An AP Placement Strategy for Fingerprint Based Indoor Localization

Thesis
Submitted in partial fulfilment of the requirement for the Degree of

MASTER OF TECHNOLOGY
IN
COMPUTER TECHNOLOGY

Submitted by
Debanjan Naskar
Exam Roll No- M6TCT23030
Registration No-154203 of 2020-21
Class Roll No-002010504038

Under the Guidance Of
Dr. Chandreyee Chowdhury

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
FACULTY OF ENGINEERING & TECHNOLOGY
JADAVPUR UNIVERSITY, KOLKATA

132, Raja Subodh Chandra Mallick Road,
Jadavpur, Kolkata, West Bengal, 700032

2023

FACULTY OF ENGINEERING AND TECHNOLOGY
JADAVPUR UNIVERSITY

Certificate of Recommendation

This is to certify that the dissertation entitled **“An AP placement strategy for fingerprint based indoor localization**” has been carried out by Debanjan Naskar (University Registration No: 154203 of 2020-21, Examination Roll No: M6TCT23030) under my guidance and supervision and be accepted in partial fulfilment of the requirement for the Degree of Master in Computer Technology.The research results presented in the thesis have not been included in any otherpaper submitted for the award of any degree in any other University or Institute.

Dr. Chandreyee Chowdhury
Department of Computer Science & Engineering
Jadavpur University

COUNTERSIGNED BY

Prof. Nandini Mukherjee
Head of the Department
Department of Computer Science And Engineering
Jadavpur University

COUNTERSIGNED BY

Prof. Arthendu Ghosal
Dean, FET
Faculty of engineering and Technology
Jadavpur University

FACULTY OF ENGINEERING AND TECHNOLOGY
JADAVPUR UNIVERSITY

Certificate of Approval

This is to certify that the thesis entitled **“An AP placement strategy for fingerprint based indoor localization”**, Debanjan Naskar (University Registration No: 154203 of 2020-21, Examination RollNo: M6TCT23030) is a bonafide record of work carried out by in partial fulfillment of the requirements of the degree of Master of Engineering in Computer Science and Engineering in Department of Computer Science and Engineering, Jadavpur University during the period of September 2020 to June 2023. It is understood that by this approval the undersigned do not necessarily endorse any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

. . . .

Signature of Examiner 1
Date:

. . . .

Signature of Examiner 2
Date:

FACULTY OF ENGINEERING AND TECHNOLOGY
JADAVPUR UNIVERSITY

Declaration of Originality and Compliance with Academic Ethics

I hereby declare that this thesis entitled "**An AP placement strategy for fingerprint based indoor localization"** contains a literature survey and original research work by the undersigned candidate as part of his Degree of Master of Engineering in Computer Science and Engineering.

All information has been obtained and presented under academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Name: Debanjan Naskar
Registration No: 154203 of 2020-21
Examination Roll No.: M6TCT23030

Thesis Title: **An AP placement strategy for fingerprint based indoor localization**

. . . .
Signature of Student with date

ACKNOWLEDGEMENT

The success and outcome of this thesis required a lot of guidance and assistance from many people and I am extremely privileged to have got this all along the completion of my project. All that I have done is only due to such supervision and assistance and I would not forget to thank them.

I owe my deep gratitude to my mentor and thesis guide **Dr. Chandreyee Chowdhury**, who took a keen interest in my thesis work and guided me all along till the completion of my thesis work by providing all the necessary information for developing a good end-to-end solution.

I would also like to thank **Prof. Nandini Mukhopadhyay, Head of the department**, Department of Computer Science and Engineering, at Jadavpur University, for extending his help to complete this thesis.

Besides my supervisor, I would also like to thank **Manjarini Mallik** for their constant support, encouragement, insightful comments, and research expertise, which helped me the most.

Most importantly, none of this could have happened without the love and support of my family. It would be an understatement to say that their unconditional love and encouragement have always helped me in my need.

Finally, I would like to thank all my Professors at Jadavpur University, my classmates, especially my guide **Dr. Chandreyee Chowdhury,** and the many well-wishers who have been a constant source of help and inspiration to me during my thesis work. My thanks and appreciation to all of them for being a part of this wonderful journey and making this possible.

....

Debanjan Naskar

Examination Roll No: M6TCT23030

Dept. of Computer Science & Engineering

Jadavpur University

Kolkata, India

Abstract

Localization in indoor areas deals with the serious problem of collecting data over a broad experimental region while maintaining the location points. The proposed work focuses on addressing the problem of finding the optimal placement of Access Points (APs) to improve AP coverage for a specific set of location points, while minimizing the number of APs required. The objective is to achieve accurate localization with minimal error, ideally less than 2.5 meters. The problem is formulated as a graph coloring problem, where each location point is represented as a node in the graph, and the goal is to assign APs (colors) to the nodes in a way that minimizes interference and maximizes localization ability. To solve this problem, the proposed algorithm, called GLOC_coloring, is introduced. The algorithm begins by applying a machine learning classifier to obtain a confusion matrix, which is used to create a weighted graph. Each vertex in the graph represents a unique location, and edges are added between vertices that have confusion in distinguishing them based on Received Signal Strength Indicator (RSSI) values. The weights of the edges are determined by the confusion matrix. The algorithm proceeds by assigning weights to each vertex based on the sum of weights of all edges connected to it. Starting with the vertex having the maximum weight, a color is assigned to it, and the process continues by selecting vertices with maximum weights from the set of connected vertices. Colors are assigned to these vertices in such a way that they differ from the colors assigned to their connected vertices. This process continues until all vertices are assigned a color, and the number of colors used represents the minimum number of APs required for improved localization accuracy.

The experiment took place in two rooms of a benchmark indoor localization dataset. For one single location point up to seven confusing (in terms of location identification) neighbour location points were obtained. This challenge was addressed with proposed GLOC-algorithm and observed that 3 new Aps are sufficient to reduce the localization confusion and their positions were found on the available floor map of the dataset.

Table of Contents

Declaration of Authorship 2

Certificate of Recommendation.. 3

Certificate of Approval.. 4

Acknowledgement.. 5

Abstract…………………………………………………………………….6

1. Introduction 9

1.1. Indoor Localization System 9

1.2. Applications of Indoor localization system 10

1.3. Motivation...11

1.4. Contribution 12

1.5. Scope of the work 13

2. Related work...14

2.1. An Indoor Navigation System for the Visually Impaired …………..14

2.2. Wi-Fi-based enhanced positioning systems: accuracy through mapping, calibration, and classification 15

2.3. An advanced exploration of indoor positioning and navigation systems and technologies……………………………………………..…..……16

2.4. Design Space Exploration of a Multi-Model AI-Based Indoor Localization System…………………………………..…………..16

2.5. Design Space Exploration of an Indoor Localization System using K-ELM for Mobile Robots……………..………..……………………...17

2.6. A Wi-Fi RSS fingerprint database is crucial for developing an indoor positioning system for mobile robots…………………….…………..18

3. Proposed work……………………………………………….…………………19

3.1. Problem Definition……………………………………………………..19

3.2. Constraints……………………………………………………………...19

3.3. Basic Graph Coloring Approach……………………………...……… 20

3.4. . Proposed Graph Coloring(weighted) Approach……………………... 20

3.5. Features of the Proposed Approach……………………………… … 23

3.6. Summary…………………………………………………………........ 23

4. Experimental Results and discussion……………………………………………..24

4.1. Experimental setup……………………………………………………...25

4.2. Results and discussion...25

5. Conclusion………………..………………………………………………...32

CHAPTER 1

1. Introduction:

An indoor positioning system (IPS) is a network of devices used to accurately locate people or objects in indoor environments where traditional satellite technologies like GPS may not provide precise positioning. IPS is particularly useful in complex indoor spaces such as multistory buildings, airports, parking garages, and underground locations. IPS employs a wide range of techniques and devices to achieve indoor positioning. These include reconfigured devices like smartphones, Wi-Fi and Bluetooth antennas, digital cameras, and clocks, as well as purpose-built installations with strategically placed relays and beacons. The system utilizes various technologies such as lights, radio waves, magnetic fields, acoustic signals, and behavioral analytics [15].

One notable advantage of IPS is its high accuracy, which can reach up to 2 cm, comparable to the precision of RTK-enabled GNSS receivers used for outdoor positioning. IPS utilizes different technologies such as distance measurement to anchor nodes (fixed positions like Wi-Fi/Li-Fi access points, Bluetooth beacons, or Ultra-Wideband beacons), magnetic positioning, and dead reckoning. It actively locates mobile devices and tags or provides contextual information to enable device sensing. However, the localized nature of IPS has led to design fragmentation, with different systems employing various optical, radio, or even acoustic technologies to achieve positioning. This fragmentation poses challenges in terms of interoperability and standardization. Overall, IPS offers an effective solution for precise indoor positioning, overcoming the limitations of traditional satellite-based systems. With ongoing advancements and standardization efforts, IPS has the potential to revolutionize navigation and tracking in complex indoor environments [9][6][4].

1.1. Application of indoor localization:

Indoor localization has many uses, they can help us locate ourselves when a GPS can't because concrete buildings block GPS signals. This can be used to about any location: malls, airports, metro stations, universities, schools etc.… However, we have many kinds of signals that can be used to precisely locate a device within a perimeter.

Most typical applications for indoor localization systems are:

1.1.1 User localization:

With the advent of the Internet of Things (IoT), real-time tracking of users' current location has become achievable. The primary objective of IoT is to enable seamless interaction and assistance for users without requiring explicit external commands. By utilizing IoT devices, users can synchronize their devices with their current location, allowing for personalized information and services.

