigned to the related field of the CSV format of dataset. Training and validation of the measurement are based on dataset. And according to the dataset the reference measurement such as ID, Zone Name, Absolute position, Time stamp were ignored in dataset. And schema for this purpose is shown in the table 3.2.

Table 3.2: CSV Schema of Dataset for Training

Attributes			**Category**
Magnetometer	Wi-Fi RSSI	Bluetooth	Zone ID
1-3	4-32	33-54	55

This dataset is organized into two classes named training and validation. And these classes had been built by performing sampling method with a ratio of 9:1. And intersection of these two sets of classes is represented by null set for the purpose to perform machine learning classifier testing. And this mean how classifier deal with unknown object in indoor environment for localization purpose. This research work involves following steps:

1. Data Collection
2. Preprocessing
3. Positioning Using ML
4. Suitable Approach

Step by step brief explanation of the above-given steps is given below.

3.3 Data Collections

Data collection is the most crucial phase of every research work that consist of different methods and processes for gathering and obtaining information about research related variables and attributes as well. In this research work Miskolc IIS hybrid positioning dataset is used that is based on three technologies and applied to give a comparison of different methods of classification in same indoor environment. And this hybrid dataset is collected and recorded in a 3-story building and available in UCI ML repository CSV format for the purpose of evaluation, preprocessing and performing classifier to detect the estimates position with respect to some coordinates. This hybrid dataset is contained 1539 fields of measurements with respect to different coordinates. Moreover, a screenshot of the CSV file containing the field of measurements with respect to different coordinates is shown below in figure 3.2.

```
measId;"measTimestamp";"Position X";" Position Y";"Position Z";"zoneId";"Zonename";"meas X";"meas Y";"meas Z";"gpsLatitude";"gpsLongitude";"gpsAltitude";"N";"109.0";"AIT-L15";"aut-sams-1";"bolyai_E4_floor3";"Bosch_Telemetry";"dd";"doa
04550b4e-b5fc-4665-a043-18e82e94399a;"2016-02-27 16:40:22.0";8.0;8.0;4.4;"07a25de0-a013-486d-9463-404a348e05ee";"1st Floor East Corridor";"0.11991008371114731";"-0.9326502084732056";"0.04995839670300484";"null";"null";'
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7f210fdb-7018-454c-978b-9a595ee39130;"2016-02-27 16:50:48.0";23.0;8.0;4.4;"07a25de0-a013-486d-9463-404a348e05ee";"1st Floor East Corridor";"-0.5067219138145447";"-0.964530348777771";"0.05549850687384 6054";"null";"null";
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```

