Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Telecommunication Engineering Graduate Program

LTE Network Coverage Hole Detection Technique using Random Forest Classifier Machine Learning Algorithm

By

Serkadis Bahiru

Advisor

Dr.–Eng. Yihenew Wondie

A Thesis Submitted to School of Electrical and Computer Engineering, in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Telecommunications Engineering

October 2023

Addis Ababa, Ethiopia

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Telecommunication Engineering Graduate Program

LTE Coverage Hole Detection Technique using Random Forest Classifier Machine Learning Algorithm

By

Serkadis Bahiru

Approval by Board of Examiners

______________________	______________	________
Chairman Department of Graduate Committee	Signature	Date
Dr.–Eng. Yihenew Wondie	______________	________
Advisor	Signature	Date
______________________	______________	________
Internal Examiner	Signature	Date
______________________	______________	________
External Examiner	Signature	Date

Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

____

Signature

Serkadis Bahiru

October 2023

This thesis has been submitted for examination with my approval as a university advisor.

____

Signature

Dr.–Eng. Yihenew Wondie

October 2023

Place: Addis Ababa

Date of Submission: __________________

Abstract

The most significant phases for the mobile operator are the performance of cellular networks and the evaluation of quality of service (QoS). Hence, Long-Term Evolution (LTE) network monitoring and measuring are necessary in determining mobile network statistics to optimize the performance of the network in a particular area. Measuring networks is an effective way to qualify and quantify how networks are being used and how they are behaving, and it helps to find voids or uncovered areas that are coverage holes in the LTE network.

A coverage hole is defined as a client's being unable to receive a wireless network signal. Traditionally, it is detected through drive tests, but it costs resources and time. In order to identify coverage holes in the LTE network, this study proposed a random forest classifier Machine Learning (ML) approach.

The data was gathered from the User Equipment (UE) via minimization drive test (MDT) functionality with low cost, which measures Reference Signal Receive Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal to Interference and Noise Ratio (SINR). The RSRP and RSRQ measure the strength and quality of the reference signal received at the device's antenna, whereas SINR is a metric that assesses the relationship between the targeted signal strength and the total power of all interfering signals and noise.

The results obtained show that the employed model's accuracy was 96.3%. However, we could use the hyperparameter optimization (HPO) technique to enhance the model's performance, namely random and grid search cross validation (CV), which increased the model's accuracy to 97.7% and 99.2%, respectively.

Keywords: *Coverage hole, Random forest classifier, Hyper parameter optimization, minimization drive test, RSRP, RSRQ, SINR*

Acknowledgment

First and foremost, I would like to thank God Almighty for helping me reach where I am in my academic career and for giving me the opportunities that enabled me to finish the thesis.

Second, I want to express my special gratitude to my advisor, Dr.–Eng. Yihenew Wondie, for his critical advice and support as I worked on my thesis. Additionally, I am greatly appreciative of his ongoing supervision and helpful feedback up until the thesis submission. I would also like to thank my evaluators, Dr.-Ing. Dereje Hailemariam and Dr. Tsegamlak Terefe, for their insightful comments throughout the thesis progress presentations.

Then, my deepest thanks go to my family for the love, encouragement, and inspiration they have shown me throughout my studies and my life.

I would also like to thank the ethio telecom wireless network planning and optimization team, especially Ato Solomon Gossa, for his technical support and guidance.

Finally, a special acknowledgement goes to ethio telecom for giving me the opportunity to pursue my master's degree and be responsible for my full sponsorship.

Lists of Acronyms

1G	1st Generation
2G	2nd Generation
3G	3rd Generation
4G	4th Generation
3GPP	3rd Generation Partnership Project
AuC	Authentication Centre
BBU	Base Band Unit
BTS	Base Transceiver Station
CDR	Call drop rate
CSSR	Call Setup Success Rate
COD	Cell Outage Detection
CQI	Channel Quality Indicator
CCO	Coverage and Capacity Optimization
CRISP-DM	Cross industry standard process for data mining
CV	Cross validation
DL	Downlink
Ec/No	Energy per chip to total received power density
eNodeB	Evolved NodeB
EPC	Evolved Packet Core
EPS	Evolved Packet System
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
ERAB	E-UTRAN Radio Access Bearer
FADD	Fast Anomaly Detection with Duplication
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HSBC	High Speed Backhaul Connected
HLR	Home Location Register
HSS	Home Subscriber Server
HPO	Hyperparameter Optimization
ICI	Inter cell interference
iRAT	Inter Radio Access Technology
IP	Internet Protocol

KNN	K Nearest Neighbor
KPI	Key performance indicator
LOF	Local Outlier Factor
LTE	Long Term Evolution
MR	Measurement Report
MDT	Minimization Drive Test
MCS	Mobile Crowdsourcing
ME	Mobile equipment
MT	Mobile Termination
MME	Mobility Management Entity
MSV	Multiple site verification
NAS	Non-Access Stratum
OPEX	Operating expenses
OFDMA	Orthogonal Frequency Division Multiple Access
OOB	Out of Bag
PGW	Packet Data Network Gateway
PCI	Physical Cell Identity
PRB	Physical Resource Block
PPI	Pilot Pollution Interference
PCRF	Policy and Charging Rules Function
PDN	Public Data Network
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
RLF	Radio link failure
RPT	Radio Planning Tool
RRC	Radio Resource Control
RRM	Radio Resource Management
RSCP	Received Signal Code Power
RSSI	Received Signal Strength Indicator
RSRP	Reference Signal Receive Power
RSRQ	Reference Signal Received Quality

RRU	Remote Radio Unit
RCEF	RRC Connection Establishment Failure
RB	Resource Block
SON	Self Organized Network
SGW	Serving Gateway
SINR	Signal to Interference and Noise Ratio
SC-FDMA	Single Carrier Frequency Division Multiple Access
SCFT	Single Cell Function Test
SSV	single site verification
SIM	Subscriber Identity Module
TCE	Trace Collection Entity
TA	Tracking Area
TE	Terminal Equipment
TTI	Transmission Time Interval
TT	Trouble Ticket
UICC	Universal Integrated Circuit Card
USB	Universal Serial Bus
USIM	Universal Subscriber Identity Module
UMTS	UMTS Subscriber Identity Module
UL	Uplink
UE	User Equipment
VoIP	Voice over Internet Protocol
WCDMA	Wideband Code Division Multiple Access

Table of Contents

List of Figures

List of Tables

Chapter 1

1. Introduction

This chapter provides the background of this research and describes the statement of the problem and the objective of the thesis. In addition, it briefly describes the reviewed literature that are related to the study, the methodology used, as well as the contribution, scope, and limitations of the research.

1.1. Background

Nowadays, cellular communication is expanding quickly and has made great advancements in both voice communication and data streaming. Because of this, technology advanced from the 1st Generation (1G) to the 4th Generation (4G). The demand for high-speed voice and data is crucial. The necessity for users to access high-speed data and voice with low latency is supported by 4G technology [1]. LTE mobile networks are being developed by the 3rd Generation Partnership Project (3GPP) because of the growth in mobile data usage caused by the rise in mobile subscribers and the emergence of new applications like mobile television and online gaming that require the highest level of service. Due to this network's promising quality of service, service providers are migrating to this network to assist them in meeting the growing end-user demand for more bandwidth, high security, and faster connectivity [2]. Estimating coverage and assessing capacity are both part of the planning for the LTE radio network. The basic goal of network planning is to achieve maximum capacity without sacrificing service quality. Future growth and expansion should be considered when making plans. Users will benefit financially from wise spectrum reuse and strategic site placement. The network planning process is done step by step while meeting the requirements. Planning for parameters, coverage, and capacity [1].

The primary considerations that must be addressed during the radio-planning phase are where to install base stations and how to set up base stations (antenna type, height, sector orientation, tilt, maximum power, device capacity, etc.). The signal strength in the service area is guaranteed by coverage planning, which is the percentage of the area covered by cellular service where mobile phone service is provided. Determining where to place base stations, specific antenna designs, and constraints on signal strength in the area. Whereas capacity planning determines which radio resources can be utilized by each cell, as well as the number of calls that can be handled in a specific area within a particular period and the likelihood that users will be blocked access to a system due to a lack of radio channels [3].

Although providing coverage to customers during a rollout is the highest priority, it is equally important to increase the network's capacity when it is in operation. As a result, both coverage and capacity are taken into account in the use case and enabled by the self-organized network (SON) function. The coverage and capacity optimization (CCO) SON function should be configured through appropriate objectives and targets in order to fulfil the operator's requirements for coverage, capacity, and ordered between them [4]. The need for services in the telecommunications industry, as well as the success and quick growth of this industry globally, have prompted mobile phone providers to compete to offer the finest services to customers. Mobile phones are among these communication tools. Simply put, a mobile phone is an electronic device that primarily supports unwired telecommunications through a cellular network of unique base stations known as cell sites [5]. Each cell in a mobile network is supplied by at least one fixed-location transceiver, also known as a base station. Cells are land-based geographic regions where the radio network is dispersed. To prevent interference in a cellular network, each cell makes sure that it receives a unique set of frequencies from its neighbors [6].

There are numerous challenges or issues in the realm of communications, and the relevant companies and organizations should find answers to these challenges. The existence of a coverage hole in cellular networks is one of the problems facing mobile operators. A coverage hole is an area where the pilot signal strength is below a threshold, which is required by a UE to access the network, or the SINRs of both serving and neighbor cells are below the level needed to maintain the basic service. It is usually caused by physical obstructions such as new buildings, hills, unsuitable antenna parameters, or just inadequate radio frequency (RF) planning. UE within the coverage hole will suffer from call drop and radio link failure. A typical phenomenon of coverage hole is either handover failure, which happens frequently and cannot be optimized by handover parameter optimization, or call drop, which happens frequently and cannot be rescued by Radio Resource Control (RRC) re-establishment [7].