The process of tracking users' real-time location through IoT involves analyzing the Received Signal Strength (RSS) of radiofrequency (RF) signals emitted by location beacons. These beacons are strategically placed within the environment to provide reference points for location determination. By measuring the RSS of these signals, the IoT device can accurately determine the user's current location. This real-time location tracking capability opens up a multitude of possibilities for personalized services and assistance. For example, based on the user's current location, IoT devices can provide relevant information such as nearby points of interest, directions, recommendations, or customized notifications tailored to the user's preferences. By leveraging IoT and utilizing the RSS of RF signals, users can experience a seamless and personalized interaction with their surroundings. The integration of IoT devices and location beacons enables dynamic and context-aware services that enhance the user experience and provide valuable assistance without the need for explicit commands [12][16].

1.1.2 Object detection:

Indoor object localization has posed a significant challenge as traditional GPS systems are unable to operate effectively within buildings. To address this issue, wireless sensor networks (WSN) have emerged as a viable solution. WSN involves the use of a network of wireless sensors to identify and locate objects within an indoor environment. By deploying these wireless sensors strategically throughout the space, they can communicate and collaborate to accurately determine the position of objects. This allows for precise indoor localization without relying on GPS signals. WSN offers a versatile and scalable approach to indoor object localization, making it applicable in various settings such as factories, warehouses, and healthcare facilities [20].

Another technology that has gained prominence in indoor object localization is ultra-wideband (UWB). UWB provides centimetre-level positioning accuracy even in highly cluttered areas. This technology has found applications across industries, particularly in scenarios where precise location information is critical for improving productivity.

One example of UWB's usage is in identifying bottlenecks in process flow. By accurately localizing objects within a manufacturing or logistics environment, UWB technology enables the identification of areas where inefficiencies or congestion occur. This information can then be utilized to optimize routes, streamline operations, and enhance overall productivity.

UWB technology's high level of accuracy and its ability to operate in complex indoor environments make it a valuable tool for various applications beyond process optimization. It can be utilized for asset tracking, indoor navigation, proximity-based services, and even in safety systems. In summary, the challenge of indoor object localization has been addressed through the use of wireless sensor networks (WSN) and technologies such as ultra-wideband (UWB). WSN leverages a network of wireless sensors to identify objects, while UWB offers exceptional positioning accuracy even in cluttered indoor environments. These technologies have opened up new possibilities for improving productivity, optimizing processes, and enhancing overall efficiency in various industries [11].

1.1.3 Robot Navigation: This research initiative focuses on the development of devices for assisted living, specifically targeting older adults in navigating complex indoor environments. One of these initiatives is DALi, an EU-based project that aims to create a wheeled robotic assistant called C-Walker. This device utilizes electromechanical brakes and haptic interfaces to assist users in finding optimal paths to their destinations. A C-Walker is designed to support older adults in navigating various complex indoor environments, including train stations, shopping malls, and airports. It provides guidance and assistance to ensure users reach their desired destinations efficiently and safely.

In addition to the C-Walker, another technology called multi-sensor integrated navigation has been applied to indoor robot navigation and positioning. This approach combines visual and inertial sensors to enhance localization accuracy. The visual sensor, such as the Kinect camera, captures color and depth images, which are then processed using the improved scale-invariant feature transform (SIFT) algorithm for feature matching. Subsequently, the absolute orientation algorithm is employed to calculate the rotation matrix and translation vector between consecutive frames, enabling accurate robot positioning. These research initiatives demonstrate the ongoing efforts to develop advanced technologies for indoor navigation and positioning, particularly for assisting older adults and improving their mobility within complex indoor environments [19].

1.2. Motivation:

The need for new Access Point (AP) placement arises from the challenge of achieving better AP coverage for a specific set of location points while still providing appreciable coverage for the remaining points in an experimental region. The objective is to ensure good AP coverage, enabling accurate user localization within the coverage area with a minimal localization error of less than 2.5 meters. This necessitates an optimal AP placement strategy that minimizes the number of APs required while maximizing the localization ability.

The graph coloring approach is well-suited to address this AP placement problem. By mapping the problem to the graph coloring problem, each unique location point is represented as a node in the graph. The graph coloring problem involves assigning colors to the nodes of a graph in such a way that adjacent nodes do not share the same color. In the context of AP placement, the colors represent the APs, and the goal is to assign APs to location points in a manner that nearby points do not share the same AP.

This approach significantly enhances coverage while reducing interference. In real-life scenarios, we can apply this approach to safety-critical areas within environments like airports or hospitals, where user navigation services are absolutely essential. By strategically deploying APs based on the graph coloring technique, we can ensure reliable and accurate localization, benefiting users who rely on navigation services in these critical settings.

1.3. Contribution:

The proposed work makes several contributions in the field of indoor localization and access point (AP) placement:

1. Problem Formulation: The work addresses the problem of finding an optimal placement of APs to achieve better AP coverage for a specific set of location points while still providing appreciable coverage for the remaining points. The objective is to ensure accurate user localization within the coverage area with a minimal localization error. This problem is formulated as a graph coloring problem, where each location point is represented as a node in the graph and APs are assigned as colors.

2. Graph Coloring Approach: By mapping the AP placement problem to the graph coloring problem, the proposed work leverages existing algorithms and techniques developed for solving graph coloring problems. This approach enables the utilization of efficient algorithms to determine an optimal placement of APs that maximizes the localization ability while minimizing the number of APs required.

3. Weighted Graph Representation: The work introduces a weighted graph representation based on a machine learning classifier's confusion matrix. Each vertex in the graph corresponds to a location point, and edges are assigned weights based on misclassifications between locations. This weighted graph captures the connectivity and misclassification information, aiding in the assignment of colors (APs) to vertices.

4. GLOC_coloring Algorithm: The proposed GLOC_coloring algorithm utilizes the weighted graph representation to assign colors (APs) to the vertices. The algorithm identifies vertices with maximum weights, assigns them unique colors, and ensures that nearby vertices do not share the same color. By iteratively assigning colors based on weights and connectivity, the algorithm determines the minimum number of APs required to improve localization accuracy at prioritized locations.

5. Practical Application: The proposed approach has practical implications for indoor localization systems. By determining the optimal placement of APs, it enables enhanced AP coverage and reduced interference, resulting in improved localization accuracy. The algorithm provides insights into the number of APs needed for desired localization performance, aiding in the efficient deployment of wireless infrastructure.

The proposed work contributes to the field by addressing the specific problem of AP placement for improved AP coverage and localization accuracy. The utilization of graph coloring techniques, weighted graph representation, and the GLOC_coloring algorithm provides a systematic and efficient approach to solving this problem. The analysis and evaluation of the proposed algorithm in comparison to other localization methods can further enhance the understanding of its effectiveness and performance. Additionally, the exploration of optimization strategies for the algorithm contributes to improving its computational efficiency and practical implementation.

1.4. Scope of work:

The scope of this thesis includes several key tasks. Chapter 1 introduces indoor positioning systems (IPS) and their application in locating people and objects in complex indoor environments. It discusses the various techniques and devices used in IPS, highlights the advantages of high accuracy, and addresses the challenges of design fragmentation. The chapter also explores the applications of indoor localization, including user localization, object detection, and robot navigation. In Chapter 2, the state of the art works on indoor localization have been summarized. The proposed algorithm along with problem formulation is detailed in Chapter 3.In Chapter 4 we discussed our experimental setup and results. And finally in Chapter 5 we wrote the final conclusion of this work.

CHAPTER 2

2. Related Work:

In this chapter, we will examine and discuss several notable works from the existing literature that are pertinent to the AP placement problem, which is the focal point of investigation in this thesis. Our objective is to provide a comprehensive overview of the research that has been conducted in this field and establish its relevance to our own study.

2.1 An Indoor Navigation System for the Visually Impaired

Indoor positioning systems are tailored to help users navigate within indoor environments using signals such as radio, Wi-Fi, acoustics, or Bluetooth. Unlike standardized external GPS systems, indoor navigation systems lack comprehensive commercialization and recognized standardization mechanisms. The key focus of these systems is the localization and positioning of entities within indoor spaces, without relying on pre-existing map data. They provide real-time data based on internal parameters specific to the building [21].

Advantages:

1. Enhanced Navigation in Indoor Environments: Indoor positioning systems provide users with assistance in navigating complex indoor spaces, such as malls, airports, or office buildings. They help users locate specific points of interest, find the shortest routes, and efficiently move within the building.

2. Real-Time Data: Since indoor navigation systems rely on internal parameters within the building, they can provide users with real-time data. This enables users to receive up-to-date information about their surroundings, such as the current location, nearby facilities, or any changes in the environment.

3. Flexibility in Signal Technologies: Indoor positioning systems utilize various signal technologies like radio, Wi-Fi, acoustics, or Bluetooth. This flexibility allows the systems to adapt to different building structures and environments, ensuring wider compatibility and accessibility.

Disadvantages:

1. Lack of Standardization: Unlike external GPS systems that have established standards, indoor navigation systems lack a recognized standardization mechanism. This lack of standardization can result in a fragmented market with different systems and technologies, leading to potential interoperability issues.

2. Limited Commercialization: Indoor navigation systems have not been fully commercialized, which can limit their widespread availability and adoption. The development and deployment of these systems in various buildings require coordination and investment from stakeholders, which may slow down their implementation.

3. Building-Specific Design: Indoor positioning systems are designed to work within specific buildings or environments. This building-specific design means that each system needs to be customized and calibrated to the unique parameters of the particular

building. This can increase the complexity and cost of implementing these systems in multiple locations.

4. Reliance on Internal Parameters: Indoor positioning systems rely on internal parameters within the building, such as signal strength or physical structures, to determine user location. Factors like signal interference, signal propagation limitations, or changes in the building layout can affect the accuracy and reliability of the positioning system.