```
[ ] df.head()
```

	measId	measTimestamp	Position X	Position Y	Position Z	zoneId	Zonename	meas X	meas Y	meas Z	...	DM06082 48:5A:B6:54:35:DC	EV3 00:16:53:4C:E9:1D	00:1
0	04550b4e-b5fc-4665-a043-18e82e94399a	2016-02-27 16:40:22.0	8.0	8.0	4.4	07a25de0-a013-486d-9463-404a348e05ee	1st Floor East Corridor	0.119910	-0.932650	0.049958	...	0.0	0.0	
1	93645336-eb2d-4983-950f-cb0e4191b986	2016-02-27 16:43:13.0	12.0	9.0	4.4	07a25de0-a013-486d-9463-404a348e05ee	1st Floor East Corridor	1.275436	-1.024375	0.058756	...	0.0	0.0	
2	7f210fdb-7018-454c-978b-9a595ee39130	2016-02-27 16:50:48.0	23.0	8.0	4.4	07a25de0-a013-486d-9463-404a348e05ee	1st Floor East Corridor	-0.506722	-0.964530	0.055499	...	0.0	0.0	
3	d9b0c804-5886-4b69-a65a-0ea9a423f5df	2016-02-27 16:53:22.0	26.0	9.0	4.4	07a25de0-a013-486d-9463-404a348e05ee	1st Floor East Corridor	0.557698	-0.950144	0.127510	...	0.0	0.0	

Figure 3.2: CSV File Data Labeling Format

3.4 Preprocessing

Preprocessing is a crucial phase in the study of indoor localization systems, this contains different techniques for the purpose to enhance, maintain the data quality and remove unwanted information from the data that is available in raw form. In this research work data preprocessing is performed such as in case of Bluetooth if device is not sensed a null value is assigned in the field entry of CSV format of data, also ranges of RSSI is defined and dataset is feed up to the machine learning models.

3.5 Positioning Estimation Using ML

In this research work, three machine learning classifier are used for the purpose to estimate location according to the hybrid dataset. These three ML model named as SVM, RF, and LR.

These model are applied on the given dataset and give different accuracy with respect to position estimation like SVM, RF, and LR respectively achieved 93.5, 98.7 and 83.76%. For testing and validation purpose the training and validation sets are based on the dataset. The Measurement ID, Timestamp, Absolute Position and Zone Name were omitted from the dataset. The schema for training and validation sets can be seen in Figure 3.2. The records of each set contain attributes related to the sensors and the category label. Training set is used for building each classifier, and the classifier is tested by the validation set. The dataset is partitioned into the training and the validation subsets. Training and validation sets had been built by the shuffle sampling of the dataset with a 0.9 and 0.1 ratio. The intersection of the two subsets is an empty set, hence one record cannot be used for training and validating. In other words, classifiers are not tested with records contained in the training set. So the evaluation shows how well the classifier works with unknown object. So the position of object is detected in real time scenario for an indoor environment using three machine learning classifier as well with extended and large dataset as compare to the previous studies that are mentioned before where main focus is on sole localization technologies with KNN classifier, but here we applied three machine learning models to know their performance with respect to accuracy and error rate. These models are also explaining below for better understanding.

3.5.1 SVM Architecture

The main objective of SVM is to gain a hyper plane in a space of N-dimensional space that specifically categorized that data points. For the purpose to distinguish two different classes of that are related to data points there may be a variety of hyper planes could be selected. In this scenario our main goal is to obtain a hyper plane with higher margins. As for hyper planes these are boundaries which are related to decisions that are useful for classification. Mainly support vector are data points that are related and near to hyper plane and have an impact on position of the plan. The overall architecture of SVM is illustrated below in Figure 3.3.

Figure 3.3: SVM Architecture [73]

Cost Function and Gradient: In the SVM, main goal to gain maximize margins among data points and with respect hyper plane also here below is hinge loss is given that useful to maximize the margin and this is a loss function in equation 3 & 4.

$$\boldsymbol{C}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{f}(\boldsymbol{x})) = (\mathbf{1} - \boldsymbol{y} * \boldsymbol{f}(\boldsymbol{x})) \quad \mathbf{3}$$

$$\boldsymbol{min}_{\boldsymbol{w}} \text{入} \,||\, \mathbf{w} \,||^{\mathbf{2}} + \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} (\mathbf{1} - \boldsymbol{y}_{\boldsymbol{i}} \; (\boldsymbol{x}_{\boldsymbol{i}} \,, \boldsymbol{w})) \quad \mathbf{4}$$

3.5.2 Random Forest

As name shows, Random Forest is a collection of large number of decision trees to maintain a learning model for machine learning technique. Every decision tree of this forest shows a class and most possible class is considered as the result. Such a [74] give an indoor localization system that applied Random Forest based model for a medical system to locate patients in real time environment with RSS of RFID, Signal were disturbed by walls and other devices. Random Forest algorithm performs well with high dimensional data by predicting the features and attribute of the data Random Forest works effectively with commonly in indoor environment data with disturbed and missing value and also gives good results in case of noisy data that is very common in indoor data. The overall architecture of RF is illustrated below for a positioning system to locate objects in Figure 3.4.

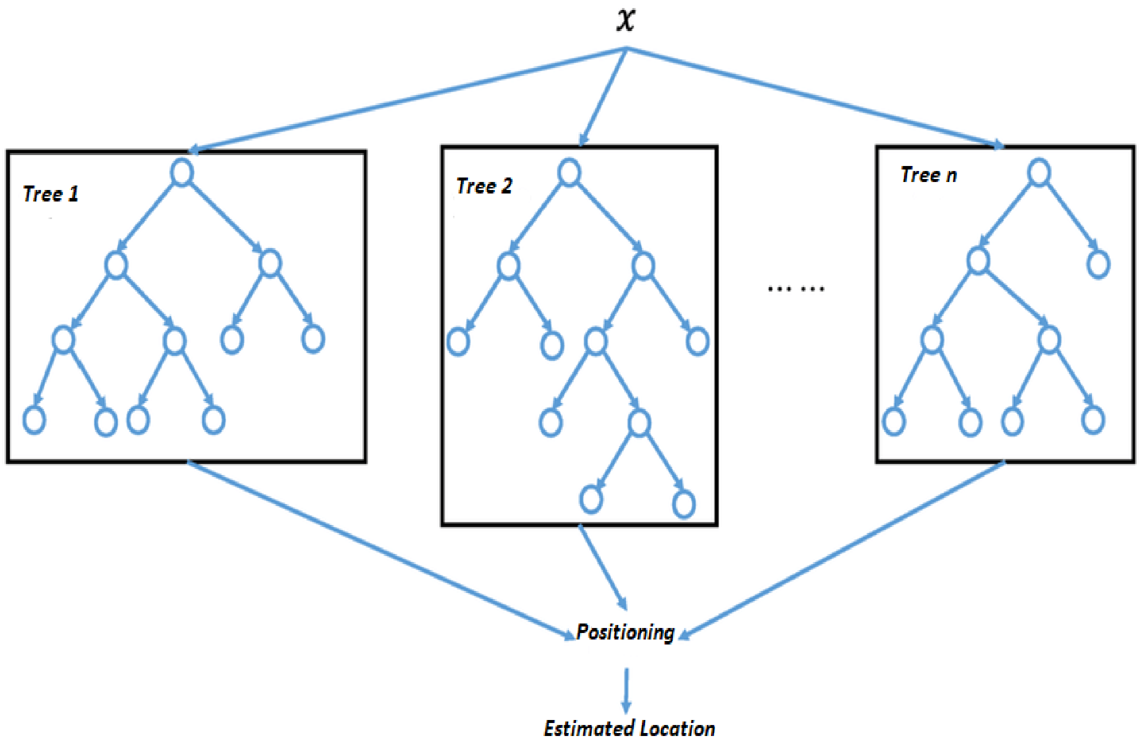

Figure 3.4: Random Forest Architecture

3.5.3 Logistic Regression

LR is the most prominent supervised learning based machine learning algorithm. This model works on the base of logistic function. This function is also sometimes termed as sigmoid function that is given by statisticians. This is an S-shaped curve that input a real-value and map this into a between 0 and 1, means this algorithm applied to predict chances of binary event in form of (yes/no). For instance, in our research work either an object position is detected or not that give outcome in the form of 0, 1 or may be (yes/no). Commonly logistic regression is used in classification related problem where results are in binary form. The overall architecture of LR is illustrated below in Figure 3.5. There are different types of logistic regression such as.

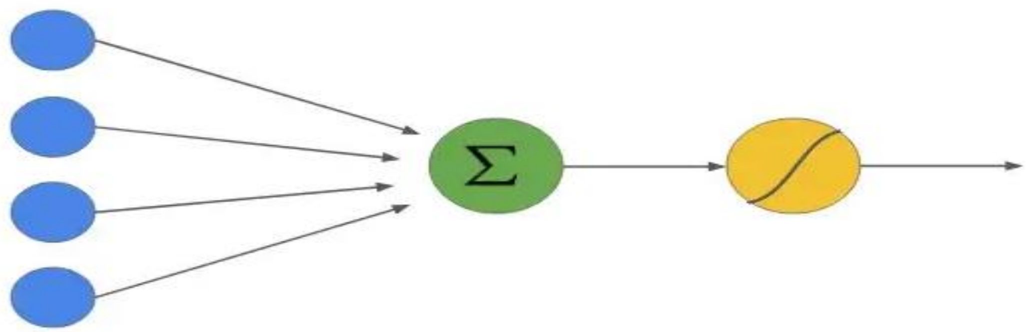

Figure 3.5: Logistic Regression architecture [75]

- **Binary Logistic Regression:** In this case only two outcomes are obtained such yes/no form.
- **Multinomial Logistic Regression:** This is type of regression may have more than two outcomes
- **Ordinal Logistic Regression:** In this type of LR results are in ordered form. The logistic function mainly an S-shaped function applied to convert data between ranges 0, 1. This function equation is given below. The overall architecture of LR is illustrated below in Figure 3.8.

3.6 Suitable Approach

Machine learning is a category of AI that works with software applications and help these applications to predict results according to the trained and tested data. Further ML is classified into two types of techniques such as named supervised and unsupervised learning. As for the supervised learning in this technique that data is provided to the model is in labeled form. Supervised learning also have a feedback mechanism based on the training dataset and further classified into regression and classification as well. In supervised learning technique a variety of algorithms available such as SVM, LR, and Logistic regression. In unsupervised learning mechanism data points that are given to the model is not in labeled form and here no feedback mechanism is applied. Unsupervised learning is also divided into clustering and association. Unsupervised learning is commonly used for analysis purpose. In this technique of machine learning different algorithm are available such prior algorithm, hierarchical clustering and K-mean clustering as well. In this research work supervised machine learning algorithms are applied for the purpose to predicate accurate location of object based on the given dataset that is collected with three technologies in a 3-story building. In this work, we have trained different machine learning technique like SVM, RF and LR on a Miskolc dataset. All types of ML techniques perform well and give better accuracy like SVM obtained 93.50%, LR obtained 83.76% and RF obtained 98.70% respectively. Based on the above results we observed that ML techniques RF provide better accuracy score and predict position of object in a better way.