While network performance data collection in telecommunications systems is getting more sophisticated, field performance data must still be gathered in order to fully understand the end-user experience. Utilizing cutting-edge equipment that covers several technologies, bands, and vendors, this data is gathered under the on-site supervision of a qualified RF engineer. The service of information gathering includes measurements of pedestrians in indoor environments, such as the walk test, in addition to outside measurements, such as the drive test. Detecting coverage holes helps find voids or uncovered areas in the LTE network. More nodes are planned for deployment in uncovered areas in order to ensure reliability by addressing the holes. Hole detection ensures service quality by minimizing data loss. The motivation for this thesis is that the traditional drive-test approaches for identifying coverage holes are costly with respect to resources and time. Hence, the proposed approach reduces the company's expenditure while enhancing performance.

1.2. Statement of the Problem

There are various challenges in telecommunications; one of the problems that researchers are working hard to solve is the coverage hole. RF transmissions from outdoor macrocarrier towers can have difficulty providing indoor coverage, which is one of the drawbacks of radio-based cellular systems. Concrete, glass, steel, and other building materials may block the signals. In the modern digital world, weak coverage is a challenge, particularly for large establishments and businesses like airports, transit hubs, stadiums, hospitals, retail, office buildings, and manufacturing sites. In order to improve network performance, ethio telecom planned indoor and outdoor network coverage using the urban propagation model; however, there are still call drops and handover failures due to coverage outages. This shows that there is an undetectable coverage hole in the planning tool. Data accuracy declines because transmission links are disconnected due to a coverage hole in the network, and effectively enhancing network service quality requires the prompt discovery of coverage outages. When users enter a coverage hole, they will experience call loss and handover failure. A call drop occurs when a connection is suddenly disconnected before the user's desired service is finished. The bad thing that could happen for the user is that they completely lose their connection, leading to customer displeasure. As a result, users complain endlessly about call drop, handover failure, and poor performance in locations with LTE coverage holes.

Currently, coverage holes have been detected through drive tests in the case of ethio telecom. However, it has two significant drawbacks. First, manual drive testing involves a lot of resources, including time, specialized tools, and the engagement of highly skilled engineers; this results in high operating expenses (OPEX). Second, given that the majority of UE-generated traffic from indoor areas and since manual drive testing tends to be limited to on-road testing, it is challenging to adequately evaluate coverage across all regions. This makes drive testing an expensive task with practical limitations due to cost and accessibility issues.

So far, many research has been done on the detection of network coverage holes using approaches like decision trees, density-based anomaly detection, and data mining. One of the research was to develop a decision tree for detecting coverage holes, but the problem is that we can't generalize the model, which leads to overfitting.

Therefore, the proposed approach develop a coverage hole detection technique based on the random forest classifier algorithm using Measurement Report (MR) data via MDT functionality. In order to minimize overfitting, random forest create numerous trees and train each tree (model) separately using a variety of data sets. The outcome is then predicted by each model, and the final prediction will be decided by the majority vote and the model offers a high degree of accuracy.

1.3. Objective

1.3.1. General objective

The main objective of this thesis is to investigate a coverage hole detection technique in LTE networks based on the random forest classifier ML algorithm, and the proposed technique uses MR data such as RSRP, RSRQ, and SINR as input, which are collected from UE using mentor tool.

1.3.2. Specific objectives

- Review related literature on coverage hole detection and study different techniques.
- Select area and collect the required parameters from the mentor tool.
- Data preprocessing.
- Classify the collected parameters using the selected algorithms as per their pre-defined classes.
- Building the model, splitting it into training and testing models.

- Evaluating the performance of the random forest classifier algorithm.
- Visualize the detected area of coverage hole on a Google Earth Pro.
- Discuss the results and give recommendations based on the findings.

1.4. Scope and Limitation

The scope of the thesis is to investigate the coverage hole detection technique based on the random forest classifier algorithm in the ethio telecom LTE network through MDT MR data from UE. In the Addis Ababa area, cluster 20, which includes 324 eNodeBs and 1208 cells, are selected. The thesis is limited to only detecting coverage holes and does not address the root cause of the problem or optimization. Fortunately, the idea behind coverage hole detection is similar across all mobile technologies, but the thesis work is limited to only LTE networks.

1.5. Contribution of the thesis

This work provides a non-drive-test detection method for coverage holes that can increase the effectiveness of RF coverage planning. Enabling ethio telecom resources to be used effectively in terms of time and cost might help the company provide swift customer service and improve its performance. Additionally, it categorizes according to signal levels and can offer signal status information for network planners and optimization teams. Moreover, the detection method takes into consideration indoor environments where drive testing cannot be addressed.

1.6. Literature review

Many studies have been done on applying ML algorithms in the domain of telecommunications and detecting network coverage holes. Within this section, related studies that highlight coverage detection and optimization application cases are mentioned.

A. Gomez-Andrades, R. Barco, and I. Serrano [8] conducted a method of assessment of the LTE network coverage hole. A method for identifying cells with coverage holes and determining their type and severity is suggested. Furthermore, the authors propose a technique that can simultaneously evaluate the effects of each coverage hole on consumers in both LTE and the underlying RAT. The strength of the study was demonstrating its ability to detect and diagnose coverage holes. The limitation of this work is since only the heterogeneous deployment situation has been considered, the homogeneous deployment option cannot be addressed.

[9] Abdissa G. conducted coverage hole detection using decision tree classifier-supervised ML algorithms on the Universal Mobile Telecommunications System (UMTS). The author used important performance indicators to identify the coverage hole in the 3G network. The data collection was done by using the Nastar tool from UEs that measures received signal code power (RSCP) and energy per chip to total received power density (Ec/No). The approach follows four coverage categories based on good and bad coverage conditions: good coverage and good quality, good coverage and poor quality, poor coverage and good quality, and poor coverage and poor quality. The study's limitation is that the model overfits, which is a frequent problem that must be addressed while training a decision tree model.

Chethan K. Anjinappa and Ismail G. Uvenc [10] proposed an unsupervised learning approach to detect coverage holes for mmWave networks. They offer a unique method for unsupervised coverage hole identification utilizing uniform manifold approximation and projection. The main goal is to maintain the local connectivity structure present in the unlabeled channel samples that were gathered so that the coverage holes in the service region can be identified. Their findings on the deep MIMO dataset scenario show that the suggested method is capable of learning the structure inside the data samples and providing visual holes in the low-dimensional embedding while maintaining the coverage hole boundaries.

Bisrat A. [11] and Bekele S. [12] developed a technique for cell outage detection (COD). Both studies used handover information and applied density-based anomaly detection methods, namely, Local Outlier Factor (LOF) algorithms. In addition to this, they applied other anomaly detection techniques, such as K-Nearest Neighbour (K-NN) and Fast Anomaly Detection with Duplication (FADD), respectively. The study [11] utilized traffic data, which originated from base stations and terminated at mobile devices, as well as incoming handover data to capture the typical network status and automatically detect the outage of the target cell in a pre-set time period in the UMTS network environment. The AUC of the K-NN model is greater (0.99) than the LOF model (0.53). According to his findings, the K-NN anomaly detection performed better than the LOF. Whereas [12] the model detects a cell outage without taking alarms or performance measurements from the impacted nodes into account. An important component of the adopted model is utilizing incoming handover statistical data to detect sleeping cells and cell outages. As a result, the author contrasts the two techniques and gets the original LOF's 75% detection rate and FADD's 89%. The strength of both studies was the ability to compare two algorithms and choose the best one. Whereas, the weakness was that they did not take into consideration other performance measurement parameters for further grading of the cell status.

1.7. Methodology

The methodology of this research encompasses the analysis of the problems and focuses mainly on the improvement and assessment of the proposed approach. The following methodologies will be employed to accomplish the objectives of this research:

The research work started with a literature review to better understand the purpose of coverage hole detection techniques, the network performance parameters, and the ML algorithm. The next step is to collect the necessary MR data from the UE via the mentor tool and identify a targeted deployment working area based on the high data traffic generated on Ethio Telecom. In addition, for data preprocessing, Microsoft Excel and

Python tools are used. After that, target classes were developed based on current Ethio Telecom thresholds for signal quality and strength of the LTE network, and classification of the collected data was done using the random forest algorithm. The simulation results are analyzed, and the system's performance is evaluated using metrics like accuracy, precision, recall, f1 score, and area under the curve (AUC). Finally, the results have been discussed using Google Earth Pro visualization and plots, and the data have been presented in a comprehensive manner. Figure 1.1 illustrates an overview of the general methodological steps for the thesis work.

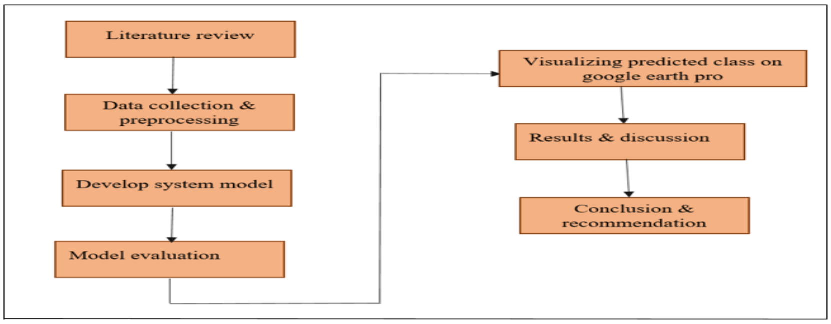


Figure 1. 1 Methodology of the research

1.8. Thesis organization

There are six chapters in the thesis's organization. Chapter 2 presents a brief overview of LTE, network architecture, and LTE frame structure. This section also includes LTE network performance data collection, coverage problems, scenarios, and the effects of coverage holes. Chapter 3 introduced ML. It also contains an overview of random forest, algorithm learning, HPO, and the evaluation of the random forest algorithm. The experimentation, which includes area selection, coverage class definition, and a system model, is presented in Chapter 4. The results and discussion of the proposed scheme's analysis, evaluation, and comparison between the original random forest classifier and HPO are discussed in Chapter 5. Finally, in Chapter 6, the key points of the thesis work are summarized, and further work is recommended.

