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Department of Electrical and Electronic Engineering

INDOOR HUMAN TRACKING SYSTEM USING MOBILE NETWORKS

Master Thesis

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Supervisor
Assoc. Prof. Dr. Indrit MYDERRIZI

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

Ali Mohammed Hassan ALAMERY

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The thesis study of Ali AL-AMERY titled as Indoor Human Tracking System Using Mobile Network has been accepted as MASTER in the department of Electrical-Electronics Engineering by out jury.

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SUMMARY

Position estimation and approximation is one of the most significant and challenging tasks in indoor location detection using global navigation systems. This reserch deal with the indoor human tracking system. The practical model the use study interlocks handles a floor containing seven rooms of different dimensions to add more challenges to the system and give realism to this work. It consists of hardware types of equipment and software.

The hardware equipment used contains Node MCU ESP8266 Microcontroller, serial communication, micro USB charger, polymer lithium-ion battery, OLED 128*64 display, and HC-05 Bluetooth model. These a kind of equipment are small in size with low power, low cost, and high-speed response. The data information of this model is collected by using Wi-Fi and transmitted via Bluetooth. This work presents the design and analysis of Wi-Fi RSSI from the received radio frequency signals for human location detection in an indoor environment. The way of working with the information was done offline to gather site information for the project and online to be utilized in identifying the location during system operation.

The purpose of using the software was that after collecting the information and by using the machine learning (ML) support vector machine (SVM) theory, the information was trained and a model of the location detection system was built using online data. Python has been used as a system programming language that is efficient in that and it contains libraries that support machine learning. The classification accuracy and speed employing SVM theory as a linear method exhibits high accuracy and good speed of the system, it reaches up to 87% accuracy within a few seconds.

Keywords: Mobile Network, Tracking System

ÖZET

Konum tahmini ve tahmini, küresel navigasyon sistemleri kullanılarak iç mekan konum tespitinde en önemli ve zorlu görevlerden biridir. Bu proje, iç mekan insan takip sistemi ile ilgilidir. Bu projedeki pratik model, sisteme daha fazla zorluk eklemek ve bu işe gerçekçilik kazandırmak için farklı boyutlarda yedi oda içeren bir katı ele alıyor. Donanım türleri, ekipman ve yazılımlardan oluşur.

Kullanılan donanım ekipmanı Node MCU ESP8266 Mikrodenetleyici, seri iletişim, mikro USB şarj cihazı, polimer lityum iyon pil, OLED 128*64 ekran ve HC-05 Bluetooth modelini içermektedir. Bu ekipman parçaları, düşük güç, düşük maliyet ve yüksek hızlı yanıt ile küçük boyutludur. Bu modelin veri bilgileri Wi-Fi kullanılarak toplanır ve Bluetooth ile iletilir.

Bu çalışma, bir kapalı ortamda insan konum tespiti için alınan radyo frekansı sinyallerinden Wi-Fi RSSI'nin tasarımını ve analizini sunar. Bilgilerle çalışma şekli, proje için saha bilgisi toplamak için çevrimdışı ve sistem çalışması sırasında yerin belirlenmesinde kullanılmak üzere çevrimiçi yapıldı.

Yazılımın kullanım amacı, bilgileri topladıktan sonra ve makine öğrenmesi (ML) destek vektör makinesi (SVM) teorisini kullanarak, bilgilerin eğitilmesi ve çevrimiçi veriler kullanılarak konum tespit sisteminin bir modelinin oluşturulmasıydı. Python, bu konuda verimli bir sistem programlama dili olarak kullanılmıştır ve makine öğrenmesini destekleyen kütüphaneler içermektedir. SVM teorisini doğrusal bir yöntem olarak kullanan sınıflandırma doğruluğu ve hızı, sistemin yüksek doğruluk ve iyi hızını sergilemekte, birkaç saniye içinde %87'ye varan doğruluğa ulaşmaktadır.

Anahtar kelimeler: Mobil ağ, Takip Sistemi

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ABBREVIATIONS

Wi-Fi	: Wireless Fidelity protocols
GPS	: Global positioning system
RSSI	: Received Signal Strength Indicator
LOS	: Line-of-sight
NLOS	: Non-line of sight
(ToA)	: Time of arrival
Zigbee	: Zonal Intercommunication Global-standard.
WiMAX	: Worldwide Interoperability for Microwave Access
AoA	: Angle-of-arrival
TDoA	: Time-difference-of-arrival
RFID	: Radio-frequency identification tags
ML	: Machine learning
KNN	: K-nearest neighbors
ANN	: Artificial neural network
CNN	: Convolution neural network
SVM	: Support vector machines
LSTM	: Long-Short Term Memory
EKF	: Extended Kalman Filter
WCL	: Weighted Centroid Localization
RFID	: Radio Frequency Identification
CSI	: Channel State Information
5G, 6G	: 5 generation, 6 generation
WLAN	: Wireless Local Area Network
WPAN	: Wireless Personal Area Network
WMAN	: Wireless Metropolitan Area Network
Bluetooth	: Bluetooth is a short-range wireless technology
AI	: Artificial intelligence
DNNs	: Deep Neural Networks
FFNNs	: Feed-Forward Networks
RNN	: Recurrent Neural Network
OLED	: Organic light-emitting diode
LCD	: Liquid-crystal display
Arduino IDE	: Arduino Integrated Development Environment

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CHAPTER ONE

INTRODUCTION

1.1. INTRODUCTION

Real-time indoor localization is the key to obtaining a user or a device located in a bounded environment. The global positioning system (GPS) is the most used technique of localization in outdoor environments; however, the GPS is not usable in an indoor environment. Indoor localization or positioning is the determination of the location of a person or a mobile point within a particular building. The challenge here can be in the different ways of determining the location inside the buildings from the outside. Signal propagation results in unmanageable shadowing, scattering, attenuation, and distortion. With the development of technology and the increasing use of smart devices, these challenges have increased. As a result of these challenges, scientific research is discovering many ways to determine locations inside buildings based on different elements. Indoor localization is difficult because to the variety of forms and sizes, as well as the lack or presence of stationary and moving objects. These challenges significantly change both line-of-sight (LOS) and non-line-of-sight (NLOS) radio blind spots that affects the performance of indoor positioning. However, because of the high demand for indoor localization systems, considerable research has been done for the investigation positioning systems (Bulusu, Heidemann, et al. 2000). Several indoor localization techniques have been developed such as time of arrival (ToA) (Xiong and Jamieson 2013), received-signal-strength-indicator (RSSI) (Wang, Chen, et al. 2012) , angle-of-arrival (AoA)(Zheng, Sheng, et al. 2018) and time-difference-of-arrival (TDoA) (Zhang, Höflinger, et al. 2013).

To discover the unknown target location, most indoor localization techniques require at least three known nodes. These approaches suffer from several aspects including high technical complexity, low accuracy, and unreliability (Bulusu, Heidemann, et al. 2000).

Furthermore, the existence of infrastructural barriers may lead to signal weakening and scattering. Also, indoor position estimation suffers from signal instability, as the received signal strength can easily be fluctuated becauseof the presence of several interference-generating sources such as smartphones, Bluetoot, ZigBee, WiMAX, wireless devices, microwave ovens, and fluorescent lights. For these primary reasons, many notable researchers have worked to provide indoor positioning services with a variety of methodologies centered on the principle of different technologies (Alarifi, Al-Salman, et al. 2016).

These localization methods use different access technologies such as Wi-Fi (Li, Li et al. 2016), Bluetooth (Luo and Hsiao 2019), radio-frequency identification tags (RFID) (Yoon, Zihajehzadeh, et al. 2016), etc… for indoor positioning based on properties of angulation and alteration, and inertial measurement based on sensors like motion, power, or energy sensors. In RF angulation and alteration, the position is determined by detecting the distance between the target position and reference position using signal strength analysis. However, biometric approaches with machine learning techniques are utilized to match the user's position with a predefined set of positions based on sensor signals databases, known as access points. Among these techniques, fingerprinting using Wi-Fi based on received signal strength (RSSI) has shown great dominance as a promising technique when other technologies face these localization challenges. It is also widely deployed with low-cost infrastructure and ease of compatibility with multiple smart embedded devices. In comparison with the traditional Wi-Fi localization techniques such as TOA, angle of arrival (AOA) and TDOA, the Wi-Fi-based localization system that dependson the received signal strength (RSS) has mostly been used due of its advantage of not requiring any extra infrastructure. It also shows satisfactory performance in the line-of-sight (LOS) and non-line-of-sight (NLOS) environments (Alarifi, Al-Salman, et al. 2016).

In general, Wi-Fi localization method based on fingerprint that uses RSS can be classified into two phases: offline and online phases. To extract the distance information, raw RSSI signals are received through access points (APs) and then the position is estimated using these values. These access points may be gathered from smart devices or signal transmitters. During the offline phase, a fingerprint database is established in the form of RSS vectors using the Wi-Fi APs. These reference points are then entitled radio maps which are proportioned to the project working environment.

During the online phase, a real-time RSS value is measured by the router or any other smart device embedded with a Wi-Fi-based communication system. Both the pre-defined RSS radio maps during the offline phase and measured RSS vectors are then compared for location estimation. Recently, machine learning (ML) algorithms showed good performance for indoor-based localization applications (Hoang, Yuen, et al. 2019). ML algorithms are able to deliver effective performance utilizing experiment data without complex mathematical equations.

However, the RSS datasets are very limited to training effective machine learning models. Therefore, there are serious challenges in implementing such a technology in the current situation. In this regard, there is a gap for research in finding a compatible and useful machine learning technique. The non-linearity in acquiring the RSS values has pushed researchers to dive deeper into utilizing advanced machine learning algorithms based on deep neural networking. Therefore, new Wi-Fi RSSI-based positioning systems using deep learning techniques have been explored which shows promising improvements in collecting and training RSS radio map databases. Until now, models such as Random Forests (RF), convolution neural network (CNN), and long short-term memory (LSTM) for indoor localization have been widely used. Although these models provide high accuracy, SVM based Wi-Fi RSSI fingerprinting system has shown the most promising positioning detection performance due to its simplicity and the required processing time. In fingerprint localization systems, data mapping and overfitting are serious challenges. SVM is generally used for pattern detection in the fingerprint method, SVM does not deliver the optimal performance for large and high-dimensional datasets. In irregular and noisy environments, collected data can have high dimensionality due to the presence of noise and attenuation (Farjow, Chehri, et al. 2011). To overcome these limitations, SVM can be effective solution because it uses kernels to detect differences between two separate classes and provides better generalization performance for linear and non-linear relations in the collected dataset.

In this thesis, the main contributions are listed as follows:

- ✓ Providing an overview and implementation of Wi-Fi-based indoor localization algorithms.

- ✓ Setting up a rereal-timeest that handles different scenario cases which captures the transmitted data of a typical indoor environment.

For this purpose, the proposed system was developed using low-cost and low-power consumption hardware devices including two access points, and MCU ESP 8266 microcontroller node with an ESP-12E-based Wi-Fi chip to collect the user transmitted data for analysis using ML.

Evaluation of the indoor localization using the collected data by applying ML algorithms with SVM and reporting achieved accuracy.

1.2. Motivation and Contributions of this Thesis

The motivations behind investigating an indoor positioning system built on real evaluation of radio signal strength are due to the following reasons. Firstly, with the increased number of communication networks such as the deployment of futuristic 5G and 6G networks, indoor-based positioning systems deployment made possible. Secondly, in the field of health care systems, human/animal tracking systems, object tracking, and automatic vehicle detection systems, and especially for security and safety purposes, there is a vast requirement to have efficient and active detection systems. This thesis aims to test the feasibility of Wi-Fi signal technology as an effective source of data for localization in an indoor environment. Generally, it is important to test the effectiveness of developing a low-powered and off-the-shelf system in a practical indoor setup for accurate indoor localization. Therefore, this thesis investigates whether developing low power consumption and low-cost indoor localization solution can be useful in typical indoor scenarios such as hospitals, shopping centers, or office buildings, where indoor localization is challenging to achieve. The major contributions of this thesis are as follows: A Wi-Fi based on RSSI signal localization system using two access points and RSSI data collected using MCU ESP 8266 microcontroller Node with ESP-12E based Wi-Fi chip was created and implemented. The microcontroller uses an Arduino-based code that shows the strengths of RSSI signal at a given location in the designated location. A real-time Wi-Fi RSSI database is collected from locations in experimented area. The RSSI measurements were conducted in a multi-room movement scenario. Results from experiments show that there were distinctive features in the collected data which enabled the ML to achieve accurate indoor localization. Additionally, the sensitivity of RSSI values was examined in different test conditions to justify the system performance.

1.3. Thesis Organization

- **Chapter One** This chapter includes the Introduction to the topic and defines the motive and objective behind the thesis theme selection.
- **Chapter Two** The fundamental ideas of IPS technologies have been reviewed, including indoor and outdoor positioning, i.e, introduce a brief overview of indoor positioning and, machine learning algorithms technologies.
- **Chapter Three** This chapter focuses on the embedded system hardawre, and the positioning project equipments.
- **Chapter Four** The proposed model including support vector machine for indoor location identification purpose. Results are also discussed here.
- **Chapter Five** This chapter concludes and suggests for the thesis work.

CHAPTER TWO

THEORITICAL BACKGROUND

2.1. Introduction

Indoor localization system is able to track the location of concerned objects or human in a continuous manner without the use of GPS. Generally, there are two stages, distance measurement of the phase and position estimation phase (H. Liu, Darabi, Banerjee, & Liu, 2007). In the distance measurement of the phase, the indoor localization system can measure the distance between the targets and given positions are previously known nodes using a suitable range. Next, the indoor localization system utilizes these measurements to find the location of a given target by employing various positioning approaches. The most used localization techniques are given as follows:

2.2. RANGING TECHNİQUES

2.2.1. Received-Signal-Strength-Indicator (RSSI)

Generally, Received-Signal-Strength-Indicator (RSSI) is an easy parameter to be obtained, Although, RSSI is a simple and robust positioning technique, sometime it may produce inaccurate distance measurement, especially for small-scale environments because of fading, interference, signal-shadowing, and scattering. Hence, ML algorithms have been utilized to reduce the RSSI fluctuations, as well as, using signal filters like Kalman Filter (KF) or Extended Kalman Filter (EKF) (Kilani, Raymond, Gagnon, Gagnon, & Lavoie, 2014) may enhance its operation.

2.2.2. Time-of-Arrival (ToA)

ToA calculates the distance between the target and the reference node using signal propagation time. ToA is more preferred than the RSSI method for small scale areas. However, synchronization and processing time affect distance measurement of ToA (Kilani et al., 2014). To reduce the time synchronization error, the symmetric double-sided two-way can be employed (Song, Zhang, Long, & Hu, 2017). This method takes the average error by considering several back-and-forth trials of propagated signal between the nodes.

2.2.3. Time-Difference-of-Arrival (TDoA)

In this approach, different techniques is used in signal propagation times between the reference nodes and the target node to locate the position of the target node (Du, Zhang, Chen, Alphones, & Zhong, 2018). This method uses approximately three stationed nodes to find out the target location at the crossing line of the hyperboloids. The synchronization error issue can partially resolved by using TDoA technique because of it is ability to manage the transmitters synchronization. (Do & Yoo, 2014). However, the Non-line-of sight (NLOS) propagation of the signal affects the performance of the TDoA-based systems. Therefore, NLOS mitigation proposed to enhance the TdoA accuracy of localization (Guvenc, Chong, & Watanabe, 2007).

2.2.4. Angle-of-Arrival (AoA)

This method uses the signal angle with an antenna array for position localization (Wielandt, Thoen, & De Strycker, 2018). AoA is an improved ranging method given that both the distance and the angle measurement are applied. However, the main limitation of this method is the need for antenna arrays which is expensive and complex (Sakpere, Adeyeye-Oshin, & Mlitwa, 2017). Additionally, this method uses the difference in signal arrival at separate antenna arrays, however, this requires more complex equipment and careful calibration.

2.3. METHODS OF LOCALIZATION

The localization methods for an indoor environments are described as following:

2.3.1. Multilateration and Trilateration

This technique is used to estimate the unknown node position with the help of known nodes and their identified distances (Carotenuto, Merenda, Iero, & Della Corte, 2018). For a given 2D, the node location is found by crossing line of 3 imaginary circles. However, due to the NLOS issues in an indoor environment, the circles can not intersect at the same area resulting in massive issues in the localization. Therefore, the trilateration methods have two main problems:

- Target node is not localized in the intersection center of the imaginery circles because of inaccurate localization methods.
- The reference nodes may be co-linear referred as non-ideal case.

Various algorithms such as least or weighted least square approaches have been proposed to resolve these issues, for example in (Subhan, Hasbullah, & Ashraf, 2013), a combination of fingerprinting and trilateration technique have been utilized to overcome the first problem mentioned above. Also, in (ITRelease, 2018), they presented a least-square approach to resolve both problems.

2.3.2. Triangulation

This technique can be applied to obtain an accurate position when the angle of arrival is available and it needs two reference nodes at least. The location localization performance in this technique subject to the precision of the angle of arrival method. Additionally, depending on many reference nodes can improve the performance of the localization.

2.3.3. Fingerprinting Method

Fingerprinting is a commonly utilized indoor localization technique in several wireless access technologies such as ZigBee and Wi-Fi (Faragher & Harle, 2015; Yan et al., 2017). Wi-Fi based fingerprinting on received signal strength has shown great dominance as a promising technique. It is also widely deployed with low-cost infrastructure and ease of compatibility with multiple smart embedded devices. In comparison with the traditional Wi-Fi localization techniques such TDOA, TOA, and AOA, the Wi-Fi based locating system using received signal strength (RSS) is preferred due to its advantage of not requiring any extra infrastructure. It also shows acceptable efficiency under non-line-of-sight (NLOS) environments.

In general, fingerprint methods using RSS are classified into two stages: the offline stage and the online stage. To extract the distance information, raw RSSI signals are received through access points (APs) and then the position is estimated using these values. These access points may be from smart devices or signal transmitters. During the offline phase, a fingerprint database is established in the form of RSS vectors using the Wi-Fi APs. These reference points are then entitled radio maps. During the online stage, a real-time RSS value is measured by the router or any other smart device embedded with Wi-Fi based communication system. Both the pre-defined RSS radio maps during the offline stage and measured RSS vectors are then compared for location estimation.

Figure 1. shows the indoor positioning system based on Wi-Fi fingerprint.