2.2 Wi-Fi-based enhanced positioning systems: accuracy through mapping, calibration, and classification:

In their research, Bell et al. developed a Wi-Fi-based positioning system called SaskEPS, specifically designed for a two-floor building located within a university. The system operates based on four key steps. Firstly, a database is created and recorded, containing the locations of access points. Secondly, signal strength is calibrated and converted into distance measurements. Thirdly, the system scans the surrounding environment for wireless signals, averaging and filtering each signal. Finally, the trilateration method is employed to estimate the user's location by calculating distances from three or more Wi-Fi access points with known locations installed inside the building [22].

Advantage:

1. Accurate Positioning: The Wi-Fi-based positioning system allows for accurate positioning within the indoor environment. By utilizing the trilateration method and known access point locations, it can estimate the user's location with reasonable precision.

2. Utilization of Existing Infrastructure: Wi-Fi signals are already prevalent in many indoor environments, making Wi-Fi-based positioning systems advantageous as they can leverage the existing infrastructure without requiring additional hardware installations.

3. Cost-Effective Solution: Implementing a Wi-Fi-based positioning system can be cost-effective compared to other technologies that may require specialized equipment or infrastructure. Utilizing Wi-Fi signals and existing access points reduces the need for additional investments.

Disadvantage:

1. Limited Coverage: Wi-Fi-based positioning systems are constrained by the coverage area of Wi-Fi signals. In larger or more complex buildings, signal coverage may vary, leading to potential inaccuracies in positioning or gaps in coverage.

2. Vulnerability to Signal Interference: Wi-Fi signals can be susceptible to interference from various sources, such as physical obstructions, electronic devices, or network congestion. Signal interference can impact the accuracy and reliability of the positioning system.

3. Building-Specific Implementation: The SaskEPS system, designed for a specific two-floor building, highlights a disadvantage in terms of scalability and adaptability. Each

building requires its own database of access point locations, calibration, and customization, making it less flexible for deployment in different environments.

4. Reliance on Wi-Fi Infrastructure: Since Wi-Fi signals are necessary for the system's functioning, any issues or disruptions in the Wi-Fi network can affect the performance of the positioning system. This reliance on Wi-Fi infrastructure introduces a potential point of failure.

2.3 An advanced exploration of indoor positioning and navigation systems and technologies:

The widespread adoption and usage of mobile devices have revolutionized computing, making it more mobile, versatile, and context-aware [3]. Among mobile devices, smartphones have emerged as the most popular and widely used devices in this information age [7]. Compared to their analog counterparts with limited functionality, smartphones offer multifunctionality and have become indispensable [8]. However, the effectiveness of mobile devices is contingent upon ideal situations and environments [2]. For instance, voice and text communication rely on network availability [3] and accessing online learning environments and downloading applications depend on network or Wi-Fi connectivity.

Similarly, using a mobile phone for outdoor navigation relies on uninterrupted satellite signals and network or Wi-Fi availability. In environments with limited network or Wi-Fi coverage, such as indoor spaces, basements, and underground areas, users may encounter difficulties in utilizing their mobile devices [2]. This challenge is particularly prevalent in indoor environments, where internet access and certain applications become challenging. Consequently, indoor navigation has gained popularity as a means of addressing these difficulties. As a result, research and implementation of positioning and navigation technologies have experienced significant growth, particularly in outdoor environments. This progress has prompted researchers to explore ways of simplifying navigation in indoor spaces, leading to a multitude of studies in this area. These studies have employed various techniques and technologies, each with its own strengths and weaknesses, impacting their performance [17].

Advantage:

The widespread adoption of mobile devices, particularly smartphones, has revolutionized computing, making it more mobile, versatile, and context aware. Smartphones offer multifunctionality and have become indispensable tools in the information age. Research and implementation of positioning and navigation technologies have experienced significant growth, leading to advancements in both outdoor and indoor navigation.

Disadvantage:

The effectiveness of mobile devices is dependent on ideal situations and environments, such as network availability and Wi-Fi connectivity. Using mobile phones for outdoor navigation relies on uninterrupted satellite signals and network or Wi-Fi availability, which may not always be guaranteed. Limited network coverage in indoor spaces poses challenges for utilizing mobile devices and accessing certain applications or online resources.

2.4 Design Space Exploration of a Multi-Model AI-Based Indoor Localization System:

Positioning systems and their associated services have gained significant popularity due to their ability to assist users in various applications. The increasing investments in infrastructure, advancements in technologies, and improved performance of user devices implementing positioning solutions contribute to this growing popularity. While there are mature technologies available for outdoor positioning systems that offer high accuracy down to the centimetre level, the same cannot be said for indoor positioning systems (IPSs). This is primarily because mature and stable technologies for IPSs rely on satellite constellations, which require a clear line of sight to function effectively. However, IPSs face challenges due to the presence of obstacles and the complexity and energy requirements of user devices. Signal multipathing, degradation, and line-of-sight loss further affect non-inertial-based positioning systems, particularly in confined indoor environments with numerous obstacles that can reflect and degrade electromagnetic positioning signals. Additionally, IPS solutions must consider the requirements of mobile applications and the compatibility with modern mobile communications and wireless sensor networks for execution on portable devices [13].

Advantage:

Positioning systems provide assistance to users in various applications, offering accurate positioning and improving user experiences. Mature outdoor positioning technologies achieve high accuracy down to the centimeter level, enabling precise location tracking and navigation in outdoor environments.

Disadvantage:

Indoor positioning systems face challenges in achieving the same level of accuracy as outdoor systems. They rely on different technologies that are affected by obstacles, signal multipathing, degradation, and line-of-sight loss, which can degrade the performance of the positioning system. Additionally, the complexity and energy requirements of user devices pose constraints on the range of applications for indoor positioning systems.

2.5 Design Space Exploration of an Indoor Localization System using K-ELM for Mobile Robots:

The design space exploration of an indoor localization system utilizing K-ELM for mobile robots aims to address the growing demand for accurate positioning in indoor environments. This system offers a promising solution by leveraging K-ELM (Kernel Extreme Learning Machine) algorithm, which enables efficient and robust localization for mobile robots. Unlike traditional methods, K-ELM provides a flexible and adaptable framework for modelling and learning the complex relationships between sensor data and robot position. This approach allows for improved accuracy and robustness, making it suitable for a wide range of indoor applications. However, the design space exploration process involves considering various factors such as sensor selection, feature extraction, model optimization, and system integration. Additionally, the implementation of K-ELM requires computational resources and training data, which can pose challenges in real-world deployment. Nonetheless, by exploring the design space and optimizing the system parameters, this approach holds great potential in revolutionizing indoor localization for mobile robots [10].

Advantage:

Efficient and robust localization: The utilization of K-ELM algorithm enables efficient and robust localization for mobile robots, leading to improved accuracy and robustness in indoor environments. Flexible and adaptable framework: Unlike traditional methods, K-ELM provides a flexible and adaptable framework for modelling and learning the complex relationships between sensor data and robot position, making it suitable for a wide range of indoor applications.

Disadvantage:

Complex design space exploration: The design space exploration process involves considering various factors such as sensor selection, feature extraction, model optimization, and system integration, which can be complex and time-consuming. Resource and data requirements: The implementation of K-ELM requires computational resources and training data, which can pose challenges in real-world deployment, especially in terms of availability and scalability.

2.6 A Wi-Fi RSS fingerprint database is crucial for developing an indoor positioning system for mobile robots:

Wi-Fi RSS fingerprint database construction is a vital component of developing an indoor positioning system for mobile robots. This technique utilizes Wi-Fi signals and their received signal strength (RSS) to create a database that associates RSS values with specific locations within an indoor environment. By doing so, it enables accurate localization and navigation for mobile robots. The construction of a Wi-Fi RSS fingerprint database offers several advantages. Firstly, it is a cost-effective solution as it leverages existing Wi-Fi infrastructure without requiring additional hardware installation. This makes it an attractive option for various indoor environments such as offices, warehouses, and hospitals. Additionally, Wi-Fi-based positioning systems are compatible with a wide range of devices, including smartphones and tablets, enabling seamless integration and accessibility (A.H. Ismail1, 2016).

Advantage:

Cost-effectiveness: Wi-Fi RSS fingerprint database construction utilizes existing Wi-Fi infrastructure, eliminating the need for additional hardware installation. This reduces the overall cost of implementing an indoor positioning system for mobile robots. Compatibility and accessibility: Wi-Fi-based positioning systems are compatible with a wide range of devices, including smartphones and tablets. This enables seamless integration and accessibility, making it convenient for users to leverage the system.

Disadvantage:

Access point distribution: Challenging and time-consuming to evenly distribute Wi-Fi access points in complex indoor spaces. Signal interference and accuracy: Interference from Wi-Fi devices and physical obstacles can impact RSS measurement accuracy. Dynamic Wi-Fi signals: Fluctuations in Wi-Fi signals over time require regular updates and recalibration of the database to maintain accuracy.

CHAPTER 3

3. Proposed Work:

3.1. Problem Definition:

In an experimental region, there is a problem of finding the optimal placement of Access Points (APs) in order to achieve better AP coverage for a certain number of location points, while still providing appreciable coverage for the remaining location points. The objective is to ensure good AP coverage, which means being able to accurately locate a user within the coverage area with a minimal localization error, ideally less than 2.5 meters. The goal is to achieve this optimal AP placement by minimizing the number of APs required while maximizing the localization ability.

The problem statement can be mapped to the graph coloring problem. In this analogy, each node of the graph represents a unique location point. The graph coloring problem involves assigning colors to the nodes of a graph in such a way that no two adjacent nodes share the same color. Similarly, in this context, the colors represent the APs, and the goal is to assign APs to location points in a way that nearby points do not share the same AP, ensuring better coverage and reducing interference.