Chapter 2

2. LTE Coverage Hole Detection

2.1. LTE Overview

The actual LTE (4G) is based on 3GPP Release 11. It is one of the most attractive radio technologies available today and in the years to come. By providing high data speeds with minimal latency, enhancing services, reducing costs, and enabling spectrum refarming thanks to its flexibility in frequency and bandwidth. In 2G and 3G networks, voice is circuit switched; however, Voice over Internet Protocol (VoIP), also known as IP telephony, is used on LTE networks. Three significant technologies that have contributed to the development of the LTE radio interface are multicarrier technology, multiple-antenna technology, and the integration of packet switching. The channel bandwidths that the LTE air interface offers range from 1.4 MHz to 20 MHz. Multiple-access solutions provide orthogonality between the users, reducing interference and improving network capacity [13]. LTE downlink (DL) and uplink (UL) use orthogonal frequency division multiple access (OFDMA) and single carrier frequency division multiple access (SC-FDMA) multiple-access techniques, respectively [14]. The frequency dimension in the packet scheduling is one reason for the high LTE capacity. This chapter will describe the 3GPP system architecture of the LTE network and its basic elements. LTE frame structure, LTE network performance data collection, and LTE network coverage problems are also introduced, and the final point of this chapter is discussed about LTE network scenarios and the effects of coverage holes.

2.2. LTE Network Architecture

The Evolved Packet System (EPS) is made up of the UE, the Evolved UMTS Terrestrial Radio Access Network (e UTRAN), and the Evolved Packet Core (EPC). This layer's main function is to enable IP-based connectivity; all services will be provided over IP [14]. Figure 2.1 shows that the LTE network structure is organized into four high-level domains: UE, E-UTRAN, EPC, and the Services domain.

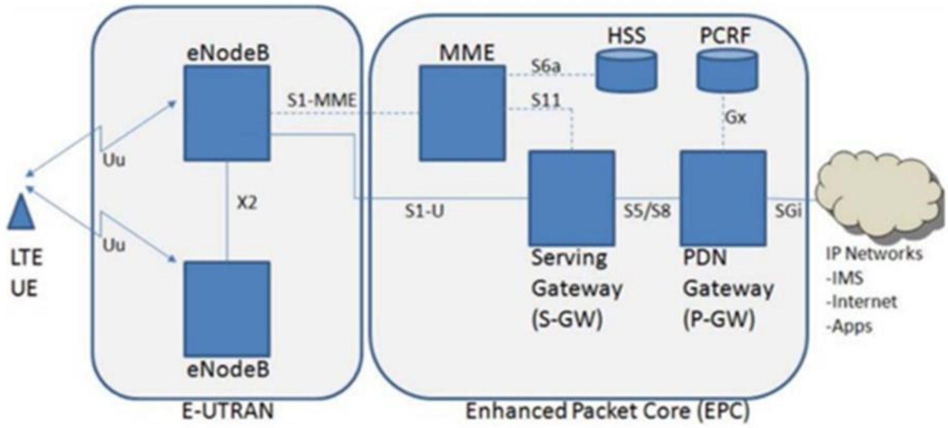


Figure 2. 1 LTE network architecture [15]

2.2.1. User Equipment

UE is a tool or device used for communication in a data-oriented (voice) service. A mobile device, tablet, or laptop with a USB dongle is referred to as a UE in the LTE specification. Mobile equipment (ME) is the UE for LTE's internal architecture. The ME is made up of the following significant modules: Mobile Termination (MT), the first module, deals with all communication-related tasks; Terminal Equipment (TE) also terminates the data streams; and the next module is the Universal Integrated Circuit Card (UICC), also known as the Subscriber Identity Module (SIM) card. The MT and TE are basically the antennas. In LTE, the SIM card can either run the application known as the Universal Subscriber Identity Module (USIM) or store user-specific data to keep information about the user's mobile phone number, home network identification, and a security code [16].

2.2.2. Evolved-UTRAN

Evolved Node B (eNodeB), also known as the base station, it is the most sophisticated node in the LTE network and is made up of two main components. The first component is the remote radio unit (RRU), also known as remote radio heads, which is made up of antennas and is the most visible part of the mobile network. All signals transmitted or received on the air interface must be modulated and demodulated by RRU. The second component is the Base Band Unit (BBU), which is made up of a digital module that processes all signals transmitted and received from the air interface and acts as the interface to the core network of High Speed Backhaul Connected (HSBC). The eNodeB's primary duties are radio resource management (RRM), which includes radio bearer control, radio admission control, connection mobility control, and scheduling, i.e., dynamic resource allocation to UEs in both UL and DL. Additionally, it is in charge of IP headers encrypting and compressing the user data stream's selection of an Mobility Management Entity (MME) at the UE attachment when no routing to an MME can be determined from the information provided by the UE, routing of user plane data towards the serving gateway, scheduling transmission of paging messages (originated from the MME), and scheduling and transmission of broadcast information [16].

2.2.3. Evolved Packet Core

EPC is essential for end-to-end IP services and enhances network performance by separating control and data planes and utilizing a flattened IP architecture that minimizes the hierarchy between mobile data elements. It is carried out by four components: MME, Serving Gateway (SGW), Packet Data Network Gateway (PGW), and Policy and Charging Rules Function (PCRF) [17].

- Mobility Management Entity

MME provides mobility session management for the LTE networ. Whenever the UE is communicating with the LTE core network by means of signaling, in reality it is directly communicating with the MME. When the UE is in the off state and then back in the on state, it registers itself with the LTE network (MME). Moreover, as a part of this registration procedure, the MME needs to authenticate and make sure that this UE is connected to the MME. So MME manages and runs authentication procedures using the security keys that it gets from the Home Subscriber Server (HSS). Once a UE has registered with the MME, the MME assigns temporarily identified and default bearers to the UE and manages and establishes them using the MME. As a part of the establishment of default bearers, the MME selects the SGW and the PGW through which default bearers are passed. The other function of MME is mobility management; a UE is either idle or connected. When a UE is in an idle state, its location is known to the network (MME), which is registered at the level of the tracking area (TA). TA is simply a group of cells. While UE is connected to the network (connected state) during the call, in that case, the location of UE is known to the network at the cell level. If UE is in one cell and moves to another cell, it needs to update the cell location with the network (MME). Another important function of MME is selection for inter-MME handover. The UE is in the coverage area of one eNodeB, and it moves to another eNodeB, which is connected to another MME, to perform handover. But this eNodeB is connected to a different MME, and this MME needs to be selected during this handover procedure. So this selection of MME is done by the old MME for inter-MME handover [14] [16].

- Home Subscriber Server

HSS performs the role of the Home Location Register/Authentication Centre (HLR/AuC). It is the home network for the user and contains the central database, which is going to have the subscriber profile for every user in the network. Then it sends relevant information to MME, and based on that information, MME authenticates the end user. The HSS engages with the MME in all UE-related monitoring activities that are administered by the EPC [17].

- Serving Gateway

SGW is an element of the user plane and plays a significant part in inter-frequency handover. During session establishment, the MME exchanges signaling with the eNodeB and the SGW to establish the tunnel to directly pass user-plane data between each other. So that user data will move directly between the eNodeB and the SGW without passing through the MME. Therefore, the SGW is the first point in the EPC that receives user-plane data from an eNodeB; in turn, the SGW serves as the mobility anchor point for user data while the UE is moving between different eNodeBs [16].

- Public Data Network Gateway

PGW is connects between EPC and the Public Data Network (PDN), which is the external network that connects the UE to the internet or any other network. The control traffic is used to pass signaling messages between each other, and the signaling messages will be passed from the UE to eNodeB, which provides the UE's radio interface. User data is transferred and received between the UE and PDN using data traffic [17].

- Policy and Charging Rules Function

The PCRF sends control information to the PGW based on its predefined policies and QoS-related rules. It is transferred between the PCRF and the PGW when a new bearer is set up, such as when a new UE activates a new PDP on the network or when a new UE needs a data plane bearer with a different QoS policy [17].

2.2.4. LTE Network Interfaces

The LTE Uu interface, also referred to as the LTE radio interface, is used to transfer data between the ENodeB and the UEs. It manages all of the data traffic between the UE and the S-GW as well as all of the signalling messages between the eNodeB and the MME. In addition to the air interface, the X2 and S1 interfaces are very important from the radio point of view. Since a direct site-to-site link is not required, the X2 interface provides a logical interface between eNodeBs. It can also be routed through the main network. It is used for inter-eNodeB handovers to forward data between the source and target eNodeB without involving the core network. In order to facilitate interference management, it is also involved in RRM operations, such as the exchange of load information between nearby eNodeBs. While there are two interfaces in the S1 interface, between the eNodeB and the S-GW, there is a user-plane interface called the S1-U interface. The S1-MME interface serves as the control plane interface between the eNodeB and the MME for the exchange of Non-Access Stratum (NAS) messages between the MME and UE (such as paging, tracking area updates, and authentication) [13].