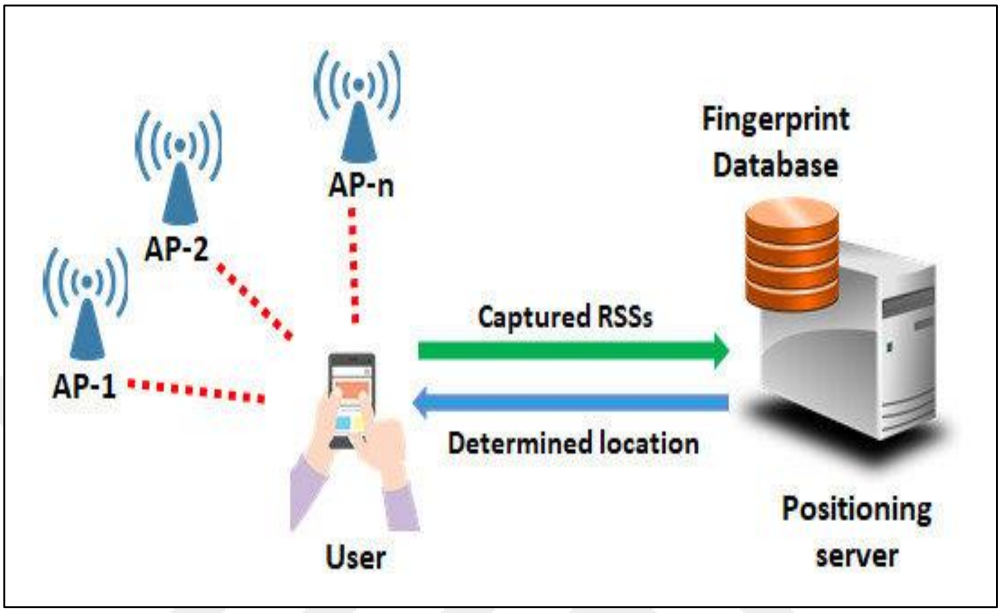


Figure 1. Illustration of Wi-Fi fingerprint-based indoor positioning system.

Even though indoor localization research is still quite active, it is clear that there are several problems to be solved. The difficulties are determined by the application's specifications for the desired levels of precision and dependability. As a result of recent technological breakthroughs, a variety of technologies have been developed to identify, locate and track resources (Guo, Li et al. 2017). One of these technologies is adopting one of the ML algorithms, which is used to help recreate radio maps and improve the accuracy of fingerprinting. For example, K-Nearest Neighbors (KNN) is applied in localization methods that employes Wi-Fi fingerprinting, where, K refers to the number of closest neighbors. In KNN, the distance between observations in the training and the observations of the target at several access points is calculated using the Euclidean distance method.

2.3.4. Centroid Method

The centroid method uses a geometric relationship to find the unknown node location rather than using angle or measurement of distance. Anchor nodes positions are decided when a reliable communication channel is setup between the unknown target and each anchor node. The center of the geometric shape is regarded as the unknown nodes location because the anchor nodes position is related to the target nodes and creates a fixed geometric shape. Several techniques have been used in the previous studies that employed the centroid approach. For example, a Bluetooth Low Energy (BLE) using Weighted Centroid Localization (WCL) for indoor positioning system has been presented in (Belmonte-Fernández, Puertas-Cabedo, Torres-Sospedra, Montoliu-Colás, & Trilles-Oliver, 2016).

2.4. INDOOR LOCALIZATION USING WIRELESS TECHNOLOGIES

This section presents the most commonly used wireless technologies for indoor localization.

2.4.1. RFID Based Indoor Location

Radio Frequency Identification (RFID) is a reliable technique against environmental conditions and can be employed in any application. However, it is an expensive technology (Hameed & Ahmed, 2018). The fingerprinting localization approach that depends on RSSI can be utilized in indoor localization applications using RFID (Ruiz, Granja, Honorato, & Rosas, 2010). LANDMARC method has been proposed by Ni et al (Ni, Liu, Lau, & Patil, 2003) where user location is found using active RFIDs. However, this technique experience tracking delay issue. Huang et al. (Huang, Lee et al. 2014) suggested another approach for real-time RFID indoor localization in which Kalman filters were employed to eliminate drifts and inside position was determined using Heron bilateration.

2.4.2. Wi-Fi

Wi-Fi is the most used technology for indoor localization due to the wide availability of Wi-Fi systems (Ali, Hur, & Park, 2019). It can cover relatively large distances however; the WLAN systems power consumption is higher (F. Liu et al., 2020). Generally, the Wi-Fi localization methods are based on fingerprinting or trilateration. ToA, AoA and RSSI techniques are employed for trilateration methods (Z. Li, Braun, & Dimitrova, 2015). CSI and RSSI are generally applied create the fingerprint map. RSSI technique is widely used as the data can be gathered from different access points without complex hardware setting (Qian, Wu, Yang, Liu, & Zhou, 2014). However, the RSSI fluctuation often lowers the performance. Several ML methods used to reduce the effect of RSS fluctuations (Calderoni, Ferrara, Franco, & Maio, 2015). For pattern matching, SVM (Sabanci, Yigit, Ustun, Toktas, & Aslan, 2018), deep learning (J. Bai, Sun, Meng, & Li, 2021) and KNN are widely used. However, to measure Channel State Information (CSI), Network Interface Cards (NICs) are needed which can add extra cost.

2.5. Wearable Indoor Localization System

Wearable devices are one of the most promising embedded system technologies in the field of medical electronics for health safety and monitoring. These devices include smart watches, hearing aid, and other medical devices. Smart watches are quite useful for indoor location detection systems, due to the fact that they can be used for communication purposes (Minoli & Occhiogrosso, 2019). These devices may include on-chip Wi-Fi, Bluetooth, or NFC systems and also embody sensors like gyroscope, compass, accelerometer, ambient light intensity and magnetometers. Therefore, this equipment is one of the leading wearable devices for indoor localization systems as illustrated in Figure 2.

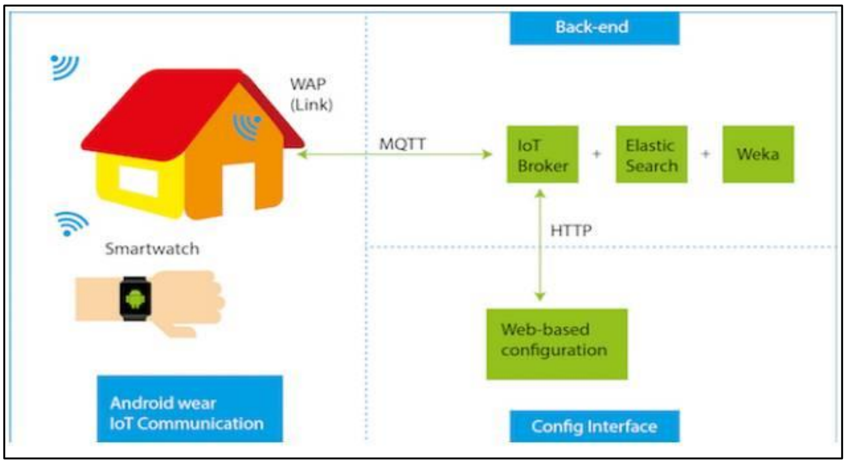


Figure 2 Smart Watch for Indoor Localization System (Agnihotri, 2021; Belmonte-Fernández, Puertas-Cabedo, Torres-Sospedra, Montoliu-Colás, & Trilles-Oliver, 2016).

2.6. ULTRA-WIDE BAND MEASUREMENT

Ultra-Wide Band (UWB) Location Measurement system has one the most growing user-based applications for sensing or positioning locations. It provides very good precision and accuracy in contrast to previously discussed technologies in this field. One of the greatest advantages of this technology is the detection range that UWB offers which is much longer than Wi-Fi or RFID based systems. The typical range for a UWB is between 1 and 10 m. Due to Ultra-High bandwidths and short-range frequency signals, the communication speeds are very high with large data transferable ranges. Instead of using the traditional RSSI measurements, UWB positioning operates on the Time of Flight (ToF) measurements. Thus, UWB signals assure better positioning and location estimations for indoor settings (Belmonte-Fernández et al., 2016; Hoang et al., 2019; ITRelease, 2020). Among many advantages, UWB is unaffected by noise and shadowing because of other communication networks and walls or human interferences. There has been a great number of research going around for the improvements of UWB positioning algorithms. These localization techniques can be arranged into five different groups according to the used techniques. A detailed list is shown below which summarizes these UWB positioning algorithms as shown in Figure 3.

1.Time of Arrival (ToA).
2.Time Difference of Arrival (TDoA)
3.Angle of Arrival (AoA)
4.Received Signal Strength (RSSI)

5.Hybrid Algorithms.

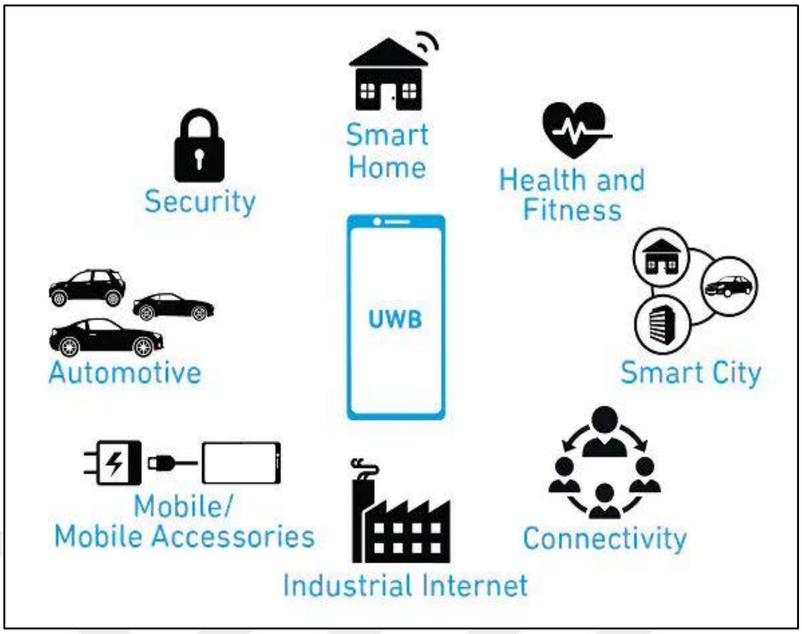


Figure 3 Application of UWB. (“ITRelease”, 2020).

2.7. IMU- BASED MEASUREMENT

The Global Positioning based measurement system is one of the most preferred systems for outdoor location identification and estimation. It provides fine accuracy and precision for finding and estimating continuous location and direction. There are a vast number of applications that uses GPS technologies from military to commercial purposes. Although it offers a wide range of applicability for outdoor environments, it rarely provides much applicability for indoor based environments due to signal shadowing. For this reason, indoor positioning posits deep research requirements. Inertial Measurement Unit (IMU) utilizes motion sensors in the daily use of electronic devices to identify and estimate the position and location. These commonly used sensors are accelerometers, gyroscopes, magnetometers etc. In today’s advancing digital world almost every human is carrying a cell phone which ensures the availability of these sensors. So far research has been around pedestrian dead-reckoning (PDR) algorithms, which are very cost-effective, have fewer power requirements, and does not require inbuilt infrastructure. Using DNN, CNNs and well-recognized filtering techniques IMU-based systems have a great future ahead.

However, this method is still insufficient due to the lack of databases and measuring devices.

2.8. INERTIAL (MOTION) BASED SENSING AND MEASUREMENT

These sensors can use electrical signals to calculate the motion, inclination and vibrational movements. IMUs have a number of applications in the field of the automotive industry to medical equipment. Micro-electromechanical systems (MEMS) inertial sensors are divided into two categories.

2.8.1. Accelerometer

An accelerometer is a type of inertial measurement sensor used for the detection of motion. It does this by measuring linear acceleration in the back and forth direction. It is made up of MEMS-based sensing elements. Based on the measurement range, accelerometers are further classified into two categories as shown in Figure 4.

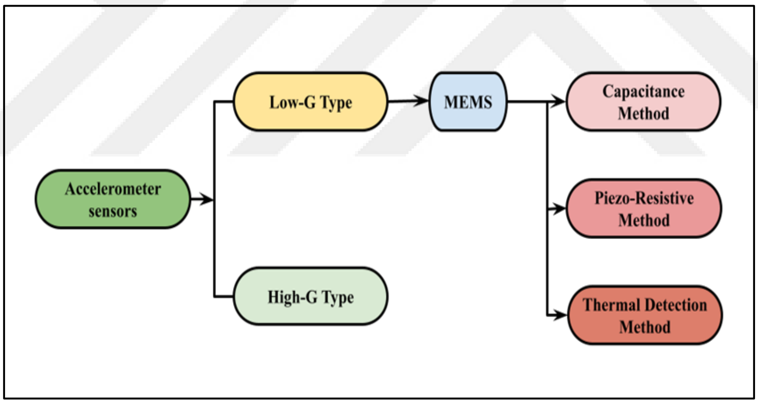


Figure 4 A Classification of accelerometer sensor.

1. Piezoresistive Accelerometers

A piezoresistor is attached using a proof mass in this type of accelerometer. An electronic circuit is also connected through this resistor. A change in the resistor assures that there is movement in the proof mass, therefore the resistance of the piezoresistor is changed according to the applied force. The biggest disadvantage of using these accelerometers is their thermal steadiness. For this reason, the peizoresistance can ominously change and may lead to false as shown in figure 5.

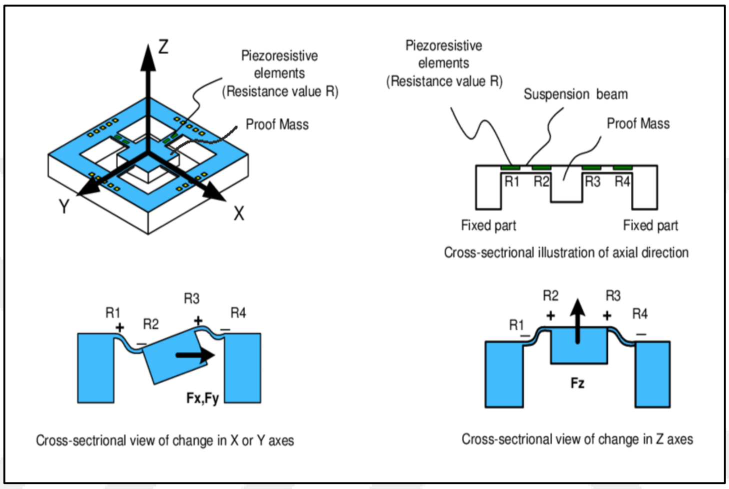


Figure 5 Piezoresistive Accelerometer (Agnihotri, 2021).

2. Capacitive Accelerometers

In capacitive accelerometers, a flexible plate is used in between two sensing electrodes. In this case, the proof mass utilizes the capacitive sense fingers which adjust along an axis when there is a displacement of the proof mass. During the displacement process, the proof mass moves in the opposite direction of the change, whereas the flexible plate moves in the direction of the proof mass. This causes the capacitance to change along with the electrode plates. To measure this change as an electrical signal output, read-out electronics are used. In contrast to piezoresistive accelerometers, this type of resistor is thermally stable. Their drawback is that they are prone to electromagnetic interference which is due to parasitic as shown in figure 6.

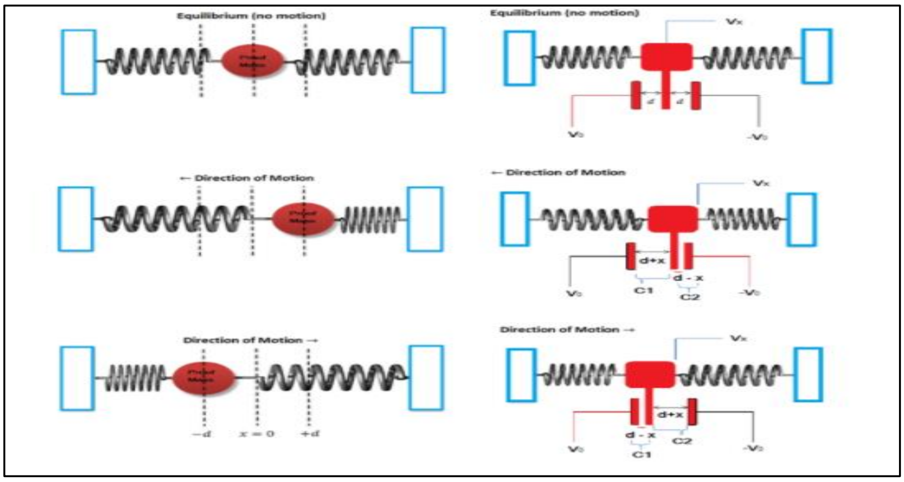


Figure 6 Capacitive Accelerometer (Agnihotri, 2021).

3. Piezoelectric Accelerometers

Like macroscopic accelerometers, microscopic accelerometers also utilize the principle of detection of motion using proof mass. A proof mass is a piezoelectric material used for the detection of motion. One of the main drawbacks of this accelerometer is the leakage current, due to which it has very poor resonant frequencies. The piezoelectric material is consistent in producing proportional electric signals against measured displacement of the proof mass as shown in figure 7.

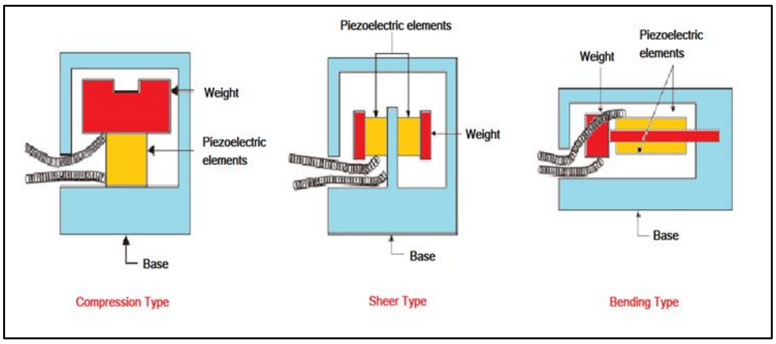


Figure 7 Piezoelectric Accelerometer (Agnihotri, 2021).

4. Resonant Accelerometers

A resonant accelerometer is used to detect displacement in the resonant frequency by using a proof mass, which is attached to a resonator. A frequency counter circuit is also used in such accelerometers to convert frequency signals into digital electrical signals. These accelerometers are also resistant to noise and are quite reliable due to their working principle as shown in 8.