By treating the problem as a graph coloring problem, it becomes possible to leverage existing algorithms and techniques developed for solving graph coloring problems. These algorithms can help determine an optimal placement of APs that maximizes the localization ability while minimizing the number of APs required.

Overall, the problem of finding the optimal placement of APs for improved coverage can be approached by formulating it as a graph coloring problem, where each location point is represented as a node in the graph and the objective is to assign APs (colors) in a way that minimizes interference and maximizes localization ability.

3.2. Constraints:

For each pair of location points, for which confusion arises to distinguish them based on RSSI values, there is a connectivity link between them. For example, let L1 and L2 are connected by an edge. It means that difficulties arises to distinguish L1 and L2, but L1 and L3 can be distinguish without confusion. Hence, there is no connectivity edge between L1 and L3

The challenge is to color the graph with minimum number of colors maintaining that no two connected nodes are connected by same color. Here, each color represents unique AP. Since, confusion between location points arises due to receiving similar RSSI value, we need new placement of different APs to distinguish confusing location points.

3.3. Basic Graph Coloring Approach:

Algorithm:

Step 1. Start with an uncolored vertex and assign it a color.

Step 2. Select the uncolored vertex with the most colored neighbors, prioritizing the one with the fewest available colors among its neighbors in case of ties.

Step 3. Assign the lowest available color to the chosen vertex.

Step 4. Repeat steps 2 and 3 until all vertices are colored.

Graph coloring is a fundamental problem in graph theory, which involves assigning colors to the vertices of a graph such that no two adjacent vertices have the same color. The goal of graph coloring is to minimize the number of colors used to color the graph.

A simple graph coloring problem involves coloring a graph using a minimum number of colors, such that no two adjacent vertices have the same color. The problem can be formulated as follows:

Given an undirected graph G = (V, E), where V is the set of vertices and E is the set of edges, find a coloring function $c : V \rightarrow \{1, 2, ..., k\}$ such that for every edge $(u, v) \in E$, $c(u) \neq c(v)$, and k is the minimum number of colors required to color the graph.

3.4. Proposed Graph Coloring(weighted) Approach:

Algorithm: GLOC_coloring

Input: Set of m locations: $L= [l_1, l_2, \ldots\ldots\ldots\ldots, l_m]$ for a positive finite integer value of m.

Output: Minimum number n of required APs to improve localization accuracy at prioritized locations.

Step 1. Apply ML classifier on the L and obtain the confusion matrix CM.

Step 2. Create a graph G in which each vertex represents a unique location from L. Two vertices V_x and V_y representing locations l_a and l_b respectively, are connected with an edge if V_x is misclassified as V_y or vice-versa or both.

Step 3. Each edge E in G connecting two vertices V_x and V_y representing locations l_a and l_b is assigned with a weight $W_e = CM [l_a, l_b] + CM [l_b, l_a]$.

Step 4. Each vertex V is assigned with a weigh W_v which is the sum weights of all edges connected to V.

Step 5. Identify the vertex V_s in G having maximum weight. Assign it a unique color C_s and add C_s in an empty array ***Color_used***. Add V_s to an empty array ***Visited***.

Step 6. Identify the set S_v of all vertices connected to the vertices present in the array ***Visited*** and find the vertex V_m with maximum weight in S_v.

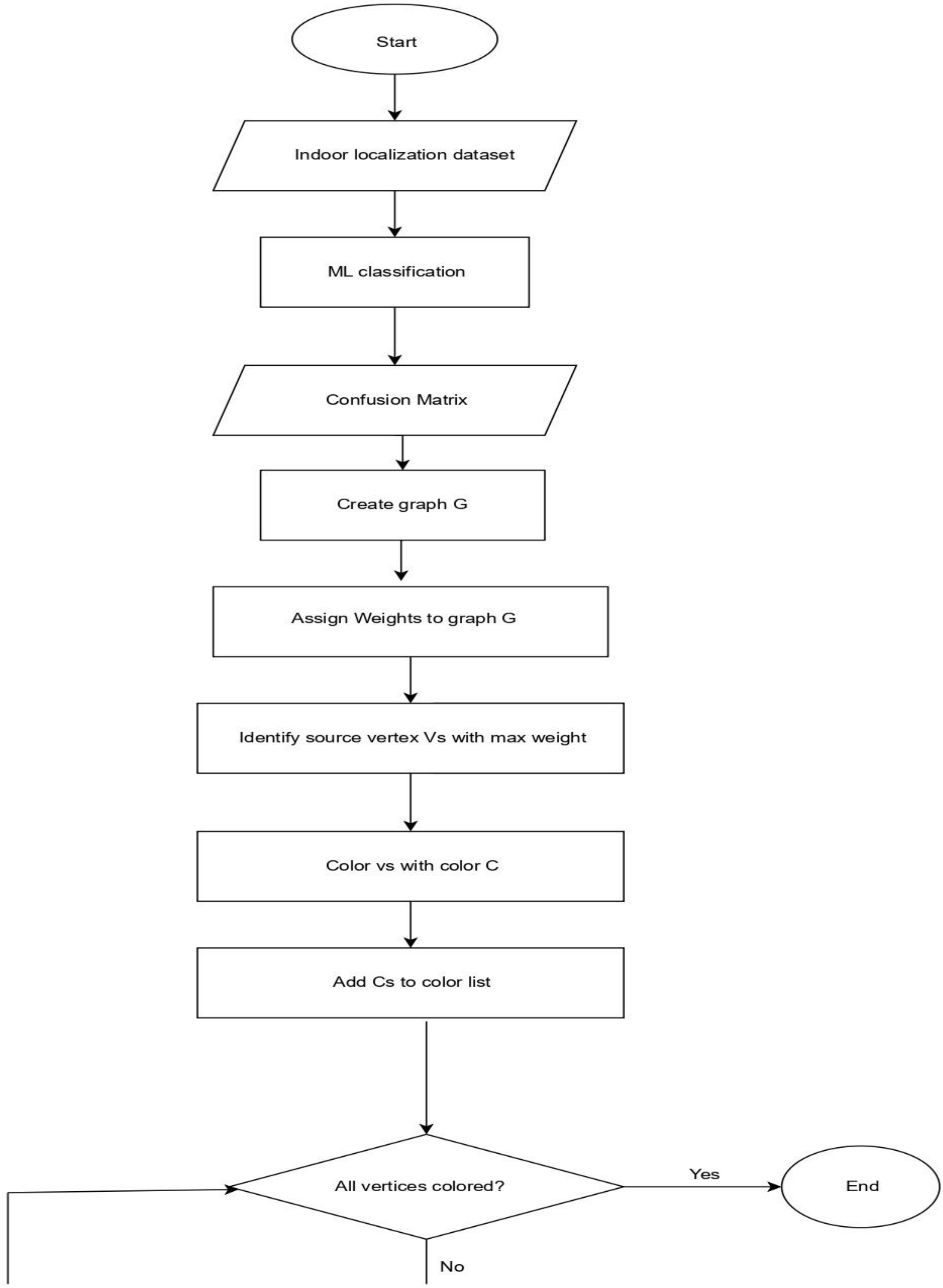
Step 7. Pick a color C from ***Color_used*** that is not assigned to any connected vertex of V_m.

Step 8. If C is null then go to step 10. Else assign C to V_m and go to step 10.

Step 9. Assign a new color C_{new} to V_m and go to step 10.

Step 10. Repeat steps 6 to 9 until all vertices in G are assigned to a color.

Step 11. ***n*=** number of colors in ***Color_used***.



