BACHELOR OF SCIENCE IN ELECTRONIC AND TELECOMMUNICATION ENGINEERING

Enhanced Localization Infrastructure for 6G Cellular Network

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Declaration

It hereby states that we have completed this work and that no portion of the work found in this thesis has been submitted elsewhere for this thesis has not been before submitted for any degree or certificate

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Certificate of Approval

The thesis titled **“Enhanced Localization Infrastructure for 6G Cellular Network”** Submitted by **Md. Aminul Islam** bearing Matric ID **T191062** to the Department of Electronic and Telecommunications Engineering (ETE) of International Islamic University Chittagong (IIUC) has been accepted as satisfactory for the partial fulfillment of the requirements for the Degree of Bachelor in Electronic and Telecommunications Engineering and approved as to its style and contents for the examination held on 24 February 2024.

Approval of Supervisor

The Caption of this Study is **"Enhanced Localization Infrastructure for 6G Cellular Network".** This study is submitted by **Md. Aminul Islam (T191062)** to the Department of Electronic and Telecommunication Engineering (ETE) of International Islamic University Chittagong (IIUC). It has been satisfactory for the partial fulfillment of the requirements for the bachelor's degree of Science in Electronic and Telecommunication Engineering (ETE). It was approved by our supervisor.

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Abstract

Information about the whereabouts of oneself or our cell phones has always been crucial to humans. Technological advancements have supported us across various domains, spanning from interior environments to outdoor global positioning systems. However, achieving real-time indoor positioning has remained a formidable task. The requirement for enhanced positioning has gained prominence in the context of the emergence of 6G cellular networks. The introduction of novel radio technologies, characterized by reduced end-to-end latency, specialized control protocols, and increased processing capacity at the network edge, has opened doors to harnessing the 6G cellular network's full potential for precise localization in indoor and outdoor settings. Within the 6G cellular network context, this study successfully implemented the classic signal fingerprinting approach using the Received Signal Strength Indicator in a combination with machine learning algorithms. Consequently, it proposed an improved positioning strategy designed for indoor localization scenarios in the next 6G cellular network environment. Using this method, with two datasets, the mean error distance of 0.08025523, meaning an accuracy of 99.92% and 0.10692412 was achieved, which is 99.89% accuracy respectively.

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List of Abbreviations

APIT	Approximate Point-in-Triangulation Test
NMT	Nordic Mobile Telephones
TACS	Total Access Communication Systems
TA	Timing Advance
RTT	Round-Trip Time
MDS	Multidimensional Scaling
ToA	Time of Arrival
ToF	Time of Flight
TDoA	Time difference of Arrival
RToF	Round Trip Time of Flight
PoA	Phase of Arrival
PD	Partial Discharge
AoA	Angle of Arrival
DoA	Direction of Arrival
FDoA	Frequency Difference of Arrival
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
LQI	Link Quality Indicator
CSI	Channel State Information
OTP	Open Transport Protocol
GNSS	The Global Navigation Satellite System
CID	Cell Identity
CBIR	Content Based Image Retrieval
IPS	Indoor Positioning System
LBS	Location Based Service
AP	Access Point
WSN	Wireless Sensor Network
RP	Reference Point
TP	Test Point
PCA	Principle Components Analysis
LS-SVM	Least Squares Support Vector Machine

OAI	Open Air Interface
SDN	Software-Defined Networking
CFT	Curve Fitting Technique
RBS	Radio Base Station
kNN	k-Nearest Neighbors
SVM	Support Vector Machine
IoT	Internet of Things
GSM	Global System Mobile Communication
GPS	Global Positioning System
RDEI	Radial Distance Error Indicator
LEI	Localization Error Indicator
LOS	Line-of-Sight
FCC	Federal Communications Commission
UE	User Equipment
EDGE	Enhanced Data rate for GSM Evolution
AMMS	Access Multimedia Messaging Services
ITU	International Telecommunication Union
LTE	Long Term Evolution
TA	Timing Advance
RTT	Round-Trip Time
ML	Machine Learning
mW	milliwatts
dBm	decibel milliwatts
3GPP	Third Generation Partnership Project
API	Application Programming Interfaces
OTD	Observed Time Difference
RF	Radio Frequency
WLAN	Wireless Local Area Network
SVM	Support Vector Machine
LS-SVM	Least Squares Support Vector Machine
RBS	Radio Base Stations
BS	Base Station

Chapter 1

Introduction

1.1 Introduction

People have been dreaming of personal, transportable robotic assistants that will improve our daily lives for the past century. Originally designed to democratize voice communication, cellular communications have undergone distinct evolutionary phases. The 2G network brought phone services to the general public, while 1G catered to business users. The development of 3G was driven by the growing demand for mobile data. The goal of 5G was to introduce the tactile internet, enabling real-time control of both physical and digital entities. The next ten years should see the maturation of robotics technology, but the wireless networking infrastructure is not there yet. 6G intends to solve this by making control function orchestration and sensing possible. By 2030, 6G will have advanced mobile communications beyond previous generations, bringing the fantasy of robotic assistants closer to reality [1].

1.2 Evolution of Cellular Technologies

The upgradation from 1G to 6G did not happen without the creativity and innovation of each generation of telecommunications to achieve what it is today. Roughly every ten years since 1979, each new generation has changed the way we communicate, further improving our lifestyles.

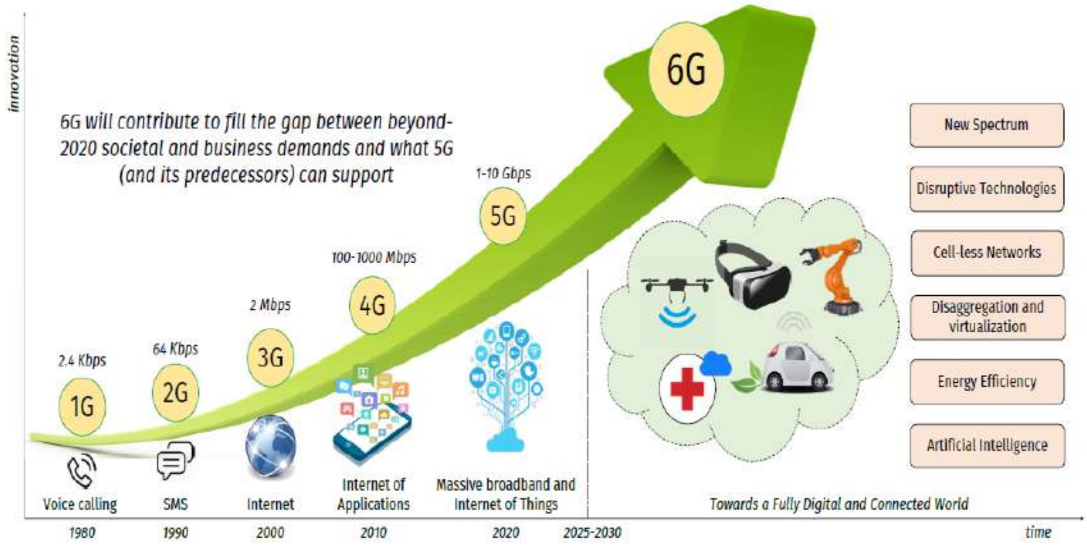

Figure 1 Evolution of cellular networks, from 1G to 6G, with a representative application for each generation [2]

Mobile technology has progressed from the first to the fifth generation (5G) to respond to the demands of end users and network operators. But with millions of sensors implanted in homes, offices, and other public spaces, as well as autonomous systems, society is become more automated, data-centric, and data-dependent. In these new paradigms of smart systems, communication networks will be essential, but they will have to move more data faster. Sixth generation (6G) will completely actualize the Internet of Things (IoT) concept, going beyond individualized communication [2].

1.2.1 First Generation (1G)

First generation cellular system provided voice service by using analog transmission. 1G was first made available to Tokyo residents in 1979 when it was provided by Nippon Telegraph and Telephone. Japan was the first nation to have 1G service available nationally in 1984 when the first generational network completely spanned the nation. Not until March 6, 1983, did Ameritech launch 1G in the US market. Canada began to receive attention in the middle of the 1980s. Total Access Communication Systems (TACS) and Nordic Mobile Telephones (NMT) were the two most widely used analogue systems [3]. The operating frequencies ranged from around 800 to 900 MHz, with a channel capacity restriction of 30 KHz. It had low reception, a small capacity, poor battery life, interference from background noise, and other issues [4].

1.2.2 Second Generation (2G)

2G cellular technology was introduced in the 1990s. It was based on digital system technology; it marked a significant advancement in wireless cellular technology. Limited data services were first made available for purchase in the early phases of 2G. The first 2G network to offer combined phone and data services was GSM. GPRS, or 2.5G as it is commonly called, is an improvement in GSM technology that allows for 150 Kbps faster transmission speeds. Technology known as EDGE (Enhanced Data rate for GSM Evolution) was released under the 2G umbrella after 2.5G [4].

GSM technology is used by 2G phones to provide better speech quality, however there were only a few data services available. Demands increased, leading to improvements in coverage and transmission quality. Digital voice data multiplexing and compression in 2G networks were accomplished using the compression decompression method. The 2.5G cellular wireless technology, which was created in the interim between 2G and 3G, employs email, WAP, Access Multimedia Messaging Services (AMMS), and

World Wide Web Access in addition to providing General Packet Radio Services with data speeds ranging from 56Kbps to 115Kbps. It usually has around 2.75G, which is a GPRS upgrade with a maximum data rate of about 384 Kbps [5]. GSM (2G), GPRS (2.5G), EDGE (2.75G) are the different technologies under 2G.

1.2.3 Third Generation (3G)

In 2000, third generation (3G) technology was developed. With the development of data transmission speed, which went from 144 Kbps to 2 Mbps, came this technology. It is intended for usage in multimedia mobile phones, sometimes referred to as "smart phones" in modern society. The primary motivation behind increasing 3G's bandwidth and data transmission rate was to provide more room for music and video files, as well as web-based applications. 3G provides extremely fast speed in comparison to 2G, allowing the download of a 3-minute MP3 music in just 11 seconds. Three cellular access technologies are compatible with 3G: TD-SCDMA, WCDMA (UMTS), and CDMA 2000 [5].

Larger data formats, such as HTML sites, movies, and music, were increasingly available with 3G connection, while 2G networks continued to employ MMS for little data, text messaging, and phone calls. Nevertheless, mobile operators have to plan their (revolutionary) new mobile broadband networks at the same time as making evolutionary improvements to the current networks in order to transition from 2G to 3G. In order to enable mobile multimedia applications, packet-switched data with higher speeds and better spectral efficiency have to be provided by 3G technology. In 2000, the ITU (International Telecommunication Union) unveiled 3G cellular technology, known as IMT-2000. It was successfully possible to attain 3G data rates of 144 Kbps for mobile users, 384 Kbps for pedestrian users, and 2 Mbps for interior users. 3G technology standards include CDMA-2000 (Code Division Multiple Access – 2000), WCDMA (Wideband Code Division Multiple Access), and TD-SCDMA (Time Division Synchronous Code Division Multiple Access) [6].

1.2.4 Fourth Generation (4G)

4G, which comes after 3G, is the fourth generation of wireless mobile telecommunications technology. The ITU's IMT Advanced capabilities must be offered by a 4G system. Modified mobile online access, IP telephony, gaming services, high-definition mobile TV, video conferencing, and 3D television are some examples of potential and existing uses. Two 4G candidate systems are now in operation on a commercial basis: the first-release Long Term Evolution (LTE) standard, which has been in use in Oslo, Norway, and Stockholm, Sweden since 2009, and the Mobile WiMAX standard, which was initially used in South Korea in 2007 [7].

The primary advancements in 4G compared to its predecessors are the switching type and its core network, which utilizes the internet as the core network and all IP networks as switching types (3G utilized packet network, 2G used PSTN). Fourth-generation communications services serve low-to-high mobility applications and provide sophisticated mobile services. Generally Digital Broadband Packet technology used in 4G. Converged data and voice over IP, entirely packet switched network, Higher bandwidth to provide multimedia services at lower cost (up to 100Mbps), Services Enhanced, Audio, Video Streaming, IP telephony, HD mobile TV etc. are the main features of 4G [8].

1.2.5 Fifth Generation (5G)

A recently developed technology called 5G is attracting attention in the research and development community and has the potential to change consumers' perceptions about sluggish wireless cellular technology. The primary distinction between the current generation and the anticipated 5G techniques must be something other than higher maximum throughput; additional requirements include reduced battery consumption, improved coverage and high data rates available at the cell edge, approximately 1 Gbps data rate in mobility, greater security due to improved cognitive radio security, and lower traffic fees as a result of lower infrastructure deployment costs [9].

5G, or the fifth generation mobile and wireless communication network, is IPv6.5G, LAS-CDMA, OFDM, MC-CDMA, UWB, and Network-LMDS compatible. It is the ideal wireless environment. It is strong and will be in great demand in the future since it provides unrestricted access to information and data exchange. For interoperability, 5G is entirely IP-based; standardization work started this year, and commercial availability is anticipated in 2020. Open Transport Protocol is used in 5G technology to mitigate the greater bit rate loss (OTP). The session layer and transport layer support the OTP. The management of quality of service across different kinds of networks is done at the application layer. Some Important features of 5G are- Large-scale gigabit data broadcasting is possible with 5G, Different modulation and error-control strategies are used in 5G, Incomparable consistency in transporter class gateway is provided by 5G technology, compared to 1Gb, 5G offers 25Mbps connection speed and more data bandwidth [10].

1.2.6 Sixth Generation (6G)

The Sixth Generation, or 6G, Mobile and Wireless Communication Network is a cutting-edge technology that promises to deliver Internet speeds of up to 11 Gbps across wireless and mobile devices, along with absurdly high data rates. Its primary backbone is believed to be built using 5G technology. Ensuring consistent high Internet service rates for users, even while they are traveling or in remote areas, is unfeasible.

To transmit such high-speed electromagnetic signals, specially built nano antennas will be installed at various sites or positions along roadsides, villages, malls, airports, hospitals, etc. Fly sensors will use 6G technology to adorn the world. By enabling secure information dissemination, air fiber combination will advance humankind's understanding of alien civilizations. Radio over fiber networks are already in place thanks to 6G technology, which is connecting people worldwide. [11].

1.3 Requirements of 5G versus 6G

A comparison analysis of 5G and 6G looks at a variety of aspects, such as the systems' capabilities and necessary requirements.