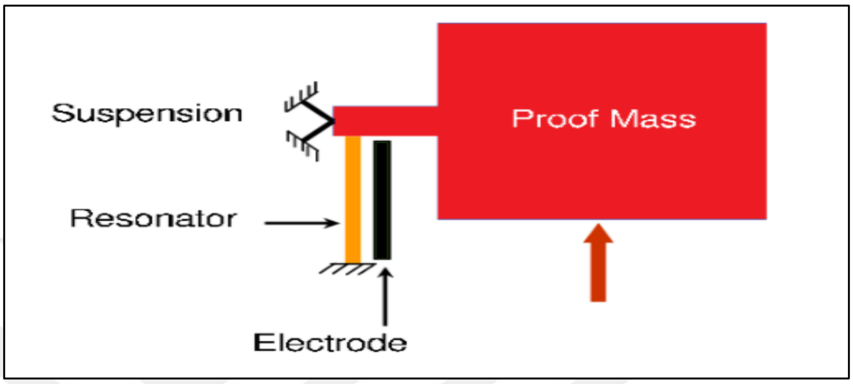


Figure 8 Resonant Accelerometer (Agnihotri, 2021).

2.8.2. Gyroscope

A gyroscope is used to determine and measure the level of an object. The MEMS gyroscopes use the methodology of Coriolis force. It is a force which is perpendicular to the axis of rotation of mass moving in the direction of motion.

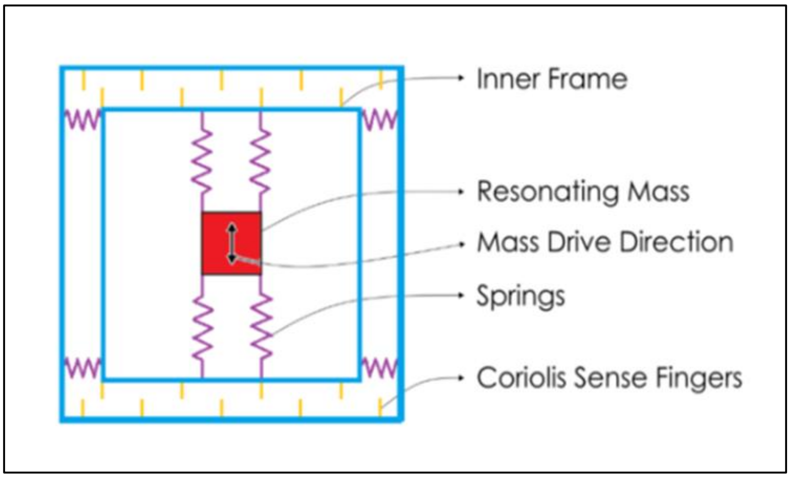


Figure 9 Gyroscope (Agnihotri, 2021).

2.8.2.1. Mechanical gyroscope

It is a type of MEMS gyroscope which consists of a mechanical structure. Pairs of springs are used to interconnect the resonance mass structure (mass proof) to the inner frame of the structure as shown in figure 9. They also encapsulate the capacitive sense fingers inside the inner frames. They are used to sense angular velocity and angular orientation.

2.9. IMAGE-BASED MEASUREMENT SYSTEM

With the widely used number of mobile phones and security cameras, the prospects of using image-based indoor localization are very bright (Pham, Yang, & Sheng, 2018). This technology can easily avoid the difficulties faced by other wireless communication-based methods. It not only provides the output in 3 point positioning but also collects and estimates the 3 point angle positioning. (Xu, Ahn, Shmaliy, Chen, & Li, 2018; Zhang, Hu, Chen, & Zeng, 2019) shows that image-based methods are growing popular in indoor positioning technology. Due to the advent of technologies such as unmanned armed vehicles, indoor service robots, and augmented reality, vision-based techniques are now matured and widely being utilized. Also, the rise in AI, ML, cloud computing and the availability of big data has given a boost inapplicability of vision-related technologies in the field of indoor localization.

A simple RGB camera is used to detect the image information and the depth of the image. Multiple kinds of research have been done so far in this regard and there are ample amount of research papers focused on using deep learning methods to extract maximum possible feature recognition and position estimation. (H. Liu et al., 2007) proposed image-based positioning using a portable camera with a computer. They utilized hue histogram-based image features. Later scale-invariant feature transform (SIFT) and speeded up robust features (SURF) based matching systems were developed (Boltes, Adrian, & Raytarowski, 2021; He & Chan, 2015). However, these techniques are not time efficient. Figure 10. explains the flow chart for model tanning and pose solving

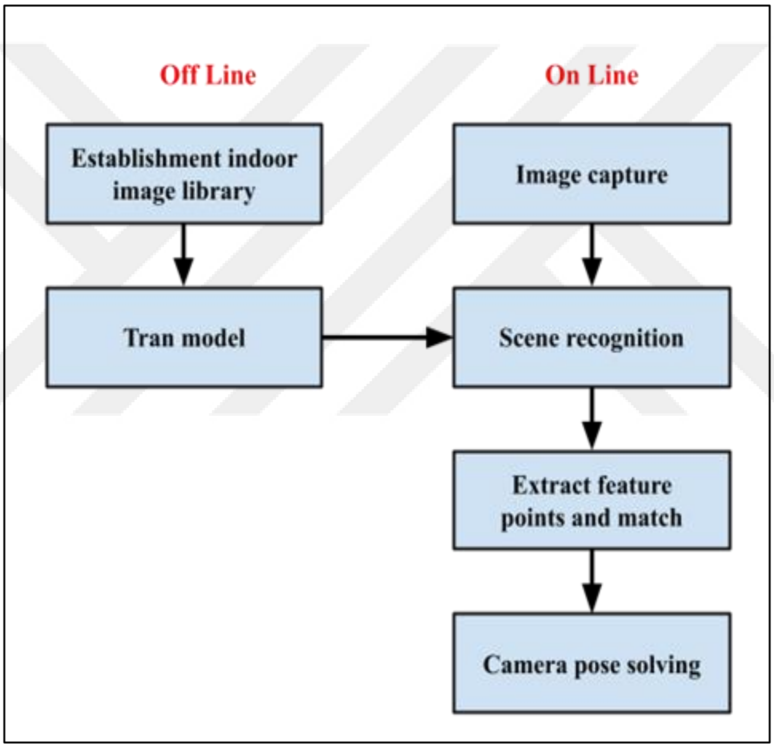


Figure 10 Flow chart for model tanning and pose solving (S. Li et al., 2021).

2.10. MACHUNE LEARNING FOR INDOOR LOCALIZATION

Machine learning algorithms can overcome the problems in the traditional techniques for localization in indoor environments. Traditional localization methods cannot perform effectively in large areas such as airports or shopping centers. Additionally, localization methods are not adaptable to changing environments and heterogeneous sources of data. The ML algorithms offer the advantage of learning useful features from input data, for example, deep learning models can effectively investigate the RSSI time series calculations and apply the path information to reduce fluctuations of RSSI (Poulose & Han, 2019). The presence of high dimensional data is one of the limiting factors for fingerprinting localization method. Dimensionality reduction methods such as principal components analysis (PCA) and dimension reduction based on Gaussian (Salamah, Tamazin, Sharkas, & Khedr, 2016) can be applied to switch the high dimensionality data to a less complex dimension to reduce computational and storage requirements of fingerprinting-based localization.

Classification algorithms are primarily applied to learn core features from the signal. Feature extraction using ML algorithms is also important for indoor localization using non-line-of sight. Practically, in fingerprint-based localization, a large amount of data describing the fingerprint map is collected in the offline phase. Therefore, it is time-consuming to estimate the online data with the fingerprint map data points. Hence, the offline data is divided into groups and only the data in the required node is experimented with the data of the identical group. Additionally, it is crucial in fingerprint-based localization that the extracted features from each reference point to be different from other references. However, not all the extracted features are useful for the ML as they can contain random or repeated information. In this case, it is important to use dimensionality reduction techniques to result the ML model’s complexity and shorten training time.

2.10.1. SUPERVISED LEARNING

Supervised learning is a machine learning technique used to classify or predict data using labelled information. As the name goes in this type of method a model learns by training data points. Thus, this learning algorithm model learns from trained data and helps to predict the outcome of unanticipated data. It requires highly skilled data scientists or engineers to build and deploy highly accurate machine learning models to make sure the models are well suited. In supervised learning both the inputs and outputs are provided to the machine-learning model for optimization. The main objective of such an algorithm is to map optimized outputs against inputs. There are an abundant number of uses of supervised ML, some of them are,

a. Risk Assessment

b. Image Classification

c. Fraud Detection

d. Spam Filtering

The working principle of supervised learning is very simple. The first step as discussed above is to train the data using past experienced data. After the training process, the model is tested using the generated test data and then it predicts the output. An exemplary supervised ML model is shown in figure 11. (javatpoint, 2020).

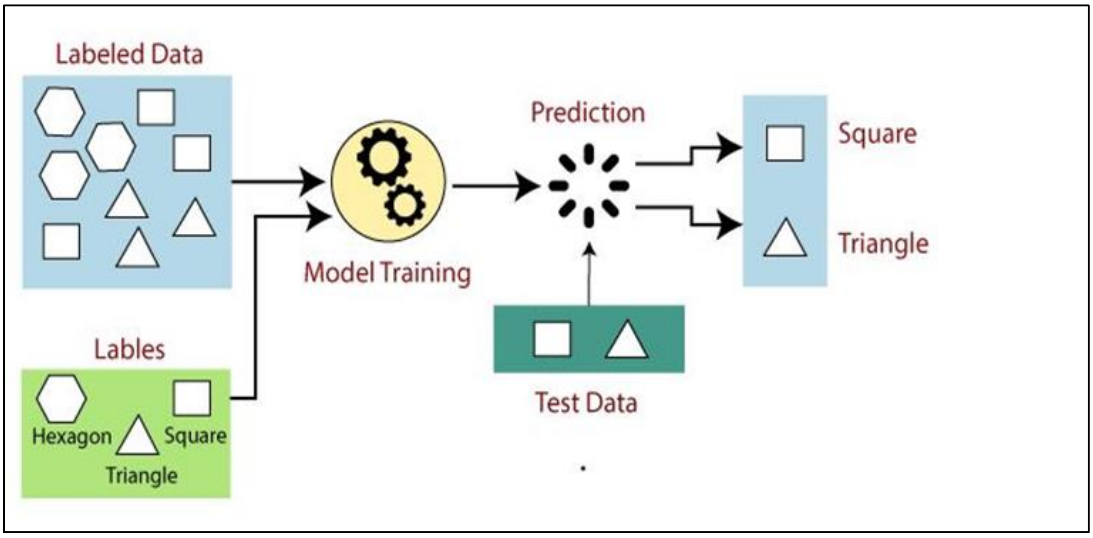


Figure 11 Supervised learning Algorithm (javatpoint, 2020).

2.10.2. Types of supervised Machine learning Algorithms

Supervised machine learning can be further divided into two categories based on the type of problems the algorithm has to deal with.

2.10.2.1. Classification

This includes problem solving algorithms that are categorical in nature, meaning they only have Yes or No outputs. These are used in real-world scenarios, such as distinguishing different types of objects or detecting such as classifying spam in emails. There are various classification techniques which might include:

1. Linear classifiers.
2. Support vector machines.
3. Decision trees.
4. Random forest.
5. Naive Bayes Classifier.
6. Logistic Regression.

2.10.2.1.1 Support vector machines (SVM)

Object or human tracking using visual tracking technologies are becoming the hotspot for indoor positioning purposes. With the availability of Wi-Fi networks, the number of wearable devices and smartphones are increasing rapidly for indoor environments. Therefore, the prospects of using fingerprint-based method for indoor positioning has increased. Support vector machine is an efficient machine learning algorithms used for classification and regression purposes (N. Bai et al., 2020; Lu, Uchiyama, Thomas, Shimada, & Taniguchi, 2019), (Battiti et. Al) proposed the use of SVM by comparing it to statistical learning approach. In (J. Bai et al., 2021) used SVM during online phase of RSS measuring to reduce the reliance on access points, thus achieved better accuracy with the availability of multiple APs. The study done by (J. Bai et al., 2021) proposed the use of SVM for wireless sensor positioning and estimation. Additionally, (J. Bai et al., 2021) implemented mass-spring optimization to improve location estimation. In (Le, Meratnia, & Havinga, 2018) presented his analysis on hierarchical SVMs and calculated the average error and variance for achieving accurate positioning. (Deng, Xu, & Ma, 2012) explored position estimation using support vector regression models on GSM based communication. Using SVR with kernels, both theoretical and experimental analysis for location detection and estimation are provided. It was proven to be a better approach in the case of variations in external environmental factors. However, this technique was not specified for Wi-Fi based indoor localization aim.

(Deng et al., 2012) clustered RSS radio maps into multiple series of radio maps using k-means clustering (KNN). KNN is another type of supervised learning algorithm technique that is used to predict continuous data by using the relationship between dependent and independent variables. It is mostly used for weather forecasting and to predict market trends.

Some popular regression algorithms are

1. Linear Regression.
2. Regression Trees.
3. Non-Linear Regression.
4. Bayesian Linear Regression.
5. Polynomial Regression.

2.10.3. Unsupervised Learning Algorithms

Unsupervised learning is commonly used to solve the problems associated in the case of missing and incomplete datasets. The aim of this algorithm is to find common patterns and generate predictions output accordingly. In unsupervised learning, data is provided to the machine. The main task of the trained machine is to find hidden features. Finally, the machine is responsible to cluster the data for understanding the predicted outcomes. The need for this type of machine learning algorithm has increased as unsupervised learning which can’t be directly used for classification or regression problems. There are no inputs and outputs which fed to the ML model, therefore the key objective is to find patterns and group the data accordingly.

2.10.4. Types of Unsupervised Learning

Unsupervised algorithms are divided into two categories which are clustering and association based on the type of problems the algorithm has to deal with.

2.10.4.1. Clustering Method

As an unsupervised learning method, Clustering is a technique used to find patterns or structures from uncategorized data. The main task of these algorithms is to find structures or patterns and group them depending on differences or similarities. One of the most important aspects of clustering is to modify the model according to the need which gives the user a huge advantage.

Table 1 Advantages and Disadvantages of Unsupervised learning.

NO.	Advantages of Unsupervised learning	Disadvantages of Unsupervised learning
1	Used to deal with complexity	Higher Difficulty
2	Used for Unlabbled data	Requires Expertise
3	Does not need inputs or outputs	Requires more training
4	Vast Applications	Less accurate

2.10.4.2. Association Method

The association method is used for discovering the associations between features in an unlabelled large database. Based on this, this method finds the set of features that occurs frequently in the dataset.

2.10.5. Types of Unsupervised Learning algorithms

1. K-means clustering.
2. KNN (k-nearest neighbors).
3. Hierarchal clustering.
4. Anomaly detection.
5. Neural Networks.
6. Singular value decomposition.

2.10.5.1. K-Means Clustering Algorithm

It is a type of unsupervised ML algorithm utilized to deal with clustering problems. This type of algorithm is used to group unlabeled data into different clusters. From its name, “K” suggests the number of clusters that are required to be predefined. If K=1, it will create only one cluster and if K=N, it will create N number of clusters. In grouping unlabeled or scattered data, it is of utmost importance to identify the data set without external training. Thus, a centroid based algorithm is designed in order to minimize the loss that can happen due to the difference in distances between data points. It defines a cluster according to the commonalities and differences between the data points as shown in Figure 12. (Kumar, 2017).

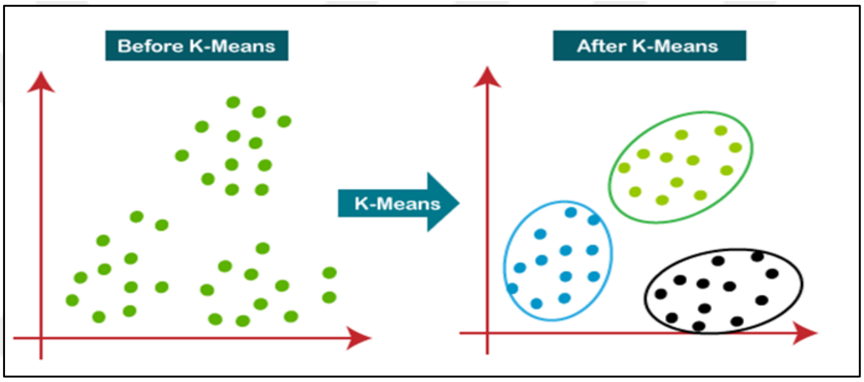


Figure 12 K- Means algorithm (Kumar, 2017).

2.10.5.2. K-Nearest Neighbor (KNN) Algorithm

Unlike K-Means, KNN is a supervised learning algorithm methodology based on a classification mechanism. It is also used to identify and cluster new data using old clustered data based on similarities and differences as shown in Figure 13. Thus, it overcomes the drawback of K-means algorithms. This type of algorithm can be utilized for both classification and regression problems, therefore it provides a lot of advantages for machine learning-based applications. It is also known as a non-parametric algorithm, due to the fact that it doesn’t assume data on its own. During the training time, data is only stored and then compared with new data at the run time. After this, it categorizes the new data based on old data by training the algorithm to be better and better each time ahead. The KNN algorithm uses a method called Euclidean distance (Kumar, 2017).

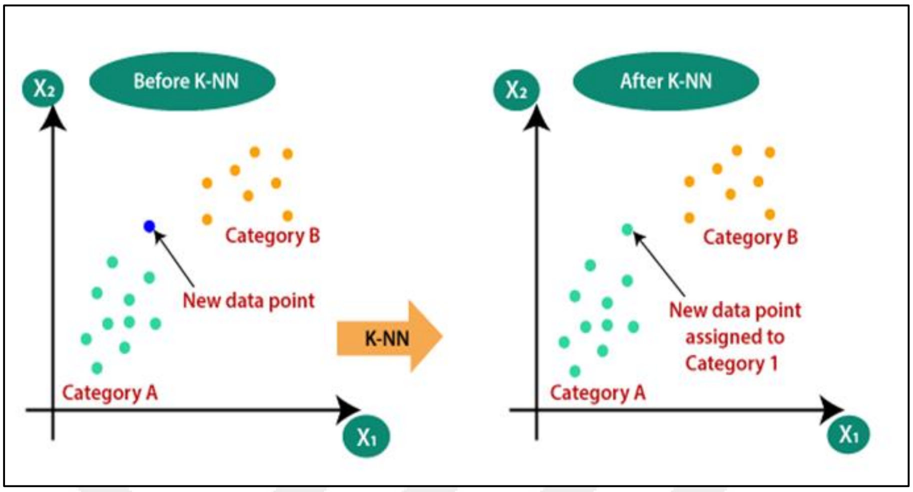


Figure 13 KNN algorithm (Kumar, 2017).