On the basis of this real time indoor localization system results and previous literature study it is clear that in complex positioning environments random forest is suitable and reliable machine learning classifier. There are several reasons for this high accuracy and better performance i.e. mostly localization datasets contain noise and outliers that are caused by different obstacles like multipath interference and signal attenuation for such noise and outliers random forest model are best as they aggregate predictions from multiple decision trees and take the noisy instances at low level. Second, indoor localization datasets frequently have a high number of features, such as Wi-Fi signal strengths or sensor readings. Random Forests can handle high-dimensional data effectively by randomly selecting feature subsets for each tree during training. This helps mitigate the curse of dimensionality and reduces the risk of overfitting. Third, indoor localization datasets often exhibit complex, nonlinear relationships between features and location. Random Forests excel at capturing nonlinear relationships and interactions among features, as each decision tree in the forest can learn different splits based on different subsets of features. Moreover, the ensemble nature of Random Forests improves prediction accuracy and stability. By combining the predictions of multiple decision trees, the risk of overfitting is reduced, and generalization performance is enhanced. Random Forests also offer interpretability by providing insights into feature importance. This allows identifying the most relevant features for indoor localization, aiding in understanding the underlying factors contributing to accurate localization. Lastly, Random Forests are scalable and can handle large datasets efficiently, making them suitable for indoor localization datasets that may contain substantial amounts of training data. Overall, the robustness to noise, handling of high-dimensional data, ability to capture nonlinear relationships, interpretability, scalability, and ensemble-based accuracy make Random Forests an excellent choice for indoor localization tasks.

3.7 Summary

In this chapter of proposed methodology, research work over all architecture, implementation of work is explained with the help of a figure and a comprehensive discussion, information is also provided about methodology for hybrid indoor localization system. A step by step explanation of all phases of system methodology is also given for the purpose of better understanding. At initial stage a detailed review of technologies is given, after that selection of technologies is explained, furthermore dataset, preprocessing mechanism, and ML techniques are explained at last an accuracy comparison of these classifiers is also given for the purpose of accurate position of object.

CHAPTER 4

TECHNICAL BACKGROUND & EXPERIMENTAL SETUP

4.1 Overview

It is very important to understanding about positioning, indoor localization, localization technologies, techniques, machine learning and its techniques to design an efficient and accurate positioning system. For this purpose, in this section of technical background firstly it gives a comprehensive detail of positioning, technologies, techniques, basic related theories of machine learning, remaining all other prominent component of the research work to solve the problem in an efficient and organized way. In experimental section, here will explain about implementation of the work, programing language, libraries and frameworks and performance parameters that have been applied for evaluation and experimental purpose.

4.2 Technical Background

4.2.1 Positioning

One of the most essential components of contextual information is a description of the position and placement of a person or device inside a particular environment. The extensive use of sensors has led to the production of an ever-growing volume of information. Simply on its own, location has gained a lot of attention due to the fact that it has the potential to be leveraged in a variety of different business applications, including advertisement and social networks. The design of information systems and services for the next generation has placed a significant emphasis on the user context, which is defined as all of the essential elements that are located in close proximity to the user. The ability of those systems of the future generation to adapt to new circumstances is precisely what gives them their flexibility and robustness.

GPS technology has been used to provide location detection in outdoor settings with great success. Due to its support for a wide range of navigation, mapping, and other applications, the GPS has had a significant influence on our daily life. However, due to the absence of line of sight and attenuation of GPS signals as they pass through walls, the utility of the GPS or analogous satellite-based locating systems is constrained in interior contexts. In a business environment, accuracy of about 50 meters is worthless for tasks like finding a specific item on a shelf. As a result, it is commonly acknowledged that indoor location systems (also known as indoor positioning systems, or IPS) require unique techniques and technology.

4.2.2 Types of Positioning System

The terms "localization" and "positioning" refer to the same thing, however the terms for the different kinds of positioning systems are different: an indoor positioning system and an outdoor positioning system. An indoor positioning system, also known as an IPS, is a network of devices that is used to locate people or objects in environments where GPS and other satellite technologies either do not work at all or do not work with sufficient precision. These environments include multistory buildings, airports, alleys, parking garages, and underground locations, among other places.

For the purpose of providing indoor positioning, a wide variety of methods and devices are utilized. These methods and devices range from reconfiguring devices that have already been deployed, such as smartphones, Wi-Fi and Bluetooth antennas, digital cameras, and clocks, to constructing purpose-built installations that contain relays and beacons that are strategically placed throughout a particular area. IPS networks make use of a variety of technologies, including but not limited to lights, radio waves, magnetic fields, magnetic fields, auditory signals, and behavioral analytics. IPS has a wide range of applications across a variety of industries, including the retail sector, the military, and inventory tracking. There are a number of commercial options available, however there are no industry standards for intrusion prevention and security systems. Instead, each installation is adapted to the specific proportions of the space, the building materials, the degree of precision required, and the limits of the budget.

It is very crucial to have an outdoor positioning system in order to determine the location of object and people when they are inside in an open area or outside. In most cases, it is produced by integrating a base station, wireless communication, and internal navigation location with a number of other important technologies. The Global Positioning System (GPS) is a satellite positioning system that was created by the United States government and has found widespread use around the globe. The primary idea behind the Global Positioning System is to send radio frequency satellite signals utilizing a system of 24 satellites that circle the planet. When a GPS receiver on the ground receives signals from more than three satellites, it places the satellite at the center of a circle and calculates the distance between the satellite and the GPS receiver by using TOA, which stands for time of arrival. The radius of the circle is the distance between the satellite and the GPS receiver. After finding that there are more than three circles in the region, it next uses the triangulation method to locate the sites at where the circles cross.

4.3 Localization Technologies

4.3.1 Wireless Technology

The transmission of data from one location to another is accomplished through the use of radio waves, rather than cables or wires. Despite the fact that wireless communications have been in use since 1876, the technology is currently being utilized extensively in the creation of wireless computer networks. Bluetooth, DECT, and WiMAX are just a few examples of the various wireless communication technologies now available. Wi-Fi, often known as 802.11, is a collection of standards developed for wireless Ethernet LANs (local area networks). It is the protocol that all of our tiny PCI wireless cards use. Data transmission that is carried out and transmitted wirelessly is known as wireless communications. This is a general term that encompasses all processes and ways of joining and interacting with two or more devices utilizing a wireless signal using wireless communication technologies and equipment [76]. Figure 4.1 below shown different wireless applications and devices.

Figure 4.1: Indicate Different Wireless Applications and Devices [76].

4.4 Machine Learning