The 6G network was expected to provide more mobility, reduced latency, increased dependability and sustainability, and a larger data throughput in terabits than the 5G network. 6G can offer more dependability, broader device compatibility with lower latency, and improved data throughput and mobility. These advancements are made possible by the massive growth in linked devices and the need to support applications that require speed, such wireless brain-computer connections, extended reality, driverless cars, and more. 5G has some limitations but 6G provide more facilities than 6G. 5G was released in 2020 and 6G will be fully available in 2030.

The spectrum of 6G is 73-140 GHz and 1-10 THz and in 5G it was 3-300 GHz. The Spectral efficiency in 5G was 30 bps/Hz and in 6G it will be 100 bps/Hz. It is anticipated that the 6G cellular network would link people on the ground and in the air, as well as integrate them with aerial vehicles. The term bandwidth has evolved due to the shift in spectrum consumption from spatial (aerial) to volumetric. As a result, 6G cellular systems must continue to achieve high energy and spectrum efficiency (SEE) in terms of volumetric unit (bps/Hz/m3/joules) [12].

A comparison table given below about Requirements of 5G versus 6G [12].

TABLE I. **R**EQUIREMENTS **O**F **5**G VERSUS **6**G [12]

Subject	**5G**	**6G**
Release year	2020	2030
Spectrum	3-300 GHz	73-140 GHz and 1-10 THz
BW	0.25-1 GHz	up to 3 THz
Data rate	1-20 Gbps	>1 Tbps
Mobility	up to 500 km/h	up to 1000 km/h
Spectral efficiency	30 bps/Hz	100 bps/Hz
End-to-end delay	5ms	<1ms
End-to-end reliability	99.999%	99.99999%
Connected devices	Smart phones, sensors, and drones	Smart phones, DLT devices, CRAS, CR and BCI equipment

1.4 Importance of Developing 6G Technology

Exploring the potential applications of 6G technology is crucial to comprehending its significance. For example, it is predicted that the density of mobile communication devices would rise in addition to phones. These include implanted sensors, integrated headsets, and wearable technology. Depending on where it is used, every new device needs a specific communication system in addition to a variety of ambient factors. Only 6G offers the more sophisticated environmental conditions needed for higher grade devices. It may not be easy to offer smooth, excellent connection with current generations everywhere, even with the advancements in 4G and 5G technologies. These generations could still experience issues with things like high mobility, doppler shift, handoffs often, and coverage gaps in some places [13]. In addition to providing worldwide coverage, the 6G development will address these problems.

1.5 Localization/ Positioning Technique

Several measurement techniques, including commonly used ones like Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA), Frequency Difference of Arrival (FDOA), and Angle of Arrival (AOA), can be harnessed to improve the accuracy of the positioning system within the context of the 6G cellular network. Here a comprehensive evaluation of the current positioning and localization methods and algorithms, categorized based on the signal measurements used provided below in the figure with details [14].

Figure 2 shows the entire categorization of Localization/Positioning techniques.

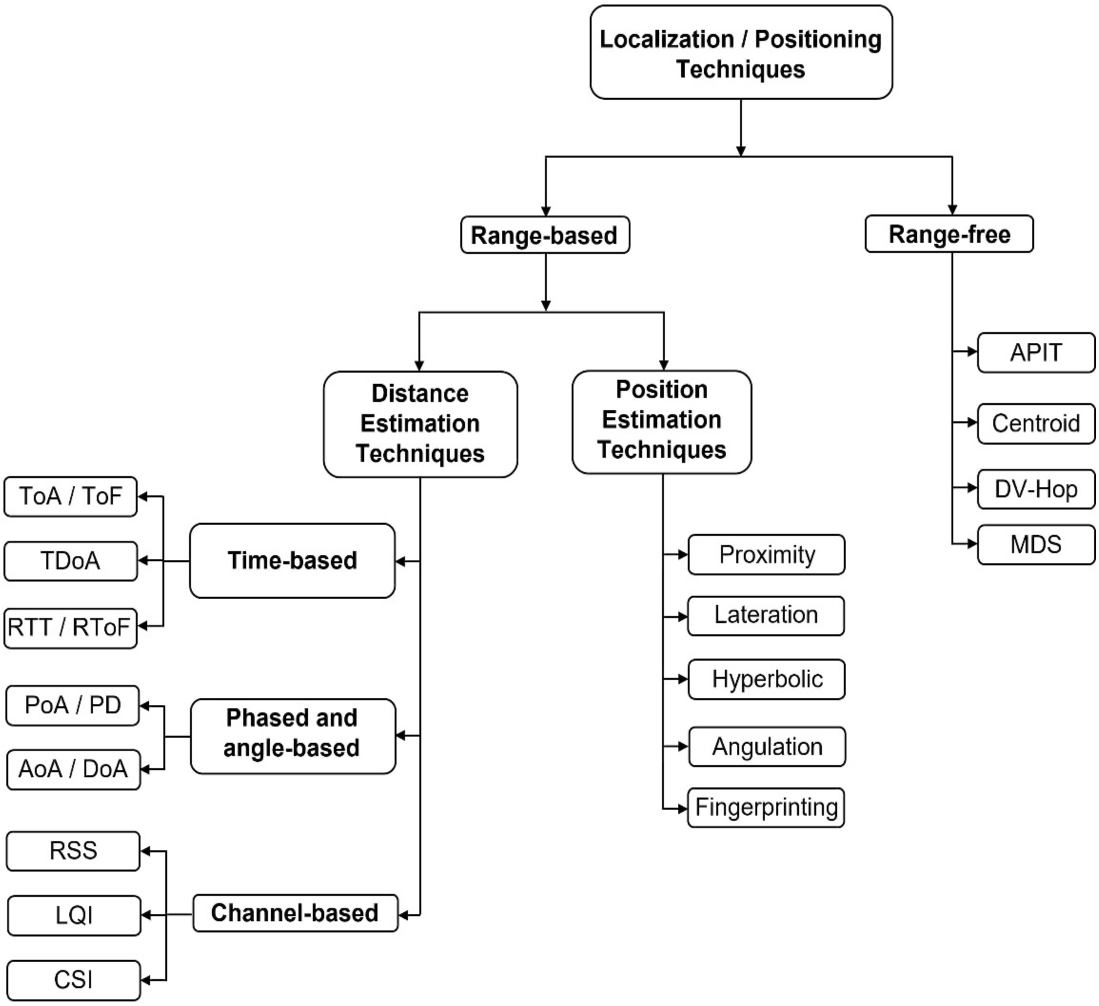

Figure 2 Localization/Positioning Techniques Classification [14]

1.6 Positioning in Cellular Network

Over the past few decades, cellular Positioning has drawn a lot of interest. Originally, it was intended to offer an E-911 subscriber safety service. Positioning is becoming a crucial feature of cellular networks, facilitating communication and allowing location-based services in response to the growing demand for location data.

Though there are many types of cellular-based localization technologies, from these The Global Navigation Satellite System (GNSS) has a high-power consumption and subpar positioning performance in interior conditions, despite offering user equipment (UEs) a precise location estimation. Furthermore, only active positioning including user participation may make advantage of GNSS. Cellular positioning is hence a desired addition to GNSS positioning. The fast expansion of location-based services has prompted the U.S. Federal Communication Commission to require cellular network carriers to identify user equipment (UEs) with an accuracy of one meter by 2020 [15].

1.6.1 Classification of Cellular-based Localization/Positioning Method

There are four primary types of cellular-based localization technologies: range-based, angle-based, fingerprinting-based, and cell identity-based [15].

1. Cell-Identity-Based Localization Techniques: The combination of four methods is the Cell identity (CID), also known as proximity-based, which primarily depends on determining if the item to be positioned is located within a certain radio coverage region. To estimate where the UE is, it is required to know the position of the serving base station and the area of the included serving cell. Not suitable for wide regions or low-density people, it needs a large number of base stations to get equivalent accuracy to other approaches [16].

2. Angle-Based Localization Techniques: The Angle-of-Arrival (AoA), the Angle-of-Departure (AoD), or possibly both are used in the angle-based approaches. The direction from which a radio signal is received is known as the arrival angle, and the direction from which it is broadcast is known as the angle of departure. The base station (BS) in 5G networks with massive MIMO will be furnished with hundreds or thousands of antennas, enabling beam-based operations and offering a large array aperture [17].

3. Range-Based Localization Techniques: Range-based localization methods use measurements of the distance between transmitters and a receiver (or vice versa) to approximate the unknown position of the user equipment. By extracting the data from the received signal, such as the Received Signal Strength (RSS), Time of Arrival (ToA), and Time Difference of Arrival (TDoA), these measurements may be made. A typical offset, or bias, taints the measurements in the event of a misalignment between the user receiver clock and the synchronized transmitter clocks, leading to pseudoranges (a range estimate with an unidentified inaccuracy). This kind of offset doesn't exist for completely synchronized (ToA) or non-timing-based systems (like RSS) [18].

4. Fingerprinting-Based Localization Techniques: An offline (training) phase and an online (positioning) phase make up the most popular fingerprinting-based positioning technique. Known as signatures or fingerprints, the offline or training phase involves building a database by measuring certain signal or antenna properties at predetermined sites. The received signal intensity is one such signal property that the UE may measure. Apart from the aforementioned characteristics, the device's orientation, the kind of mobile unit, the TA (Timing Advance) or RTT (Round-Trip Time) value (or any other sort of timing information), the floor number (if indoors), etc., could also be saved. The radio map or fingerprint database is the name given to this collection of places and the corresponding fingerprints. This database makes it possible to use Machine Learning (ML) techniques to create one or more models. Using the attributes measured by the mobile unit and the model, localization is carried out in the online phase by estimating the user's position [19].

1.7 Positioning/Localization in 6G Cellular Network

Networks beyond 5G will have to adhere to more stricter placement rules in order to meet the demands of future technologies. Commercial use cases including as logistics, transportation, and industrial automation impact the development of cellular location technologies. Cellular network development beyond 5G will be influenced by cutting-edge uses including XR gaming, telemedicine, driverless cars, and autonomous industrial systems. With the use of technical innovations including increased frequency ranges, larger bandwidths, and AI-based methods, the 6G network will tackle these issues with higher accuracy. There are undoubtedly many obstacles in the way of 6G, especially those related to the development and integration of artificial intelligence and machine learning, which are anticipated from networks that go beyond 5G. The creation of user-friendly AI systems with minimal storage requirements [19].

1.7.1 Machine Learning Algorithm

To train machines how to handle data more effectively, machine learning, or ML, is employed. There are instances when we are unable to decipher the information extracted from the data after examining it. Then, we utilize machine learning. The need for machine learning is growing as a result of the availability of available datasets. To extract pertinent data, machine learning is used in many sectors. Machine learning aims to extract knowledge from data. The topic of teaching computers to learn on their own without explicit programming has been the subject of several research. Numerous mathematicians and programmers employ multiple strategies to solve problems with large amounts of data. There isn't a single, universal answer for data issues; instead, machine learning employs a variety of techniques to tackle them. The model, variable number, and problem all influence the algorithm that is selected. Algorithms like Naïve Bayes, Decision Trees, and Support Vector Machines are frequently employed in machine learning. For smaller data sets, supervised learning is appropriate, whereas unsupervised learning is better suited for bigger datasets. Machine learning may be done in either way. Large data sets work well with deep learning algorithms. Successful machine learning requires an understanding of neural networks, including their uses and limits [20].

1.7.2 Received Signal Strength (RSS)

RSS is often expressed in milliwatts (mW) or decibel milliwatts (dBm), indicates the actual power strength measured at the receiver's node. Frequently this is referred as the received signal strength indicator (RSSI), and chip suppliers typically define it in a range of 0 to 255. It can be utilized as a distance indication (link strength indicator), with the maximum value being defined by each vendor. It offers comprehension of the underlying location attributes and location-dependent RSS patterns. The majority of existing algorithms rely on interior environment similarity for positioning and training, and are range-free-based employing RSSI. These approaches don't consider variables that alter throughout the placement stage [21].

1.7.3 Received Signal Strength Indicator (RSSI) and Machine Learning (ML) based Indoor Localization

A simple yet effective localization technique that makes use of RSSI readings to calculate distances between the transmitter and sensor nodes is the Received Signal

Strength Indicator (RSSI) ranging-based localization algorithm. Three ways are used in RSSI-based localization systems: fingerprinting, trilateration, and triangulation. Because fingerprinting is so accurate, it is the most often used strategy.

Algorithms for Machine Learning (ML) were applied to develop and evaluate indoor localization and building occupancy. These models are mathematical depictions of latent structures or patterns in the data. ML models formalize these patterns when trained on training data, which enables them to predict values or identify links in the data. In supervised learning, input-output pairs are used to train a model using a labeled dataset. It may be applied to both regression and classification tasks, producing discrete outputs for classification and continuous outputs for regression, such as size-based house price prediction [22].

A widespread indoor localization function is called Received Signal Strength Indication (RSSI), which gauges the strength of the signal that is sent from an access point to a client device. As long as mistakes do not lead to inaccurate readings, the inverse-square law may be used to approximate the distance between devices. The separation between devices may be calculated by combining this with a propagation model. More information may be gathered from access points, which improves accuracy but also increases signal interference. Errors in range measurements present a difficulty to wireless localization systems. Although RSSI approaches are inexpensive, they need to be filtered in order to increase system accuracy. [23].

1.7.4 RSSI Fingerprinting Based Positioning

The theory behind received signal strength indicator fingerprinting is that an ensemble of radio signal intensities should be able to uniquely identify a point in space, ideally with no further propagation impact than route loss. The precision of this approach can be limited in practice by multipath propagation, fading, and other phenomena but better in various ways compared to other conventional positioning methods. Since the type and qualities of location fingerprints recorded in a radio-map are greatly impacted by in-path interferences and the distance between the transmitter and receiving equipment, received signal strength-based fingerprinting techniques are commonly utilized for localization. Traditionally, a major component of many indoor positioning systems has been fingerprinting based on received signal strength indicator (RSSI). Two steps make up most location fingerprinting algorithms: an online/positioning phase and an offline/training phase. During the training phase, RSSI is gathered at predetermined, recognized locations known as Reference Points (RPs). These RPs are kept in a radio-map as a fingerprint. Real-time data is gathered during the positioning phase at an unidentified site known as a Test Point (TP). The position of a TP is determined by the localization method using the radio-map and the Euclidean distance between each RP fingerprint and a TP [24].