2.10.5.3. NEURAL NETWORKS

2.10.5.3.1. Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) as shown ın Fıgure 14. are classically Feed-Forward Networks (FFNNs) which means data only flows in one direction that is, from the input layer to the output layer. The links between them do not touch the same node it leaves. However, in contrast to a simple neural network, there are more convolutions or hidden layers, which increases the complexity. Therefore, in-depth knowledge of input and output data parameters is required to completely understand and train the model. The model must be able to process loads of information to predict the output data. More hidden layers in a model means greater complexity. DNNs have a very important role in today's automated society. DNNs are used in a wide area of applications these days (Kumar, 2017).

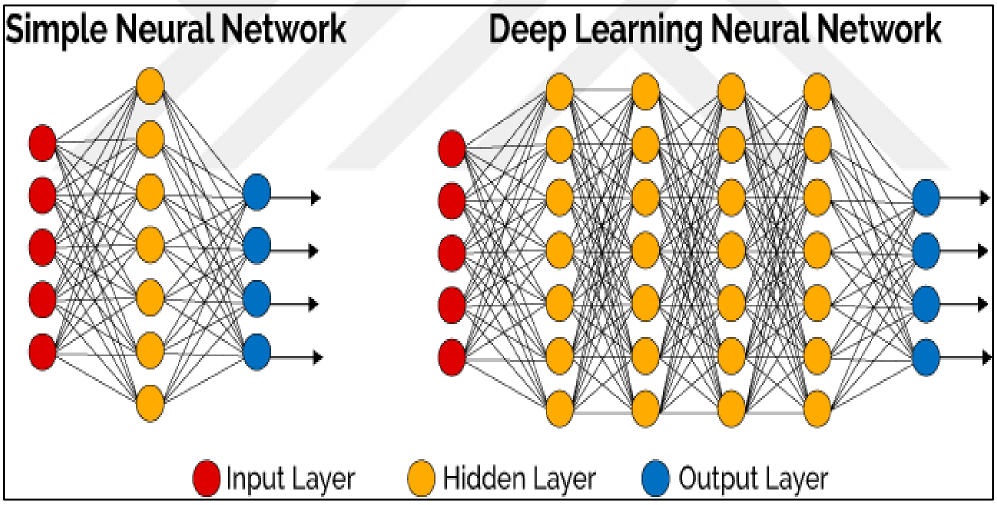


Figure 14 Model for (Kumar, 2017).

2.10.5.3.2. Recurrent Neural Network (RNN)

A recurrent NN (RNN) uses Feed forwarding and also feedback loops through its nodes. This allows data to flow back and relearn new information as shown in Figure 15. This requires a sophisticated level of understanding of each layer and sequencing. In RNN the inputs and outputs both are in time series. The complexity level of RNNs is very high, thus they are very time-consuming and expensive to train. They are very helpful when data is in sequential forms, such as DNA sequence and financial sequential data. In a feed-forward type of NN, there is no memory as the output layer only relies on the previous node. In contrast to that, in RNN due to self-loops and feedback loops, the output can learn from previous values as well predicted values. This is possible because of long term and short term memories in the RNN model (SHARMA, 2019).

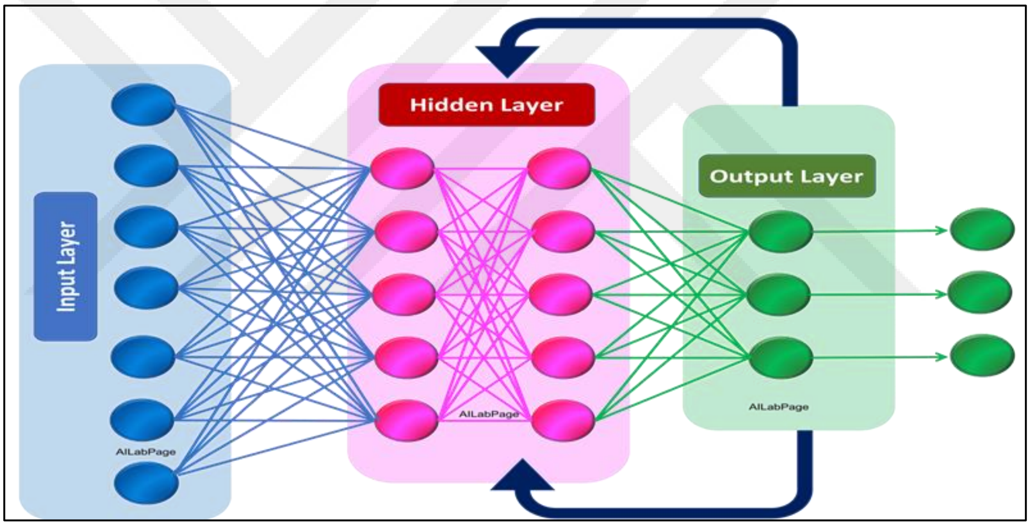


Figure 15 Model for RNN (SHARMA, 2019).

CHAPTER THREE

HARDWARE IMPLEMNTATION

Following the explanation of all of the electronic components utilized in the project, these elements were gathered and used to design and build the project's final system. The aim of the proposed system is to provide users with their current position through an indoor tracking system that depends on Wi-Fi signals.

3.1. Hardware Design

3.1.1. NODE MCU ESP8266 MİCROCONTROLLER:

The Node MicroController Unit (NodeMCU) is based on the ESP8266 and it is available as an open source development environment. The Espressif Systems ESP8266 delivers essential functionalities of a computer, including a Central Processing Unit (CPU), Random Zccess Memory (RAM), WiFi, and an operating system and software Development Kits (SDK). Therefore, it is widely used in low cost hardware applications.

With the all-around availability of Wi-Fi, 5G, and 6G networks, the IoT-based smart embedded devices are considered to be the future of automation. Internet of things is a name given to any kind of a system that integrates processors, sensors, actuators, and other computing devices all together through a network for the process of control and automation. It does this by transferring data over the network without any human intervention. The sensor is used to transform analog signal inputs and feed them to the microcontroller. The microcontroller then processes this information and gives commands to the actuators in the form of electric signal outputs to control the change in the environment. A good quality development board with proper prototyping and firmware is a must for an optimized and reliable system. Espressif systems have created an ESP8266 microcontroller board with on-chip Wi-Fi capabilities for such a purpose, as illustrated in Figure 16. This model is specifically designed for automation and control-based small and medium-scale projects. Using this module one can monitor and control things with a simple user interface from anywhere in the world (components101, 2020)

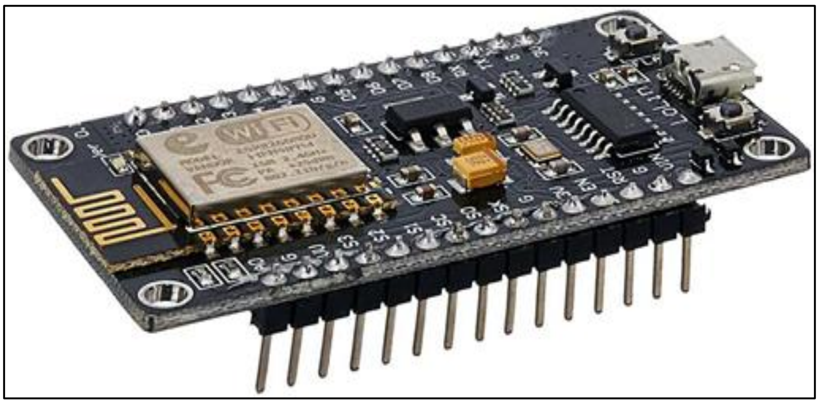


Figure 16 Node MCU ESP 8266 (“components101”, 2020).

3.1.2. ESP-12E Module

The ESP-12E is a tiny Wi-Fi chip used to setup a wireless network connection for a microcontroller or processor. The ESP-12E is based on the ESP8266EX, a high-integration wireless System on Chip (SoC).

ESP-12E Module is the microprocessor module having 32- a bit RISC LX106 microprocessor chip made by Tensilica Xtensa. It is specifically designed for small projects. The working clock frequency ranges between 80 to 160 MHz. It also contains antenna with 2.4GHz ESP-12 Chip (“components101”, 2020) as shown in Figure 17.

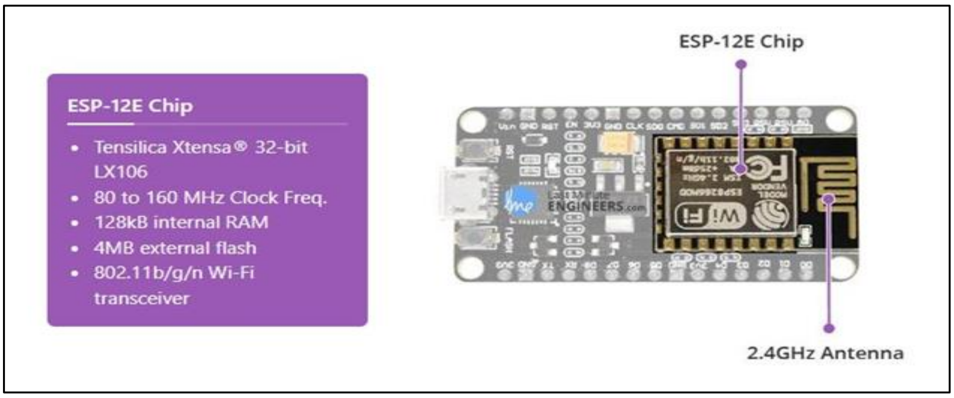


Figure 17. ESP-12E Chip (“components101”, 2020).

3.1.3. NodMCU Power Requirements

NodeMCU runs on 5V and 3.3V. There is already a Linear and low-dropout (LDO) voltage regulator for 3.3V to keep the voltage constant. The NodeMCU is fueled through a Micro USB jack and a VIN pin (External Supply Pin). The power requirements for the NodeMCU ESP8266 development board are shown in Figure 18.

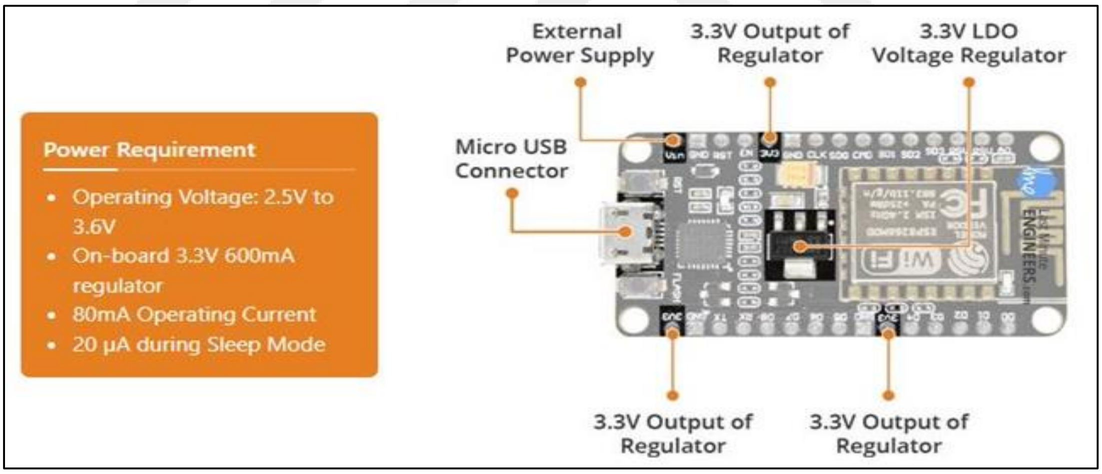


Figure 18 NodeMCU ESP 8266 Power Requirements (“components101”, 2020).

3.1.4. Serial Communication

CP2102 USB-to-UART Bridge Controller shown in Figure 19 is used to convert USB signal to serial signal with flow control capabilities between the computer and the microcontroller for programming.

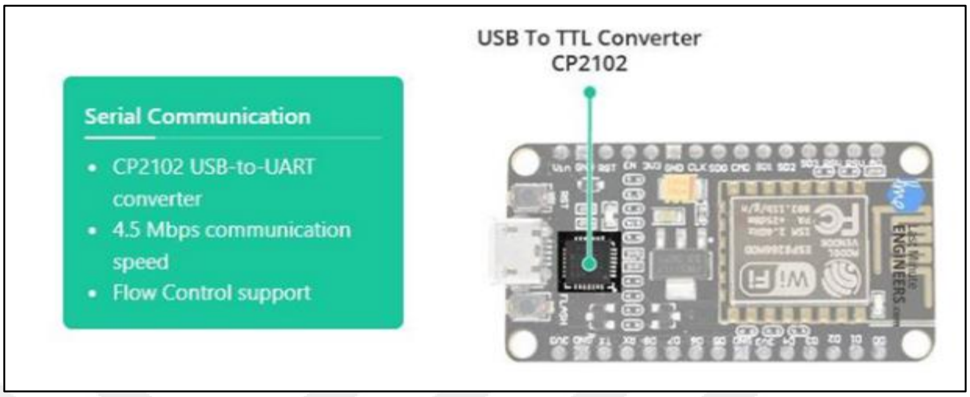


Figure 19. Node MCU ESP 8266 Serial Com(“components101”, 2020).

3.1.5. Node MCU ESP 8266 Pinout Diagram

The PINOUT diagram shows that this module includes all the required components for a reliable and efficient process. It comprises 30 pins in total. There are two 12C pins “SCL” and “SDA” for interfacing sensors. It supports up to 100 KHz clock frequency. 17 GPIO pins are also there and assure multifunctional purpose. GPU interrupts can be generated by edge or level-triggering. A 10-bit ADC is embedded in this module, which is used for testing voltage for power supply and input voltage of TOUT pin. Two UART interfaces are also supported for asynchronous communication. The Secure Digital Input Output (SDIO) interface ports (“components101”, 2020). includes many interfaces components like Pulse Width Modulation (PWM) interface, Serial Port Interface (SPI) interface Shown in detail in Figure 20.

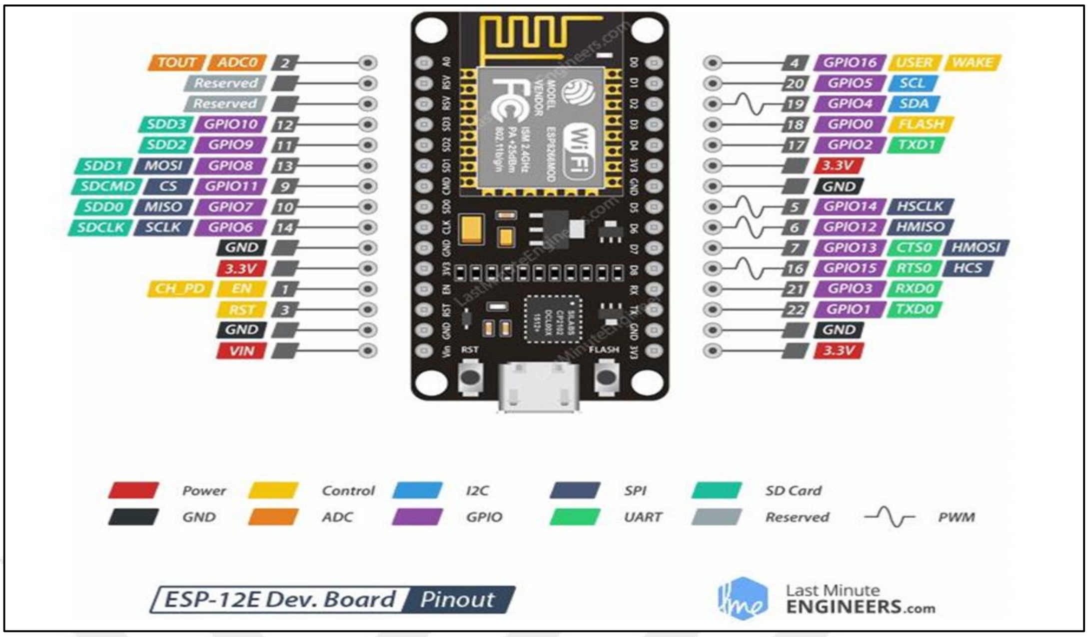


Figure 20 Node MCU ESP 8266 Pinout Diagram (LastMinuteEngineers.com, 2022) .

3.1.6. MICRO USB CHARGER MODULE

A MICRO USB CHARGER has a built-in Micro USB 5V 1A CHARGER as shown in Figure 21. It is a small size MODULE that is used in the project for charging and protection TP4056 Lithium Battery with 5V input voltage (components101, 2020) (LastMinuteEngineers.com, 2022).

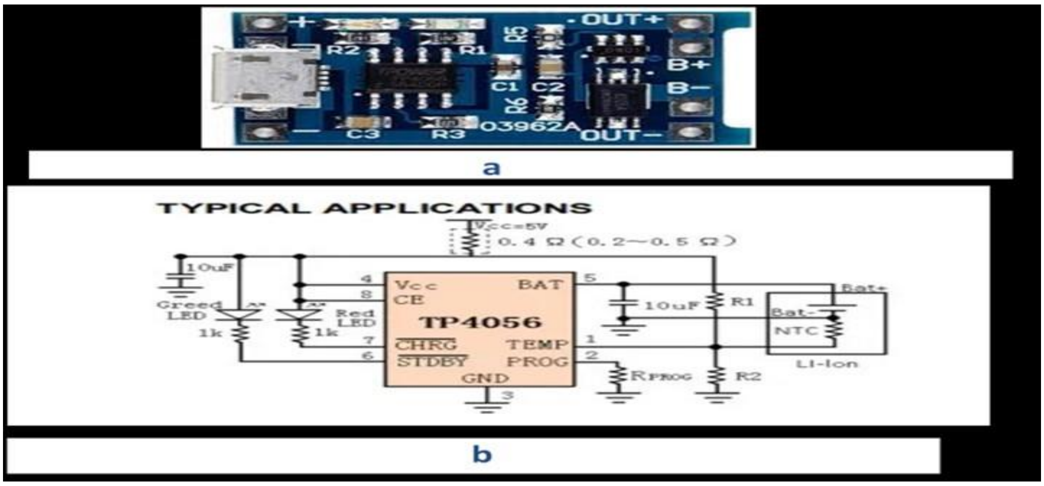


Figure 21 Micro USB Charger Module a) The hardware module and b)) Schematic diagram (Quispe Coaquira. Condori Yucra, Beltran Castanón.& Negrão Macedo. 20216.