2.3. LTE Frame Structure

In LTE, OFDM symbols serve as the key transmission method for both UL and DL transmission directions. In the DL access mode, the time domain is constructed by frames, sub-frames, and slots from the eNodeB to the UEs. Each frame has a 10 ms duration and is broken down into ten similar-sized sub-frames. Each sub-frame has a 1 ms duration. Additionally, each sub-frame is split into two identically sized time slots, each of which is 0.5 ms [18]. Furthermore, OFDM divides the carrier frequency bandwidth into several small subcarriers in the frequency domain spaced at 15 kHz and modulates each individual subcarrier using the digital modulation formats Quadrature

Phase Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (QAM), or 64-QAM. Each user is given the necessary bandwidth through OFDMA for their transmission. In LTE, a Physical Resource Block (PRB) is the smallest radio resource that can be assigned to a user for data transmission during packet scheduling. The Resource Block (RB) pairs (in time domain) are allotted to a UE for data transmission in a Transmission Time Interval (TTI) of 1 ms. The smallest time-frequency resource unit is called a resource element. It is referred to as a single subcarrier in an OFDM symbol and has a frequency of 15 kHz. Radio resources are defined in the time-frequency domain (Figure 2.2), and a RB is a time-frequency radio resource that spans over one time slot of 0.5 ms in the time domain and one sub-channel (180 KHz) of 12 subcarriers in the frequency domain [19] [20].

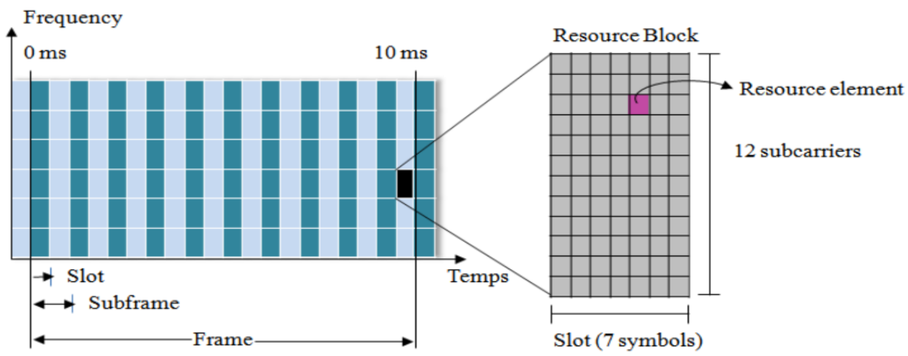


Figure 2. 2 LTE network structure [20]

2.4. LTE Network Performance Data Collection

The most significant phases for the mobile operator are the performance of cellular networks and the evaluation of QoS, because they are connected to revenue and subscriber satisfaction. Thus, the QoS for the cellular network is an essential factor in the competition for subscribers, and it may be achieved when the network is correctly optimized to meet the minimum services required of the users. However, because of the continuously increasing number of customers, it is challenging to optimize the cellular network and requires evaluation of network performance. Hence, LTE network monitoring and scanning are necessary in determining mobile network statistics to optimize LTE networks' performance in a particular area [21].

Measuring networks is an effective way to qualify and quantify how networks are being used and how they are behaving. For identifying network problems and performance issues, it is essential to understand network behavior. Additionally, the behavior provides helpful information for creating future network services and applications [22]. To determine the performance of the network, different measurements are used. Key performance indicator (KPI), mobile crowdsourcing (MCS), radio-planning tools (RPT) (coverage map simulation tools), user satisfaction surveys, drive tests, and MDT are the most common tools used to measure the data.

2.4.1. LTE KPI

KPIs are the best tool for assessing the effectiveness of the LTE network. In order to deliver high QoS and improve resource utilization, mobile network performance must be monitored and optimized with the help of KPIs [21]. In all countries, the regulatory bodies set minimum KPI values that wireless network operators must meet in order to maintain compliance with the standards. These indicators are standardized by the 3GPP and can often be divided into the following subcategories: accessibility, retainability, mobility, availability, utilization, latency, and integrity. As shown in Figure 2.3, some of these indicators are measured at the network level, while others are measured at the cluster level of the cell groups [23] and are described below [15] [23].

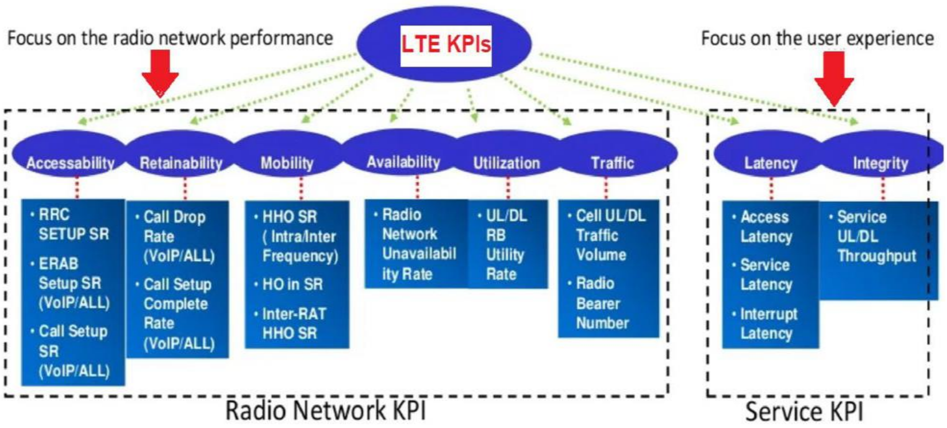


Figure 2. 3 LTE KPI categorization [21]

- Accessibility

Accessibility is used to assess whether users can receive the services they have requested under a given condition and is also related to the degree to which services are readily available to users when needed. For instance, the user requests to access the voice or data call. The network operators must look at ways of improving accessibility if the accessibility measurements don't seem OK. It is crucial to analyze E-UTRAN metrics like RRC, E-UTRAN Radio Access Bearer (ERAB), and Call Setup Success Rate (CSSR) for accessibility.

The RRC CSSR measures the call success rate in a cell or cluster.

$$RRC\ CSSR = \frac{RRCConnectionSuccess}{RRCConnectionAttempt} * 100\% \tag{2.1}$$

The ERAB setup success rate is calculated using the setup success rate for each service in the cell or group of cells.

$$ERAB\ SSR = \frac{ERABSetupSuccess}{ERABSetupAttempt} * 100\% \tag{2.2}$$

CSSR is used to assess the call success rate at the cell or cluster level.

$$CSSR = RRC\ CSSR * ERAB\ SSR * 100\% \tag{2.3}$$

- Retainability

Retainability is a term used to describe how well a network is able to hold on to the user's data or the ability to maintain uninterrupted services. Metrics like call drop rate (CDR) are used to evaluate the retainability of E-UTRAN.

The CDR is determined by monitoring the VoIP ERAB abnormal release rate. ERAB radio bearer abnormal releases could be the cause of the call drop rate.

$$CDR = \frac{ERABaAbnormalRelease}{ERABRelease} * 100\% \tag{2.4}$$

- Mobility

Mobility is utilized to evaluate how well a network performs while a user is moving around and maintaining service for the user. It is essential to evaluating E-UTRAN parameters such as intra-frequency handover out success rate, inter-frequency handover out success rate, and inter-RAT handover out success rate [23] [24].

The intra-frequency handover success rate represents the percentage of successful intra-frequency handovers between the local cell or radio network and its intra-frequency neighboring cell or radio network.

$$IntraFreqHOOut\_SR = \frac{EntraFreqHOOutSuccess}{IntraFreqHOOutAttempt} * 100\% \tag{2.5}$$

The inter-frequency handover success rate shows the inter-frequency handover success rate of the local cell or radio network to the inter-frequency (different frequency) neighboring cell or radio network.

$$InterFreqHOOut\_SR = \frac{EnterFreqHOOutSuccess}{InterFreqHOOutAttempt} * 100\% \tag{2.6}$$

The inter-RAT handover out success rate indicated that the success rate KPI handover from the LTE cell or radio network to a WCDMA cell.

$$IRATHO\_L2W\_SR = \frac{IRATHO\_L2W\_Success}{IRATHO\_L2W\_Attempt} * 100\% \quad (2.7)$$

- Availability

The availability KPIs measure the percentage of time the network cells have been unavailable. In terms of 3GPP, a cell is considered available when an eNodeB can provide E-RAB services in a particular cell [24].

The E-UTRAN cell availability measures the percentage of time in order to assess the degradation of service and network performance at the cluster level.

$$Availability = \frac{Meas - \sum RRUCellUnavailableT}{Meas\_period} * 100\% \quad (2.8)$$

- Utilization

In order to evaluate the effectiveness of the EPC network's utilization, this KPI measures the ratio between the average number of active dedicated EPS bearers and the maximum number of active dedicated EPS bearers provided by the EPC network [25].

$$Utilization = \frac{SM.MeanNbrActDedicatedBearer}{Capacity} * 100\% \quad (2.9)$$

- Latency

Latency is used to achieve a delay measurement that is unaffected by the size of an IP data block; only the first packet broadcast to Uu is measured. The IP throughput measure and the IP latency measure can both be used to compute the delay for a specific packet size (after the first block on the Uu, the remaining time of the packet can be calculated using the IP throughput measure) [23].

$$IP\ Throughput\ DL = \frac{ThpVolDl}{ThpTimeDl} \quad (2.10)$$

ThpVolDl is the volume at the IP level, and ThpTimeDl is the amount of time that has passed on Uu for the transmission of the volume included in ThpVolDl.

$$Latency\_DL = \frac{\sum T\_Lat\_DL(s)}{\#samples} \quad (2.11)$$

T_Lat is the interval between the time an IP packet is received and the moment the eNodeB transmits the first block to Uu

- Integrity

The integrity KPI parameters indicate how E-UTRAN has an impact on service quality. It is used to measure the character or honesty of a network towards its users and relies on factors like throughput and latency. The following parameters are computed at the level of cells or clusters: Cell DL maximum throughput, cell UL maximum throughput, and latency [24].