1.8 Global Positioning System (GPS)

The most widely used locating system is the Global Positioning System (GPS), which uses triangulation methods and signals from three satellites. However, non-line-of-sight waves and environment can interfere with it, leading to severe positional inaccuracies.

1.8.1 GPS Technology

The GPS is an American government-developed satellite positioning system that broadcasts radio frequency signals from 24 satellites in orbit around the planet. In the event that the GPS receiver receives signals from more than one satellite, it centers the satellite in a circle using TOA (Time of Arrival) to calculate the distance between the satellite and the receiver before employing triangulation to identify places where the signals cross.

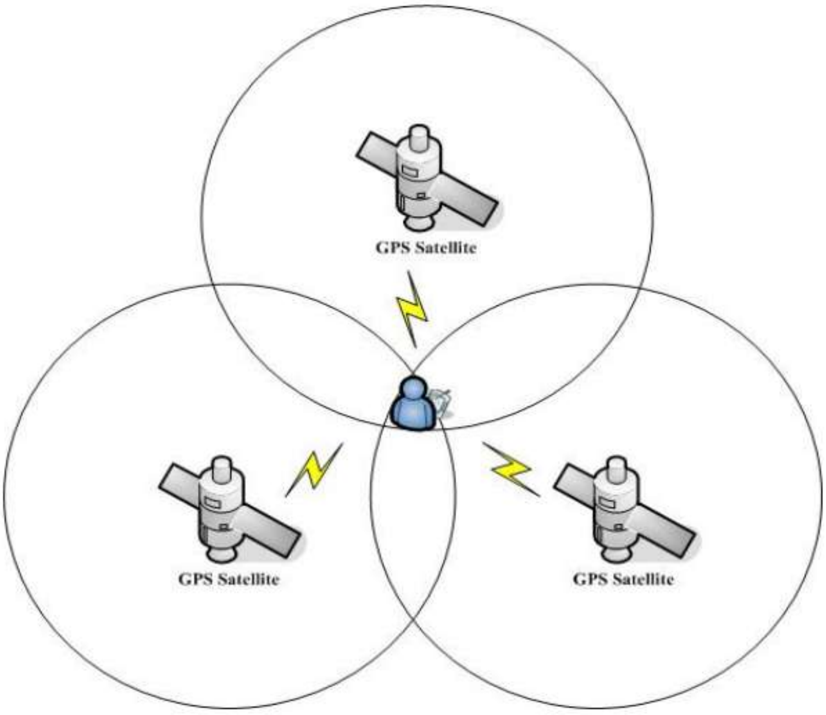

Figure 3 The triangulation method of GPS [25]

The GPS triangulation process is shown in Figure 3. In most cases, four satellites are enough to determine the mobile stations' positions. When there is Line-of-Sight (LOS) between the satellite and GPS receiver, the positioning accuracy is between 5 and 40 meters [25].

1.8.2 Positioning in GPS

The twenty-four satellites that make up the GPS network are spread out across six distinct 12-hour orbital trajectories, allowing at least five of them to be visible from every location on Earth. Satellites transmit signals that carry data regarding their location and orientation; the distance between the satellite and receiver is measured by the signal travel time. When calculating the position of a client, satellites are used as reference points. They transmit signals all the time that carry data on their own direction and position. Exact time which needs for a signal to travel from the satellite to the reception's antenna is used to measure the distance between the satellite and the receiver’s node. To estimate a position, three distance measurements must be made. The estimated position is really the intersection of three spheres, the radii of which are the computed distances and the centers of which are the satellites. Numerous issues, including multipath distortion, satellite clock problems, receiver noise, and other environmental sounds, significantly degrade GPS accuracy. After determining the separations among the GPS receiver and accessible satellites, the consumer's location is approximated using the trilateration method [26].

1.9 Comparison between GPS based System and RSSI Method

The global position system (GPS) is extensively used in mobile phones, automobiles, and other devices. Nevertheless, sensor nodes cannot support its installation because it is too hefty. In addition, putting GPS units or other high-tech sensors on each node is not economically possible. A highly accurate position may be sent to network anchors by the GPS device. Nonetheless, GPS performance is not always reliable in actual outside settings. GPS-based localizations relate to absolute localization, and localization systems enable nodes to establish their locations in a global coordinate system using a very minimal number of beacon nodes that know their position from external measurement (e.g., GPS). Considering inevitable mistakes from inaccurate GPS measurements, the localization result will not be accurate [27]. While the customers have always appreciated its outdoor equivalents, indoor localization and location-based services have made significant waves in the media recently. Indoor location data may improve the usability and friendliness of services in a number of ways, including indoor navigation in malls, indoor location-based ads, and monitoring friends and family in indoor public spaces. Indoor positioning solutions are often far more complex than direct GPS reception since standard GPS receivers cannot function indoors owing to poor GPS signal strength and multipath effects [28].

RSSI is a wireless communication metric utilized in smartphones and IoT systems. It measures the strength of received radio signals in decibels (dBm). This metric is widely compatible with various wireless devices and is cost-effective, making it a prevalent and practical choice for applications related to determining the location of devices. Like the earlier technique mentioned, signal fingerprinting with RSSI holds great potential for indoor localization [29] [30].

1.10 Motivation

In Cellular based localization Positioning method are classified into two main categories: (1) Mobile Based, where the user equipment itself calculates its location, and (2) Network Based, where the network location server computes the position of the user equipment. Network based positioning are centralized which allows the operator full control of the location service. For location-based services and improving wireless communication performance in various ways such as channel estimation, medium access control, routing and network acquiring accurate location information is extremely useful. Existing GPS, conventional network based, positioning solutions can’t satisfy the requirement of indoor positioning within the domain of new technologies network beyond 5G hence 6G. More enhancement can be done with the help of machine learning along with the conventional indoor positioning systems.

Chapter 2

Literature Review

2.1 Literature Review

To effectively improve positioning accuracy, it is crucial to conduct an extensive review of relevant works by other researchers. "**Enhanced Localization Infrastructure for 6G Cellular Network**". Thus, to improve positioning strategy designed for indoor localization scenarios in the next 6G cellular network environment.

2.2 Paper Review

The need for location-based services has grown dramatically as a result of the Internet of Things and machine learning, especially for interior positioning and navigation. Because GPS is unusable indoors, there is growing interest in machine learning-based techniques and the Received Signal Strength Indicator (RSSI) for localization and navigation within buildings. Methods based on RSSI are preferred since they are easy to use and economical. The accuracy and robustness of indoor localization may be increased by integrating RSSI with machine learning methods; however, the decision should be made based on the needs of the application, the degree of precision required, the cost, and system complexity. The ideal settings for location-based services rely on the particular requirements of the application. Every parameter has benefits and drawbacks, and the situation will determine which one is best used. For example, when accuracy requirements are not too high, RSS can be utilized for localization in areas with a large density of access points or beacons [30].

Cellular positioning in the 4G era was utilized for authorized interception and emergency services. Logistics, transportation, and industrial automation are examples of business use cases covered by 5G. With an emphasis on automated forklift tracking and placement and location services for emergency equipment, the 5G technology standard for broadband cellular networks is changing. New use cases give rise to new technological demands. For commercial applications such as AR/VR/XR, gaming, sensing, low-cost tracking, and high-accuracy industrial applications, positioning and location services will be essential as 6G gets closer. Placing and location services must be developed as a core component of 5G development to meet these demands, which also include low-cost positioning and improvements in latency and accuracy [31].

For cellular network applications, positioning is essential for meeting emergency call criteria as well as enhancing coverage and accuracy. It covers both sophisticated equipment-like robots and self-driving cars as well as low-cost, low-power, and simple gadgets. Mobile devices with GNS capability can obtain a few-meter accuracy outside thanks to help data from cellular networks. A research and work item on placement in indoor circumstances resulted from the FCC's stricter criteria for calls made indoors. It is being suggested to broadcast assistance data to UEs in order to ensure that the right positioning information is transmitted and to lessen signaling burden as UEs support network-assisted positioning information. Early on, positioning in cellular networks depended on approximations of the distance between devices, resulting in imprecise estimations. Wireless operators were required by the FCC in 1996 to identify emergency call locations and notify the PSAP. Until 5G is completely implemented, LTE will be essential to locating services. As a result of LTE networks' ability to support a variety of positioning techniques, there is a growing interest in hybrid solutions, which integrate many techniques to provide high accuracy requirements under varied deployment scenarios. While standalone 5G positioning techniques are being considered, they won't become a reality until Rel.16 improves standalone 5G. 5G architecture leverages scalability in the network and efficient signaling across air interfaces to minimize device cost, power consumption, and network complexity [32].

Tracking and localizing moving targets is a topic of extensive research with many practical applications. Aiming to accomplish accuracy, energy efficiency, security, or a mix of these depending on the application, major techniques include Range Based, Range Free, and Prediction Filter based systems. Active range-based active localization and tracking systems, or RSSI-based systems, don't need extra hardware. They use either trilateration or multilateration approaches to determine the target's position after measuring the RSS value sent by an active target at certain receiving nodes, converting it to distance using a route loss model. This technique is necessary for efficient localization and tracking even if it is inexpensive. The distance between the target and signal receiving nodes (beacon nodes) is estimated using a route loss model in RSSI-based target localization. The RSSI-based approach is the most often utilized range-based strategy for tracking and localization, despite its multiple problems (TOA, TDOA, AOA). The main benefit is that it doesn't require additional hardware because the majority of electronic devices already have RSSI circuitry built in to read RSS. By utilizing this RSSI data and a proper mathematical model of signal attenuation, one may determine the distance between the transmitter and the receiver. However, the RSSI readings are infamously unreliable due to the high level of dynamic nature of the wireless environment. [33].

Techniques for cellular-based localization include Cell Identity (CID), Angle-Based Localization, and Fingerprinting-based methods. The fifth-generation (5G) standard for broadband mobile networks is evolving, with a focus on automated forklift tracking and placement as well as location services for evacuation equipment. New use cases lead to new requirements in terms of technology. Traditional 5G network positioning methods include pure 5G-based positioning and assisted positioning, but 5G positioning systems are based on measurements of signal strength, time of arrival, and angle measurements. Positioning and location services will become increasingly important as 6G develops for commercial uses like as gaming, sensing [34].

The accuracy of positioning techniques that rely on received signal strength (RSS) measurements to determine mobile station placements is dependent on how well propagation models fit real-world scenarios. Because RSS is dynamic, indoor wireless networks have a hard time anticipating these situations. Mobile station placements are determined via positioning techniques using measurements of received signal strength. However, the accuracy of these approaches depends on the adequacy of propagation models, particularly in indoor wireless networks where circumstances might be dynamic. Location systems that determine a mobile station's position by measuring radio-frequency signals that flow between the station and stationary stations are commonly developed utilizing WLAN IEEE 802.11 wireless networks. Any wireless network may readily yield RSS numbers, but 802.11 networks in particular make this possible due to the ease of extracting the RSS indicator (RSSI) [35].

The single wireless device proposed in this study can track user locations with minimum tracking error in both indoor and outdoor contexts. Utilizing enhancement algorithms and the Received Signal Strength Indication (RSSI) approach, the solution is implemented. There are two phases to the RSSI-based tracking technique: the probabilistic phase involves estimating the distance to the user's position by repeated trilateration, and the deterministic phase involves calibrating RSSI coefficients. The shortcomings of previous methods that concentrate on indoor or outdoor settings are addressed by this strategy. This paper's experimental results show that accurate estimations of signal intensity are possible. Nonetheless, there are still significant estimating mistakes at several points. To further enhance the location estimating algorithms' performance, a variety of expansions might be investigated. Research is being done on the effects of utilizing various propagation models, such as calculating the minimum, average, and maximum RSSI signal propagation constant rather than just the average value and using a smoothing algorithm on distances rather than RSSI to improve location accuracy. [36].

The fingerprinting technique is a popular, affordable, and highly accurate localization approach. It is sometimes referred to as scene analysis or fingerprint matching. With the use of current wireless infrastructure, including Wi-Fi and cellular, fingerprinting is straightforward, easy to integrate into IoT devices, and may achieve acceptable accuracy by using RSSI as pattern matching criteria to detect device locations. Using large amounts of data, machine learning-based RSSI fingerprinting may successfully handle problems with the system, such as hardware malfunctions or variations in signal strength, reducing the likelihood of multipath fading. There are two stages to the fingerprinting process: offline and online. Using sensors or smart devices, fingerprints are gathered from a predetermined number of places to construct a radio map during the offline phase. Learning the mapping between device locations and real-time RSSI data is the goal of a localization function during training. The similarity between training and testing fingerprints is determined by pattern matching in conventional fingerprinting methods. Using training point location data, the objective is to identify a pair of nearest testing and training points in the fingerprint space. The two propagation models that are commonly used in RSSI-based wireless sensor networks are free-space models and log-normal models. While ideal, these models frequently have limitations since they do not account for impediments that may exist between transmitters and receivers [37].

The RSSI may be found on virtually any device using practically any sort of wireless communication technology, which is the key factor in its popularity as it doesn't require any additional hardware. Measurement of packet signal intensity on the receiver is how RSSI operates. It is frequently used to determine how far apart the transmitter and the receiver are. The Third Generation Partnership Project (3 GPP) introduces positioning techniques up to the most recent version (Rel 15) [38].

The popularity of machine learning (ML)-based positioning solutions has increased recently because of their effective outcomes and quick development. Location-based services have grown rapidly with the adoption of mobile intelligent terminals, but conventional approaches have drawbacks such as expensive resource input, inaccurate positioning, and complicated system utilization. Both industry and academics are paying more and more attention to location services powered by machine learning. It explores different signals and recent research accomplishments by examining LBS and location technologies with an emphasis on machine learning viewpoints. Although the LBS system is convenient, it has drawbacks such as a high starting cost, complicated operation, and poor positional precision. Researchers are using AI and machine learning to enhance LBS systems in order to solve these problems, which include high labor and resource costs. Future directions include seamless indoor-outdoor environment connectivity and the integration of heterogeneous LBS systems. Machine Learning is going to be very important for LBS applications. Environmental variations, population density, temperature, humidity, and obstacles all have a major impact on RSSI. The validity of the algorithm and placement accuracy are impacted by how RSS volatility is represented. For practical use, current fingerprint data from various contexts must be normalized [39].