3.1.7. POLYMER LITHIUM-ION BATTERY

The polymer lithium-ion battery shown in Figure 22. is used in each portable system with a small size and two cells connected in series, each cell voltage is of 3.7 Volts with quick charge speeds and the BATTERY has a minimum voltage protection circuit is built-in as a suitable choice to power the system equipment. These batteries are used to ensure the prepared power for system design during operation and to make the system portable and stable.

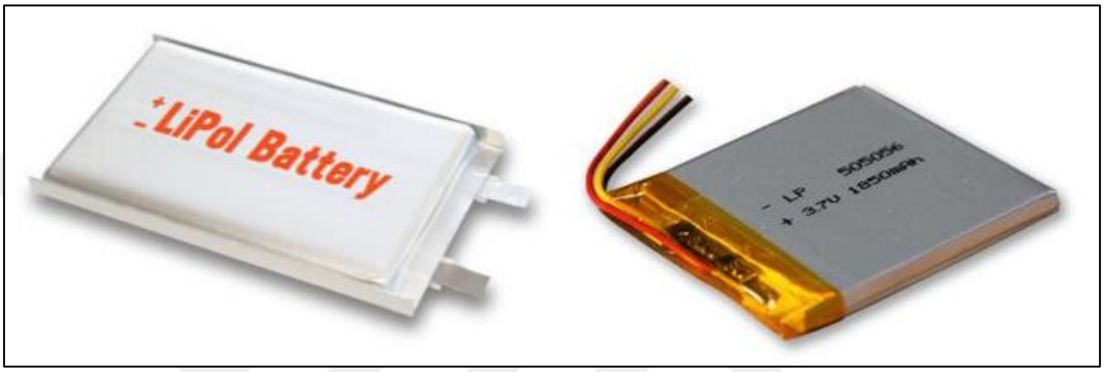


Figure 22 Polymer Lithium Ion Battery.

3.1.8. OLED 128*64 DISPLAY

A single display unit as shown in Figure 23 used in the central system is designed to display any text or data information. Herein, it is used to show the identification number of the portable Wi-Fi device connected to the designed system ("components101", 2020)

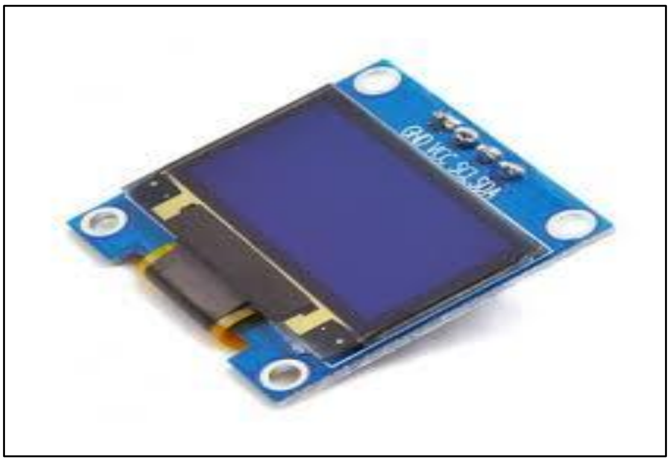


Figure 21 OLED 128*64 Display ("components101", 2020).

3.1.9. HC-05 BLUETOOTH MODULE

A single BLUETOOTH model as shown in Figure 24. is used in each mobile system designed to send data such as the location of the mobile device to the host system. The BLUETOOTH module is connected to the nodeMCU through the serial port.

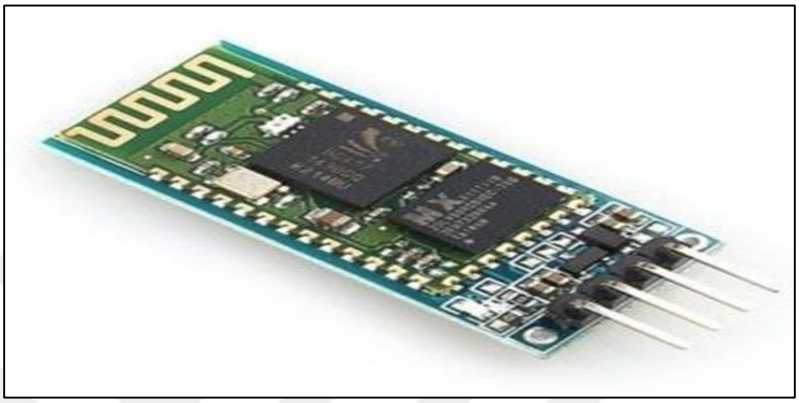


Figure 24 HC-05 Bluetooth Module (Mnati, Van den Bossche, & Chisab, 2017).

3.2. SYSTEM HARDWARE SETUP

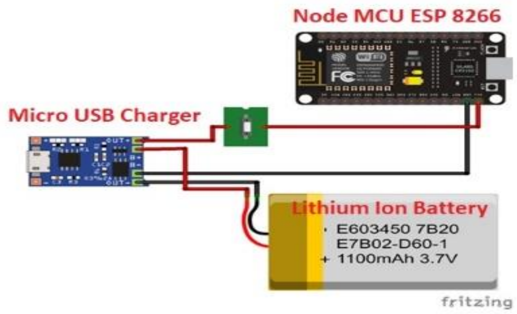
To build the hardware circuits with a large library of electrical circuit elements, it needs to preemploy suitable electrical software like LTSPICE, PROTEUS, MULTISIM. All electronic circuits were simulating and drawing by using Fritzing software. Fritzing is an open-source project which is compatable with Arduino microcontroller that aims to provide the users CAD software for the design of electrical hardware in order to assist designers and artists who are ready to go beyond prototyping to making a more permanent circuit. Fritzing is free software licensed under the GPL 3.0 or later, with the source code accessible for free on GitHub and the binaries offered for a fee, as permitted by the GPL(fritzing.org, 2020).

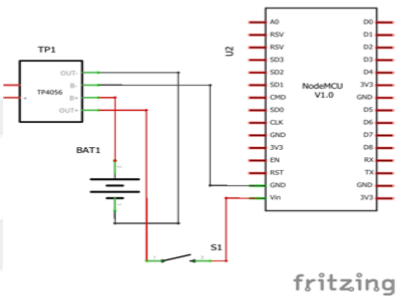
The proposed tracking system contains two peers which are Wi-Fi station Node and Tracking Node, as follows:

3.2.1. The electronic circuit for Wi-Fi station Node

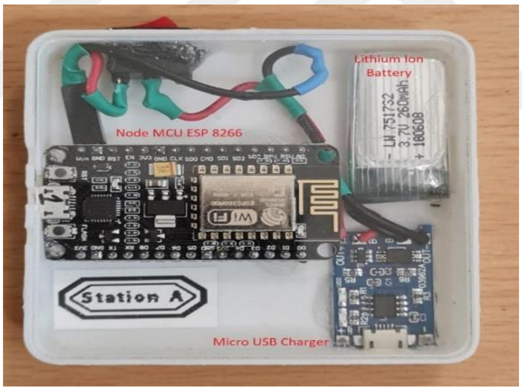
Figure 25.a and 25.b present the block diagram of the Wi-Fi node and the schematic diagram, while the final hardware circuit of the Wi-Fi station is shown in

Figure 25.c The core of this circuit is the TP4056, it is a single cell lithium-ion battery constant-current/constant-voltage linear charger. The TP4056 is appropriate for portable applications because to its SOP packaging and minimal external component count. Furthermore, the TP4056 is compatible with USB and wall adapters. Because of the internal PMOSFET design, no blocking diode is needed, and the circuit prevents negative charge current. The TP4056 is a single-cell constant-current/constant-voltage linear charger.





a b

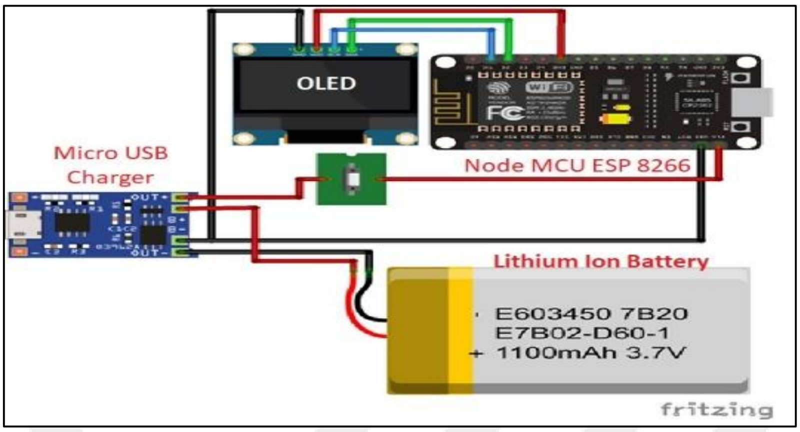


c

Figure 22 Wi-Fi station Node: a) Block Diagram b) Schematic diagram.

3.2.2. The electronic circuit for Tracking point without Bluetooth

The circuit in Figure 26. is used to check the location inside the building. Figure 26.a present the block diagram of the Wi-Fi end station for tracking, the schematic diagram is presented in the Figure 26.b and the final hardware circuit is shown in Figure 26.c. This circuit represnets a local node unit, it needs to use OLED to display the current location. After that, adding transceiver unit which is the Bluetooth in next section is necessary.



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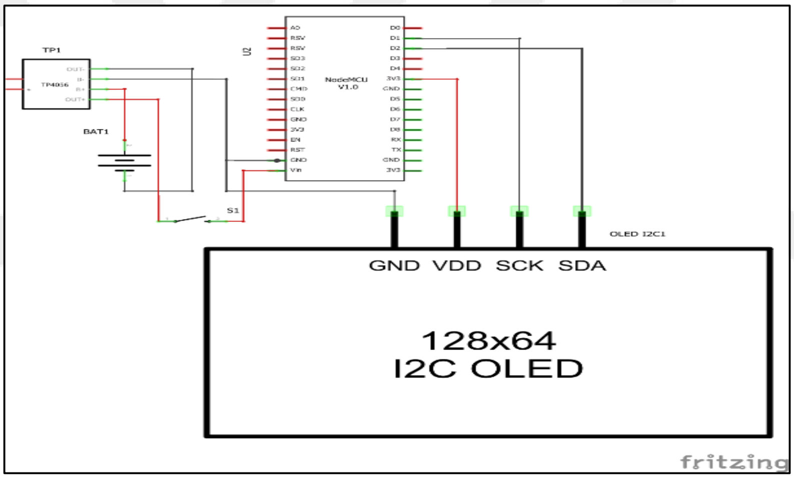


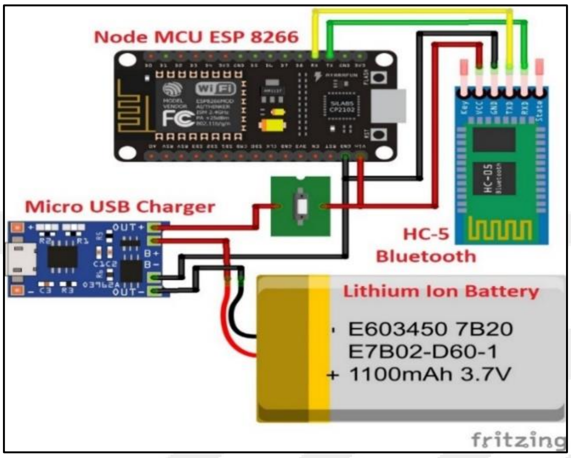
b

c

Figure 26 Tracking Node without Bluetooth.

3.2.3. The electronic circuit for tracking point with Bluetooth

Figure 27. present the circuit used for tracking the location inside the building. Figure 27.a presents the block diagram of the Wi-Fi end station that is used for tracking and send the room identification to the main station by using HC-05 Bluetooth module, the schematic diagram is presented in the Figure 27b and the final hardware circuit is shown in Figure 27c.



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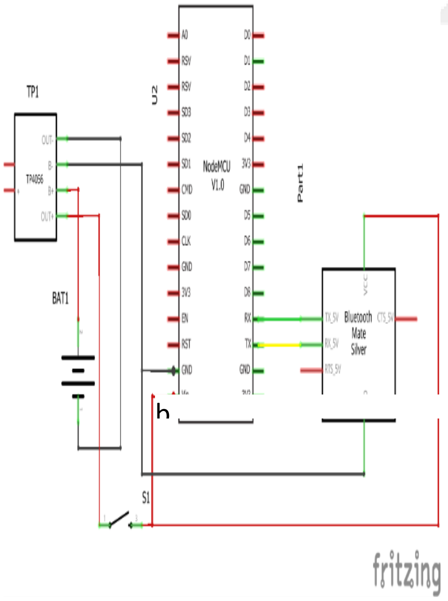


b

Figure 27 Tracking Node with Bluetooth a) Block Diagram, b) Schematic diagram and c) Final hardware system board.

3.2.4. The monitoring station circuit

The main station for monitoring circuit is presented in Figure 28. Figure 28.a illustrates the block diagram of the node with Bluetooth and OLED, the schematic diagram is presented in the Figure 28.b and the final hardware circuit is shown in Fig 28.c. The Bluetooth is used to receive the signals from the real tracking units to display the current status after classifing and taking correct decision.

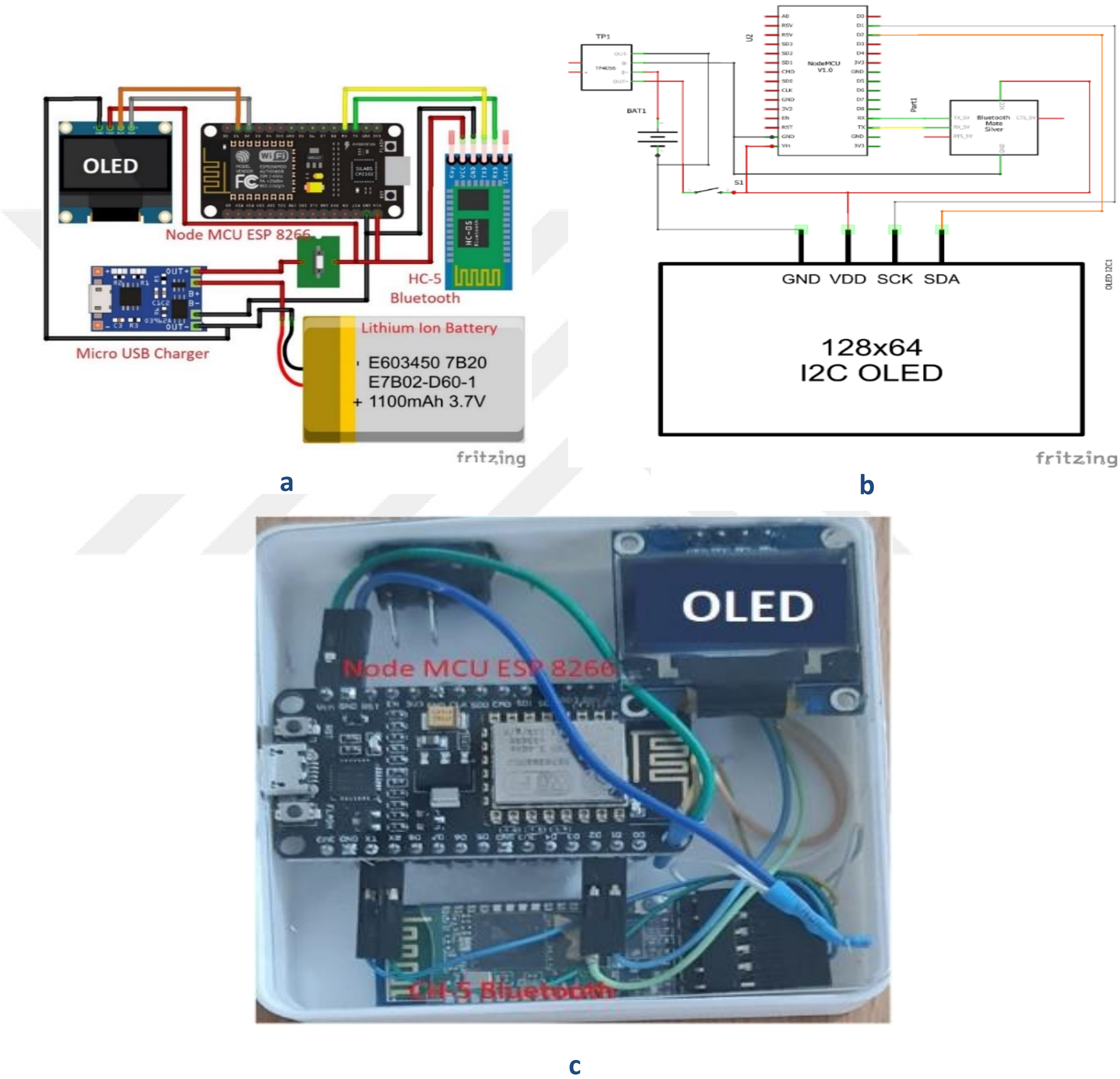


Figure 28 Monitoring station: a) Block Diagram, b) Schematic diagram and c) Final hardware system board.

CHAPTER FOUR

WORKFLOW AND RESULTS

4.1. Introduction

In order to achive the main purpose from the system which is let the people to get the required location using an interior tracking system that relies on Wi-Fi signals, the explanation of programming and the work flow for this project are developed in this chapter. In addition to displaying practical results and calculating the efficiency of the system. Following the explanation of all of the classification techniques and their programming that are used in the project. The software training model and machine learning were programmed using Python language.

4.2 ANALYSIS OF USED TECHNIQUES

The work process is often divided into three stages: collecting data, training the model, and using the model which gets supplied input and gives predictions about location accordingly. The ESP8266 is a low-cost micro-processing chip that contains a micro-controller and NodeMCU, but it is not competent enough to run such a systematic model to predict the locations or to get trained to understand. So, the python way of coding got utilized to program the model through PC to make ESP8266 competent enough for structuring an Indoor positioning system. As ESP8266 unable to process the indoor positioning system programming and python, the model may be classified as a port model because some requirements were loaded in it from outside sources to make it functional in IPS.

The second step of the proposed technique is training the model, which needs to process the gathering data. Data here including the powers and the coordinates that were collected from several positions within a specific area. The data depends upon the signal strength of the MCUs that works as Wi-Fi routers where each MCU represents a node. This project uses many nodes or Wi-Fi routers at several positions in the whole specified area to be identified by setting up each Wi-Fi router set to each location. ESP8266 divides the building structure into many imaginary points, where each zone belongs to a preset specific location. When the model stands at any of those points, it predicts the position according to the exact point it stands on the LCD installed at breadboard. The model utilized the Bluetooth technique with high power and acceptable range to transmit all data outside the building to be able to monitor the targets like people or moving subjects inside the building from outside.