Cell DL maximum throughput is used to determine the maximum bitrate in the DL, which is measured every second.

$$CellDLMaxThp = \frac{CellDLMaxTraffVolforEach1s(bit)}{1000(ms)} * 100\% \quad (2.12)$$

Cell UL maximum throughput is used to determine the maximum bitrate in the UL, which is measured every second.

$$CellULMaxThp = \frac{CellULMaxTraffVolforEach1s(bit)}{1000(ms)} * 100\% \quad (2.13)$$

2.4.2. Mobile Crowdsourcing

MCS in mobile networks comprises gathering information from user terminals or specialised collection equipment during the quality of experience assessment phase. It collects data from a group of people who willingly gather and exchange data using easily accessible mobile devices, usually with the aid of an app. The apps used in various mobility test modes, such as walk or drive tests, may be offered by a mobile operator or research group. This data is processed and made available to third parties who are interested in integrating it via a data-sharing infrastructure. A cheap way for operators or academics to address large areas is by MCS using user terminals. This method may also help to enhance how resources are allocated for a particular service and/or how some network segments are provisioned [26].

2.4.3. Radio Planning Tools

The primary objective of LTE coverage planning and optimization is to make sure the network and its services are reachable. Likewise, the capacity planning process determines the number of resources needed to provide users in an area with the traffic needed to let them send the maximum amount of data in the shortest possible period with a small degree of blockage. The tool used for radio network planning is known as a RPT. These are specialized tools often used for the initial planning of radio parameters. The planning process typically entails assigning radio frequencies, choosing sites and site locations, planning traffic, analyzing interference, and planning configuration parameters in order to provide a radio network with sufficient coverage and capacity. In addition to these RPTs, they make use of geographic data (such as terrain data, type of land use, building data, and road data), site and antenna (equipment) information, and other information. This data has to be entered into the tools [27]. In order to meet the coverage needs of white areas, it is also utilized to perform simulations of national and population coverage. LTE radio network planning used a planning tool to analyze the collected data. The input parameters to the planning tool are related to quality, coverage, and capacity. For each stage, the network planners require a specific tool in order to have a thorough understanding of the network. An Atoll planning tool is employed in [28], and it is an open, scalable, and versatile multi-technology (dedicated project templates and propagation models for all supported technologies) and optimization platform that spans the entire network lifespan, from densification through optimization.

2.4.4. User Satisfaction Survey

A customer satisfaction survey is designed to gather user feedback and sentiment regarding the company's goods or services, brand, and user experience (including customer service, technical assistance, and feature usage). One of the most crucial tools for facilitating the interaction between a business and a client is a customer satisfaction survey [29]. Telecom operators who provide excellent customer service have an advantage over competitors because their clients are less interested in them. Companies can get helpful insights into problems and patterns that result in customer success by using customer satisfaction surveys.

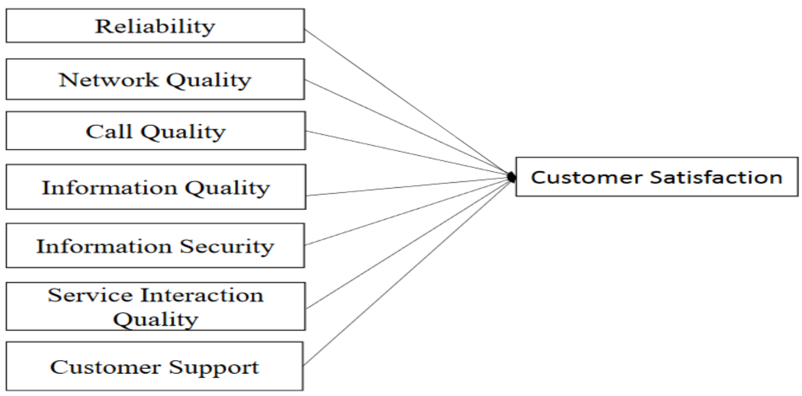


Figure 2. 4 Factors of customer satisfaction [29]

2.4.5. Drive Test

A driving test is a method for recording data on LTE cellular networks. The big data measurements provide insights that can be used to build and improve wireless networks. The operators conduct drive testing when installing new base stations, creating new roads, railroads, and tall buildings, as well as when customers complain about poor coverage, poor voice quality, or poor data quality [30]. It needs to be carried out manually using site engineers, and manual tests can be very time-consuming and expensive. In addition, these measures only cover a small portion of the network's time and space due to the fact that on-road testing. Drive test is often divided into three categories: single site verification (SSV), or single cell function test (SCFT), multiple site verification (MSV), or cluster drive test, and operator benchmarking drive test (market level drive test) [21].

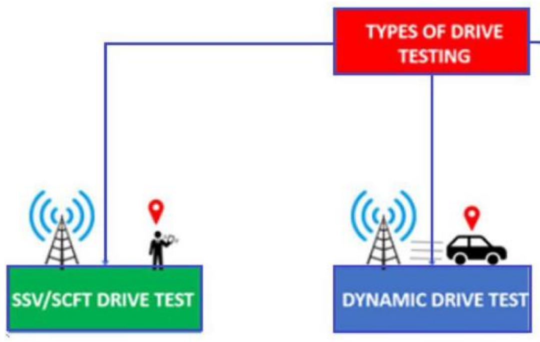


Figure 2. 5 Types of drive testing (SSV, MSV, and benchmarking) [21]

2.4.6. Minimization of Drive Tests

Due to the fact that only spot measurements can be made during driving tests and that human effort is required to collect measurement data, automated methods have been developed that incorporate UEs from the end user. This strategy should offer measurement data for fault detection and optimization at every potential network site. Utilizing every device that is active on the network is a novel idea for collecting data remotely; this approach is known as MDT. This means that measurements should be made using standard mobile phones in order to give operators data. The primary distinction between drive tests and MDT is that MDT uses low-cost cell phones, while drive tests use highly advanced measurement tools [30]. The LTE Release 10 MDT functionality supports two operation modes: Immediate MDT and Logged MDT [31], [32].

The immediate MDT measurement mode is used for gathering MDT data from UEs that are in an eNodeB or RRC-connected state. It is based on the current RRC measuring technique with an extension to include available location information in the MR, such as latitude and longitude collected from Global Navigation Satellite System (GNSS) receivers. Because of this, MDT enables configuring RRC measurements so that RSRP and RSRQ measurements are reported periodically from the serving cell and neighboring cells (including intra-frequency, inter-frequency, and iRAT) with the available location information [32].

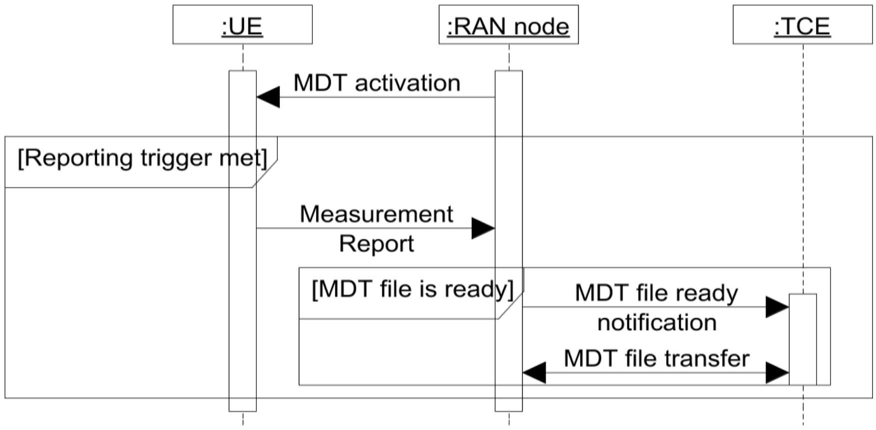


Figure 2. 6 Immediate MDT [30]

When the configured triggers meet the requirements or the reporting configuration matches, the UE immediately reports the measurement data. As seen in Figure 2.6 above, these results are gathered at the RNC node, which alerts the Trace Collection Entity (TCE), which collects all MDT measurements. After the notification, the TCE uses a file transfer protocol for downloading the MDT log [30].

Whereas logged MDT measurement mode is used for gathering MDT data from UEs that are in an eNodeB or RRC idle state. When a UE in idle mode arrives at a region with coverage holes, it tries to set up the RRC connection but is unsuccessful (the RRC Connection Establishment Failure (RCEF) report is logged). It is also possible to configure recurring triggers using MDT logs. The UE retains the measured data if these triggers are satisfied [31]. Additionally, it provides the possibility of storing failures if the network is not reachable. Furthermore, battery usage and network signaling load are decreased by the decoupling of measurements and reporting.

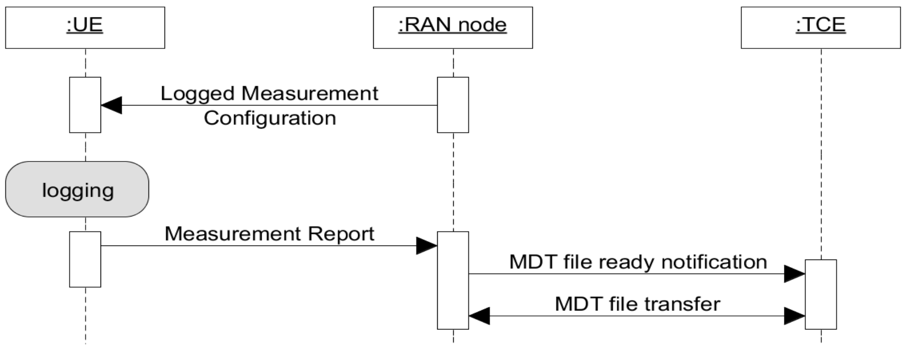


Figure 2. 7 Logged MDT [30]

Figure 2.7 illustrates how the UE keeps the measurements locally, but after a defined trigger, they are transferred to the radio access network (RAN) node and to the TCE [30].