The widely available usage of wireless networks has made location-based services, like GPS, indispensable in our day-to-day existence. However, GPS signals might lose reception owing to buildings, leading to poor connectivity. Indoor Positioning Systems are utilized to solve this problem as well. In this paper, they created an indoor positioning system that uses the trilateration approach and the ITU indoor path loss model to estimate the position of wireless devices in a room using Received Signal Strength Indication (RSSI) from wireless networks.

The model they used, estimates wireless device locations using trilateration and ITU indoor path loss models, utilizing Received Signal Strength Indication (RSSI) data as coordinates and reference points. Received Signal Strength Indication (RSSI) is utilized to determine distance. To estimate wireless device locations with reduced inaccuracy, the Indoor Positioning System model makes use of trilateration and the ITU indoor route loss model. Because of the limits of GPS, this model is suitable for interior navigation and may be put in a variety of settings, including retail malls, hospitals, large industry and factory. [40].

Mobile devices are starting to be equipped with location-based service (LBS), which makes outdoor activities even more enjoyable. However, due to poor signal or NLOS situations, GNSS design is not appropriate for indoor or urban canyons. A power level indication called RSSI is utilized in Bluetooth and WiFi location systems. The Application Programming Interfaces (API) of common WiFi services can be used to access it. Through passive scanning, mobile devices such as smartphones can gather RSSI observations, as WiFi access points transmit beacon frames containing the necessary data. Nevertheless, location is incompatible with Bluetooth access points since they modify transmission power to minimize mistakes and conserve energy, and Bluetooth devices, such as smartphones, can only obtain RSSI data while connected. In WiFi positioning, the received signal strength indicator (RSSI) offers a fingerprinting technique, examines Wi-Fi and Bluetooth networks, deals with interference problems, and carries out tests. While the accuracy of Wi-Fi location may be lowered by nearby Bluetooth devices, observations become more consistent when RSSI values are stronger. Due to device variations and interference, Wi-Fi location is not consistent. It is advised to normalize various Wi-Fi modules. While it only functions when there is a Bluetooth connection established, the AFH method lessens Bluetooth interference. Wi-Fi location performance is lowered by miss-scanned samples [41].

Developing strong and discriminative wireless signatures which are sensitive to human presence, multipath, and fading because of their high operating frequency remains a difficulty for precise fingerprint-based indoor localization. Like GPS, indoor positioning technology has the potential to completely change how people search, locate, and navigate within buildings. Real-time instructions to stores may be obtained by mobile devices with precise indoor positioning technology. This enhances customer targeting effectiveness by enabling companies and marketers to provide coupons and deals to users depending on their present location. When FM RSSI measurements are paired with physical layer signal reception data for wireless signal signature, localization is 5.7% more accurate than when using WiFi-based methods. Because FM signals have different frequencies and wavelengths from WiFi signals, they are more resilient to temporal changes. When combined, FM signals may achieve up to 83% greater accuracy than WiFi signals [42].

Higher precision is needed for indoor localization, and GPS or AGPS are impractical. The trilateral localization technique based on RSSI is gaining popularity since it is inexpensive, requires no extra hardware support, and is simple to comprehend. As the number of WiFi access points in buildings rises, mobile smart devices may more easily recognize known hotspots, making self-localization simpler. However, there are significant computation mistakes in this approach due to the RSSI value's sensitivity to the physical environment. Due to the widespread use of ICT, there is an increasing need for indoor location data in public places such as airports, retail centers, and military training facilities. This allows for the integration of smart spaces and the effective management of space and inventory. Due to its short-time precision, people can only locate themselves in regions with three or more WiFi access points and can only utilize a minimal frequency between the gyroscope sample rate and WiFi scan rate. This prevents them from gathering unnecessary data [43].

There are several uses for location-aware technologies in the industrial, living, and public services sectors. The location, localization, and localizability of wireless ad hoc and sensor networks are discussed in this article. These concerns are important for network operations such as border detection, routing, topology management, and coverage. Since low-cost, low-power, and multipurpose sensor devices have been made possible by technological breakthroughs, location data is essential to wireless sensor networks (WSNs). Due to the limitations of current positioning systems, a new cooperative, ad-hoc, in-network localization, or self-localization method has been developed. In this scheme, specific nodes share geographic information to establish their worldwide positions. Past research shows that measurement mistakes have a major effect on localization; certain nodes that are uniquely localizable under ideal distance ranging may have location ambiguities, which strengthens the validity of localizability tests [44].

Thereby applying deep learning models, namely WiFi RSSI fingerprinting, researchers are able to improve indoor location systems. For both stationary and mobile scenarios, they estimate node locations using conventional offline survey data. This paper suggests a method integrating RSSI and motion data from smartphone sensors for mobility situations, and also examines indoor location techniques using machine learning models in static settings. The ideal point in the mobile node's trajectory history is located using this approach, which yields great accuracy. Here A probability distribution of the RSSI values at each particular site was produced as a map using the Wi-Fi RSSI fingerprint data from neighboring access points. Signal intensities from nearby access points are recorded over time at a reference location to form a fingerprint. Locations may be distinguished using these distinctive fingerprints. Machine learning models typically perform two phases: training, where multiple WIFI RSSI fingerprints and coordinates are scanned at each reference point and recorded in the database. [45].

Technologies for monitoring and location are developing quickly, becoming more widely accepted and having more uses in daily life. In order to enable new services in cellular and wireless networks, researchers from all over the world are pushing the frontiers of accuracy, low cost, component reusability, and simplicity of field deployment. Positioning methods, including signal strength, time of flight, or fingerprinting, might provide new applications based on the position of wireless nodes or improve established services like data routing and aircraft navigation [46].

The expanding number of applications for wireless sensor networks has led to an increase in research on localization. Localization algorithms for measurement techniques are classified as one-hop or multi-hop. The capacity to self-localize is provided by wireless sensor networks, which is helpful for environmental monitoring applications like precision farming and bush fire surveillance. Reconnaissance, surveillance, road traffic monitoring, health monitoring, inventory management, and intrusion detection all benefit from location estimation. Algorithms for sensor network localization use inter-sensor measures and absolute positions to infer unknown sensor locations. While connectivity-based localization techniques are easy to use and visually appealing, they are only ideal for applications that need an approximate position estimate since they only offer a coarse-grained estimate of each node's location. The topology, network density, and anchor count all have a significant impact on the localization error; higher mistakes occur in smaller networks or with non-uniform topologies. The low influence on local power consumption, sensor size, affordability, and absence of extra hardware make techniques based on received signal strength indicator (RSSI) in wireless devices appealing. [47].

In order to provide enhanced end-user information and effective network performance, positioning is essential in 5G networks for location-based applications, particularly inside. Future 5G location-based services and apps, which target both machine and human users, will depend heavily on indoor positioning, with consumer and industrial applications becoming more significant. With a focus on the significance of location data, especially inside, for improved end-user information and effective network performance, 5G seeks to concurrently address all of the pillars. The objective behind RSS fingerprinting is that an ensemble of radio signal intensities should be able to uniquely identify a point in space, ideally with no further propagation impact than route loss. Triangulation employs the geometric qualities of triangles to estimate position, whereas location fingerprinting compares a place with a set of criteria. [48].

A complex web of interrelated technologies, including interface technologies like WAP for mobile internet access and network technologies like GSM, GPRS, and UMTS for dynamic content, provide the foundation of mobile location services. Different technologies, such as network-based and handset-based ones, are employed for location-aware services in outdoor situations. Network-based solutions such as Time of Arrival (TOA), Observed Time Difference (OTD), and Cell-Identification (Cell-ID) and Enhanced Cell-ID rely on a mobile device's signal reception. There are benefits and drawbacks to any technology. Originally, infrared sensors were used for indoor positioning systems; transmitters were suspended from different parts of a structure. These signals were used by a computing device to determine its current position. On the other hand, object blocking has made radio-based location seem like a better option. In a variety of settings, including supermarkets, museums, libraries, exhibits, warehouses, and other cramped areas where location data is important, indoor mobile communication devices might be useful. By enabling mobile users to access apps, mobile communication technologies hold the potential to completely transform eBusiness. In indoor settings such as museums, exhibits, and hypermarkets, location awareness plays a vital role in providing value-added services [49].

The use of indoor positioning and tracking has grown in significance in recent years. It may be used for staff tracking, large-scale building navigation, etc. Owing to the shortcomings of GPS, several researchers have employed the received signal strength indicator (RSSI) within a wireless environment to achieve indoor location. Trilateration methods and fingerprinting are the two main ways that have been offered. An RSSI-based Distributed Real-time Indoor Positioning Framework for the BLE environment is presented in this research.

It detects mobile nodes using Anchor Nodes and utilizes a channel model to estimate distance. In order to minimize interference from the surroundings and dynamically adjust the channel model parameters, Anchor Nodes employ a Kalman Filter. The backend server determines the real-time position of mobile nodes by gathering RSSI and distance data from Anchor Nodes. [50].

The fingerprinting technique, used to locate people, instruments, or devices in indoor environments, has limitations due to its reliability. This work extends power level measurement using multiple anchors and radio channels, considering different alignment methods. This work investigates how to improve fingerprinting performance through the use of supervised machine learning in a lab setting, where samples are gathered for localization using RSS fingerprints. Two phases are involved in the localization process for RSS-fingerprinting. During the offline training stage of RSS-fingerprinting based localization, an indoor environment map with finite spatial resolution is created. At locations of interest, fixed beacon radio frequency (RF) signals are gathered and added to the environment map. During the online testing phase, the location of an object is estimated by comparing its observed signal intensity with the RSS-fingerprint map. The accuracy of RSS measurement and the alignment method dictate how well this localization performs.

The outcomes of RSS fingerprinting using machine learning demonstrate that very precise localization is possible with the right algorithm selection and a sufficient number of training examples. Three of the top-performing algorithms have reached accuracy levels of more than 99%. This research evaluates machine learning techniques' performance in predicting location under fixed settings while controlling for several external influences. [51].

Effective indoor positioning technology is being researched because the Global Navigation Satellite System (GNSS) has difficulty with indoor positioning. Positioning Bluetooth beacons is popular, however because Bluetooth varies over time, conventional techniques suffer from significant range errors. This work presents a Bluetooth gateway-based real-time RSSI fluctuation correction technique for nearby Bluetooth nodes. By identifying these variations and uploading them to a cloud server, the technique makes precise calculations and reduces positioning error.

Typically, the RSSI distance approach uses algorithms to estimate the user's position after obtaining the received signal strength (RSS) from the Bluetooth anchor point to establish the distance-loss model. In offline phases, the method uses the RSSI-distance model learned by PSO-BPNN and corrects RSSI in real-time. Data is smoothed by the Kalman filter, and the PSO-BPNN RSSI distance model is used to calculate the separation between blind and BLE nodes. Trilateration or positioning techniques are used to identify the ultimate location; however, real-time binary equation solution adds complexity and new issues because of various approximations. [52].

With the ability to provide services like tracking, navigation, healthcare, and invoicing, location-based services (LBS) are becoming more and more significant in wireless communication networks. They use positioning technology to identify mobile customers' mobility activities and provide precise data to the client at the appropriate time and place. The main technique for indoor localization is fingerprint matching, which involves compiling scene details from nearby signage and creating a fingerprint database at each place. This approach does not require time synchronization between stations or specialist hardware on either the mobile device or the receiving end. Calibration and localization are the two stages of the location fingerprinting procedure. During the calibration stage, maps are set either using analytical or empirical methods. Radio maps with dots at predetermined sites with radio signal properties as RSS, signal angles, or propagation time are made during the localization phase for site surveys. Precise placement and effective site surveys are guaranteed by this procedure. Recalculating the signal strength map through calibration on a regular basis is necessary to ensure positioning accuracy. Algorithms for fingerprint-based placement make use of KNN, SVM, artificial neural networks, and Bayesian inference as pattern recognition approaches [53].

This research presents a unique trilateration-based RSSI-based localization strategy that makes use of the current cellular network architecture. Multipath fading distorts traditional localization techniques and introduces inaccuracies into the calculation of radial distance. The suggested plan makes use of two novel metrics, the Localization Error Indicator (LEI) and the Radial Distance Error Indicator (RDEI), to increase localization accuracy. The position measurements of RSSI-based solutions are dependent on the measurement place and time; they do not require directional antennas or additional time synchronization devices. Localization errors and radial distance were successfully decreased by the suggested system, which included RDEI and LEI components. LEI made it possible to evaluate localization error and exclude Cell ID combinations with the least amount of inaccuracy. An additional time synchronization hardware or directional antennas are not needed for RSSI-based solutions, in contrast to angle- and time-based methods. [54].

In wireless sensor networks, autonomous localization is essential for reducing complicated jobs and increasing network lifespan; yet, multi-path propagation impedes accurate indoor localization. Currently, the Global Positioning System (GPS) is used to monitor mobile devices both indoors and outdoors. However, it requires line of sight, consumes energy, and is costly to incorporate on sensor nodes with limited resources. In order to reduce complicated self-organization tasks and increase network lifetime, autonomous localization in wireless sensor networks is important, as this study explains. It combines techniques like frequency diversity, averaging numerous recorded data points, and weighted centroid localization to handle issues like multi-path propagation of signals caused by reflections. The localization techniques now in use assume that beacons or anchors are aware of their whereabouts. Different models map the impacts of indoor signal propagation, where unknown RSSI is converted into matching distance. Although translating real surroundings to models is difficult and not always acceptable, complex premeasurement is not essential. Low power hardware and algorithms are required, along with packet forwarding nodes that can carry out subtasks like data aggregation and CRC verification, in order to guarantee the durability of sensor networks [55].

Mobile devices and wireless access infrastructure are becoming more and more popular for ubiquitous multimedia access. Indoor positioning is a critical strategy for providing context-aware services, which are increasingly sought after and dependent on current infrastructure. By lowering the time and angle of arrival signal measurement and requiring specialized hardware, location fingerprinting—a technique that uses received signal strength (RSS) at sampling locations—can improve positioning accuracy and mitigate the disadvantages of a LOS between transmitter and receiver in typical indoor environments. Location fingerprinting has two stages: offline and online, and it is appropriate for indoor placement. In the offline step, a site survey is conducted in order to gather RSS from adjacent base stations; preprocessing is necessary. Using information from offline sources, the online stage estimates position coordinates and measures RSS in real-time. For location-based services and applications, positioning methods that estimate location based on signal strength information, such as neural networks, k-nearest-neighbor, and probabilistic approach, are crucial [56].