4.3 The System Work Flow

The flowchart in Figure 29 represents the program for each Wi-Fi node. This program works after turn switch ON, the devices continue to send the data that including (2D-coordinate, available RSSI for the working units) and will not stop until the device switch is remotely or manully turned OFF.

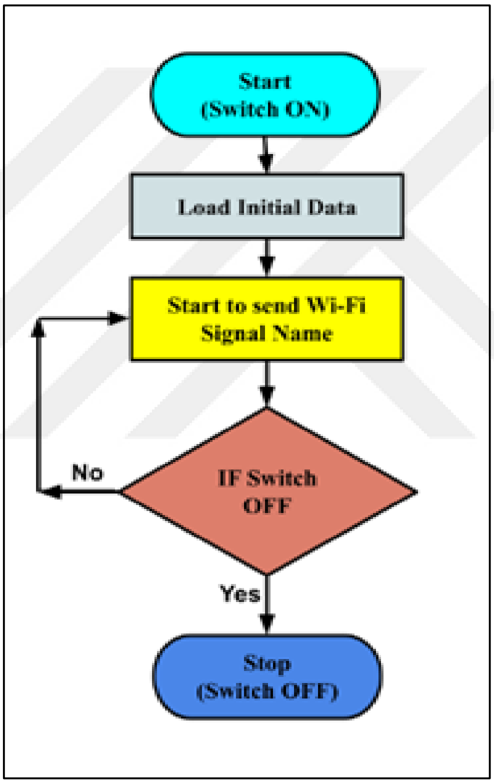


Figure 23 The flowchart of the system for Wi-Fi node software.

The flowchart in Figure 30 represents the special device program for determining and finding location to display the results on the OLED in same device without sending results to the control station. The initial data that is loaded to all units represents the 2D-coordinate, available RSSI for the working units, and their classes (identification room). The machine learning algorithm is now able to classifiy the correct target room from these collected data and then display it on the OLED. After the success of this step, it can sent the decision to main monitoring station via Bluetooth as in next charts.

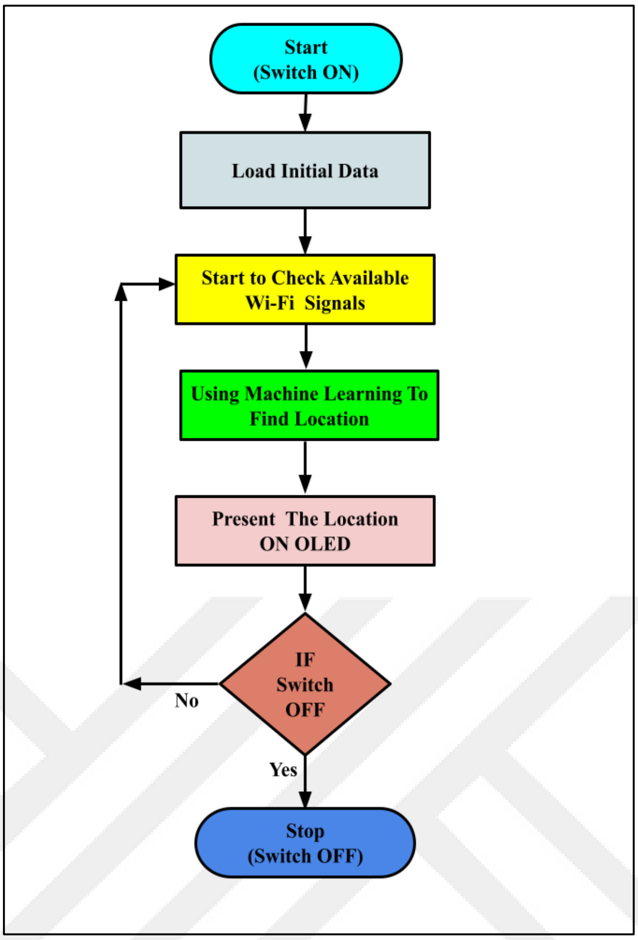


Figure 30 The flowchart of the system for the end node for tracking without.

Figure 31. shows how the program works after adding the HC-05 Bluetooth module to the system. The data is sent to the main station for the purpose of remote monitoring and knowing the where abouts of people inside the building. To enhance the classification system and check the pre-decision, the main station can also carry out its classiciation algorithm.

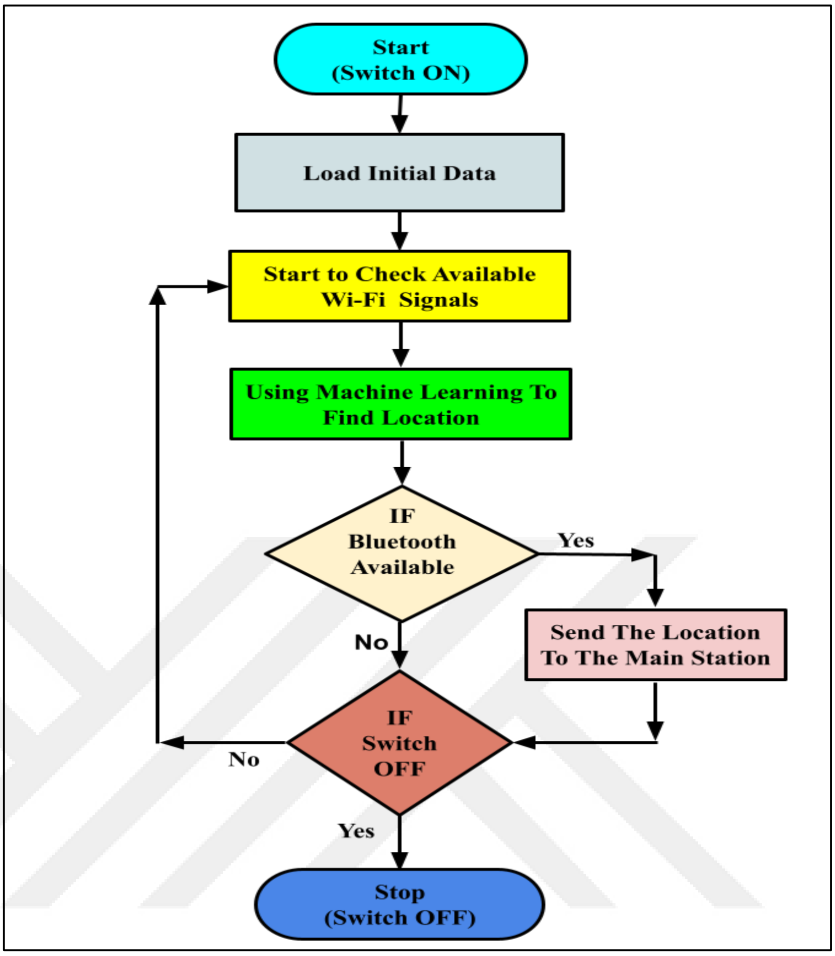


Figure 24 The flowchart of the system for the End node for tracking with Bluetooth module.

Figure 32. describes the final program of the main station (the receiver) outside the building. It shows how to receive data via HC-05 Bluetooth and display it on the OLED to identify the whereabouts of people inside the building.

4.4 ESP-PROGRAMING SOFTWARE (ARDUINO IDE)

Writing codes and uploading them to the board is simply implemented using the open-source Arduino Software (IDE), which is concerned to all Arduino or ESP

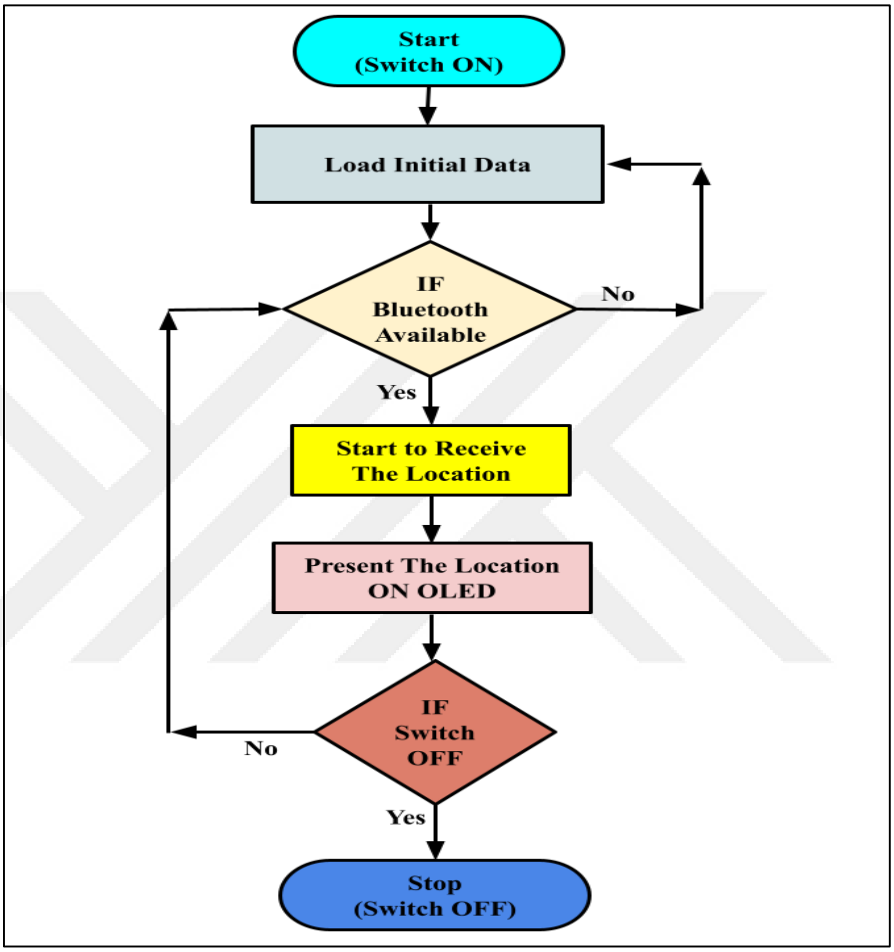


Figure 25 the flowchart of the monitoring main station outside the building.

boards. The Arduino Software interface provides a text editor environment, a message displaying interface and several other menus. The Arduino Software provides easy connection to the Arduino hardware, enabling the device to upload and interact with programs. The window of the Arduino platform are presented in Figure 33. (arduino.cc, 2022).

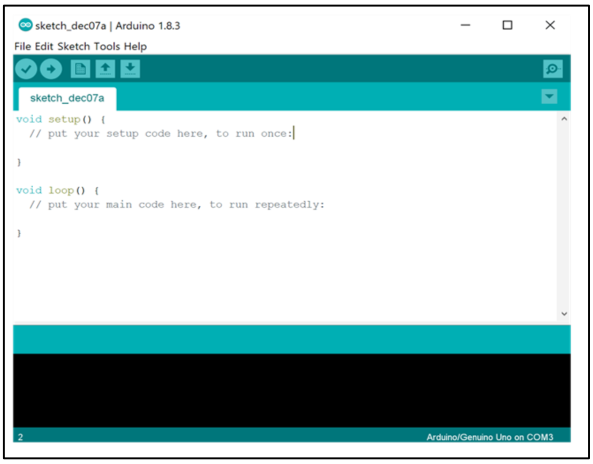


Figure 26 ESP- Arduino IDE Platform (arduino.cc, 2022).

The language used to program the models of machine learning is the Python language with Anaconda environment, it is implemented on a PC which has the characteristics: Processor Intel core i5 CPU @ 2.4 GHz with RAM 16 GB.

The reasons for choosing the Python language are:

1- There are many libraries in this language.

2- Most of these libraries are open source.

3- This language is flexible and can handle and give great advantages to any project in which this language is used.

This model was built to train the data to make the SVM Model and then test the performance-like accuracy.

4.5 SVM-BASED LOCATION METHOD

In SVM based location method the measured RSSI data is collected by the Node MCU ESP8266 microcontroller and is compared to real-time geographical location based on SVM algorithm. The proposed method is shown in Figure 34, the ESP-12E based Wi-Fi chip find extracts local data using the RSS data gathered from Wi-Fi access points installed at the predefined location using Wi-Fi and node MCU ESP8266 mıcrocontroller. The location finding process formed of two stages, the offline training stage and the stage. Initially during the offline stage, RSS data is collected through a laptop’s Wi-Fi module whereas their locations are determined based on an efficient machine learning classification method like SVM. The microcontroller is deployed at multiple predefined access points to create the radio map database. To overcome the complexity of the indoor system and its settings, corresponding data filtering techniques are used to enhance the performance and the quality of the training data.

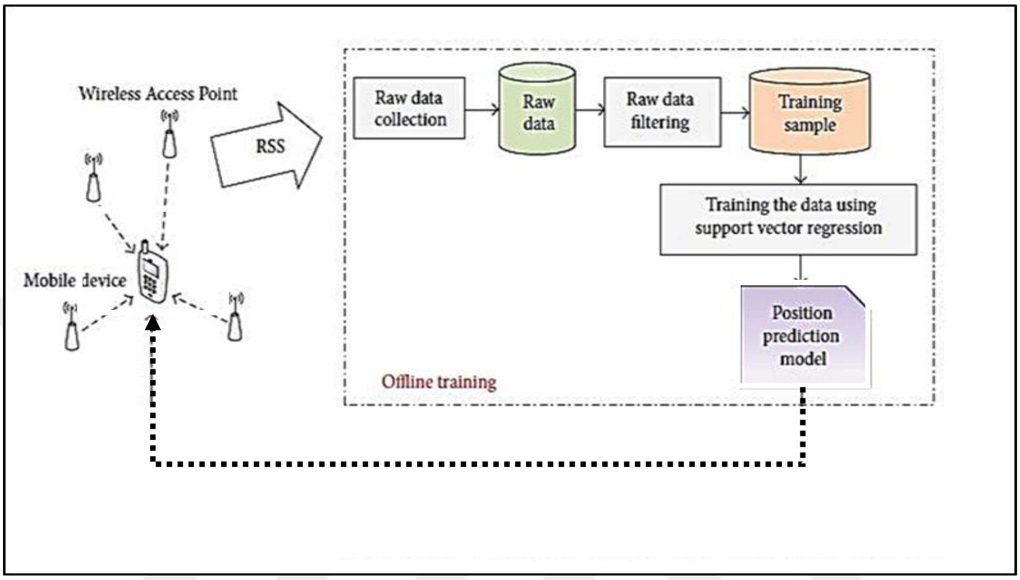


Figure 27 Steps involved in data acquisition.

Data is trained using SVM algorithms. At this stage the data is saved in the server and ready to be utilized by the microcontroller to detect location during the online stage. During the online location identification phase, ESP-12E collects the RSS information and feeds new data to the input of data processor. Due to the inconsistency of received signals k-times continuous measurement techniques adopted in the next step to get accurate RSS values (S. Li et al., 2021). Model Description of SVM Using Node MCU ESP8266 Microcontroller shown in figure 35. (Shi, Ma, Zhang, Hu, & Chen, 2015).

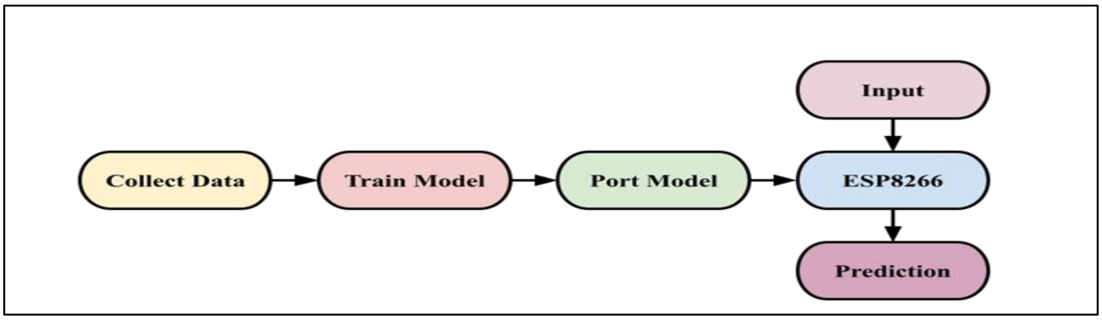


Figure 28 Model Description of SVM Using Node MCU ESP8266 Microcontroller (Shi et al., 2015).

4.6 FLOOR MAP FOR INDOOR TRACKING SYSTEM

In the beginning, the dimensions of the house and rooms are located on the virtual map. The ground floor for the house which was chosen for this project was divided based on the existing rooms into seven closed areas as in Figure 36 The dimensions of the rooms are not identical to enlarge the complexity of the system and to simulate the reality. Then Wi-Fi Nodes were distributed to these rooms (one for each room).

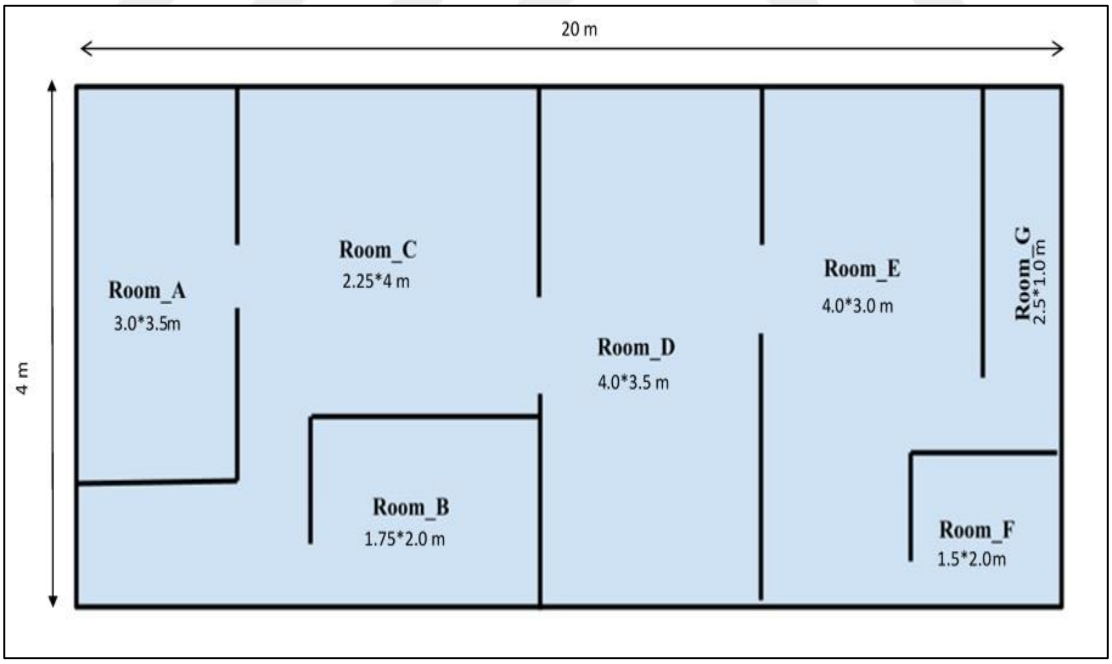


Figure 29 Floor Map for indoor tracking system.