In general, we have seen several kinds of data measurement tools with different parameters. These tools are used to evaluate the LTE network's performance. Mobile network performance needs to be monitored and improved using those parameters in order to provide high QoS and increase resource utilization.

In ethio telecom, the tool used for the MDT functionality is Mentor to access UE MR LTE data. The MDT parameters are RSRP, RSRQ, SINR, Received Signal Strength Indicator (RSSI), Channel Quality Indicator (CQI), and Physical Cell Identity (PCI). We could only measure RSRP, RSRQ, RINR, and CQI with the tool. For current LTE networks, RSRP and RSRQ are important indicators of signal strength and quality. When a mobile device moves between cells and performs cell selection, reselection, and handover, it must assess the signal quality and strength of the neighboring cells. In an LTE network, a UE measures two parameters on the reference signal RSRP and RSRQ. For this study, we used these two parameters including SINR for assessing channel quality [33]. The following is a brief overview of the LTE UE-related measurements of RSRP and RSRQ, as defined in 3GPP specifications, including SINR [34].

- **RSRP**: It is the LTE signal power received by the UE at a specific frequency. Measurements of RSRP should guarantee that clients are always connected to the cell with the greatest received power [35].

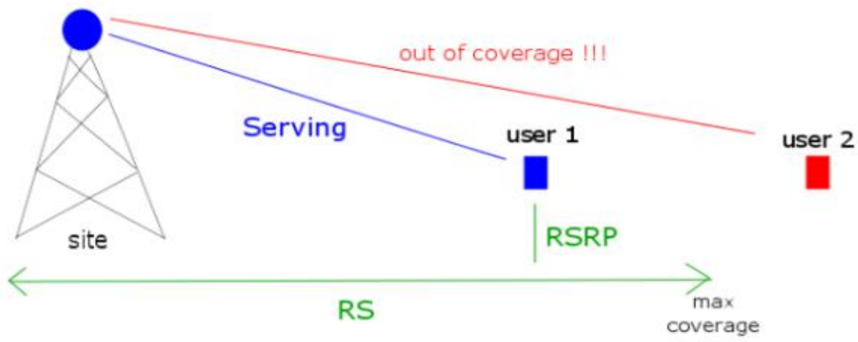


Figure 2. 8 Illustration of RSRP measurement [36]

The greater the distance between the site and the user, the smaller the RSRP received by the user. The reference signal, or RSRP, at each point of the range of coverage, and if the user is out of range, then it will not get LTE service [36]. The measurement of signal strength in LTE cells helps to re-rank the different cells as an input, which is used for handover and cell reselection algorithms.

- **RSRQ:** It is defined as the ratio of N×RSRP/ (E-UTRA carrier RSSI), where N denotes the number of RBs in the E-UTRA carrier RSSI measurement bandwidth. The same set of RBs must be used for both the numerator and denominator measurements [34]. It is a measure of the reference signal's quality. When RSRP is insufficient to make a reliable handover or cell reselection decision, the RSRQ measurement offers additional information. High cell utilization is could be a factor in low RSRQ because, as cell utilization rises, RSSI rises as well. In certain areas where interference leads to service quality reduction for the user (which RSRP measurement is not able to detect), there could be situations where a quality-based measurement may enable better system performance. The main purpose of the RSRQ measurement would be to enable proper initiation of inter-frequency or iRAT handovers to maintain received quality [35].

- **SINR:** It is typically employed as a network quality indicator and equates to the quality of the desired signal being low due to high interference. Thus, interference is a key element that affects the functioning of cellular networks, along with capacity, coverage, and more frequent dropped calls [37].

  However, it should be emphasized that the 3GPP does not specify SINR, and as a result, UEs do not report SINR to networks. However, the majority of UEs measure and record SINR internally for use by test tools. It is a straightforward way to describe the relationship between radio conditions and throughput because signals near interference and noise levels are subject to data corruption, which requires retransmissions between the transmitter and receiver. The retransmitted signals will consume more airtime in the wireless environment, which will reduce wireless throughput and latency.

2.5. LTE Network Coverage Problems

In order to monitor and identify network coverage issues, the MDT data from the UEs and RAN may be used. Here are a few use cases [31] for monitoring and finding coverage issues:

2.5.1. Weak Coverage

It occurs when the signal level SNR (or SINR) of the serving cell is below the level needed to maintain a planned performance requirement. SINR, which is required to identify RSRP or RSRQ, is the signal strength divided by the signal strength of any interference [31]. When the SINR signal level is low, it usually implies that interference levels are high, which means that RSRP and RSRQ are poor. Weak coverage happens when the mobile device is far from the base station or is restricted by numerous constraints (physical barriers), and it often has trouble receiving a strong enough signal.

2.5.2. Pilot Pollution

Pilot pollution implies a situation in which an excessive number of pilots (or reference signals, in the case of LTE) are received in one area. As a result, there is no dominant pilot signal at all [38]. In areas where the coverage of different cells overlaps a lot, interference levels are high, power levels are high, energy consumption is high, and cell performance may be low. This phenomenon has been called pilot pollution, and the problem can be addressed by reducing the coverage of cells. Typically, in this situation, UEs may experience high SNR to more than one cell and high interference levels. As shown in Figure 2.9, the pilot pollution interference (PPI) situation is due to the existence of the serving base station and the other three paging cells at the same time.

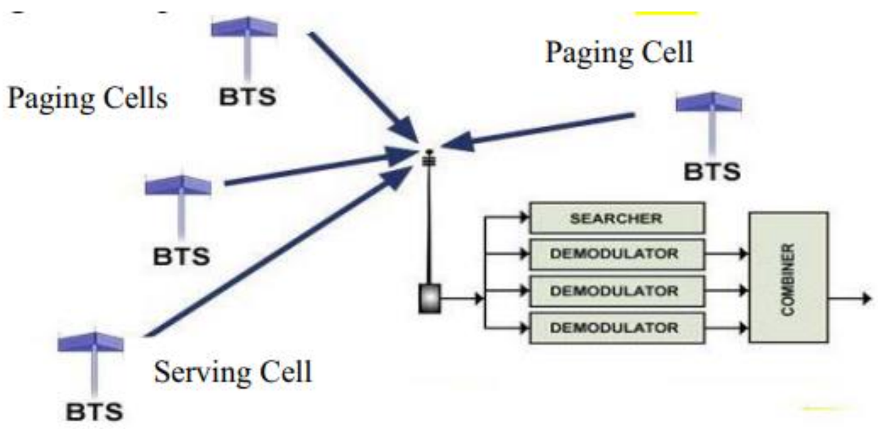


Figure 2. 9 Pilot pollution interference [39]

As a result, the serving base station boosts its power level to reach the mobile station at the overlap fringe area (soft handoff region). This causes the different pilot signals in the overlapping fringe area to become non-orthogonal, and consequently, the mobile receiver suffers from the occurrence of the PPI effect [39].

2.5.3. Overshoot coverage

An overshooting situation occurs when coverage of a cell reaches far beyond what is planned. It can occur as an 'island' of coverage in the interior of another cell [38]. A mobile station is overshooting when its SINR from the neighboring base station is larger than the SINR of its serving base station [40]. Reasons for overshoot may be reflections in buildings or across open water, lakes, etc. In addition, antenna parameter settings that are not optimal are the primary source of this issue. UEs in this area may suffer call drops or high interference (bad quality of experience). Possible actions to improve the situation include changing the coverage of certain cells and blacklisting certain cells for mobility.

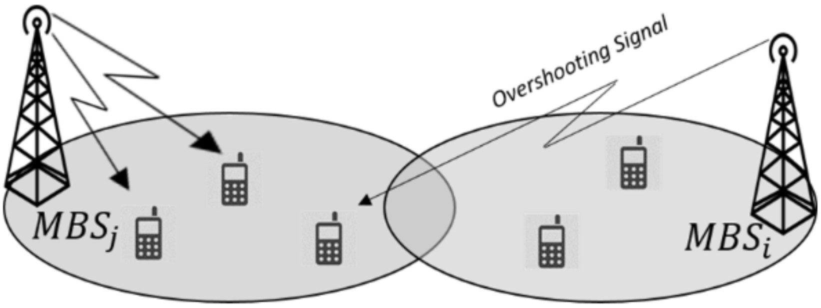


Figure 2. 10 Overshoot coverage [40]

2.5.4. Mismatched DL and UL channel coverage

Poor UL coverage may have an influence on the user's experience in terms of failed call setup, dropped calls, and poor UL voice quality. Therefore, coverage should be balanced across UL and DL connections. Possible UL coverage optimization includes adjusting cellular coverage by altering the site configuration (antennas), but it also involves adjusting UL-related parameters in a way that allows for the most effective use of UL powers in different environments [31].

Furthermore, one of the issues with LTE network coverage and the focus of this work is the coverage hole. Hence, it is described in the section below.

2.6. LTE Network Coverage Hole

A coverage hole is defined as a client's being unable to receive a wireless network signal. Which is the pilot/reference signal power (RSRP, RSRQ, and SINR) falls below a predetermined level. It can be caused by physical barriers like recently constructed buildings, hills, improperly specified antennas, or even insufficient RF planning [31].