Artificial intelligence (AI) is broken down into several subfields, one of which is machine learning. Machine learning is a subfield of AI that enables machines to automatically learn from data, improve their performance based on previous experiences, and make predictions. The term "machine learning" refers to a body of research that makes use of a variety of computational methods to analyze vast quantities of data. These algorithms are trained by having data input into them in order to develop a model, and based on the training, they build the model and carry out a specified task. The image below illustrates the many forms of machine learning that are used for the goal of localization in both indoor and outdoor settings. These may be used to both indoor and outdoor contexts. These machine learning techniques contribute to the resolution of a variety of localization and tourism-related issues, including Regression, Classification, Forecasting, Clustering, and Associations, [77] etc. All of this machine learning, deep learning, and artificial intelligence is interconnected with one another and relies on one another, as seen in the figure 4.2.

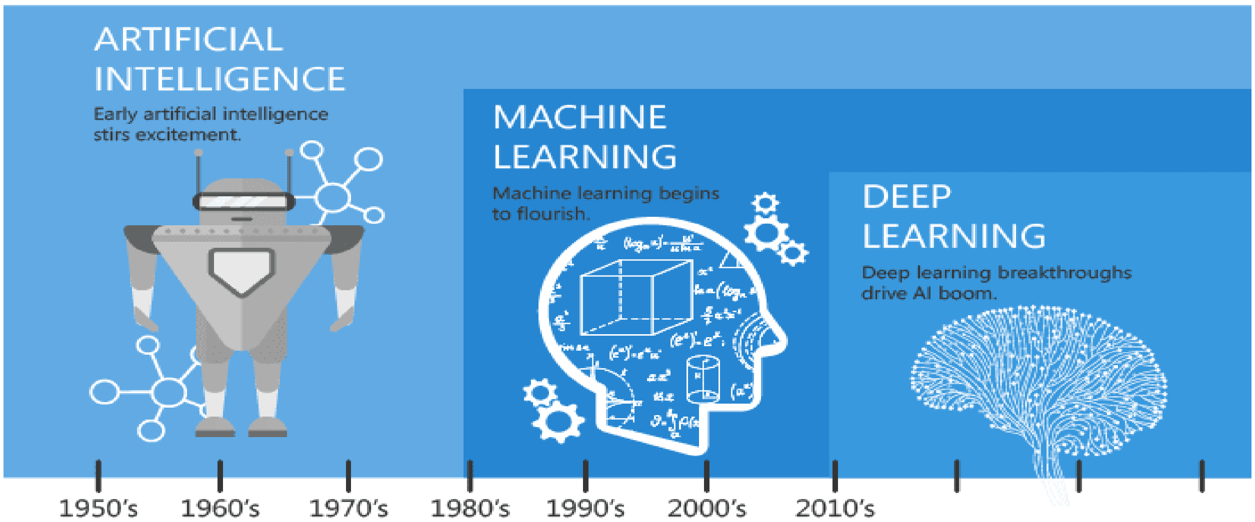

Figure 4.2: Show range of AI, ML, and DL, and how they are related to one another [78].

There are primarily four distinct forms of machine learning, and they are as follows, based on the methodologies and modes of education:

1. Supervised Machine Learning
2. Unsupervised Machine Learning
3. Semi-Supervised Machine Learning
4. Reinforcement Learning

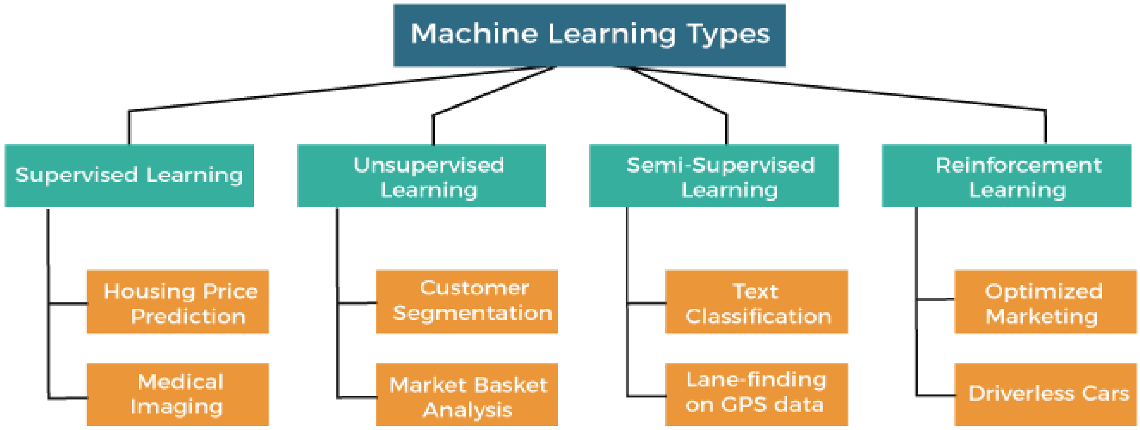

Figure 4.3: Machine Learning Types [79]

4.4.1 Supervised ML

It should come as no surprise that supervision is an essential component of supervised machine learning. It indicates that in the supervised learning approach, we train the machines by making use of the dataset that has been "labeled," and depending on the training, the machine predicts the output. In this case, the tagged data indicates that there is already a mapping between some of the inputs and the output. To put it another way, we may say that first we train the machine by providing it with the input and the output that corresponds to it, and then we ask the machine to predict the output by making use of the test dataset [80].

4.4.2 Unsupervised ML

The method of unsupervised learning is distinct from the technique of supervised learning because, contrary to what one might assume from the name, there is no requirement for supervision. It indicates that, in unsupervised machine learning, the machine is trained using the unlabeled dataset, and the system predicts the output without any supervision being provided by a human.

In the process of unsupervised learning, models are educated using data that has not been categorized or labeled in any way, and the model then makes decisions without being directed in any way by an instructor.

4.4.3 Semi-Supervised ML

There are two main categories of machine learning algorithms: supervised and unsupervised. Semi-supervised machine learning is a form of machine learning algorithm that falls in the middle of the two. It employs a combination of labelled and unlabeled datasets during the training phase, which places it in the middle ground between supervised learning algorithms (which use training data that has been labeled) and unsupervised learning algorithms (which do not use training data that has been labeled) [81].

4.4.4 Reinforcement Learning

A feedback-based technique is used in reinforcement learning. In this process, an artificial intelligence agent (a component of software) would autonomously explore its surroundings by striking and trailing, taking action, learning from its experiences, and improving its performance. Because the agent is rewarded for each good activity and penalized for each poor action, the objective of a reinforcement learning agent is to maximize the rewards [82].

4.5 Experimental Setup

4.5.1 Google Colab

In this work all type of machine learning models run and build on the base of Google Colab platform. I have used Google Colab as it provides 8GB of RAM and high speed computational power of GPU's. This platform specializes in the areas of machine learning and data analysis. Colab is a hosted service that does not require any setup to use, while also giving access to free computing resources including GPUs. This product offered by Google may also be obtained free of charge. Colab is a free environment for working with Jupyter notebooks that is hosted fully in the cloud. The most essential feature is that it does not need to be set up, and the notebooks that you create may be modified simultaneously. The majority of the most prominent machine learning libraries are supported by Colab, and can be loaded into notebook quite easily [83].

4.5.2 Python Language

Python: Python is a programming language that is preferred for programming due to its vast features, applicability, and simplicity. The Python programming language best fits machine learning due to its independent platform and its popularity in the programming community. In this study all programing tasks have been performed by using this high level language and it's different libraries. A few of these are discussed here that we utilize often in our work [84].

Pandas: Data manipulation and analysis are the primary purposes served by the Pandas software library, which was developed for the Python programming language. Particularly, it provides the data structures and processes necessary for the manipulation of numerical tables and time series. It is open-source software distributed with the BSD license that has three clauses. Data scientists make extensive use of Pandas, which is an essential library. It is a ML library that is open-source and provides customizable high-level data structures in addition to a number of analytic tools. Data manipulation, data cleaning, and data analysis are all made simpler as a result. Pandas are capable of performing a wide variety of operations, including sorting, reindexing, iteration, concatenation, data conversion, visualizations, and aggregations, among others [85].

NumPy: A library that supports the Python programming language is known as NumPy. It is a well-known machine learning package that provides support for big matrices as well as data that possesses many dimensions. It has built-in mathematical functions for doing computations quickly and easily. Even frameworks like as Tensor Flow use NumPy internally to execute a variety of operations on tensors. One of the most notable capabilities of this library is its Array Interface. NumPy is software that is freely available to the public and has been developed by a large number of individuals [86]. In this study all type of mathematical operations are applied by using this library.

Matplotlib: For Python and its numerical extension NumPy, Matplotlib is a cross-platform package for graphical data visualization and charting. This makes it a strong open source substitute for MATLAB. In this research work all type of machine learning graphs are drawn by using this library such as representation of Confusion matrix of different machine models.

PyTorch: is a machine learning framework that is based on the Torch library. It is utilized for applications such as computer vision and natural language processing. PyTorch was first created by Meta AI and is now a part of the Linux Foundation's umbrella of free and open-source software [87]. A table of experiment setup is given below in table 4.1.

Table 4.1: Experiment Setup

Development Environment	Google Colab
Hardware	Laptop DELL Inspiron Core i5-6200U, 8GB RAM DDR3-SDRAM, 500 GB HDD
Programming Language	Python 3.7.0
Libraries	PyTorch, Matplotlib, NumPy, Pandas
Evaluation Metric	Accuracy, TPR, FPR

As I mentioned above that I have used Google Colab for implementation and dataset execution in this research work. In the first stage, I have set path after that I load dataset into Google Colab. After path set up, when data is loaded properly, the next phase is to import and install all required important libraries and APIs. For the purpose to make dataset reliable preprocessing is performed and data is divided into training and testing. Finally, in this stage I applied machine learning classifier named as SVM, LR and RF on the dataset for the purpose of training and testing. Furthermore, these machine learning model give best and different accuracy with respect to locating object.

4.6 Summary

In this chapter mainly technical background and experimental setup is explained for the purpose of better understanding of this proposed system implementation. Firstly, positioning background is provided, technologies and wireless setup is explained, machine learning is defined then programing language and libraries knowledge is briefly provided.

CHAPTER 5

RESULT DISCUSSION AND COMPARISON

5.1 Overview