4.7 NETWORK TRAINING USING SUPPORT VECTOR MACHINES

After the Wi-Fi points have been located, all of them are turned ON and a full scan is made for each room as shown in Figure 37 by using a program code. A set of Wi-Fi networks will send RSS information (like the Figure 38) that will be observed by the MCU node to be used for testing the network model to get the location at the end.

The dotted and colored lines represent the borders that were chosen for the purpose of scanning Wi-Fi networks for all rooms in the house.

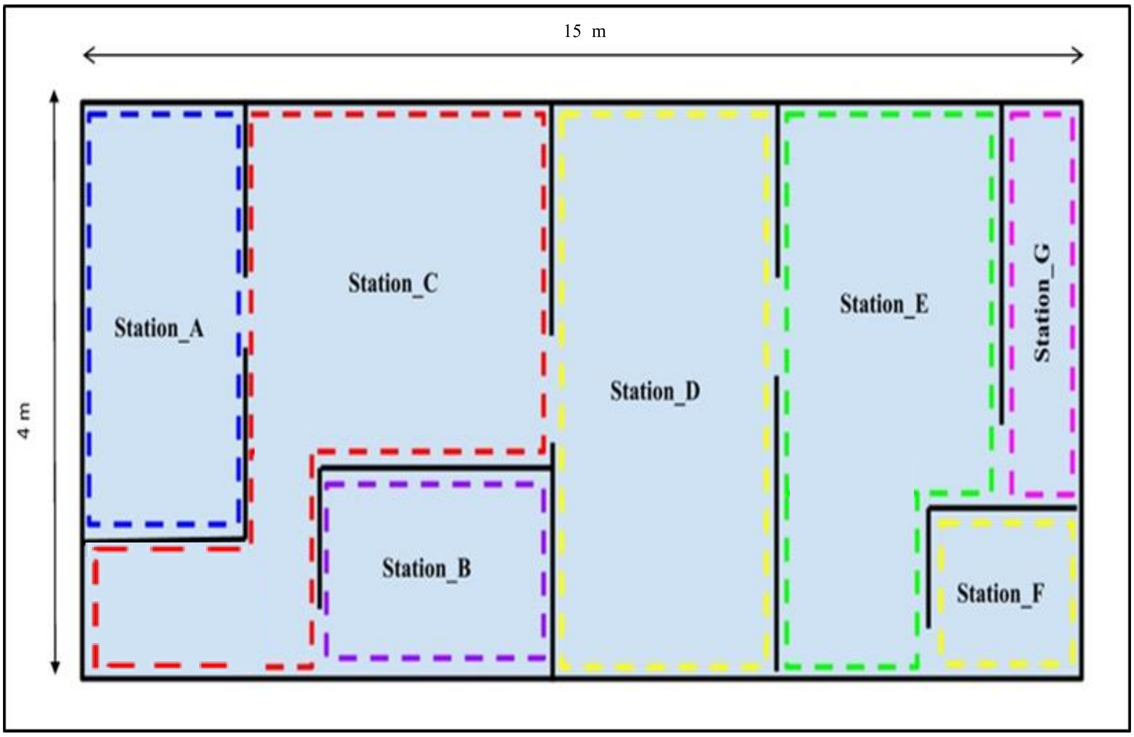


Figure 30 Floor Map for indoor tracking system with Wi-Fi scanning lines.

The machine learning model is built using training and testing of programming. Anaconda is a Python programming language distribution aimed at simplifying the developement of scientific computing applications such as data science and machine learning applications.

After executing the software, the RSSI data for each room is added and saved in the main data file, which contains information for seven rooms. The redundant data, such as Arabic names or IP addresses, is then removed. It takes some time to acquire all of the data that represents the mapping with their RSSI data. The data is now ready to be sent to the Arduino, and these files are referred to as (Classifier.h and Converter. h).

4.8 PROGRAMING AND SIMULATION RESULTS

The proposed positioning system is designed for an indoor environment with a number of reference points considered to access the performance of the developed positioning system. Wi-Fi access points were installed in 7 rooms with a total dimension of 15 × 4 meters.

The proposed method is shown in Figure 38 , at a regular time interval, positioning data are reported to the server to build the radio maps from pre-installed access points. The location detection process formed of two phases, the offline training and the online phase.

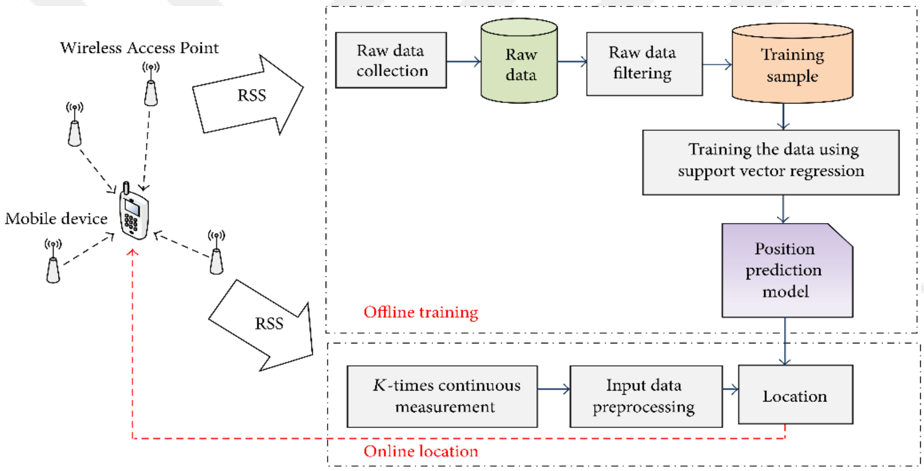


Figure 31 the entire offline and online positioning system.

The data collected from the central unit is composed of 164 × 10, where each row represents the following parameters: “X Y RSSI A RSSI B RSSI C RSSI D RSSI E RSSI F RSSI G Class”

The first two columns represent the coordinates X and Y for the node in the building that depends on the rooms dimensions. Radio signal strength identification (RSSI) represents the power of each node in the system. The last column represents the class where each room has a unique class regarding the power node installed in that room.

So, the system includes different class depending on the rooms number.

In the offline training stage, basic RSS information from the access points is precollected. Due to the complicated indoor environment, channel distortion, and limited communication coverage, the collected signal is at risk of interference and noise. To reslove these problems, data normalization and statistical features are applied to the raw signal to reduce noise and enhance the quality of the collected data. After this stage, 80% of the data is used for offline SVM classifier training and 20% of the samples are used for real-time online measurement. The python library tool which is used for machine learning that is called “sklearn.svm.SVC” implementation by Scikit-Learn (Kramer, 2016) has been chosen. To find the most optimal parameters for the SVM, sklearn.model_selection.GridSearchCV in Scikit-Learn is investigated using three different kernel functions. These kernels are linear, sigmoid, and Radial base function (RBF).

During the online stage, collected data from access points were used as input to the location detection model constructed in the previuos stage to obtain the current location. During this stage, collected raw location data is normalized to reduce the environmental effects on the data and get real input that mirror the relevance between the collected data and the real location. After this, the online data is taken as input to the SVM model for the final location prediction. As shown in Table 1 below, the proposed method achieved 87% accuracy using SVM with Radial Basis Function (RBF) with a precision of 81%, recall of 83%, and F1-score of 77% on the test dataset. The SVM classifier with Polynomial and sigmoid achieved lower performance than SVM-RBF, while SVM with linear kernel showed worse performance in all measurements. This may suggest that the collected data is non-linear and that using SVM with kernels (Radial Basis Function (RBF) or Sigmoid or Linear) is necessary. However, although classifier parameter tuning is applied, the test accuracy is still lower than the training accuracy. This indicates that more data is required in order to make the SVM model more generalized for the new test dataset.

Table 2 SVM model results on training and test data using different kernels.

Kernel	Precision	Recall	F1-score	Training Accuracy	Test Accuracy
Polynomial	0.73	0.77	0.66	70%	59%
Radial Basis	0.81	0.83	0.77	87%	77%
Sigmoid	0.70	0.68	0.65	66%	53%
Linear	0.53	0.52	0.55	53%	45%

The confusion matrix of the propsed SVM method is shown in figure 39, while the area under the curve is represented in the figure 40 .

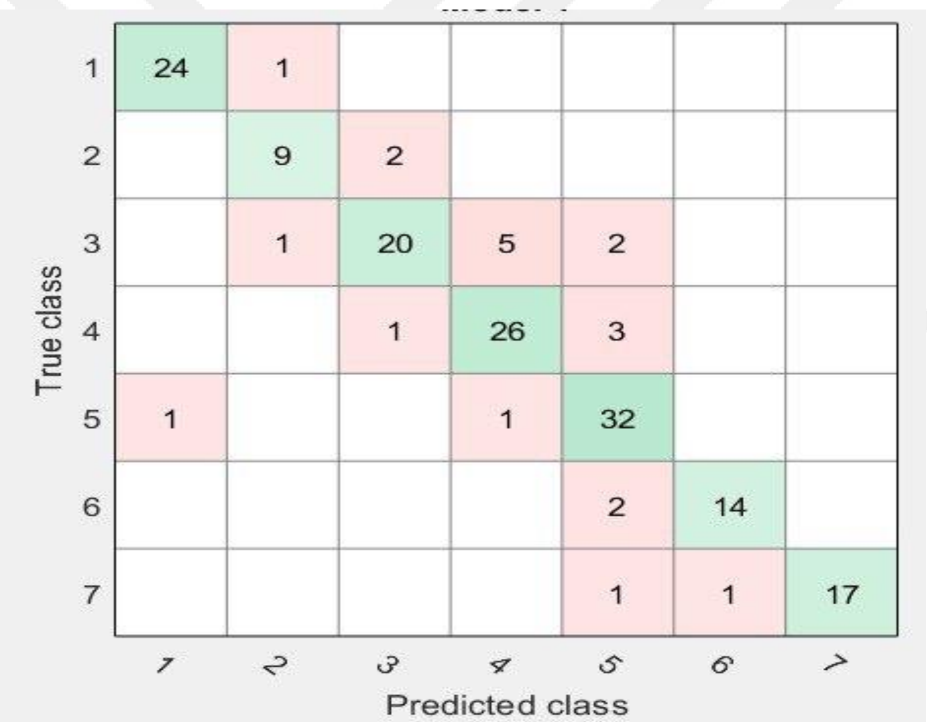


Figure 32 Confusion matrix of the proposed classificaton method.

The True positive and negative in green color for all rooms are high, while the False positive and negative are very low, which leads to high accuracy in detecting the targets.

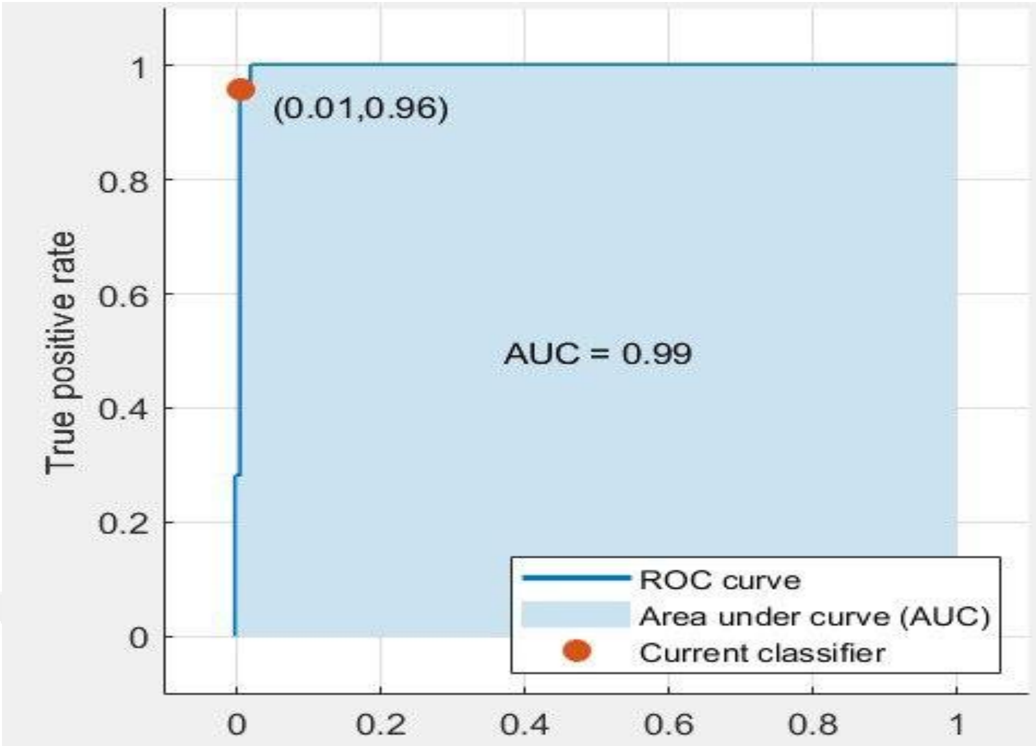


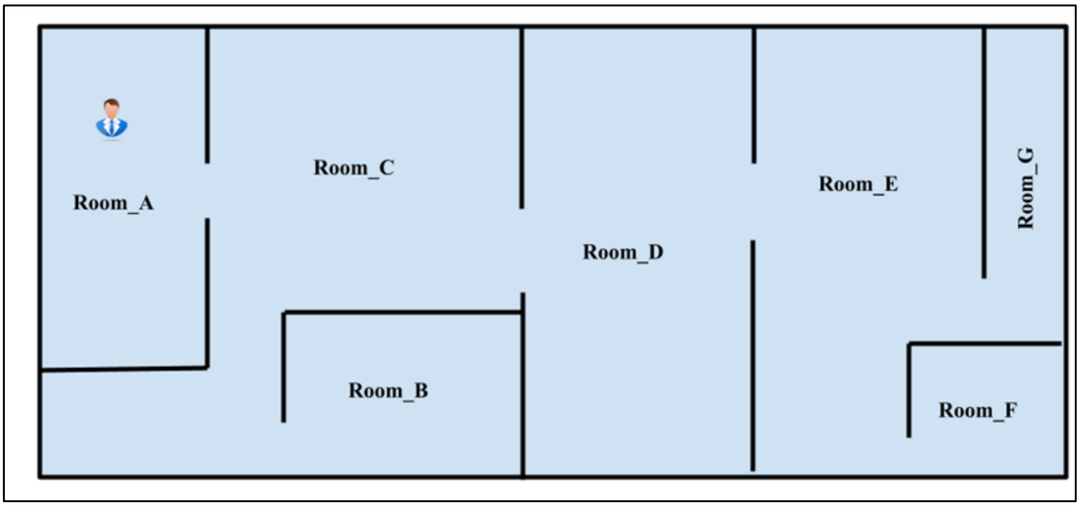
Figure 40 Regin of convergence (ROC) of the proposed classificaton method.

Figure 40 illustrate that the region under the curve is approximatlly unit curve which leads to high classification accuracy. The obtained accuracy of the system is 87.7%.

4.9 RESULTS ON THE INDOOR TRACKING CIRCUIT

The features are selected randomly to train the model, all the available features are activated on the Node MCU ESP8266 microcontroller's serial monitor using Code (index related to each station). The collected RSS values from seven rooms using scan locations in each room are identified and fed to classification model.

An ESP code (predefined index) is used to reveal the signal strength on the OLED for each room of the networks selected. Each room is given a numeric code for identification purposes. Figures 41 reveals the obtained outcomes for room A. Figure 41.a represents the location of the person in Room A and Figure 41.b represents the results after signal analysis and displaying the person's location on the OLED.



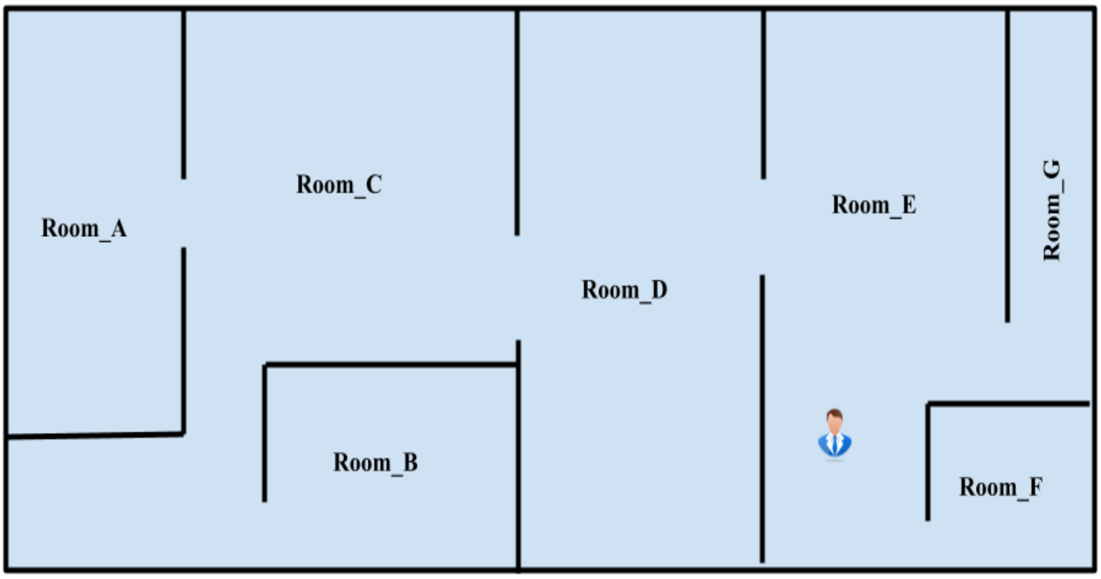
a

b

Figure 33 System results room A. a) Location of the person b) results on OLED.

Another real example, a person is presented in room E as shown in Figure 42.a. The OLED result is taken as in Figure 42.b.