Many indoor locating methods, including Bluetooth, RFID, lighting, ultrasound, wireless local area network (WLAN), and ultrasound, have been advocated. Indoor positioning systems based on WLAN have been used extensively. Because of its low cost and flexibility in signal power due to human body blocking and multipath propagation, Received Signal Strength (RSS)-based fingerprinting is extensively utilized for indoor location. The utilization of fingerprinting techniques based on Received Signal Strength (RSS) has become common place for indoor location in buildings due to its unique benefit of being less expensive than other methods. There are two types of positioning based on RSS: fingerprint-based location models and signal propagation models. Since the first model has somewhat high criteria for indoor propagation loss, this paper concentrates on the second model. Even if the second model is more advanced, the WLAN-based fingerprinting technology [57].

The Global Navigation Satellite Systems (GNSS) are not accessible for use indoors and have accuracy problems in crowded metropolitan locations. Researchers are utilizing machine learning techniques and WiFi technologies to create indoor positioning systems in order to solve this. One common technique in WiFi-based indoor location systems is fingerprinting. Its precision depends on calculating WiFi AP signal strength. Large position errors and outliers can result from factors like as scattering, multipath diffraction, and shadowing, which can all impact the received signal strength. Pattern recognition techniques are used in two stages of implementation for location fingerprinting-based positioning algorithms: training and testing. Both indoors and outside, users need alternative settings for information, including location services. Through the use of machine learning techniques, multivariate data matrix reduction, and the Principle Components Analysis (PCA) approach, the WiFi indoor localization system's performance is enhanced [58].

Smart homes are increasingly adopting location-based services that provide customized experiences. Radio approaches such as RSSI, fingerprinting, or proximity algorithms can be utilized to solve user localization problems without the need for additional equipment. By calculating user location without the need for additional hardware, a unique RSSI-based method for user localization in ZigBee home automation systems has been created, resulting in lower deployment costs. For room-level localization, the technique employs fingerprinting and a threshold-based approach, however the threshold values are dependent on the surrounding conditions. To compute thresholds, a new approach based on ROC analysis is applied. The user's contact with a sensor that has previously been installed for BA purposes is considered when calculating the real user location. Accuracy cannot be achieved by simply implementing localization and identification algorithms; instead, averaging techniques must be used to improve accuracy without appreciably compromising power consumption or battery life [59].

This paper presents an indoor fingerprinting system based on fuzzy Least Squares Support Vector Machine (LS-SVM) that estimates target placements based on received signal strength (RSS). The system uses the LS-SVM algorithm to compute fuzzy membership functions after gathering RSS data from Wi-Fi signals. The precise location data provided by GPS and GNS makes them popular for outside placement; however, their poor signal strength and limited satellite vision make them unsuitable for inside use. There are two stages to Wi-Fi location fingerprinting: offline and online. Samples of the signal intensity are collected offline at reference places and kept in a database. In order to estimate the target position online, the server uses pattern matching algorithms to compare the target fingerprint with stored fingerprints. In order to estimate target positions more accurately than using conventional approaches while avoiding noise and outliers, a unique indoor localization method utilizing fuzzy LS-SVM is developed in this paper. Training procedures for SVM and LS-SVM are susceptible to noise and outliers. By allocating low membership functions to noise and outliers and high memberships to cluster-centered fingerprints, fuzzy LS-SVM classifies data according to membership functions. In the experimental setting, RSS fingerprints are gathered from every AP and kept in a database. Fuzzy LSSVM is applied for localization formulation, and fuzzy C-means is employed to separate the data into two clusters [60].

The goal of mobile positioning research is to identify efficient, low-cost, and high-estimating-accuracy techniques. More precise methods must be developed for highly populated metropolitan areas since traditional methods like trilateration and triangulation are useless there. Techniques for mobile localization are becoming more popular, with the hope that localization can greatly improve value-added services in next-generation cellular networks. With its excellent precision, GPS is a tried-and-true technology that is frequently utilized in terrestrial wireless communication networks to provide location. In cities, fingerprint localization techniques perform better than alternative approaches and don't require extra hardware for cellular network deployment. In this paper they established a dependable location system within cellular networks that offers decent accuracy with little effort and expense, three sub-systems—NN positioning, KFtracking, and Map-matching—were created. For regions with reliable signals, a future localization system may use GPS and RSS fingerprinting; for regions with blocked signals, it might use GPS alone; and for weak GPS signals or signals from just one or two satellites, it could use both methods together. [61].

Localization may be enhanced by cellular network evolution, especially in interior situations, which is fueled by elements like smaller cells, different access methods, and reconfigurable access points. The widespread use of proximity sensors, smart appliances, and wearable technology is to blame for this. In addition to providing permanent observation stations for environmental mapping, these devices give various reference signals for localization. This Paper focuses on localization applications and proposes a centralized SDN framework for indoor femto-cell control. The platform evaluates high-density device measurement gathering techniques, reconfigures operating procedures, and allows customizable logics for measuring reports. Additionally, the platform contrasts a trained neural network with a k-nearest neighbors classifier for fingerprint-based localization. This work proposes a versatile platform to control, monitor, and create radio-maps of indoor environments for localization using OpenAirInterface (OAI). The design responds to issues with the Software-Defined Networking (SDN) paradigm. A central controller keeps an eye on the health of the network and takes choices based on the situation. Orchestration apps may create radio-maps with the use of a northbound API. That's how the proposed centralized SDN framework for indoor femto-cell control work [62].

The development of indoor positioning techniques, such as Wi-Fi fingerprinting, which is promising because of its minimal line-of-sight measurement need and great applicability in complicated interior contexts, is a result of commercial interest in indoor location-based services. Due of its inability to measure access points in line of sight, Wi-Fi fingerprinting has attracted a lot of interest. Without requiring extra infrastructure investment, using Wi-Fi positioning systems is a cost-effective solution. This article discusses state-of-the-art Wi-Fi fingerprint-based localization methods with an emphasis on effective system deployment and sophisticated localization methods. It covers innovative schemes in survey reduction, device calibration, and energy conservation. The survey's simplicity of use and indoor environment adaptability are intended to stimulate more research efforts in this exciting sector. To increase localization accuracy, several mobile devices are used for online measurement and offline data gathering; hence, accurate calibration between them is necessary. New methods are introduced for effective calibration. Wi-Fi fingerprint-based localization has been the subject of recent research and industry testing because of its adaptation to interior conditions and simplicity of implementation beyond existing networks [63].

The network localization challenge becomes increasingly difficult. A critical benchmark for any uncertain position localization based on signal strength is the received signal strength indicator (RSSI). Compared to other existing approaches, RSSI localization is both inexpensive and straightforward. Research indicates that for range and localization technologies in wireless sensor networks, the relationship between distance and RSSI values is essential. The paper assesses the effectiveness of an RSSI-based model in both indoor and outdoor settings, finding that the estimation error is 0.8831 in outdoor settings and 0.9753 meters in inside situations. [64].

2.3 Summary

The process of localization or positioning uses techniques and features of wireless technology to ascertain a node's location. "Anchors," "beacons," "reference nodes," "base stations," or "access points" are examples of transmitting or receiving nodes that are needed to do that and have known coordinates. Cellular positioning now has to fulfill far higher performance requirements due to the location-based services' explosive expansion.

2.4 Objectives

- ☐ To improve positioning accuracy in 6G cellular network.
- ☐ To evaluate performance of the network-based position estimation technique with machine learning by comparing with the existing conventional positioning system within the domain of 6G.

Chapter 3

Methodology

3.1 Methodology

The general strategy and structured framework that researchers use to carry out their investigations, collect data, examine material, and come to reliable findings is referred to as methodology in research. It includes all of the guidelines, protocols, instruments, and methods applied to answer research questions or goals. The study of such procedures may alternatively be referred to by the term "methodology" rather than the techniques themselves. We will follow some steps in this section which is given below:

- Acquiring all the available study on 6G cellular networks
- Categorizing the study based on keywords
- Shortlist the categorized study based on hardware requirements, quality of study. For example, this study is set to focus on improving positing estimation accuracy within the domain of 6G cellular network.
- Analysis of conventional positioning method and find a suitable method for indoor localization which is convenient, cost effective and how it can be improved with the help of machine learning
- Machine learning algorithm selection
- Selection of evaluation metrics and performance comparison
- Data collection and preprocessing
- Accuracy Assessment
- Implementation in Python
- Visualization
- Comparison

By completing above mentioned method, we can achieve user position estimation by using Receive Signal Strength Indicator (RSSI) values achieve from GSM base stations.

The research endeavors to advance the positioning capabilities within the ambit of 6G cellular networks by synergizing signal fingerprinting and machine learning algorithms. This comprehensive methodology elucidates the procedural steps to achieve precise user position estimation using Received Signal Strength Indicator (RSSI) values garnered from diverse GSM base stations.

Following careful consideration, this study was designed to enhance the positioning system of the 6G cellular networks.

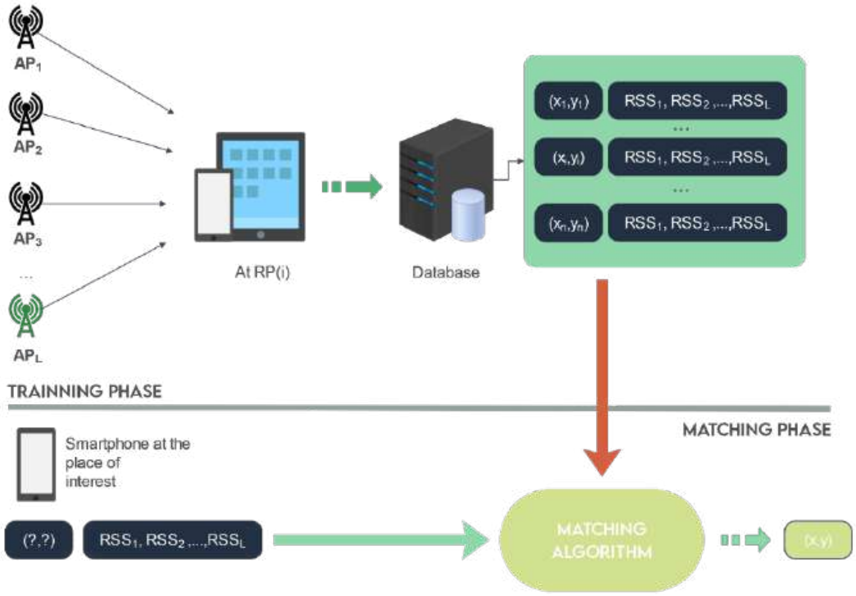

Figure 4 Signal fingerprint-based positioning [65]

Here, in Figure 4, a traditional technique called signal fingerprinting is applied, consisting of two phases: training and matching. The matching algorithm is used at the matching phase. The system demonstrates the sequence of tasks involved in generating and matching fingerprints and the process of populating the fingerprint database with geotagged signatures. In order to develop a model that can estimate the user position coordinates based on the RSSI, this study compared a wide range of regression algorithms.

This study's simulation was conducted in Python, utilizing the Pandas and Scikit-learn modules on a publicly accessible RSSI dataset.

3.2 Data Collection Processing

The foundational phase entails the acquisition of datasets inclusive of latitude, longitude, and six RSSI values from different GSM base stations. Rigorous preprocessing, executed through the Pandas library in Python, involves shuffling and normalization to render the datasets amenable to subsequent algorithmic scrutiny. The study leveraged a publicly accessible RSSI dataset and employed Python’s Pandas and

Scikit-learn modules. Data preprocessing included shuffling and normalization of attributes to prepare the dataset for algorithmic evaluation. The data used in this study contains about 2557 lines with six different measures from six different Radio Base Stations (RBSs). It has two columns that represent the user's position. Also, two additional datasets are used: one provides more information about the RBSs, such as their positions and the power of the radiated signal, and another is used as a test dataset.

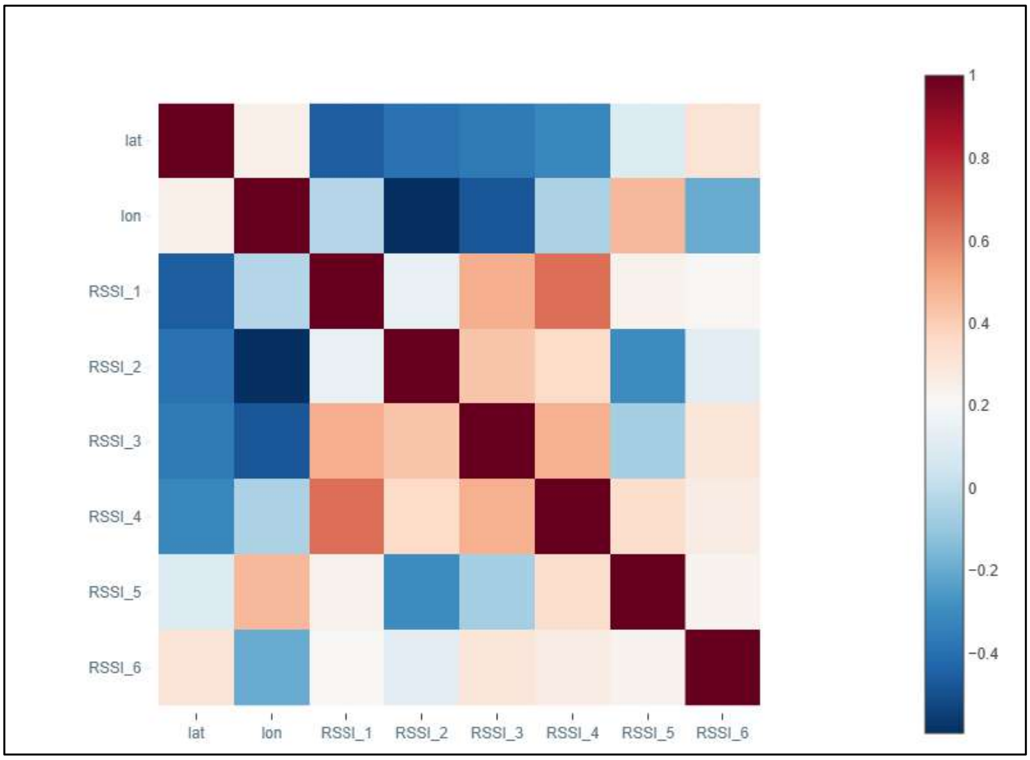

Figure 5 Heatmap showing the correlation between user positions and RSSI values from training dataset

The illustrated figure above depicts the correlation between user positions and Received Signal Strength Indicator (RSSI) values. Correlation serves as a quantitative measure of the degree of association between two variables. In this context, our focus lies in elucidating the relationship between user positions denoted by latitude and longitude and the corresponding RSSI values, indicative of signal strength. The generation of this graphical representation entails the extraction of pertinent columns from the dataset, encompassing latitude, longitude, and RSSI values from distinct sources. Subsequently, correlation coefficients are computed to quantify the relationships among these variables, forming a correlation matrix—a tabular presentation of the correlation coefficients between each variable pair. The correlation coefficient assumes values within the range of -1 to 1, where proximity to 1 signifies a robust positive correlation, indicating that as one variable increases, the other also tends to increase. Conversely, proximity to -1 signifies a potent negative correlation, signifying an inverse relationship. A value near 0 suggests an absence of a substantial correlation. The visualization of this correlation matrix is facilitated through a heatmap, utilizing colors to represent correlation coefficients. Dark blue denotes a pronounced negative correlation, dark red signifies a pronounced positive correlation, and white indicates negligible correlation.