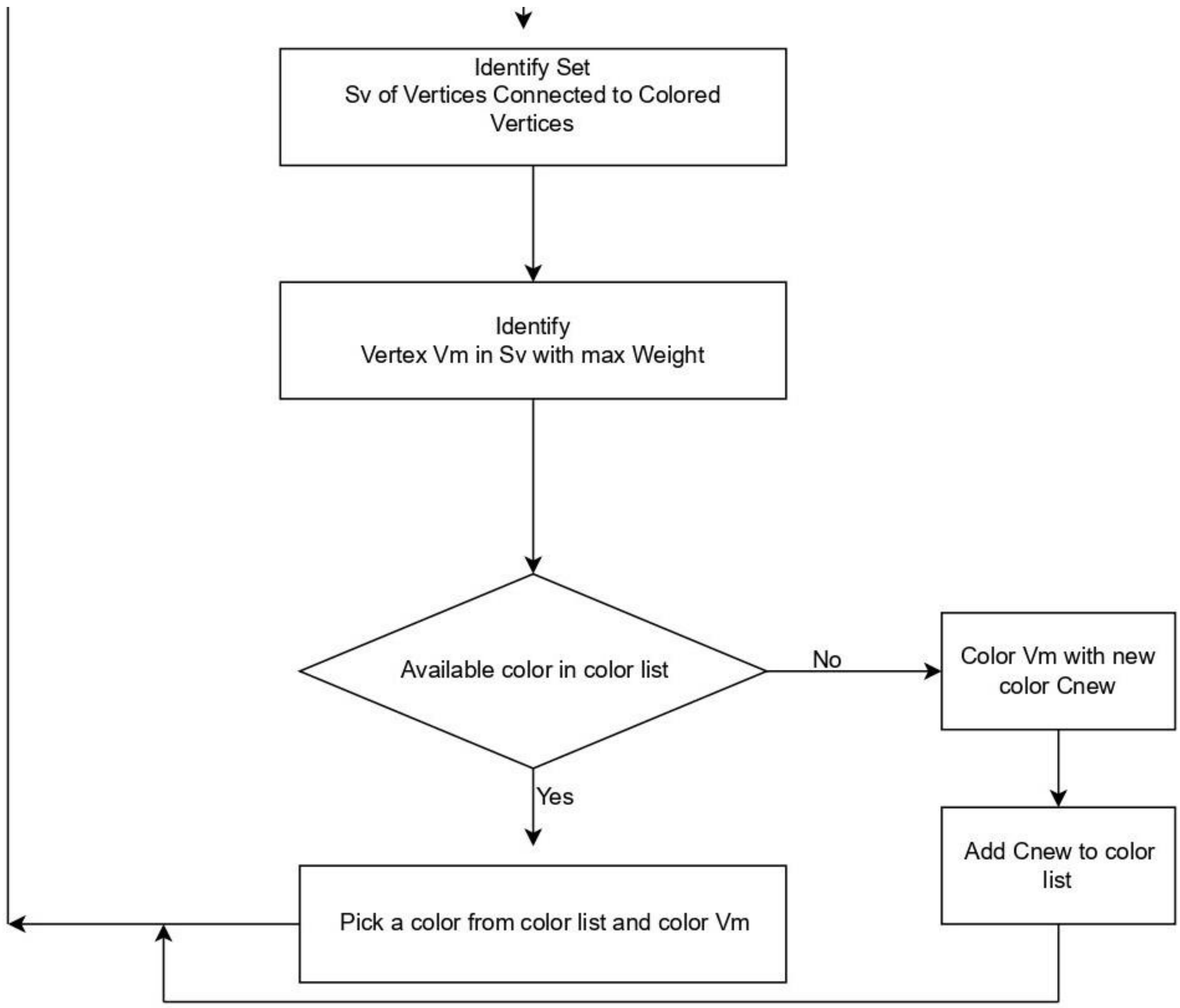


Fig_1: Flowchart of GLOC_coloring

The GLOC_coloring algorithm can be applied in indoor localization to determine the minimum number of Access Points (APs) required to improve the accuracy of the localization of specific locations. This algorithm uses a machine learning (ML) classifier to obtain a confusion matrix, which is used to create a graph. Each vertex in the graph represents a unique location from the set of locations L.

The edges in the graph are assigned weights based on the confusion matrix, and each vertex is assigned a weight based on the sum of the weights of all edges connected to it. The algorithm then identifies the vertex with the maximum weight and assigns it a unique color. The set of vertices connected to the visited vertices is then identified, and the vertex with the maximum weight in that set is selected. A color is assigned to this vertex, which is not assigned to any of its connected vertices.The process continues until all vertices are assigned a color, and the number of colors used represents the minimum number of APs required to improve the localization accuracy at prioritized locations. In indoor localization, this algorithm can help determine the optimal number of APs to deploy and their locations to achieve the desired accuracy levels.

3.5. Features of the Proposed Approach:

In the GLOC_coloring algorithm, the vertices represent locations, and the edges represent misclassifications between those locations. The goal is to assign colors to the vertices in such a way that the number of colors used is minimized while improving the localization accuracy at prioritized locations. This is achieved by using a machine learning classifier to obtain a confusion matrix, which is then used to assign weights to the edges of the graph.

The simple graph coloring problem is a well-known problem in graph theory where the vertices of a graph are colored in such a way that no two adjacent vertices have the same color. The goal is to minimize the number of colors used. The GLOC_coloring algorithm is a specific application of graph coloring in the context of indoor localization.

The main difference between the simple graph coloring problem and the GLOC_coloring problem is the context in which they are applied. The simple graph coloring problem is a general graph theory problem, whereas the GLOC_coloring problem is specific to indoor localization. The GLOC_coloring problem has a particular application domain and specific objectives, which makes it more targeted and focused than the simple graph coloring problem.

Our proposed work for the thesis based on this topic involves an in-depth analysis of the GLOC_coloring algorithm and its effectiveness in improving localization accuracy. The thesis could explore the factors that influence the performance of the algorithm, such as the size of the location set and the number of prioritized locations. The thesis could also investigate the performance of the algorithm compared to other indoor localization methods, such as fingerprinting and triangulation. Additionally, the thesis could explore ways to optimize the GLOC_coloring algorithm and make it more efficient in terms of computational complexity and memory usage.

3.6. Summary:

The problem is to find the optimal placement of Access Points (APs) to improve AP coverage for a set of location points while minimizing the number of APs required. The problem is treated as a graph coloring problem, where each location point is represented as a node in the graph, and APs are assigned as colors to minimize interference and maximize localization ability. The proposed algorithm, GLOC_coloring, utilizes a machine learning classifier to obtain a confusion matrix and creates a weighted graph based on misclassifications. The algorithm assigns colors to vertices based on weights and connectivity, determining the minimum number of APs needed for improved localization accuracy. The thesis aims to analyze the effectiveness of the GLOC_coloring algorithm, explore its performance factors, compare it with other localization methods, and optimize its efficiency.

CHAPTER 4

4. Experimental results and discussion:

4.1. Experimental setup:

In this experiment we have utilized a benchmark dataset-JUIndoorLoc for experimentation. The dataset could be found in (https://drive.google.com/open?id=1_z1qhoRIcpineP9AHkfVGCfB2Fd_e-fD) and described in [5]. To form the dataset, the authors of [5] have collected data in two phases: training data collection and testing data collection. The training data was collected over a period of 28 days, while the testing data was collected over a longer duration of 4 months.

In the indoor environment, there may be changes such as the removal or installation of access points. This means that the availability and configuration of APs can vary over time. To address this issue and ensure the stability of the access points used for testing, it is recommended to have a minimum gap of two months between the training and testing data collection periods. During the data collection process, mobile devices equipped with Wi-Fi data collectors were used. These devices were responsible for measuring the signal strength of the available access points from different locations within the indoor environment.

The main objective of the authors during this stage was to collect RSSI (Received Signal Strength Indicator) fingerprints. RSSI fingerprints represented the signal strength of the access points at various locations within the indoor environment. These fingerprints provided valuable information for location-based services, indoor positioning systems, or any other applications that relied on understanding the signal strength characteristics in a given space. By collecting RSSI fingerprints from all possible locations, the authors aimed to create a comprehensive dataset that captured the signal strength variations across the indoor environment. This dataset served as the basis for further analysis and modeling to understand the behavior of access points and improve the performance of Wi-Fi-based systems within the environment [5].

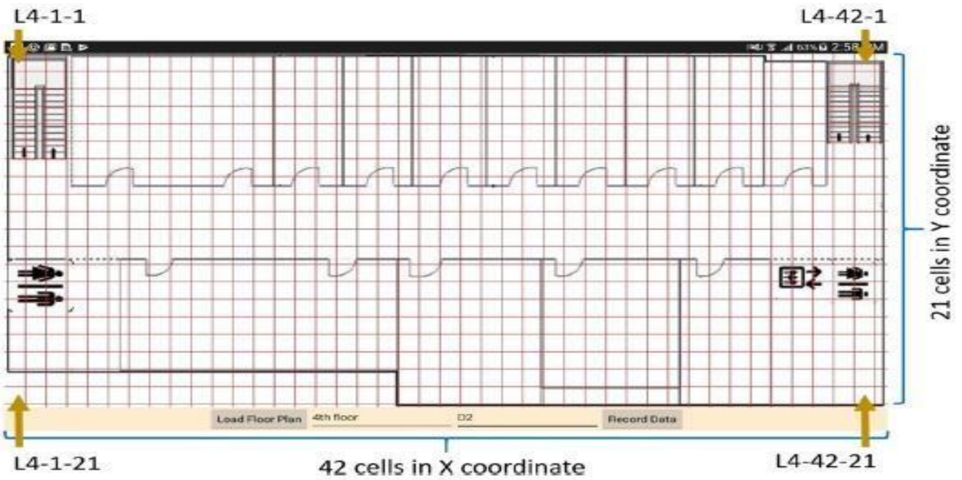


Fig_2: Floor map of JUIndoorLoc Dataset [5]

Four android devices are used for data collection to measure the variation of Wi-Fi signal. The experimental data were collected by authors from the 3rd ,4th and 5th floor of our university department building. APs are installed at specific locations of our university building covering the whole experimental regions. We divided the entire region into 1m x 1m cells and, X and Y co-ordinates of each floor is divided into 42 and 21 cells respectively. Due to obstacles RSSI values have not been taken from all the cells.

We have conducted this experiments on the data collected from room no. cc-5-3 and cc-5-1.The performance of the dataset has been analyzed by using two different methods. First, state of the art classifiers of Jupiter notebook and second one is a statistical method. But here we only use state of art classifiers for analysis purposes. All experiments are performed on Intel core i7-8750H machine with 2.20GHz processor and 16 GB RAM.

4.2. Results and discussion:

ROOM	KNN	SVM	RF	NB
cc-5-1	0.93	0.76	0.75	0.64
cc-5-2	0.78	0.77	0.50	0.70
cc-5-3	0.81	0.75	0.73	0.78
cc-5-5	0.80	0.64	0.54	0.57
cc-5-7	0.80	0.78	0.53	0.67

Table_1: Accuracies of used classifiers in different locations

In our dataset, KNN algorithm performs better than any other algorithm, as it can be observed that accuracy obtained for KNN classifier is greater than 70% in all of the 5 cases. According to Table_1, accuracy of KNN algorithm ranges between 78.01 and 93.00%, accuracy of SVM ranges between 64 and 78.00% by taking k value as 2, Random Forest and GaussianNB are 52 to 82.00%, 50.00 to 73.00% and 64 to 94.5% respectively. In most of the subsets of data KNN performs better than any other classification algorithms.

Based on these accuracy ranges, it can be concluded that the KNN algorithm consistently performs better than other classification algorithms in most of the subset of data. This suggests that KNN is a suitable choice for this particular dataset, as it consistently achieves higher accuracy in the classification tasks compared to the other algorithms considered.