Figures 43 shows the results displayed in the monitoring room. This room is positioned outside the planned building where the Bluetooth is used to convey data from within the building to the outside for monitoring purposes.



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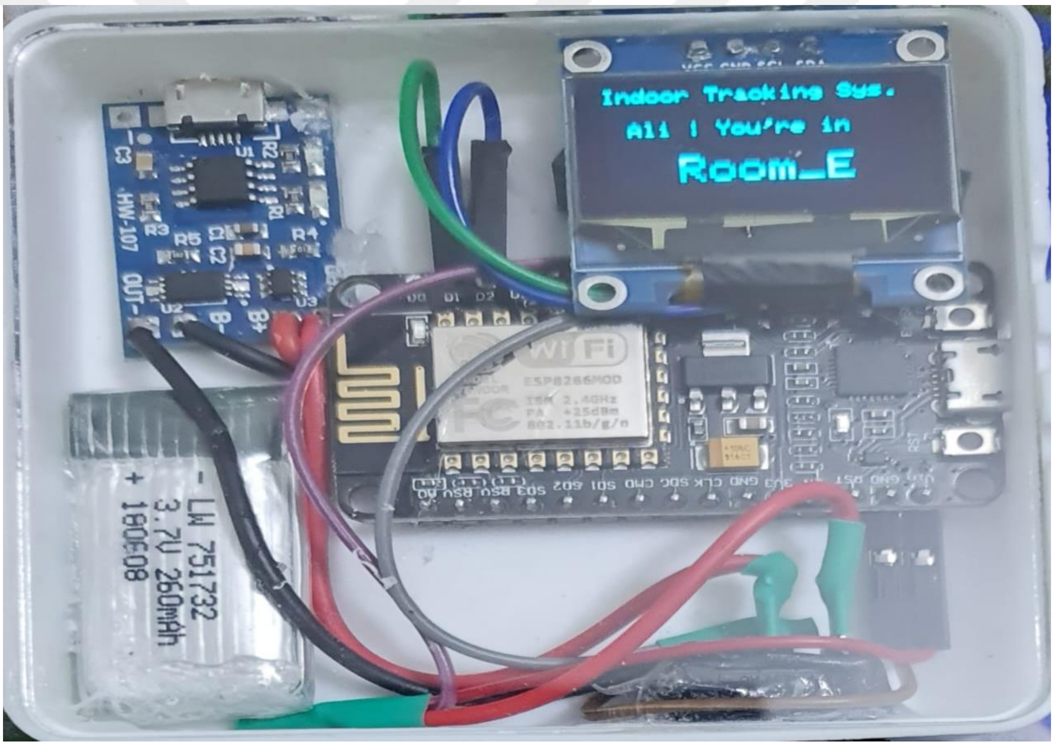

b

Figure 34. System results room E a) Location of the person   b) results on OLED.

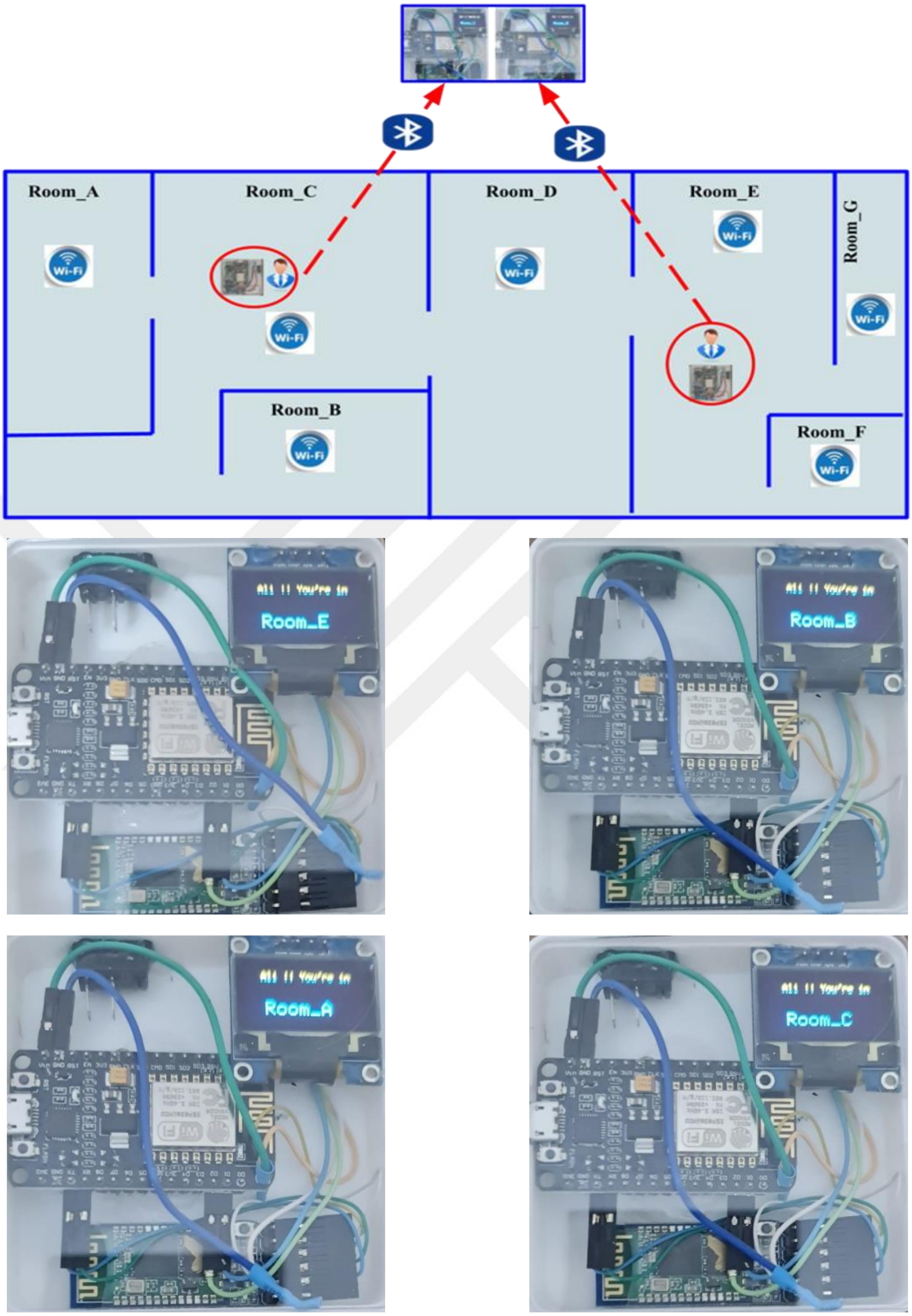

Figure 35 shows the real results displayed in the monitoring room.

CHAPTER FIVE

CONCLUSION AND FUTURE WORK

One of the most important and difficult tasks in indoor location detection utilizing global positioning systems is position estimate and approximation. The subject of IPs got studied through various processes of identifying indoor locations based on user type of microprocessor, method of machine learning, signal strength system, and medium of display or sharing positions. However with the increasing demand for ubiquitous communication networks for indoor and outdoor settings, different method have been proposed to deliver a good performance, reliability and accuracy of position estimation systems. As the indoor settings are quite complex thus, traditional Wi-Fi based positioning systems are vulnerable to wireless channel jamming, obstacles, and limitation of range. In this research project, a new postioning system with Wi-Fi is presented which is based on indoor positioning method with the use of advanced machine learning algorithms known as Support Vector Machines. In order to enhance the system perfomance, data filtering techniques and k-times continuous measurement can be employed.

This project distinctly works on identifying the location of the model based on preset programming, model training, and Wi-Fi signal strength. This work is focusing on designing such an efficient and accurate indoor positioning system by utilizing small size, low cost and low power consumption hardware components such as ESP8266 NodeMCU. Also, adopting robust Machine Learning approach like the support vector machine (SVM) method to provide robust system. A ground floor containing seven rooms of different dimensions was the model of the system. The classified data is used in offline and online types of data. The accuracy of the system up to 87% accuracy within a few seconds. The results demonstrated that the proposed localization method in this research project has a high speed response and effective positioning accuracy.

5.1. FUTURE WORK

- Adopt many machine learning or deep learning approchs that can train the data and produce more models for extreme APs scenarios.
- Adding more sensors that give more features like motion detection, speed, and connect these sensors with suitable remote sensing within the IOT concepts.
- Utilizing computer vision and image processing techniques to develop the mointoring and tracking system.
- Enhancing the tracking system using biometrics information like fingerprints.

REFERENCES

Ali, M. U., Hur, S., & Park, Y. (2019). Wi-Fi-based effortless indoor positioning system using IoT sensors. Sensors, 19(7), 1496.

arduino.cc. (2022). Arduino IDE. Retrieved from https://www.arduino.cc/en/software/

Bai, J., Sun, Y., Meng, W., & Li, C. (2021). Wi-Fi fingerprint-based indoor mobile user localization using deep learning. Wireless Communications and Mobile Computing, 2021.

Bai, N., Tian, Y., Liu, Y., Yuan, Z., Xiao, Z., & Zhou, J. (2020). A high-precision and low-cost IMU-based indoor pedestrian positioning technique. IEEE Sensors Journal, 20(12), 6716-6726.

Belmonte-Fernández, Ó., Puertas-Cabedo, A., Torres-Sospedra, J., Montoliu-Colás, R., & Trilles-Oliver, S. (2016). An indoor positioning system based on wearables for ambient-assisted living. Sensors, 17(1), 36.

Boltes, M., Adrian, J., & Raytarowski, A.-K. (2021). A hybrid tracking system of full-body motion inside crowds. Sensors, 21(6), 2108.

Calderoni, L., Ferrara, M., Franco, A., & Maio, D. (2015). Indoor localization in a hospital environment using random forest classifiers. Expert Systems with Applications, 42(1), 125-134.

Carotenuto, R., Merenda, M., Iero, D., & Della Corte, F. G. (2018). An indoor ultrasonic system for autonomous 3-D positioning. IEEE Transactions on Instrumentation and Measurement, 68(7), 2507-2518.

components101. (2020). NodeMCU ESP8266. Retrieved from https://components101.com/development-boards/nodemcu-esp8266-pinout-features-and-datasheet

Deng, Z.-A., Xu, Y.-B., & Ma, L. (2012). Indoor positioning via nonlinear discriminative feature extraction in wireless local area network. Computer Communications, 35(6), 738-747.

Do, T.-H., & Yoo, M. (2014). TDOA-based indoor positioning using visible light. Photonic Network Communications, 27(2), 80-88.

Du, P., Zhang, S., Chen, C., Alphones, A., & Zhong, W.-D. (2018). Demonstration of a low-complexity indoor visible light positioning system using an enhanced TDOA scheme. IEEE Photonics Journal, 10(4), 1-10.

Faragher, R., & Harle, R. (2015). Location fingerprinting with bluetooth low energy beacons. IEEE journal on Selected Areas in Communications, 33(11), 2418-2428.

fritzing.org. (2020). Retrieved from https://fritzing.org/

Guvenc, I., Chong, C.-C., & Watanabe, F. (2007). Analysis of a linear least-squares localization technique in LOS and NLOS environments. Paper presented at the 2007 IEEE 65th Vehicular Technology Conference-VTC2007-Spring.

Haider, A., Wei, Y., Liu, S., & Hwang, S.-H. (2019). Pre-and post-processing algorithms with deep learning classifier for Wi-Fi fingerprint-based indoor positioning. Electronics, 8(2), 195.

Hameed, A., & Ahmed, H. A. (2018). Survey on indoor positioning applications based on different technologies. Paper presented at the 2018 12th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS).

He, S., & Chan, S.-H. G. (2015). Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons. IEEE Communications Surveys & Tutorials, 18(1), 466-490.

Hoang, M. T., Yuen, B., Dong, X., Lu, T., Westendorp, R., & Reddy, K. (2019). Recurrent neural networks for accurate RSSI indoor localization. IEEE Internet of Things Journal, 6(6), 10639-10651.

ITRelease. (2018). advantages and disadvantages of wide area network wan. Retrieved from https://www.itrelease.com/2018/07/advantages-and-disadvantages-of- wide-area-network-wan/

ITRelease. (2020). What is WMAN with example. Retrieved from https://www.itrelease.com/2020/10/what-is-wman-with-example/

javatpoint. (2020). Supervised Machine Learning. Retrieved from https://www.javatpoint.com/supervised-machine-learning

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2065), 20150202.

Kilani, M. B., Raymond, A. J., Gagnon, F., Gagnon, G., & Lavoie, P. (2014). RSSI-based indoor tracking using the extended Kalman filter and circularly polarized antennas. Paper presented at the 2014 11th workshop on positioning, navigation and communication (WPNC).

Kramer, O. (2016). Scikit-learn. In Machine learning for evolution strategies (pp. 45-53): Springer.

Kumar, N. (2017). What is the difference between Machine Learning and Deep Learning Retrieved from https://medium.com/@Say2neeraj/what-is-the-difference-between-machine-learning-and-deep-learning-5795e4415be9

LastMinuteEngineers.com. (2022). Insight Into ESP8266 NodeMCU Features & Using It With Arduino IDE. Retrieved from https://lastminuteengineers.com/esp8266-nodemcu-arduino-tutorial/

Le, D. V., Meratnia, N., & Havinga, P. J. (2018). Unsupervised deep feature learning to reduce the collection of fingerprints for indoor localization using deep belief networks. Paper presented at the 2018 International conference on indoor positioning and indoor navigation (IPIN).

Li, S., Yu, B., Jin, Y., Huang, L., Zhang, H., & Liang, X. (2021). Image-based indoor localization using smartphone camera. Wireless Communications and Mobile Computing, 2021.

Li, Z., Braun, T., & Dimitrova, D. C. (2015). A passive WiFi source localization system based on fine-grained power-based trilateration. Paper presented at the 2015 IEEE 16th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM).

Liu, F., Liu, J., Yin, Y., Wang, W., Hu, D., Chen, P., & Niu, Q. (2020). Survey on WiFi-based indoor positioning techniques. IET communications, 14(9), 1372-1383.

Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of wireless indoor positioning techniques and systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 37(6), 1067-1080.

Lu, C., Uchiyama, H., Thomas, D., Shimada, A., & Taniguchi, R.-i. (2019). Indoor positioning system based on chest-mounted IMU. Sensors, 19(2), 420.

Minoli, D., & Occhiogrosso, B. (2019). Practical aspects for the integration of 5G networks and IoT applications in smart cities environments. Wireless Communications and Mobile Computing, 2019.

Mnati, M. J., Van den Bossche, A., & Chisab, R. F. (2017). A smart voltage and current monitoring system for three phase inverters using an android smartphone application. Sensors, 17(4), 872.

Ni, L. M., Liu, Y., Lau, Y. C., & Patil, A. P. (2003). LANDMARC: Indoor location sensing using active RFID. Paper presented at the Proceedings of the First IEEE International Conference on Pervasive Computing and Communications, 2003.(PerCom 2003).

Pham, M., Yang, D., & Sheng, W. (2018). A sensor fusion approach to indoor human localization based on environmental and wearable sensors. IEEE Transactions on Automation Science and Engineering, 16(1), 339-350.

Poulose, A., & Han, D. S. (2019). Hybrid indoor localization using IMU sensors and smartphone camera. Sensors, 19(23), 5084.

Qian, K., Wu, C., Yang, Z., Liu, Y., & Zhou, Z. (2014). PADS: Passive detection of moving targets with dynamic speed using PHY layer information. Paper presented at the 2014 20th IEEE international conference on parallel and distributed systems (ICPADS).

Quispe Coaquira, W. R., Condori Yucra, R., Beltrán Castañón, N. J., & Negrão Macêdo, W. (2021). Medición y monitoreo de eventos extremos de irradiancia solar mediante una plataforma sensorial de bajo costo en las condiciones geográficas y climatológicas de Juliaca.

Ruiz, A. R. J. J., Granja, F. S., Honorato, J. C. P., & Rosas, J. I. G. (2010). Pedestrian indoor navigation by aiding a foot-mounted IMU with RFID signal strength measurements. Paper presented at the 2010 International Conference on Indoor Positioning and Indoor Navigation.

Sabanci, K., Yigit, E., Ustun, D., Toktas, A., & Aslan, M. F. (2018). Wifi based indoor localization: application and comparison of machine learning algorithms. Paper presented at the 2018 XXIIIrd International Seminar/Workshop on Direct and Inverse Problems of Electromagnetic and Acoustic Wave Theory (DIPED).

Sakpere, W., Adeyeye-Oshin, M., & Mlitwa, N. B. (2017). A state-of-the-art survey of indoor positioning and navigation systems and technologies. South African Computer Journal, 29(3), 145-197.

Salamah, A. H., Tamazin, M., Sharkas, M. A., & Khedr, M. (2016). An enhanced WiFi indoor localization system based on machine learning. Paper presented at the 2016 International conference on indoor positioning and indoor navigation (IPIN).

Sharma, V. (2019). Deep Learning – Introduction to Recurrent Neural Networks. Retrieved from: https://vinodsblog.com/2019/01/07/deep-learning-introduction-to-recurrent-neural-networks/

Shi, K., Ma, Z., Zhang, R., Hu, W., & Chen, H. (2015). Support vector regression based indoor location in IEEE 802.11 environments. Mobile Information Systems, 2015.

Song, B., Zhang, S., Long, J., & Hu, Q. (2017). Fingerprinting localization method based on toa and particle filtering for mines. Mathematical Problems in Engineering, 2017.

Subhan, F., Hasbullah, H., & Ashraf, K. (2013). Kalman filter-based hybrid indoor position estimation technique in bluetooth networks. International Journal of Navigation and Observation, 2013.

Wielandt, S., Thoen, B., & De Strycker, L. (2018). Experimental evaluation of a single anchor multipath assisted indoor angle of arrival localization system in the 2.4 GHz and 5 GHz band. Paper presented at the 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN).

Xu, Y., Ahn, C. K., Shmaliy, Y. S., Chen, X., & Li, Y. (2018). Adaptive robust INS/UWB-integrated human tracking using UFIR filter bank. Measurement, 123, 1-7.

Yan, J., Zhao, L., Tang, J., Chen, Y., Chen, R., & Chen, L. (2017). Hybrid kernel based machine learning using received signal strength measurements for indoor localization. IEEE Transactions on Vehicular Technology, 67(3), 2824-2829.

Zhang, D., Hu, Y., Chen, Y., & Zeng, B. (2019). BreathTrack: Tracking indoor human breath status via commodity WiFi. IEEE Internet of Things Journal, 6(2), 3899-3911.

RESUME

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