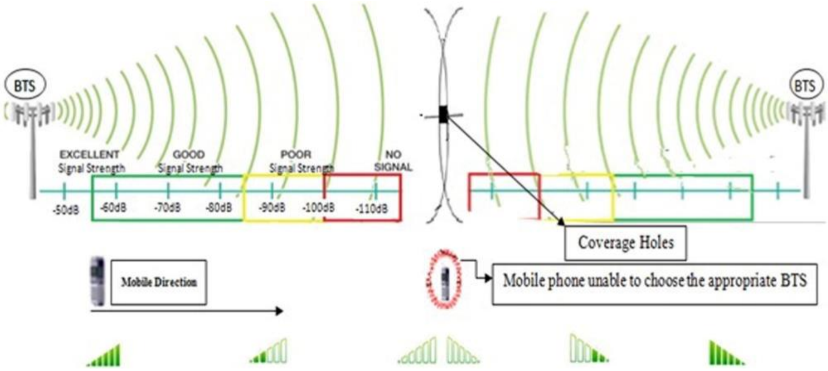


Figure 2. 11 Coverage holes [41]

When the mobile phone enters a coverage hole, which causes it to stop making calls until it finds another tower with a better signal, which enables the mobile phone to receive a signal to keep trying to connect [41].

UE in coverage holes will suffer from call drop, handover, and radio link failure. When a connection is suddenly dropped before the service requested by the user can be finished, this is referred to as a call drop. As a result, the call drops while the service is running, and the user's packets are not scheduled, either due to a lack of available resources or because the connection quality in terms of SINR falls below a certain level. This is the worst-case scenario for the user because they completely lose their connection, resulting in customer discontent [8].

2.6.1 Scenarios of Coverage Hole

Let us see some scenarios for coverage holes [33]. The first scenario is that coverage holes happen in E-UTRAN without any other radio coverage. Inappropriate planning or invalid parameter selection will result in coverage holes in some areas during the initial deployment stage of E-UTRAN, resulting in plenty of calls being dropped.

The second case is explained as E-UTRAN coverage holes that happen between multiple bandwidths (inter-frequency case) [8] [33]. In this case, mobile communication takes place between two distinct cells operating at different LTE frequencies (2G/3G coverage). In this scenario, the legacy systems, e.g., 2G/3G, that provide radio coverage together with E-UTRAN and that are experiencing poor quality are transferred to a neighboring legacy system through the inter-RAT handover (iRAT) procedure.

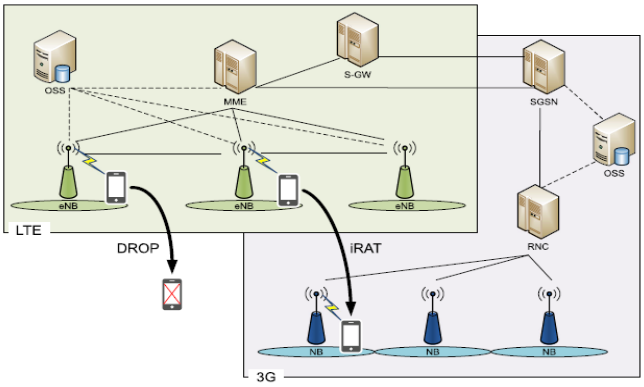


Figure 2. 12 LTE coverage hole and inter-RAT handover from LTE to 3G system [8]

With iRAT handovers, the legacy systems maintain the services needed to prevent unplanned user disconnections. However, this has a negative effect on the user experience. Because of the decreased service performance (speed reduction or increased latency). Cells are affected by coverage holes with too many IRAT handovers, and as a consequence, customers frequently complain about call drops, service gaps, and decreased performance in areas with LTE coverage holes [8].

The iRAT measurements may be used to detect coverage holes in the LTE network. Measurements (such as RSRP, RSRQ, cell ID, location, and time stamp at the time of iRAT handover) can be recorded by the network and used by the CCO function to identify coverage holes in the LTE network [33].

The other scenario is E-UTRAN with isolated island cell coverage [33], where the actual coverage area of an isolated island cell is less than the planned isolated island cell area.

The uncovered planned cell area is the coverage hole that needs to be detected and optimized through coverage and capacity optimization.

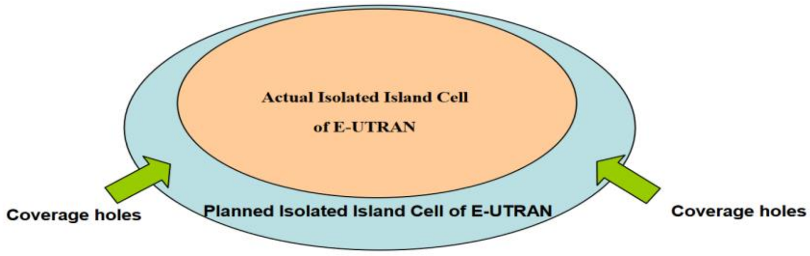


Figure 2. 13 Coverage holes with isolated island cell coverage [33]

The last scenario is E-UTRAN cells with too large coverage; in this case, the operator gradually improves the network by utilizing LTE cells in areas where more capacity is required. In this particular scenario, the real LTE coverage exceeds the planned LTE coverage. The problem with too wide coverage is that the planned capacity may not be reached. As such, it is important to keep the coverage within the planned area [33].

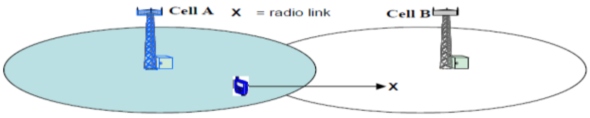
2.6.2 Effects of LTE Coverage Hole

- Handover Failure

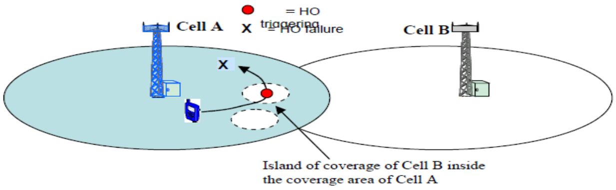
Handover failure happens when the UE moves through the radio environment's cells, measures DL signal strength and/or quality, and sends measurement reports to eNodeB. In the case where the serving cell's signal strength gets lower and the neighboring cell's signal strength may be strong enough, based on the measurement results, the eNodeB makes a decision and performs a handover with the user and engaged eNodeB [42]. RSRP is used for measuring signal strength in a particular cell, and it helps as a consideration in handover selections by ranking cells based on their signal strength. A resource element is the smallest unit of a resource, and RSRP is the average power contribution, expressed in Watts, of all resource elements carrying cell-specific reference signals within the given frequency bandwidth [34]. In order to guarantee low latency and reliable transition across various types of networks, handover is one of the essential RRM operations. Strong handover may ensure users travel freely within the networks while still being connected and provided with high-quality services. The LTE handover procedure can be considered a series of precise flows of events; the handover failure can happen at any of those processes, and the majority of failures probably happen before the handover command has been successfully transmitted due to the poor radio conditions and patchy coverage caused by shadow fading and path loss [42].

In order to boost overall network performance and minimize detrimental impacts (call dropping, handover failures, ping-pong handover), [33] shows the use of handover parameter adjustment approaches. The purpose of the handover parameter optimization function is to decrease the frequency of handover failures as well as the wasteful use of network resources caused by undesired handovers. In certain cases, the general setting of the handover parameters is incorrect. If the serving eNodeB does not start the handover at the appropriate moment, it will start too early or too late and send the handover to the wrong cell, which will lead to more radio link failure (RLF) [33] [43]. Furthermore, the radio link needs to be re-established with the serving eNodeB, which requires restarting the handover process.

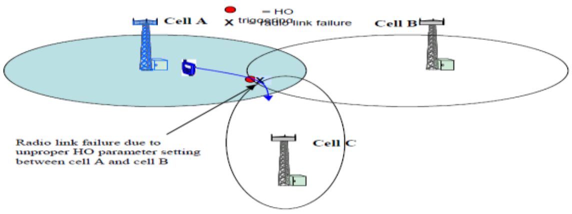
A late handover is performed if the UE mobility is more aggressive than what the handover parameter settings allow for. So due to its rapid mobility and an inadequate configuration of the handover parameters, the UE departs the source cell coverage (losing the signal from the serving cell) before the handover is activated. On a separate cell from the serving cell, the connection might be re-established. This situation is typical in places with large levels of user movement, such as by roads, rail lines, etc. [33]. While handover occurs, it is too early if the handover process is already finished when the target cell's signal quality declines for communication needs [43]. As noted in [33], when the UE enters an unanticipated island of coverage of the target cell within the serving cell's authorized coverage region, handover might be triggered, but the UE can no longer acquire the target cell when it leaves the target cell's island of coverage, and the handover fails, possibly resulting in a failed radio link. In the case of handover happening to the wrong cell, UE moves from cell A to cell C, but because the handover parameter was not optimized and cell A sent the incorrect handover command, a handover to cell B was performed, which led to an RLF. Then the UE makes contact with cell C again. The three handover failure conditions are illustrated in Figure 2.14.



a) Too late handover triggering



b) Too early handover triggering



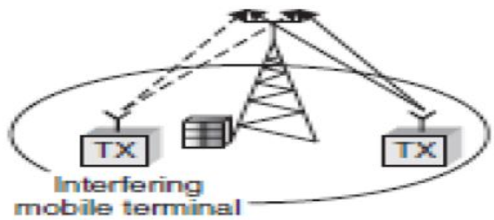
c) Handover to a wrong cell scenarios

Figure 2. 14 the three handover failure scenarios [33]

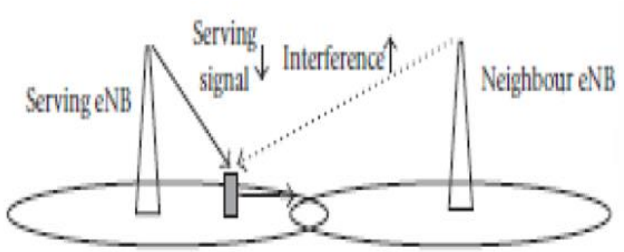
- Radio Link Failure

A RLF occurs when the UE cannot communicate with the serving cell. E-UTRAN makes use of the RCRM and transmits the measurement configuration applicable to a UE in the RRC connected using dedicated signaling. The UE then reports measurement information. Radio data supplied by UE, such as RSRP, RSRQ, and CQI, can be used to predict RLF [44]. As shown above in Figure 2.14, the three handover failure scenarios lead to RLF. In addition, congestion, a weak signal, or interference are possible causes of RLF. Let us take a quick look at interferences. There are two types of interference: intra-cell interference is caused by an interfering mobile device in the same cell. It results from spillover transmission between adjacent channels within a cell. The other is inter-cell interference (ICI), which is interference from mobile devices in adjacent (neighboring cells). It is caused by the same frequency channel being utilized by nearby cells [45].