In chapter 4 the detail about technical background is discussed like positioning, technologies such as wireless technologies, types of localization and machine learning as well. In this chapter now we will explain and presents about simulation result of real time object localization in complex indoor environments using hybrid wireless technologies that is based on machine learning models. In this research work the main contribution is performed with the help of machine learning sub field supervised learning algorithms. Here the indoor positioning hybrid dataset is tested with SVM, RF and LR classifier.

5.2 Performance Parameters for Positioning

5.2.1 Accuracy

Accuracy is one of the crucial performance metrics in indoor localization. In terms of overall system, accuracy predict or defines the reliability of the system. With respect to positioning system technologies, it is considered as how it accurately and perfectly the location of an object. Different technologies and techniques provide it differently. In positioning related system is also termed as position estimation error. Mean position estimation error may be considered as the difference among the actual and the related estimated coordinate with respect to reference that are some location coordinates [43]. In this research work the main focus is on to estimate the accuracy of machine learning models on a specific dataset for the purpose of real time object localization. In this research work, I have worked on hybrid technologies dataset by applying machine learning algorithm SVM, RF and LR to achieve a better accuracy with minimum error rate. The results that are achieved here in terms of accuracy are 0.83, 0.935 and 0.987 for LR, SVM and RF respectively with an error rate 0.162, 0.065 and 0.012.

5.2.2 Coverage

This is also a most prominent aspect that is related to area, for the purpose to choose a suitable localization technology. This term defines the area for which a system can perform localization or can locate object, means how much is covered by a localization system for predict the existence of an object. In this research work named as Real time object localization in complex indoor environments using hybrid wireless technologies the covered area is a three story building where data set is collected in real time. So, in our scenario the coverage area is a three story building of a university.

5.2.3 Cost

This is a key factor for any localization system. It means weather the positioning system feasible in terms of energy, time, and money etc. Technologies and techniques are different in terms of cost as well with respect to their performance, accuracy and infrastructure[43]. Cost is not only related to hardware cost it is related to design and space that is required for the localization is also considered. In this work as we applied hybrid technologies for data collection and all of these technologies are cost effective such as Bluetooth technology that is here used for localization with other, is cost effective. In our system we use different technologies to overcome the limitations of each other in terms of different parameters.

5.2.4 Availability

The availability parameter of an indoor localization system refers to the percentage of time or the probability that the system is able to provide accurate and reliable location information for a given user or device within an indoor environment [86]. It indicates how often the system is operational and capable of delivering location-based services. The availability parameter takes into account various factors that can affect the system's performance, such as signal strength, signal quality, and indoor physical objects.

5.2.5 Precision

This is just near to accurateness. It defines the correctness of the localization system. Precision can vary from system to system. Such as Wi-Fi is recommendable in low precision[88]. Few researchers consider the performance matric precision as standard deviation which is another most important performance matric. Researcher also used cumulative probability function (CDF) of the distance estimation error as precision. In our research work we not consider the precision but we focus on mean error analysis and compare the effectiveness of localization techniques.

5.2.6 Power Consumption

This parameter is most crucial one for the mobile node and this value is near to the device alive time [79]. Power consumption is also an important parameter to consider in an indoor localization system, as it directly impacts the performance, usability and practicality of the system. Overall, optimizing power consumption in an indoor localization system involves a combination of hardware design, software optimization, communication protocol, algorithm selection, and energy management techniques. This indoor localization system gains high accuracy, less error rate as compare to the previous paper, and low power consumption as we combine different localization technologies that consume less power i.e. Bluetooth.

5.2.7 Latency

This is the time difference that is required to send request and receive response to gain the positioning prerequisites data for the purpose to locate object for localization in a system [88]. Latency in positioning systems is an important consideration, especially in applications that require real-time or time-critical positioning information, such as navigation, aviation, autonomous vehicles, or location-based services. Minimizing latency is crucial to ensure accurate and up-to-date positioning information, and efforts are made to optimize positioning systems to reduce latency as much as possible.

5.3 Performance Parameters for Machine Learning Classifier:

Machine learning models are also based on some important parameters for performance measurement purpose, some of these are given below in table 5.1.

Table 5.1: Performance Parameters for Machine Learning Classifier:

Evaluation Metrics	Definition
Sensitivity, TPR, Recall	$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} = \frac{\mathrm{TP}}{\mathrm{P}}$
Specificity, TNR	$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{FP+TN}} = \frac{\mathrm{TN}}{\mathrm{N}}$
Accuracy	$\mathrm{Acccuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$
Precision	$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$
FPR	$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP+TN}}$
FNR	$\mathrm{FNR} = \frac{\mathrm{FN}}{\mathrm{TP+FN}}$
CV	To analyze ML methods using a small dataset sample. CV reduce over-fitting and increase model generalization due to its frequent used in training phase of predicative models.

Stands for: T = True, F = False, N= Negative, R = Rate, ROC = Receiver Operating Characteristic, CV= Cross Validation

5.4 Result Discussion and Comparison

In this section, results of the study obtained after the implementation process have been discussed. I have already discussed the implementation methodology step by step, but in a concise and comprehensive way.

5.4.1 Result Discussion

In this research study Miskolc hybrid indoor localization dataset is used with 3 supervised machine learning models for the purpose of real time object detection in complex indoor environments of a three story building. Miskolc hybrid dataset is collected for three indoor localization technologies RSSI measurements that consist of 1539 fields with different measurements attributes for classification purpose. Machine learning models are implemented in Python language with different libraries and function for implementation of this system. To make optimize and remove redundant entries and weak received signal strength from the dataset these entries are assigned a null value at preprocessing stage, such as if the RSSI value is not in the given suggested range then it is assigned this value. In this research work main focus on to overcome the sole technology limitation and gain high accuracy to locate object in real time environment. By applying three machine learning classifier gain different accuracies with distinct error rate. Three supervised machine learning classifier SVM, RF, and LR gain an accuracy to locate object in real time collected dataset are 83.7%, 93.5% and 98.7% with an error rate 0.162, 0.065 and 0.012 for LR, SVM and RF respectively. As for the accuracy and error rate of these machine learning models it is clear that these model accuracy is improved with respect to previous work and among these classifier RF is given high accuracy i.e. 98.7 with lower error rate of 0.012. Table 5.2 cited below represents the ML classifier accuracy and error rate of different models like SVM, LR, and RF.

Table: 5.2 ML Classifier Accuracy on Localization Dataset with ER

ML Classifier	Dataset for Positioning	Accuracy %	Error Rate
LR	Miskolc	83.7%	0.162m
SVM	Miskolc	93.5%	0.065m
RF	Miskolc	98.7%	0.012m

Results of the study in terms of accuracy and error rate, achieved by the SVM model are indicate below in Figure 5.1and Figure 5.2 respectively.