In essence, this chart provides insights into the interplay between user positions and the corresponding RSSI values, aiding in the identification of discernible patterns or relationships within these variables.

Figure 6 Scatter plot of correlation between the user's position and the RSSI values from all Radio Base Station from training dataset.

The presented figure, titled "Scatter Plot for All Radio Base Stations (RBS)," elucidates the correlation between the user's geographical position and the Received Signal Strength Indicator (RSSI) values derived from all Radio Base Stations. The chart's generation involves a specific data organization process. Initially, the original dataset undergoes a transformation known as "melting," reshaping it to ensure that each row encapsulates a distinctive amalgamation of the user's position and the RSSI value attributed to a particular RBS. Once the data assumes the desired format, the scatter plot is crafted, where the x-axis denotes the user's position, and the y-axis represents the RSSI value. Each data point on the scatter plot corresponds to a unique pairing of the user's position and the RSSI value emanating from a specific RBS.

To enhance interpretability, diverse colors are employed to distinguish RSSI values originating from different RBS. This color-coded approach facilitates the identification of any discernible patterns or correlations between the user's position and the RSSI values across distinct RBS. In essence, this scatter plot serves as a visual tool to comprehend the interrelation between the user's position and the RSSI values emanating from all RBS, enabling the detection of trends or patterns within the dataset.

3.2.1 Functional Design of Fingerprint-based Localization

A fingerprint-based localization system is conventionally composed of two integral modules: the fingerprint sensing module and the fingerprint matching module. This delineation provides an overview of the functional blocks inherent in a standard fingerprint-based localization system. The accompanying figure illustrates the sequential steps within the workflow.

Here are the steps of functional design of fingerprint-based localization systems:

1) Fingerprint Sensing: Any fingerprint-based localization process starts with fingerprint sensing.

2) Fingerprint Cleansing: Noise is frequently present in the unprocessed sensor data. The accuracy, energy efficiency, and latency of the entire system would suffer if this raw data were used directly for the localization process.

3) Fingerprint Generation: In the matching stage, the fingerprint generating process arranges the data from various sensors into a form that is simple to understand.

4) Fingerprint Matching: While matching strategies vary depending on the kind of fingerprint, all matching strategies take the search space's size into account to improve matching performance in terms of processing time and power consumption.

5) Populating the Fingerprint Database: A database of fingerprints containing information must be created beforehand for fingerprint-based localization systems [65].

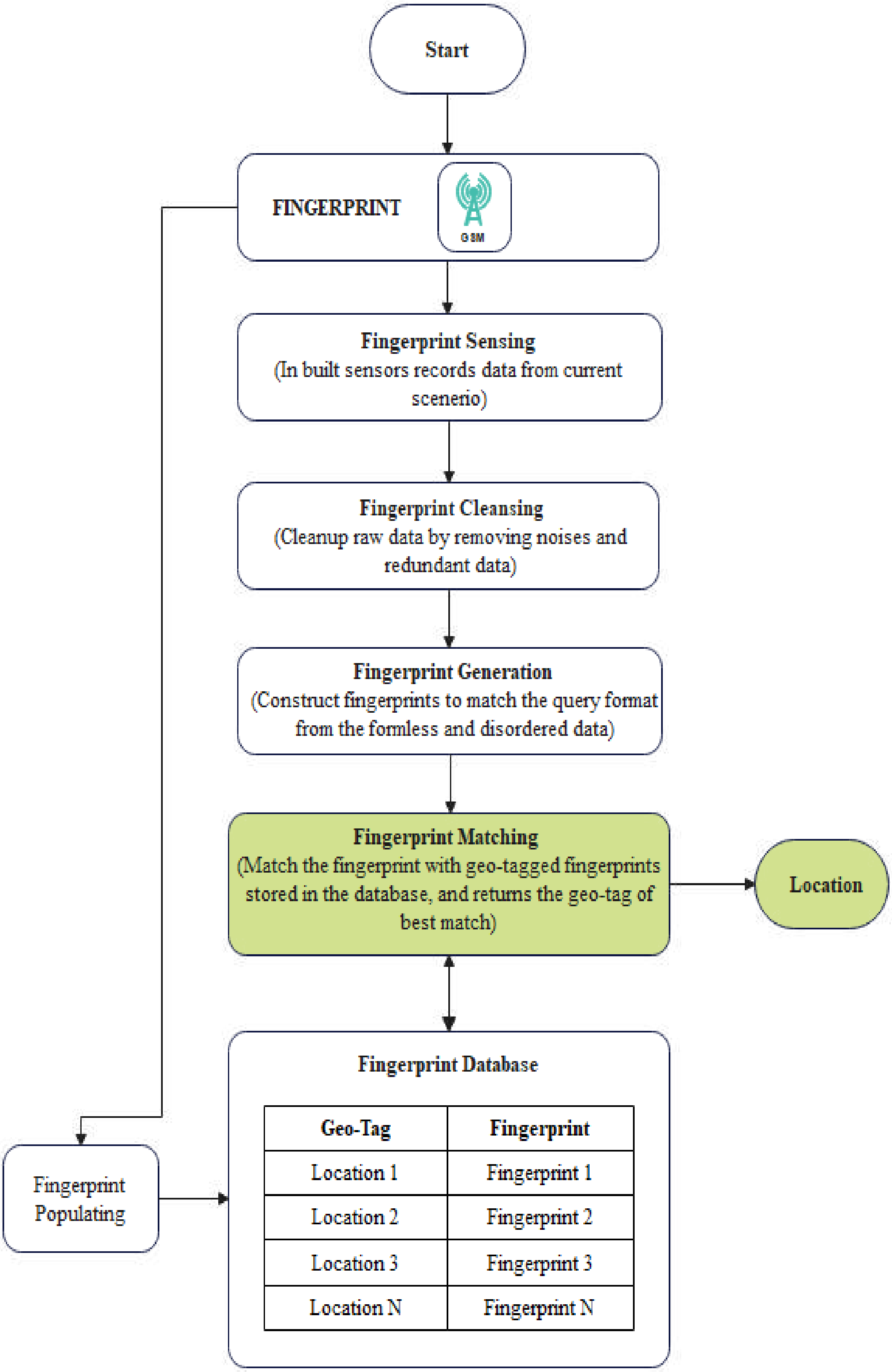

Figure 7 Functional design of fingerprint-based localization systems showing the sequence of activities for fingerprint generation and matching, as well as, populating the fingerprint database with geotagged signatures. [65]

3.3 Signal Fingerprinting

Signal fingerprinting stands as the keystone technique for capturing unique indoor environmental signatures. The creation of a signal fingerprint at each location (Fi(x, y)) serves as a pivotal preparatory step for training machine learning algorithms for accurate user position regression. The study is based on signal fingerprinting, a technique capitalizing on Received Signal Strength Indicator (RSSI) values. Conventional signal fingerprinting methods are adept at capturing the unique signatures of indoor environments.

The common signal fingerprint used in conventional techniques is:

$$\mathrm{Fi(x,y)} = [\mathrm{RSSI_1}, \mathrm{RSSI_2}, \mathrm{RSSI_N}] \quad (1)$$

Where "$Fi(x,y)$" represents the signal fingerprint created at the i^{th} mobile device location with geographical coordinates (x, y), "$RSSI_k$]" is the received signal strength indicator value at the i^{th} location from the k^{th} GSM base station (BS), and "N" stands for the number of GSM BSs.

This study employed machine learning algorithms such as k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Random Forest to regress user positions based on the captured fingerprints.

3.4 Machine Learning Algorithms

Three prominent machine learning algorithms—k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Random Forest—are judiciously selected for regression analysis. A nuanced exploration involves variations in the parameter k for kNN (k=3, k=9, k=11), with a dedicated focus on evaluating algorithmic proficiency in estimating user positions.

3.4.1 k-Nearest Neighbor (kNN)

The k-Nearest Neighbor algorithm commonly stands as a supervised learning classifier dedicated to making predictions or classifications for individual data points. This algorithm is frequently employed for classification purposes, operating under the premise that similar data points tend to cluster together but it can be applied for both regression, classification problems. Primarily functioning as a classification algorithm, KNN excels in categorizing data based on exact or proximate training data samples within specific vicinity. The method's popularity stems from its swift computation and straightforward implementation [66, 67].

The KNN algorithm boasts advantages such as simplicity, adaptability, and proficiency in handling non-linear data. This versatility positions it as a valuable tool for tasks beyond indoor localization, encompassing regression and classification challenges. Nevertheless, certain constraints accompany the KNN algorithm. Achieving optimal accuracy requires a substantial data, and performance varies by the selection of the distance metric and the different values of k. Additionally, the KNN approach is susceptible to the "curse of dimensionality," potentially resulting in optimal performance in feature spaces with high dimensions [68].

3.4.2 Support Vector Machine (SVM)

The Support Vector Machine (SVM) approach is introduced to identify a hyperplane within an N-dimension space which represents characteristic’s number, for unambiguous classification of data points. Operating as a deep learning system under supervised learning systems, SVM categorizes or predicts the behavioral changes of data groups. Noteworthy for delivering balanced performance projections, even with potentially limited sample sizes, SVMs exhibit adaptability in tackling various classification problems. While excelling in binary classification, SVMs extend their utility to computationally challenging multiclass problems by integrating multiple binary classifiers. SVMs prove effective in high-dimensional domains, demonstrating good memory capacity and adaptability. However, their performance may be compromised if the number of attributes significantly surpasses the number of samples. Originally designed for classification challenges, SVMs can address nonlinear regression problems using an insensitive loss function. Employing kernel functions like linear, polynomial, radial basis, and sigmoid, SVMs, particularly with the sigmoid function, excel in handling nonlinear connections. The linear model in the feature space is denoted by

$$f\,(x, \omega) = \sum_{j=1}^{m} \omega_i + g_{j(x)} + b \qquad (2)$$

SVM advantages encompass effective handling of high-dimensional data, generalization of unknown data samples, and prevents overfitting. Despite its computational demands, extended training time, and reliance on significant computing power, SVM proves beneficial for addressing nonlinear connections in features, making it valuable for indoor localization [69].

3.4.3 Random Forest

The Random Forest algorithm employs a unique approach where each tree relies on values from an independently and uniformly sampled random vector across the entire forest. The values from this random vector, is sampled uniformly for all the trees, dictates the values of each individual tree within the Random Forest. Functioning as an ensemble classifier, it constructs distinct decision trees through the incorporation of randomness, determining the importance of a value by its random permutation.

The generalization error tends to converge within the growth in the number of trees in the forest. The effectiveness of a forest of tree classifiers depends on the strength of each single tree and the correlation present between them. Despite initial skepticism about their precision compared to arcing-type algorithms, Random Forests prove to be an efficient prediction method, guarded against overfitting by the law of big numbers. Their proficiency as a classifier and regressor hinges on the right level of randomness. While determining in managing nonlinear connections between and handling missing data and features, the random forest algorithm may incur computational costs, especially for extensive datasets. [70,71].

3.5 Algorithm Training and Evaluation

The most vital stage in machine learning is training. Machine learning model is prepared by taking care of it arranged information for it to distinguish drifts and create expectations. As an outcome, the model increases information from the information to finish the job in question. The model works on in expectation after some time with preparing.

After this, now need to survey model's presentation in the wake of training it. To accomplish this, the model's presentation is assessed utilizing information that has never been seen. The testing set that you recently partitioned our information into is the inconspicuous information that was used. Since the model is now used to the information and perceives similar examples in it as it did in the preparation set, involving similar arrangement of information for testing won't yield an exact outcome. Your precision will increment emphatically subsequently. Understanding the numerous sorts of machine learning calculations is fundamental prior to starting the evaluation cycle. To give expectations or groupings, regulated learning calculations are prepared on named preparing information. Calculations for solo learning track down designs and examples in unlabeled information.

The chosen machine learning algorithms undergo intensive training, incorporating latitude, longitude, and corresponding RSSI values. The subsequent matching algorithm is applied to estimate user positions. The efficacy of the algorithms is assessed through the mean error distance metric, providing a robust indicator of positioning accuracy. The mean error distance metric, a robust indicator of positioning accuracy, measures the performance evaluation. By mapping the geographic distance between estimated and actual positions, mean error distance offers a tangible measure of algorithmic success. A comprehensive comparison across algorithms is performed to shed light on their efficiency and suitability for indoor positioning in 6G networks.

The evaluation is a rough estimate that we might use to examine the likely presentation of the calculation in true situations. Execution isn't ensured by it. In the wake of assessing our calculation's presentation, we might set up the last strategy for commonsense use by retraining it all in all preparing dataset. Making a proper dataset is a fundamental initial phase in Algorithm assessment.

To accomplish strength, the dataset ought to be adequately enormous, shifted, and intelligent of the current circumstance. Separating the dataset into preparing, approval, and it is additionally fundamental for test sets. The model is prepared on the preparation set; hyperparameters are adjusted on the approval set; and the last exhibition is assessed on the testing set.