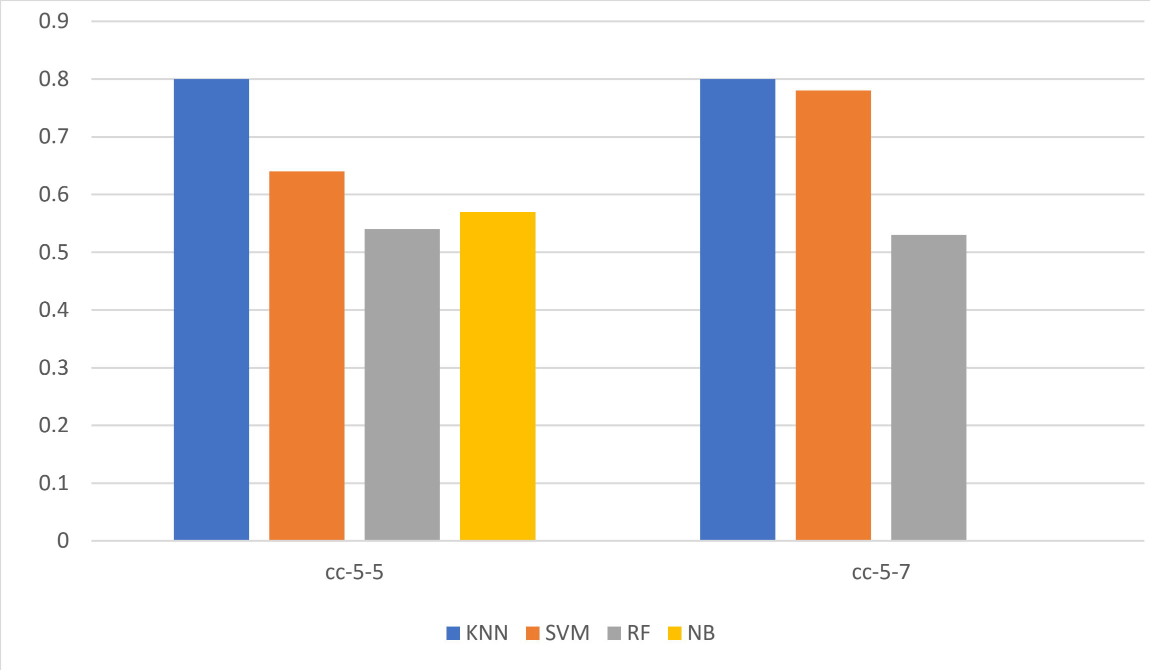


Fig_3: Localization accuracy obtained using various ML classifiers for room no. cc-5-5 and cc-5-7

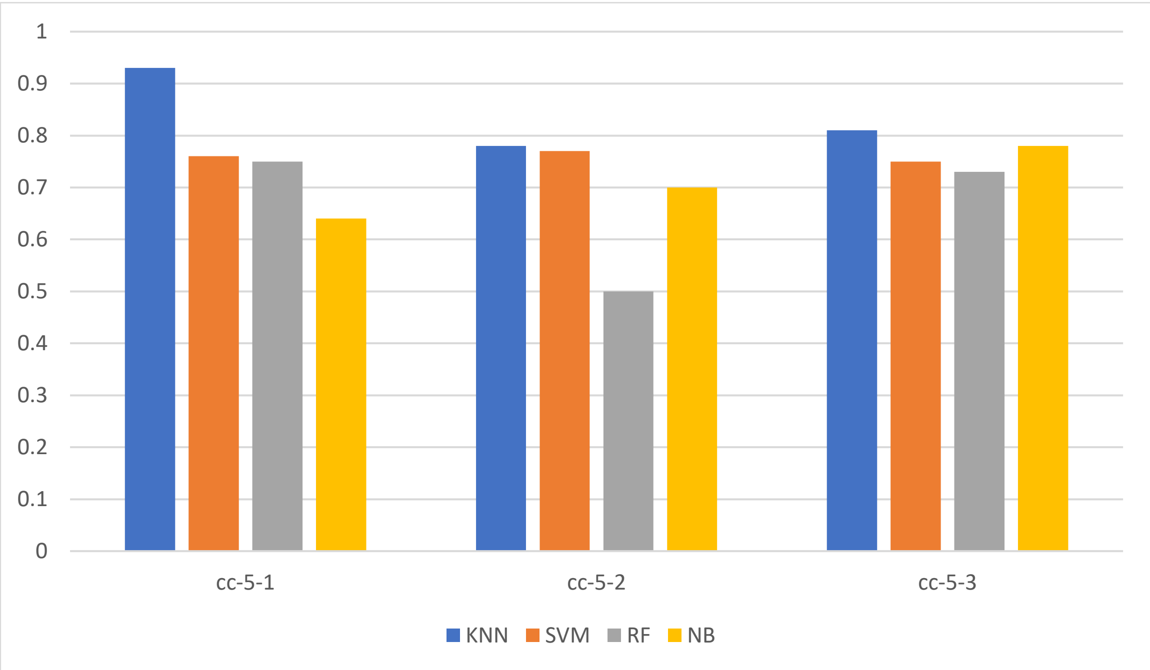


Fig_4: Localization accuracy obtained using various ML classifiers for room no. cc-5-1, cc-5-2 and cc-5-3

Fig_3 and Fig_4 depicts accuracies of KNN, SVM, RF and NB. KNN algorithm performs better than any other algorithm, as it can be observed that accuracy obtained for KNN classifier is greater than SVM, RF and NB in the above rooms.

Create Graph from Confusion Matrix: The confusion matrix displays the counts of four types of predictions: true positives, true negatives, false positives, and false negatives. These counts are organized for each class in the classification problem. True positives represent instances that are correctly predicted as positive, true negatives represent instances that are correctly predicted as negative, false positives are instances that are wrongly predicted as positive, and false negatives are instances that are wrongly predicted as negative. By examining the values in the confusion matrix, one can gain valuable insights into the accuracy and misclassification patterns of the model.

Example:

```
[[0.   0.   0.   0.33 0.   0.67 0.   0.   0.   0.  ]
 [0.   0.   0.   0.33 0.   0.67 0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.67 0.33 0.   0.   0.   0.  ]
 [0.   0.   0.   0.67 0.   0.   0.   0.33 0.   0.  ]
 [0.   0.   0.   0.   0.33 0.33 0.   0.   0.33 0.  ]
 [0.   0.   0.   0.33 0.33 0.33 0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.33 0.67 0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   0.   1.   0.   0.  ]
 [0.   0.   0.   0.   0.33 0.33 0.   0.   0.33 0.  ]
 [0.   0.   0.   0.   0.   0.   0.   0.   0.   1.  ]]
```

Fig_5: Confusion matrix of cc-5-3

```
[[1.   0.   0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.   1.   0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.33 0.   0.67 0.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.33 0.   0.   0.33 0.33 0.   0.  ]
 [0.   0.   0.   0.   0.33 0.33 0.   0.33 0.   0.  ]
 [0.33 0.   0.   0.   0.   0.   0.   0.33 0.   0.33]
 [0.   0.   0.   0.   0.   0.   1.   0.   0.   0.  ]
 [0.   0.33 0.   0.   0.   0.   0.   0.67 0.   0.  ]
 [0.33 0.   0.   0.   0.   0.33 0.33 0.   0.   0.  ]
 [0.33 0.   0.   0.   0.   0.33 0.   0.   0.   0.33]]
```

Fig_6: Confusion matrix of cc-5-1

Fig_5 and Fig_6 are the normalised confusion matrices of room no. cc-5-3 and cc-5-1. Now we select a color map for the heatmap by specifying the cmap argument. In this example, the color map 'Blues' is used, but you can choose another one if you wish.To add labels to the chart for the x-axis, y-axis and a title, we use the functions plt.xlabel(), plt.ylabel() and plt.title() respectively. Change these labels depending on your specific context.Finally, we call plt.show() to display the chart.

Fig_7 and Fig_8 depicts the heat maps representing the normalized confusion matrices for two different rooms, specifically room cc-5-3 and cc-5-1, respectively. The heat maps were generated using the Matplotlib libraries. In these heat maps, the presence of a deep blue color signifies a significant level of confusion between various location points. On the other hand, uncolored regions indicate no confusion between the points. In simpler terms, lighter colors indicate a lower degree of confusion, while brighter colors indicate stronger levels of confusion.