```
[ ]  from sklearn.metrics import accuracy_score

     accuracy_score(y_test, y_pred)*100

     93.5064935064935
```

Figure 5.1: Represent Accuracy Result of SVM

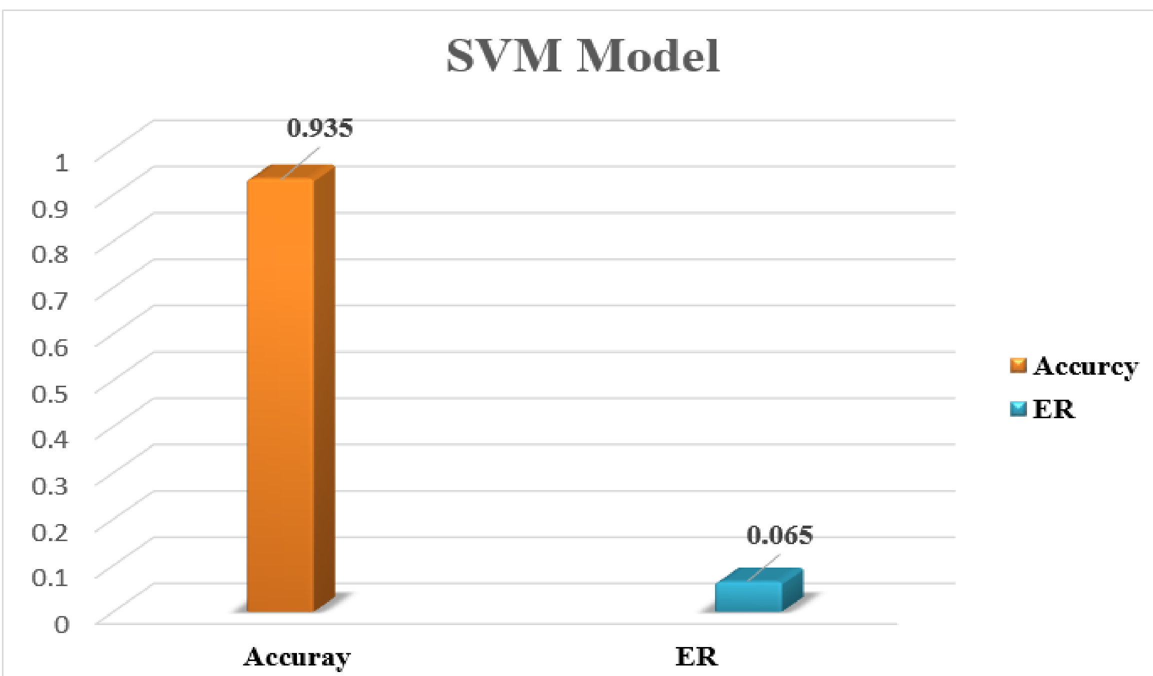

Figure 5.2: Graphical Representations of SVM Accuracy and Error Rate

Results of the study in terms of accuracy and error rate, achieved by the Random Forest model are indicate below in Figure 5.3 and Figure 5.4 respectively.

```
LogisticRegression(multi_class='ovr', random_state=0, solver='newton-cg')

[ ] y_pred=model.predict(X_test)

[ ] accuracy_score(y_pred,y_test)

83.76623376623377
```

Figure 5.3: Represent Accuracy Result of Logistic Regression (LR)

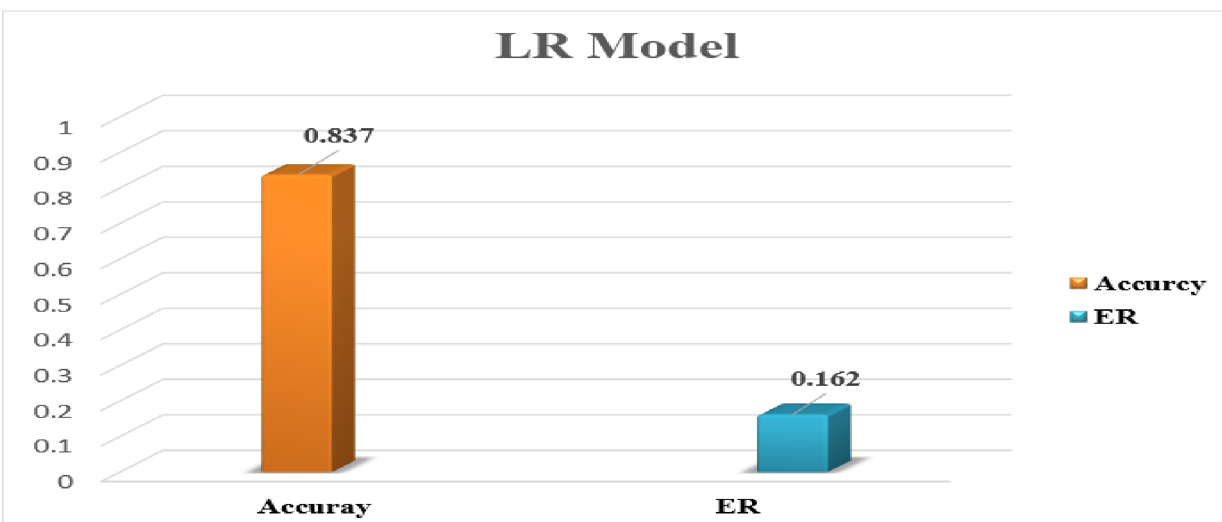

Figure 5.4: Graphical Representations of LR Accuracy and Error Rate

Results of the study in terms of accuracy and error rate, achieved by the Random Forest model are indicate below in Figure 5.5 and Figure 5.6 respectively.