3.6 Accuracy Assessment

The act of contrasting the genuine or genuine qualities with the anticipated or noticed values in a model or estimation framework is known as Accuracy assessment. It is generally utilized in areas like machine learning, measurements, and remote detecting and is a fundamental stage in evaluating the presentation of models or estimation frameworks. Nowadays, Accuracy Assessment is a significant piece of characterizing land cover since scientists the same know about the restrictions and vulnerabilities related with ordering somewhat detected pictures. Lacking examination and show of the remote detecting pictures could prompt a misleading translation. Exactness assessment is expected to create the best subject guides, bring the concentrate satisfactory, and confirm this inconsistency.

To comprehensively quantify accuracy, the mean error distance is converted into a percentage, facilitating meticulous cross-algorithm comparison.

The accuracy assessment aims to discern the algorithm consistently delivering the most precise user position estimates.

$$\text{Accuracy }(\%) = 100 - \text{Mean Error} \tag{3}$$

Accuracy in indoor localization denotes the system's ability to accurately determine the user's position. The pivotal metric for evaluating accuracy is the Mean Error Distance (MED), which calculates the average distance between the user's predicted position and the actual location. In the context of indoor localization, accuracy serves as a crucial performance indicator susceptible to various influencing factors, including signal intensity, interference, and multipath effects.

Study indicates efficacy of employing machine learning methodologies, encompassing k-Nearest Neighbor (kNN) algorithms, Support Vector Machines (SVMs), and Random Forest to enhance accuracy.

These methodologies facilitate the refinement of indoor localization precision by establishing a mapping relationship between smartphones data and the user's position [68].

The accuracy is quantified through the formula:

$$\text{Accuracy} = \frac{\text{Number of corect predictions}}{\text{Total number of predictions}} \tag{4}$$

$$= \frac{\text{TP+TN}}{\text{TP+FP+TN}} \tag{5}$$

where '*TP'* denotes *True Positive*, '*TN'* denotes *True Negative*, and *'FP'* denotes *False Positive*.

This formula encapsulates the ratio of correct predictions to the overall predictions, providing a robust measure of the system's accuracy in indoor localization [72].

3.7 Implementation in Python

Python is the programming language that supplanted ABC. We have different Python programming language executions. An application that works with the execution of Python code is called an execution of the language.

The entire simulation was done in Python, leveraging the Scikit-learn library for machine learning tasks, Pandas for adept data manipulation, and Matplotlib for insightful data visualization. The choice of Python ensures a robust and widely adopted platform for methodological execution.

Scikit-learn: The most solid and viable Python machine learning library is called Scikit-learn, or Sklearn. Through a Python consistency interface, it offers a scope of compelling devices for measurable displaying and machine learning, including as relapse, bunching, characterization, and dimensionality decrease.

The tools employed for predictive data analysis are characterized by their simplicity and efficiency, rendering them accessible to a broad audience and applicable across diverse contexts. Mainly used for machine learning in python. It’s developed on the foundation of NumPy, SciPy, and matplotlib, these tools adhere to open-source principles and are commercially usable, governed by the BSD license. This ensures their availability for widespread utilization, fostering a collaborative and adaptable environment for predictive analytics [73].

Pandas: Pandas stands as an open-source, BSD-licensed library that delivers high-performance and user-friendly data structures and data analysis tools tailored for the Python programming language. It serves as a robust and versatile data analysis solution, contributing to the Python ecosystem with its efficiency and ease of use [74].

Pandas is a Python device for controlling even information. pandas are normally utilized in information science applications, this is because of the way that pandas are used in mix with extra information science-related libraries.

Since Pandas is based on top of the NumPy library, large numbers of NumPy's designs are either copied or used. Pandas creates information that is habitually utilized as contribution for SciPy's factual examination, Matplotlib's outlining abilities, and Scikit-learn's machine learning strategies.

Matplotlib: Matplotlib stands as an extensive library dedicated to generating static, animated, and interactive visualizations within the Python programming language. Renowned for simplifying the creation of straightforward plots while enabling the realization of complex visualizations, Matplotlib empowers users with diverse capabilities.

It facilitates the production of plots adhering to publication standards, the development of interactive figures with zoom and pan functionalities, customization of visual styles and layouts, seamless export to multiple file formats, and integration into JupyterLab and Graphical User Interfaces. Additionally, Matplotlib benefits from a wealth of third-party packages that further extend its functionalities, making it a versatile tool for data visualization [75].

3.8 Visualization

A fundamental part of machine learning that helps examiners fathom and get a handle on information relationships, examples, and patterns is representation. Information representation is a fundamental piece of machine learning since it makes bits of knowledge and examples in information promptly dissected and imparted to a bigger crowd. In a bid to enhance interpretability, distance error histograms are meticulously crafted, offering a visual representation of error distributions across diverse algorithms and configurations. Scatter plots depicting actual versus predicted locations provide an additional layer of visual insights into algorithmic performance. Perception offers a way to speed this up and introduce data to entrepreneurs and partners in manners they can comprehend.

3.8.1 Visualization Approaches

Machine Learning might utilize a wide assortment of information perception draws near. That include:

Line Diagrams: A line interfaces the focuses on the chart that address the pieces of information, which are each addressed by a. Utilizing line diagrams, we can utilize the information to search for patterns and examples across time. Line outlines are frequently used to portray time-series information.

Scatter Plots: Scatter graphs are a quick and successful method for showing the connection between two factors. Every data of interest in a disperse plot is addressed by an on the chart, with one variable plotted on the x-pivot and the other variable drawn on the y-hub. Dissipate plots are a helpful device for picturing information and distinguishing patterns, bunches, and exceptions.

Bar Graphs: Regularly, classification information is shown utilizing bar diagrams. Every class in a bar diagram is addressed by a bar, and the level of the bar shows how regularly or the amount of the information falls into that gathering. Visual charts are useful for seeing patterns over the long haul and looking at numerous classes.

Heat Map: Information is shown graphically in a framework style utilizing heat maps, a sort of representation. The shade of every lattice cell relies upon the worth of the information point it addresses. Every now and again, time-series information might be investigated utilizing heatmaps to see designs or the relationship between factors.

Picking the best representation way to deal with precisely portray the information is perhaps of the most troublesome assignment in information perception. Data perception requires great information. Off base, inadequate, or conflicting information can prompt misdirecting or wrong perceptions. To assess and grasp huge, confounded informational indexes, AI examiners need to approach information perception devices.

3.9 Iterative Refinement

A pivotal aspect involves an iterative refinement process wherein machine learning algorithm parameters and signal fingerprinting techniques are systematically adjusted based on observed results. This iterative approach ensures continuous enhancement and fine-tuning for the optimal performance.

As machine learning is a continuous interaction, advancing results as often as possible requires adjusting the models. This involves altering hyperparameters, similar to choose tree profundity, regularization, and learning rate. Methods like lattice search and irregular inquiry are habitually utilized to explore different blends of hyperparameters and recognize the best set.

3.10 Comparison

Since a few calculations have been evaluated, now is the right time to differentiate their outcomes and pick the best performing one. Gauge the benefits and hindrances of every calculation while remembering the evaluation principles previously expressed. It is fundamental to pick a calculation that streamlines for interpretability, computational intricacy, and execution. Remember that a calculation that functions admirably for one occupation probably won't turn out best for another.

This section undertakes a comparative analysis with previous research focusing on Wi-Fi and Bluetooth technologies for indoor localization. Furthermore, how this study's emphasis on avoiding additional hardware aligns with the trend of utilizing existing infrastructures for innovative purposes, economizing resources, and seamlessly integrating into existing ecosystems are pointed here.

The adaptability of this proposed system is expected to drive the widespread adoption of high-precision indoor localization, enhancing user experiences, ensuring safety in critical scenarios, and enabling context-aware services are highlighted here. Finally shows the convergence of machine learning techniques with GSM RSSI-based signal fingerprinting represents a transformative leap in indoor positioning accuracy within the domain of 6G cellular network.

Chapter 4

Result Analysis

4.1 Result Analysis

This section analyzed and interpreted the performance of the algorithms employed for indoor positioning estimation within the context of 6G cellular networks.

This study used a publicly available dataset that contains about 2557 lines with six different measures from six different Radio Base Stations (RBSs). Also, it has two columns that represent the user's position. Also, two additional datasets are used: one provides more information about the RBSs, such as their positions and the power of the radiated signal, and another is used as a test dataset.

We have divided the Result analysis section into 4 different parts as:

A. Regression Algorithms

B. Distance Error Histogram

C. Actual vs. Predicted Distance

D. Comparison with other systems

4.2 Regression Algorithms

A supervised learning method called the regression is used to determine the location of fresh observations based on training data. In this process algorithms were used to do a regression of user's position based on the RSSI's values by learning from the provided dataset.

Regression algorithms are mostly used to anticipate the output for numerical data. Their primary objective is to determine the numerical values based on given dataset.

K-NN is also referred to as a lazy learner, that saves the dataset and applies operations to it during regression, avoiding assumptions about the underlying data, rather than learning directly from the training set. The Lazy Learner can also perform classification based on relevant data stored in the training dataset while storing the training dataset and waiting for the test dataset. The figure given below shows the mean error distance result of different algorithms used.

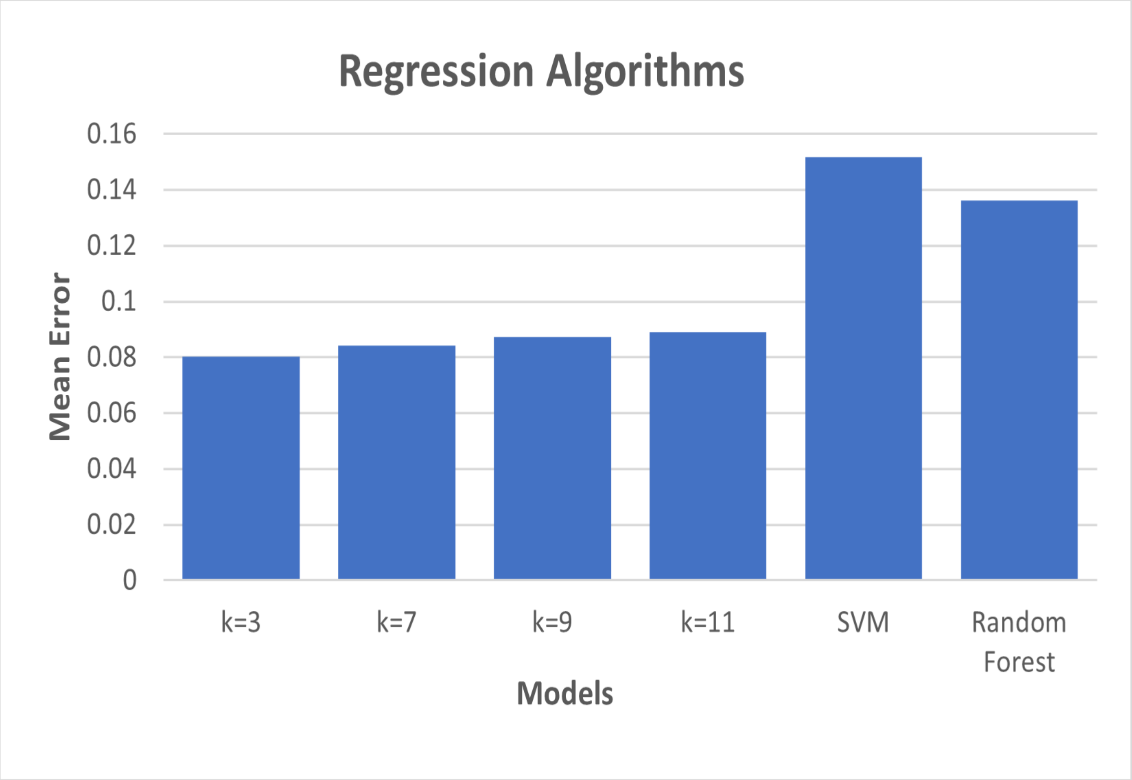

Figure 8 Mean error of different algorithms used

Figure 8 shows an algorithmic performance comparison. The mean error distance results for different k-values in kNN, SVM-based localization, and Random Forest were obtained.

The geographic distance errors were computed and averaged to ascertain positioning accuracy. From the mean error data, it's apparent that the k Nearest Neighbor (k=3) algorithm emerges as the most accurate, demonstrating a notably low mean error distance of 0.08025523 meters, about 99.92% accuracy. So, the configuration with k=3 exhibits exceptional accuracy, closely followed by k=7, k=9, and k=11. Among the main algorithm variants, the Random Forest is more accurate. SVM is less accurate than the Random Forest.

First, this study compared regression algorithms to identify a model capable of accurately estimating user positions. Through rigorous experimentation and evaluation, we found that our trained models outperformed the naive fingerprint implementation in accuracy.

The results clearly demonstrate the effectiveness of our approach in achieving improved position estimation accuracy.

4.3 Distance Error Histogram

The disparities between target and predicted values, which might be positive or negative, are represented visually by the error histogram.

The histogram gives important information about the distribution of mistakes and the occurrence of specific prediction error ranges.

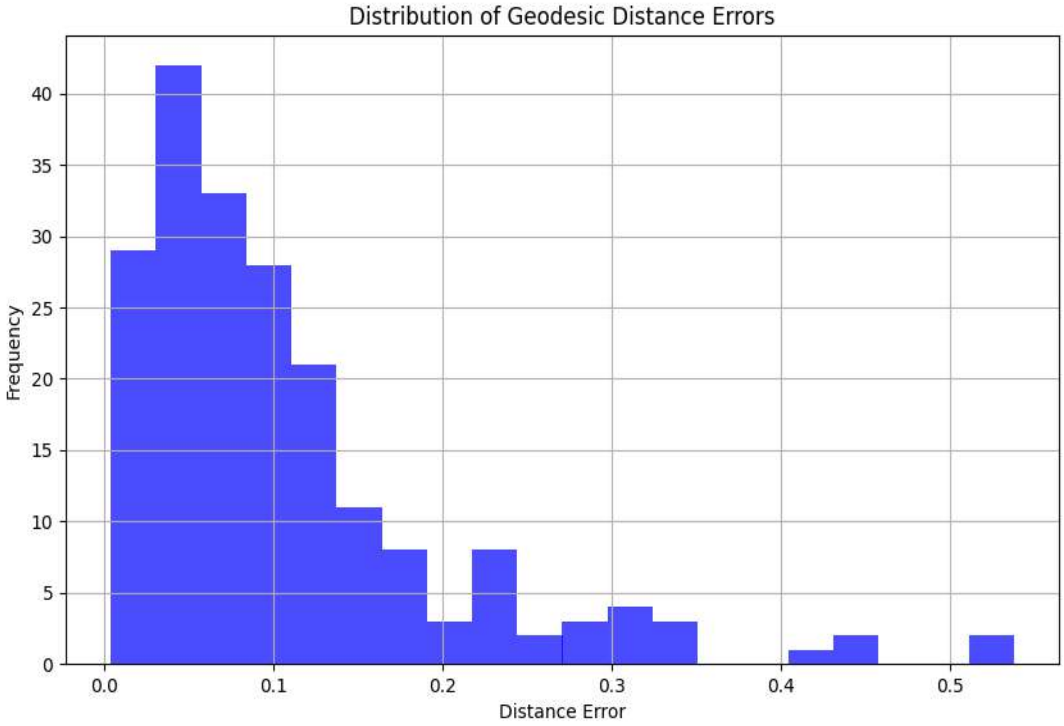

Figure 9 Distance error histogram of k nearest neighbor (k=3)

Figure 9 shows the data frame of calculated errors where kNN (k=3) predicts user location. The test dataset is used for this purpose and utilized Leave-One-Out cross-validation to assess the model's accuracy. This cross-validation filters out poorly predicted points and refines the model accordingly.