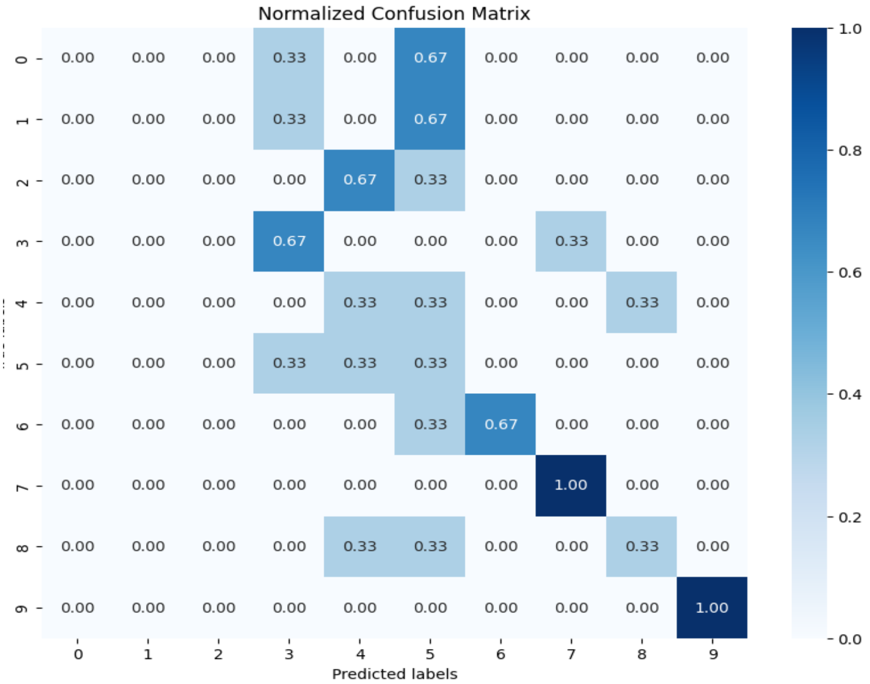


Fig_7: Heat map of cc-5-3

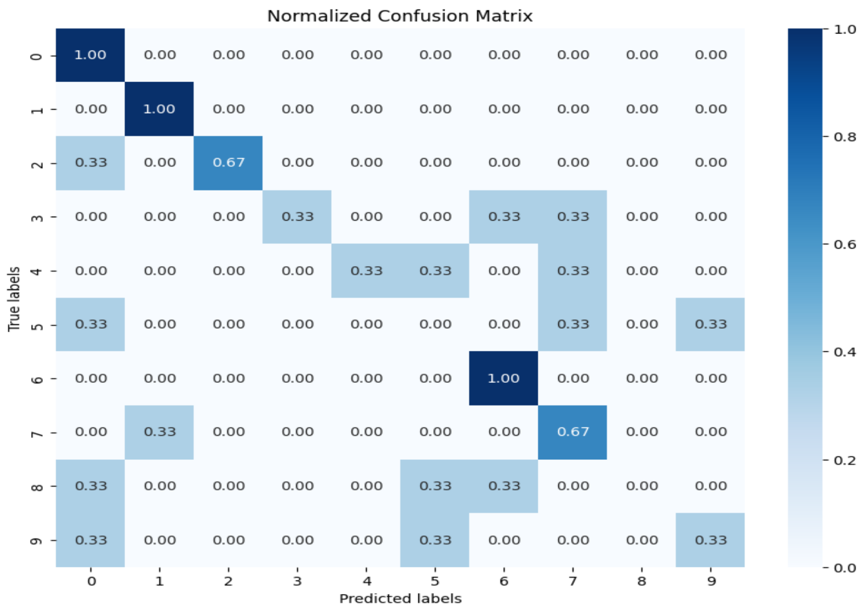


Fig_8: Heat map of cc-5-1

Mapping of new APs in map: Now, by applying our proposed algorithm(GLoc) on floor map we got minimum number of different new access points for different rooms. The following room maps are showing different Aps for room cc-5-3 and cc-5-1.

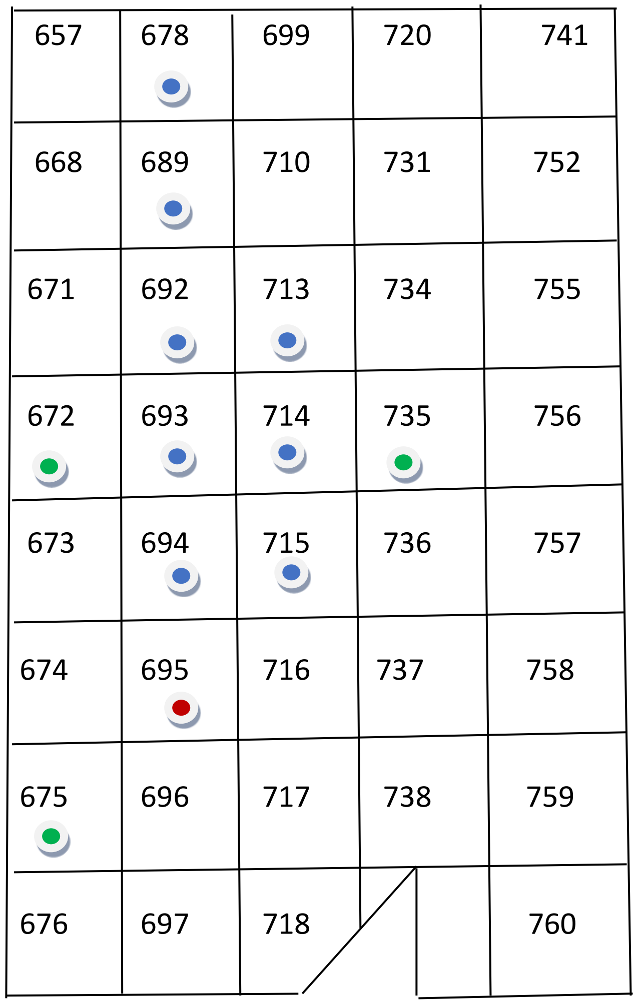


Fig_9: Floor map of room no. cc-5-3

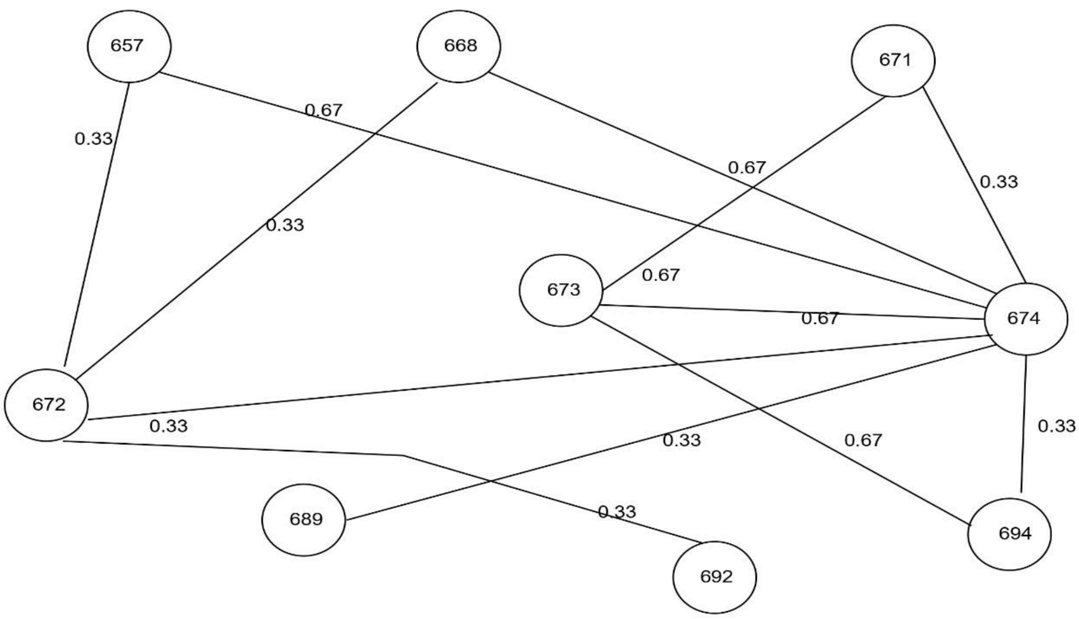


Fig_10: Graphical representation of confusion between location points in cc-5-3

Fig_10 and fig_12 shows confusions between various location points of cc-5-3 and cc-5-1 respectively. In this scenario, each edge weight indicates the level of confusion between two location points. Higher edge weights correspond to a higher degree of confusion, and lower weights indicate less confusion. To determine the minimum number of access points required for the room, we initially employed a simple graph coloring algorithm. The result of this algorithm yielded a chromatic number of 4, indicating that 4 new access points would be needed for installation. However, when we applied our proposed GLOC_algorithm, we obtained a more efficient outcome. The GLOC_algorithm suggested that only 3 new access points would be required instead of the 4 indicated by the previously used algorithm.

Our initial approach, utilizing the graph coloring algorithm, suggested the need for 4 new access points. However, our proposed GLOC_algorithm proved to be more effective, indicating that only 3 new access points would be necessary.