```
RandomForestClassifier(max_depth=5, random_state=0)

[ ] y_pred=clf.predict(X_test)
    accuracy_score(y_pred,y_test)*100

98.7012987012987
```

Figure 5.5: Represent Accuracy Result of Random Forest (RF)

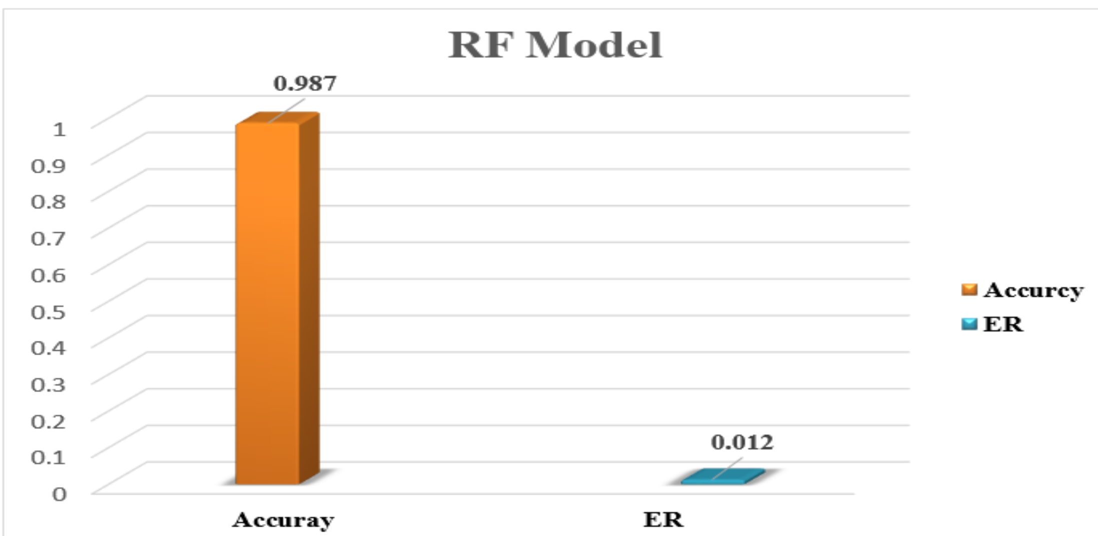

Figure 5.6: Graphical Representations of RF Accuracy and Error Rate

Furthermore, to analyze the performance of the machine learning algorithm and to calculate the error rate for the purpose of object detection I have also used important feature of machine learning algorithm Confusion Matrix for better understanding of work. Confusion matrix is just like a summary of predicted outcomes that are related to a problem and provides results in the form of maybe two or more classes. This feature of machine learning classifiers is used to determine the different values like true positive (TP), false negative (FN), false positive (FP) and true negative (TN). And a confusion matrix for just prediction and non-prediction of position estimation of result is shown below. In figure 5.7, SVM confusion matrix is displayed, figure 5.8 LR confusion matrix and in figure 5.9 RF is shown.

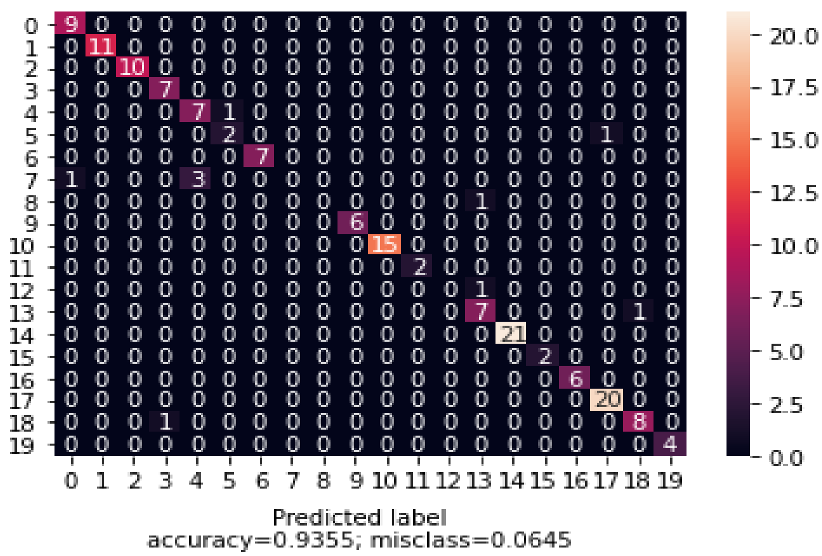

Figure 5.7: Confusion Matrix of SVM

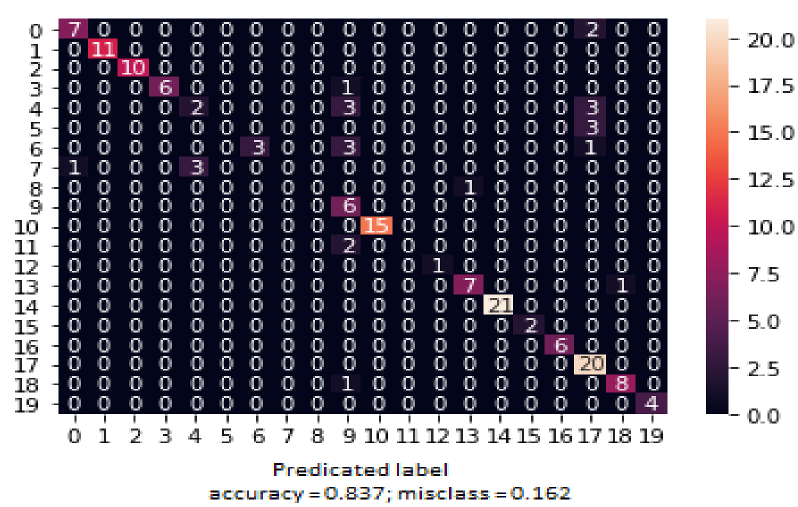

Figure 5.8: Confusion Matrix of LR

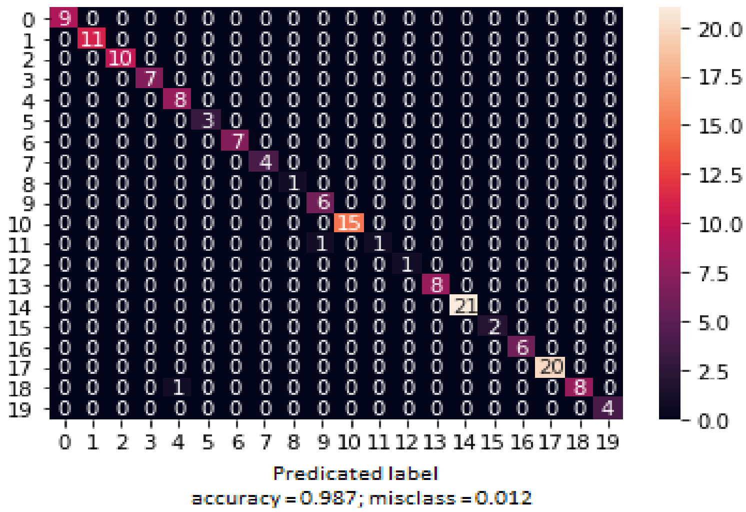

Figure 5.9: Confusion Matrix of RF

From the above given figure, it is evident that the main objectives of the study have been achieved. Accuracy has been significantly improved and false positive score has been reduced as well.

5.4.2 Result Comparison

In this research work, I have worked on hybrid technologies dataset by applying machine learning algorithm SVM, RF and LR to achieve a better accuracy. The results that are achieved here in terms of accuracy are 0.83, 0.935 and 0.987 for LR, SVM and RF respectively with an error rate 0.162, 0.065 and 0.012. A comparison table 5.3 of accuracy is given below.

Table 5.3: Result Comparison

Study	Models/Techniques	Accuracy	Error Rate	Dataset	Environment
Subedi et al.[24]	Traditional/ KNN	Not Given	0.09m	Not given	No real time
Hashim et al.[26]	KNN	71%	Not given	BLE RSSI	No Real time

Proposed Machine learning model 1	SVM	0.93%	0.065m	Miskolc	Real time
Proposed Machine learning model 2	LR	0.83%	0.162m	Miskolc	Real time
Proposed Machine learning model 3	RF	0.987%	0.012m	Miskolc	Real time

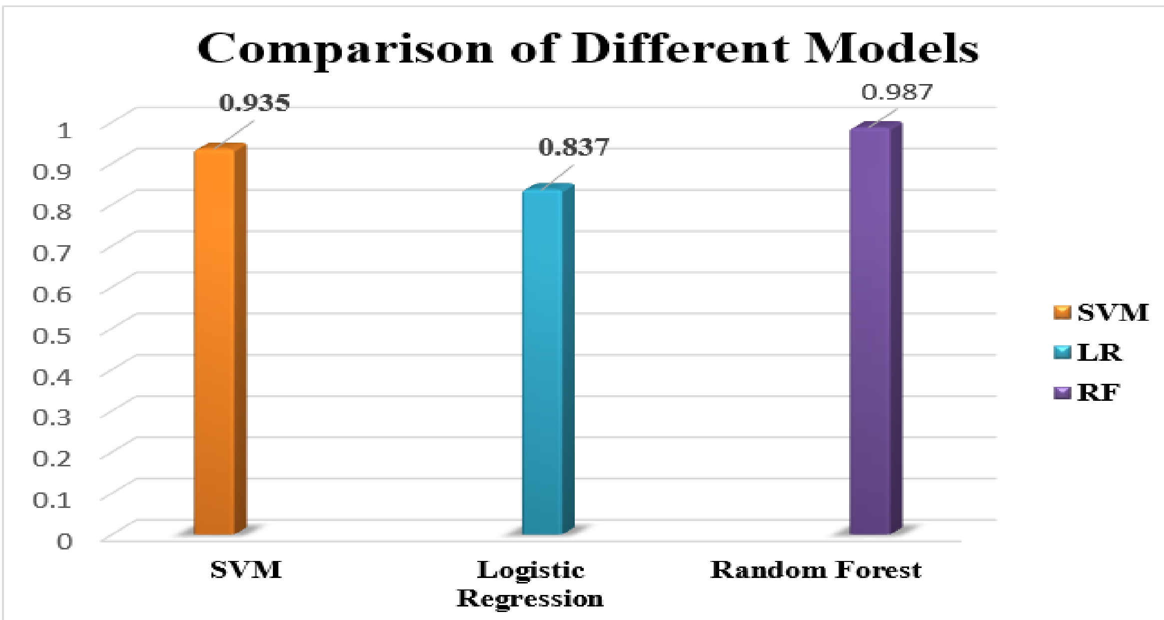

Figure 5.10: Comparison Graph of SVM, LR, and RF

According to the given table that is cited above it is apparent and clear that for locating and positioning purpose my approach is give best accuracy results as compared to the mention other two studies. These two studies mainly focus on traditional based methods with sole technologies for localization with a little bit application of machine learning models like just only KNN with an accuracy of 71%. We applied in our proposed system hybrid dataset with a combination of machine learning techniques and gained a highest accuracy of 0.987% for Random forest classifier. And above studies are also not considering the real time scenario where as we perform all this on a real time dataset and achieve high accuracy as compare these.

5.5 Summary

In chapter 5, result discussion and comparison, after achieved the results in accuracy form is discussed. Moreover, graphical and tabular comparison of this research work with previous work is also represent in this chapter for better understanding of the work. Performance parameters of a localization system such as accuracy and error rate is also explaining and represents in the form of confusion matrix is also labeled in this chapter.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Overview

Chapter is summarized and give an overview of the overall research work, to address the issues in indoor localization system for accurate object detection in real time complex environment, where different things cause an effect on locating object like furniture, electronic equipment, and even human presence. This chapter will provide an overview of contribution that made by this work, limitations and also give future directions for more enhancement of the work for enhancement and to locate object in real time in standard way.