The results are visualized to understand the distribution of distance errors, meaning the legend “Frequency” means the number of times that value has occurred.

The histogram provides us insight into the distribution of errors and how frequently certain error ranges occur in the predictions, which helps us in achieving improved position estimation accuracy.

4.4 Actual vs. Predicted Distance

Here we compared the actual distance with predicted distance. The difference between the actual and predicted outcomes from the line is known as the residual or prediction error. Below graphs shows Actual distance and Predicted distance with blue points and red dashed lines.

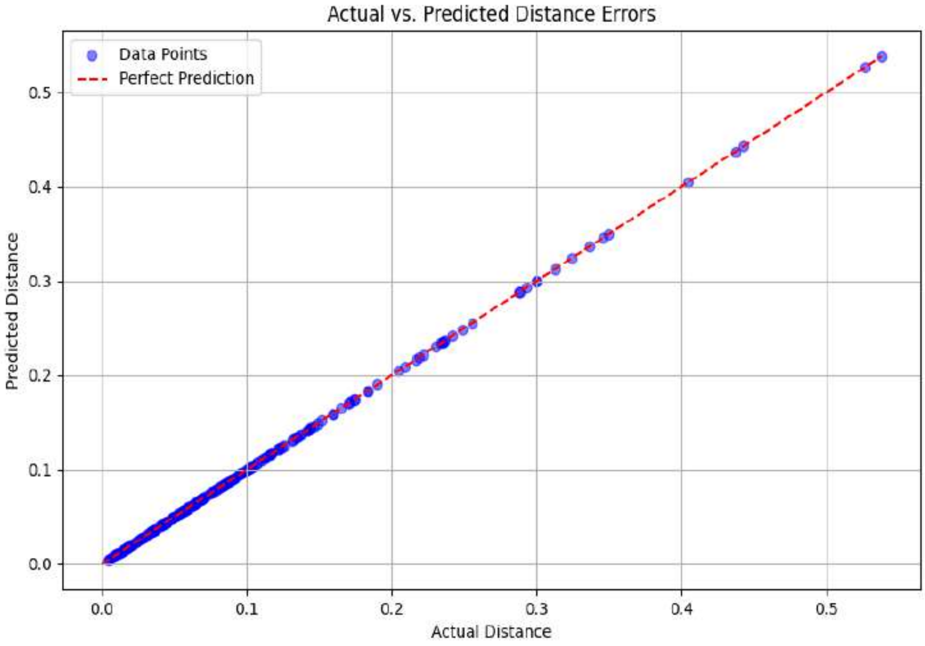

Figure 10 Actual vs. predicted data.

Figure 10 shows a scatter plot where each of the points represents an actual vs. predicted distance pair. The red dashed line represents the ideal scenario where the predicted distance perfectly matches the actual distance. The blue point represents our data point. Points close to the red line indicate accurate predictions, while points deviating from the line indicate errors in the predictions.

This test scenario's absolute mean error distance is 0.10692412 meters, which is approximately 99.89% accurate.

Finally, this study evaluated the performance of the regression models using standard metrics and evaluation criteria. The obtained results showcased significant enhancements in accuracy rates and reductions in estimation errors. These findings indicate that our proposed approach successfully captured the underlying relationships between RSSI values and user position coordinates.

4.5 Comparison

In this section, we have compared our proposed GSM RSSI Approach with ML system with other systems with various parameter.

TABLE II. COMPARISON WITH OTHER SYSTEMS

Parameter	**Wi-Fi and Bluetooth Approach**	**IoT RSSI Approach**	**Proposed GSM RSSI Approach with ML**
Technology	Wi-Fi and Bluetooth	IoT (RSSI)	GSM RSSI
Hardware Requirements	Wi-Fi access points, Bluetooth devices	Diverse IoT hardware components	Existing GSM network infrastructure
Cost Analysis	Moderate to High	Moderate to High	Low
Signal Interference	Yes, interference due to coexistence	Interference due to crowded frequency band	Minimal interference, separate frequency band
Accuracy	Average mean error around 1.22 meters [40]	Mean error around 0.664 for Wi-Fi, 0.753 for Bluetooth Low Energy [23]	Reduced absolute mean error to 0.08025523 and 0.10692412 meters respectively in two test scenarios with different dataset
Unique Features	Trilateration techniques	IoT integration, hardware-dependent	Machine learning with GSM RSSI fingerprinting
Coverage	Limited to areas with Wi-Fi access points	Limited by hardware coverage	Extensive coverage due to GSM infrastructure
Future Compatibility	May face challenges in evolving Wi-Fi scenarios	Limited by IoT development	Compatible with evolving cellular networks (e.g., 6G)
Additional Hardware	Yes, requires Wi-Fi access points	Yes, requires diverse IoT components	No additional hardware required existing GSM BSSs is used

The present investigation contrasts with prior research endeavors that have employed Wi-Fi and Bluetooth technologies for indoor localization. For instance, a notable study (referred to as [40]) employed Wi-Fi in conjunction with trilateration techniques, which is indeed efficacious.

However, this approach necessitates the availability of Wi-Fi access points for its implementation. It is worth noting that the coexistence of numerous Wi-Fi access points and Bluetooth devices within the same frequency band (2.4 GHz) can lead to signal interference, potentially compromising the Wi-Fi signals. Furthermore, scenarios in which 5 GHz Wi-Fi access points are unavailable pose an additional challenge. The aforementioned [40] study reported an average positioning error of approximately 1.22 meters.

Conversely, another referenced study [23] introduced an indoor positioning system that relies on Received Signal Strength Indicator (RSSI) measurements within the context of the Internet of Things (IoT). This approach was evaluated through experimental testing involving diverse hardware components. In contrast, the proposed method presented herein obviates the need for supplementary hardware, representing a distinctive advantage. Notably, the utilization of GSM RSSI signals provides several benefits, including extensive coverage, heightened accuracy, and compatibility with high-density environments [30].

The algorithmic frameworks harnessed in our investigation offer several distinguishing features that are not found in the studies mentioned above or in conventional methods. The efficacy of these features in bolstering indoor positioning accuracy remains unparalleled when juxtaposed with the extant body of research. Notably, the ubiquity of cellular network coverage, especially with the imminent advent of advanced cellular networks such as 6G, further underscores the feasibility of employing machine learning algorithms in conjunction with GSM RSSI signal fingerprinting to achieve superior indoor positioning precision.

The profound implications of these results extend beyond the immediate scope of indoor positioning technologies. As the world embraces the forthcoming era of 6G and the ever-expanding reach of cellular infrastructure, the integration of machine learning algorithms with GSM RSSI signal fingerprinting holds the promise of reshaping indoor positioning and various aspects of location-based services. The demonstrated reduction in absolute mean positioning error to an astonishingly fine granularity of 0.10692412 meters is approximately 99.89% accurate and 0.08025523 meters, about 99.92%

accuracy respectively. This reflects a pivotal stride towards achieving unprecedented accuracy, crucial for applications ranging from indoor navigation systems.

Furthermore, this study's emphasis on obviating the need for additional hardware aligns with the broader trend of harnessing existing infrastructures for innovative purposes. This approach economizes resources and opens avenues for seamless integration into existing ecosystems by capitalizing on ubiquitous cellular connectivity.

This adaptability is expected to be instrumental in realizing the widespread adoption of high-accuracy indoor localization, thereby fostering enhanced user experiences, bolstering safety in critical scenarios, and enabling a new paradigm of context-aware services. Finally, the convergence of machine learning techniques with GSM RSSI-based signal fingerprinting showcases a transformative leap in indoor positioning systems accuracy.

Chapter 5

Conclusion

5.1 Conclusion

This study demonstrates the successful implementation of machine learning algorithm models for estimating user position coordinates based on GSM RSSI values. The collected data are freely available and ready to be re-used in further work by other researchers. The comparison of regression algorithms and evaluation of their performance highlights the superiority of the machine learning approach over the naive fingerprint implementation. Our analysis demonstrated that the k-Nearest Neighbors (kNN) method when configured with lower values of k, consistently gave noteworthy outcomes in indoor location accuracy. The mean error values obtained for varied k values (k=3, k=7, k=9, and k=11) were startlingly close, signifying the robustness of the kNN approach within our specific case.

Furthermore, both the Support Vector Machine (SVM) and Random Forest approaches revealed promising outcomes but with somewhat raised mean error levels compared to the ideal kNN setups. We have also used the trained k-Nearest Neighbors (kNN) technique to determine the accuracy difference between the actual and predicted positions. These results emphasize the potential of these algorithms to be exploited effectively in the development of 6G indoor positioning systems with the GSM signal fingerprinting method. The outcomes gleaned from our analysis underscore the potential of these machine learning algorithms to greatly enhance indoor positioning accuracy within the ambit of the 6G cellular network. The remarkable proximity of mean error distance values and the lesser difference between the actual and predicted location in the kNN variants gives confidence to its robustness.

As the capabilities of 6G networks continue to evolve, the results of our study pave the way for innovative applications that depend on precise indoor positioning, ranging from augmented reality experiences to industrial automation.

However, additional investigations are necessary to tackle outlier-related challenges and further improve the accuracy and robustness of the system. The simulation of this study was executed in PyCharm Community Edition 2022, leveraging Python 3.10 as the base interpreter on an Intel Core i3 7020U @2.30 GHz computer. The holistic model, inclusive of the dataset, essential algorithms, and requisite Python library packages such as scikit-learn, pandas, and matplotlib, along with their dependencies, consumed a total of 349 MB of storage. Throughout the simulation, the CPU usage averaged approximately 26%, with the interpreter's RAM consumption stabilizing at around 90 MB.

5.2 Achievement

The accuracy rates and estimate errors of the regression models significantly improved, demonstrating the successful capturing of correlations between RSSI values and user location coordinates. The study generated an enhanced indoor localization strategy by effectively implementing a traditional signal fingerprinting technique in a 6G cellular network setting utilizing the Received Signal Strength Indicator and machine learning techniques. With two datasets, the proposed approach was attained 99.89% accuracy with a mean error distance of 0.10692412 and 99.92% accuracy with a mean error distance of 0.08025523.

5.3 Future Work

This study can be improved in a future version by incorporating more advanced machine learning algorithms with hybrid fingerprint-based localization techniques along with extended training. k-Nearest Neighbor (kNN), Random Forest, and Support Vector Machines (SVMs) approaches with different optimization techniques can all be used to enhance the positioning system's implementation. These methods have the potential to improve localization methods' accuracy.

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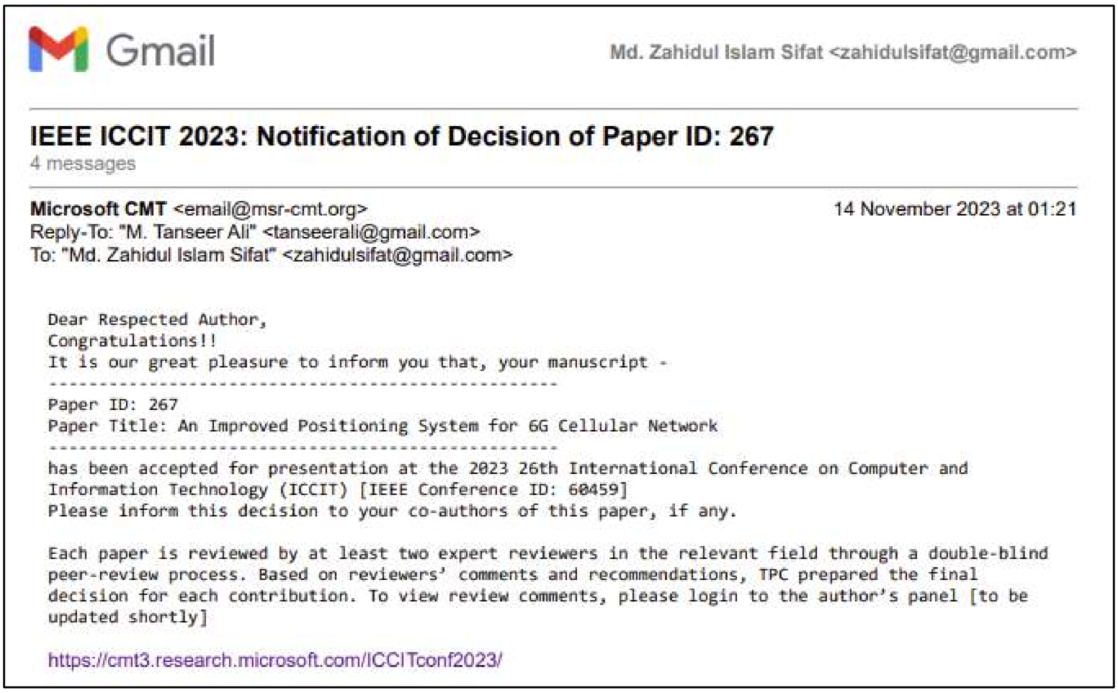
List of Achievements (Conference Paper)

[1] This study has been accepted and presented at the 2023 26th International Conference on Computer and Information Technology (ICCIT) and it is on its path to the publication process.



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