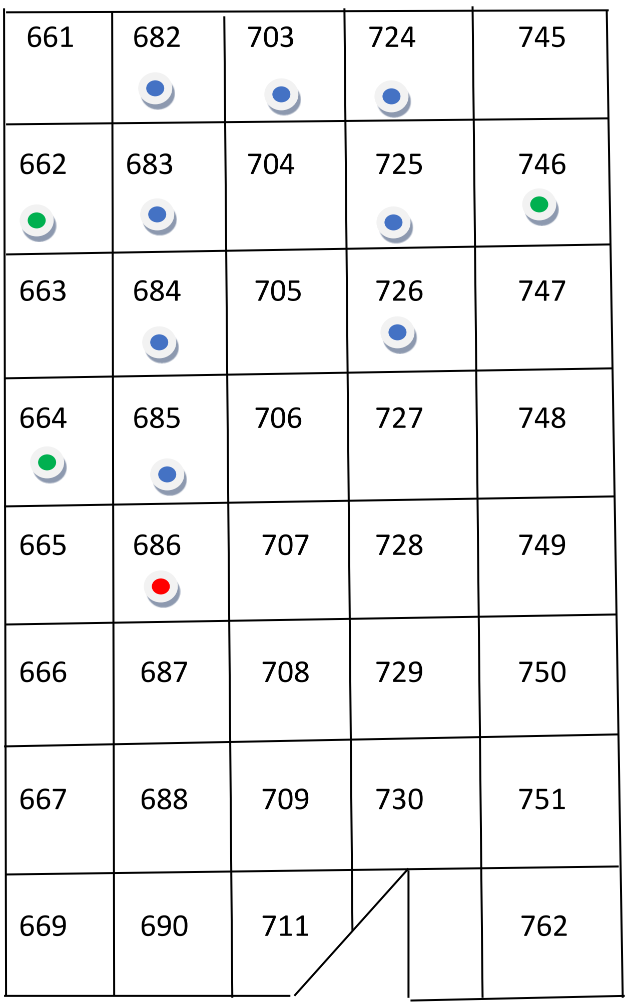


Fig_11: Floor map of room no. cc-5-1

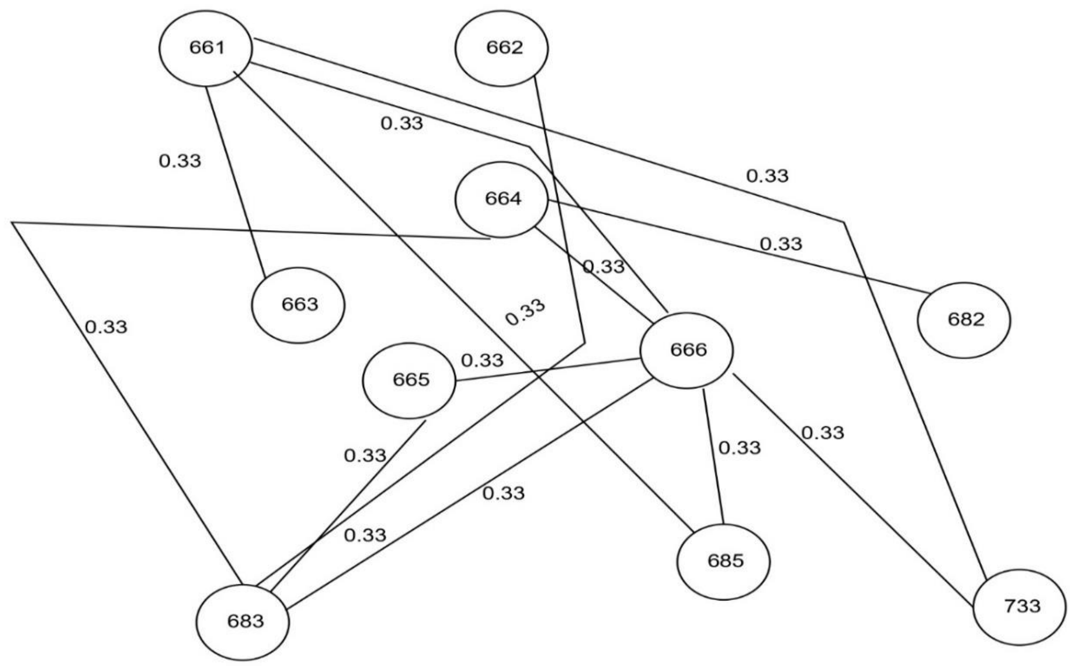


Fig_12: Graphical representation of confusion between location points in cc-5-1

In above fig_9 & fig_11 green dots represent the locations of confusion points, indicated in relation to a source point represented by a red dot. Additionally, three new access points (APs) are introduced, represented by three green dots on the map. These APs have been strategically placed in three different locations to mitigate confusion.

The purpose of introducing these APs is to improve the coverage and reduce confusion in the specified areas. By strategically placing the APs, the aim is to prioritize certain locations that require better AP coverage. These prioritized locations are likely areas where confusion is more prevalent or critical for the intended purpose.

The placement of the APs is carefully considered to ensure that these prioritized locations receive optimal AP coverage. This means that the signal strength and connectivity provided by the APs are specifically tailored to these areas, ensuring better performance and accuracy in those locations.

Simultaneously, the placement of the APs is also designed to provide appreciable AP coverage to all other location points on the map.

However, while the focus is on providing optimal AP coverage for the prioritized locations, the placement strategy also considers the need to offer appreciable coverage to all other location points on the map. This means that even though the prioritized locations receive a higher level of AP coverage, the remaining areas still benefit from adequate coverage, albeit to a slightly lesser extent. The goal is to ensure that users throughout the entire area can connect to the network and enjoy a satisfactory wireless experience, even if the prioritized locations receive a more tailored and optimized coverage.

In a nutshell, the introduction of APs aims to improve coverage and minimize confusion in specific areas. The strategy involves strategically placing the APs to prioritize locations with higher AP coverage needs, typically where confusion is more prevalent or critical. The APs are configured to provide optimal signal strength and connectivity to these prioritized locations, resulting in improved performance and accuracy. Simultaneously, the placement of the APs also considers providing appreciable AP coverage to all other points on the map, ensuring that users throughout the area can access the network effectively, although at a slightly lower level of coverage compared to the prioritized locations.

CHAPTER 5

Conclusion:

In this study, we propose a novel approach to optimize the placement of access points (APs) with the objective of improving localization accuracy while minimizing the number of required APs. To conduct our experiment, we implemented the algorithm using data from our university classrooms within the department. We collected RSSI fingerprints from the JUIndoorLoc benchmark dataset.

The main goal of our proposed algorithm is to minimize the number of new access points that need to be installed, thereby reducing potential confusion in location points within specific rooms. By strategically placing these new APs on the available floor plan. We can ensure better Wi-Fi signal coverage in the prioritized rooms of our experimental region.

References

[1] Ismail, A.H., Kitagawa, H., Tasaki, R. and Terashima, K., 2016, October. WiFi RSS fingerprint database construction for mobile robot indoor positioning system. In *2016 IEEE international conference on systems, man, and cybernetics (SMC)* (pp. 001561-001566). IEEE.

[2] Aijaz, A., Aghvami, H. and Amani, M., 2013. A survey on mobile data offloading: technical and business perspectives. *IEEE Wireless Communications*, *20*(2), pp.104-112.

[3] Aker, J.C. and Mbiti, I.M., 2010. Mobile phones and economic development in Africa. *Journal of economic Perspectives*, *24*(3), pp.207-232.

[4] Atia, M.M., Noureldin, A. and Korenberg, M.J., 2012. Dynamic online-calibrated radio maps for indoor positioning in wireless local area networks. *IEEE Transactions on Mobile Computing*, *12*(9), pp.1774-1787.

[5] Roy, P., Chowdhury, C., Ghosh, D. and Bandyopadhyay, S., 2019. JUIndoorLoc: A ubiquitous framework for smartphone-based indoor localization subject to context and device heterogeneity. *Wireless Personal Communications*, *106*, pp.739-762.

[6] Chang, N., Rashidzadeh, R. and Ahmadi, M., 2010. Robust indoor positioning using differential Wi-Fi access points. *IEEE Transactions on Consumer Electronics*, *56*(3), pp.1860-1867.

[7] Din, M.M., Jamil, N., Maniam, J. and Mohamed, M.A., 2018. Review of indoor localization techniques. *International Journal of Engineering & Technology*, *7*(214), p.201.

[8] Dinh, H.T., Lee, C., Niyato, D. and Wang, P., 2013. A survey of mobile cloud computing: architecture, applications, and approaches. *Wireless communications and mobile computing*, *13*(18), pp.1587-1611.

[9] Farid, Z., Nordin, R. and Ismail, M., 2013. Recent advances in wireless indoor localization techniques and system. *Journal of Computer Networks and Communications*, *2013*.

[10] Wang, H., Li, J., Cui, W., Lu, X., Zhang, Z., Sheng, C. and Liu, Q., 2019. Mobile robot indoor positioning system based on K-ELM. *Journal of Sensors*, *2019*.

[11] Sumitra, I.D., Hou, R. and Supatmi, S., 2017. Study of hybrid localization noncooperative scheme in wireless sensor network. *Wireless Communications and Mobile Computing*, *2017*.

[12] Seco, F. and Jiménez, A.R., 2018. Smartphone-based cooperative indoor localization with RFID technology. *Sensors*, *18*(1), p.266.

[13] Kotrotsios, K., Fanariotis, A., Leligou, H.C. and Orphanoudakis, T., 2022. Design Space Exploration of a Multi-Model AI-Based Indoor Localization System. *Sensors*, *22*(2), p.570.

[14] Kunhoth, J., Karkar, A., Al-Maadeed, S. and Al-Ali, A., 2020. Indoor positioning and wayfinding systems: a survey. *Human-centric Computing and Information Sciences*, *10*(1), pp.1-41.

[15] Chelly, M. and Samama, N., 2009, May. New techniques for indoor positioning, combining deterministic and estimation methods. In *ENC-GNSS 2009: European Navigation Conference-Global Navigation Satellite Systems* (pp. 1-12).

[16] Gomes, R., Ahsan, M. and Denton, A., 2018, May. Random forest classifier in SDN framework for user-based indoor localization. In *2018 IEEE International Conference on Electro/Information Technology (EIT)* (pp. 0537-0542). IEEE.

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

[18] Shyam, S., Juliet, S. and Ezra, K., 2022. Indoor positioning systems: a blessing for seamless object identification, monitoring, and tracking. *Frontiers in Public Health*, *10*.

[19] Šinko, S., Marinič, E., Poljanec, B., Obrecht, M. and Gajšek, B., 2022. Performance-Oriented UWB RTLS Decision-Making Approach. *Sustainability*, *14*(18), p.11456.

[20] Song, X., Fan, X., Xiang, C., Ye, Q., Liu, L., Wang, Z., He, X., Yang, N. and Fang, G., 2019. A novel convolutional neural network based indoor localization framework with WiFi fingerprinting. *IEEE Access*, *7*, pp.110698-110709.

[21] Guerrero, L.A., Vasquez, F. and Ochoa, S.F., 2012. An indoor navigation system for the visually impaired. *Sensors*, *12*(6), pp.8236-8258.

[22] Bell, S., Jung, W.R. and Krishnakumar, V., 2010, November. WiFi-based enhanced positioning systems: accuracy through mapping, calibration, and classification. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Indoor Spatial Awareness* (pp. 3-9).