6.2 Conclusion

Localization or positioning defines as to predict the real time actual locality of an object with respect to some specific known available coordinates of location. This positioning process is mainly divided into two main classes with respect to application, area and geography for locating the position of an object. This division is commonly known as indoor and outdoor localization, positioning. For the outdoor localization in an accurate and efficient way GPS is the most reliable and well known standard. GPS relied on basically satellite signals and works with LOS, user equipment's must be connected with GPS receiver to gain signals from satellites. TDOA and geometric positioning techniques are commonly applied these days for outdoor environments. To locate object with respect to accuracy in GPS depended system is related to user level of acceptance, such as if to locate a landmark in outdoor environments like Lake View Park in such case 10 to 15-meter mean error for locating place is acceptable. But this type of error in case of indoor environment is not acceptable at all due to congested area. GPS is not performing well in indoor scenarios due to different issues like attenuation and line of sight problem. Even in the current research works and environments a single indoor system is not available which accepted by every domain of localization like indoor and outdoor. This is due to different issues and challenges that every system is not acceptable such as cost, accuracy, power consumption, availability and latency etc. and many other parameters are effected the localization system performance. With all of these multiple indoor environment factors are also that effect the localization performance like furniture, distance, noise and multipath effect. In our proposed work a hybrid technology based system is presented that real time locate object with high accuracy by applying supervised machine learning based techniques in complex indoor environments of a 3 story building. Here in the proposed work main focus is on machine learning based techniques and hybrid technologies to enhance accuracy and overcome sole technology issues with respect to cost, accuracy for complex real time environments. In the previous paper the main focus is on traditional based techniques for locating object and system accuracy is effected with distance, technologies are applied solely for localization purpose and real time is also not considered. To select appropriate technologies and machine learning techniques in this work a review of these technologies and techniques is also performed. For better performance evaluation purpose, gain better accuracy three machine learning classifier are applied to real time object locating on a hybrid wireless technology dataset, these classifiers predict location and provides good accuracy. These machine learning models give an accuracy of 0.935%, 0.987% and 0.837% for SVM, RF, and LR with an error rate of 0.065m, 0.012m and 0.162m respectively on a 1539 RSSI sample of 3 different technologies with 90% in training, 10% for testing and validation purpose. In this research work, our contribution is to combine different wireless technologies and achieve high accuracy with minimum error rate.

6.3 Research Challenges and Future Work

In future, plan to expand the experiment area i.e. multiple floors with multiple building and further expand the dataset size. Our plan also includes working on a method to identify access points (AP), which could increase accuracy for indoor localization. There is also another research domain that enhanced the indoor localization system accuracy to filter the received signal that is a challenging task in indoor localization system for locating objects in real time. To design more accurate and less complex solutions, it is recommended to investigate deep learning with filtering RSSI signals of different hybrid technologies that will be a new scenario to enhance the localization accuracy.

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