Collisions between RBs that are used simultaneously by several cells result in ICI. It occurs in OFDMA systems because adjacent cell UEs reuse PRBs. The received SINR decreases as a user moves away from a serving eNodeB and gets nearer to its neighboring eNodeB because the intended received signal power drops and the ICI increases [19].



a) Intra-cell interference [19]



b) Inter-cell interference [46]

Figure 2. 15 types of interference

- Call Drop

A call drop occurs when a call is being made but neither party (the caller nor the recipient) disconnects the call at any point in time. This happens because the phone's signal quality is typically poor (handover failure, congestion, weak signal transmit power, etc.), with various parameters that can interfere with voice services [47].

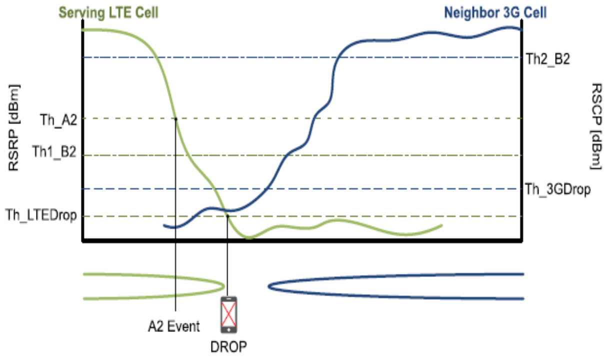


Figure. 2.16 Call drop due to coverage holes [8]

When there is a coverage hole, the received LTE signals from the serving cell and the nearby LTE cells are not strong enough to sustain good customer service. As a result, those areas with poor coverage are characterized by having a lot of users with bad RF scenarios [8].

- Packet Loss

Data is transmitted and received across the network in small pieces called packets. This holds true for all online activities, including phone calls, surfing, email, streaming, video chat, and downloading files and photographs. Packet loss happens when one or more of these packets get lost while travelling. The number of packets that are sent via a network but fail to get to their intended recipient is known as packet loss. Coverage holes, multi-path fading, channel congestion, in-transit rejection of damaged packets, and problematic hardware, drivers, or routing routines can all be factors in packet loss [48].

Chapter 3

3. Machine Learning Algorithm

ML is a broad field with applications in information technology, statistics, probability, artificial intelligence, and many others. It enables machines to pick up new skills without having to be explicitly programmed to do so. Learning happens when data and mathematical models are combined, for instance, by determining optimal values for the model's unobserved variables. The three ML types that are used to train the model are supervised, unsupervised, and reinforcement learning [49]. This thesis is focused on using supervised learning for UEs to classify MR data in order to gain insights about cellular network coverage.

3.1. Supervised Learning

A ML technique known as supervised learning uses a set of paired input-output training samples to learn the input-output relationship information of a system. An input-output training sample is also known as labelled training data or supervised data since the output is thought of as the label of the input data or the supervision. The aim of supervised learning is to develop an artificial system that can learn the relationship between input and output and predict the system's output given new inputs. We can divide supervised learning into two categories: classification (labels are defined) and regression (labels are not defined). The learned mapping results in the regression of the input results from the output taking continuous values. Whereas the learned approach for the classification of the input data if the output takes a finite set of discrete values that represent the class labels of the input [50]. It is the issue of determining whether an object belongs to a specific category based on a previously acquired model in ML or statistics. This model is learned statistically based on a set of training data whose categorization is predefined [51]. In this work, the random forest is applied for classification purposes. It is a very well-liked supervised ML technique that uses many decision trees together. Let's first take a look at a single decision tree before going into further detail regarding the random forest approach.

3.2. Decision Tree

Decision trees are a supervised classification method [52]. The structure of the tree is easy to understand, where terminal nodes show the results of decisions and non-terminal nodes represent tests on one or more attributes. Typical trees include a single root, branches, nodes (locations where branches are separated), and leaves. The branches stand for segments connecting the nodes. It is usually drawn from left to right or beginning from the root downwards, so it is easier to draw. The first node is a root, and the end of the chain, the "root branch node" is called the "leaf". From each internal node (i.e., not a leaf) may grow two or more branches. Each node corresponds to a certain characteristic, and the branches correspond to a range of values. These ranges of values must give a partition of the set of values for the given characteristic [52]. It makes predictions by asking a sequence of questions for each example and making a prediction based on the responses. This makes decision trees intuitive. One of the benefits is that we can clearly see the path of questions and answers we took to get to the final prediction.

3.2.1. Decision Tree Structure

The decision tree's nodes are organized into root, internal, and leaf nodes [53].

- **Root Node**: The root node is the beginning of the tree; when there are no incoming edges but at least one outgoing edge, the outgoing edges lead to either an internal node or a leaf node. The root node is usually an attribute of the decision tree model.

- **Internal Node:** A node that comes after an internal node or a root node and is followed by either an internal node or a leaf node. It has at least two outgoing edges and only one incoming edge. Internal nodes are always attributes of the decision tree model.

- **Leaf Node:** These are the bottommost elements of the tree and typically represent classes of the decision tree model. Each leaf node can only contain one class label or, occasionally, a class distribution. It has one incoming edge and no outgoing edges.
- **Depth:** The longest distance between a root node and a leaf node along a path.

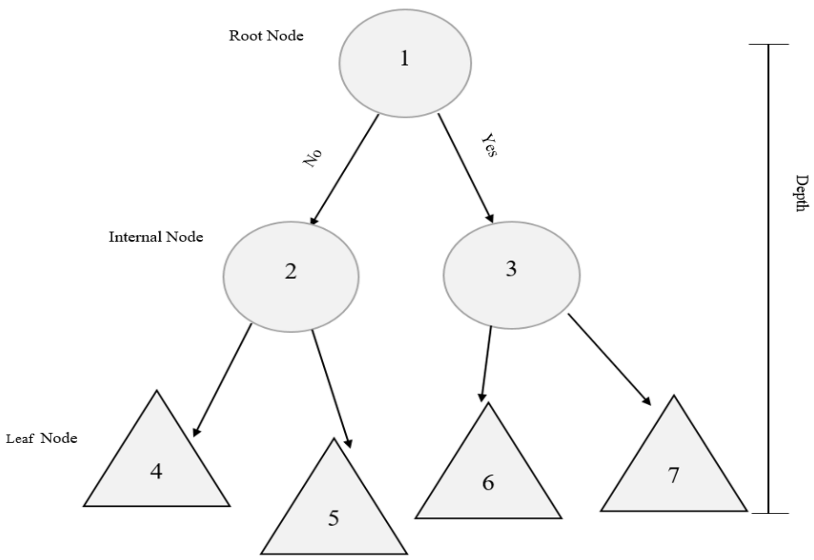


Figure 3. 1 Decision tree structure nodes [53]

The drawback of this algorithm is that it is highly sensitive to the training dataset, which could result in high variance, so our model might fail to generalize; even minor modifications to the training set might result in radically different tree architectures. Here comes the random forest algorithm. Random forest takes advantage of this by enabling different independent trees to randomly select from the dataset with replacement; the process is called bagging and was proposed by Leo Breiman (1996) [54].

3.3. Random Forest Algorithm

Random forest is a powerful supervised ML algorithm that consists of many individual decision trees to form a "forest" [54]. It can be used for both classification and regression problems. As a classification model, it uses multiple random tree classifications to vote on an overall classification for the given set of inputs. Each individual machine learner's vote is given equal weight. The process we just followed creates new data sets and ensures they are different, called bootstrapped datasets. Now we have to combine all the predictions, and we will take the majority vote; hence, the prediction from our random forest is (majority value). This process of combining results from multiple models is called aggregating, so in the random forest, we first perform bootstrapping, then aggregating, which is called bagging [55] [56]. That was how we built the random forest.

Random forest has used two randomness processes: bootstrapping and feature selection. Bootstrapping ensures that we are not using the same data for every tree, so in a way, it helps our model be less sensitive to the original training data. This decreases the variance and makes the random forest less likely to overfit. Added to this, random feature selection also helps to reduce the correlation between the trees. If you use every feature, then most of the trees will have the same decision nodes and will act very similarly, which will increase the variance. This is another benefit of random feature selection. Some of the trees will be trained on less important features, so they will give bad predictions, but there will also be some trees that give good predictions in the opposite direction, so they will balance out [49] [57].

When using a single tree as a classifier, the output of the processing is going to suffer due to the high chance of noise and outliers. Because the random forest classifier has a randomness characteristic, it is extremely robust against outliers and capable of handling missing values [58].

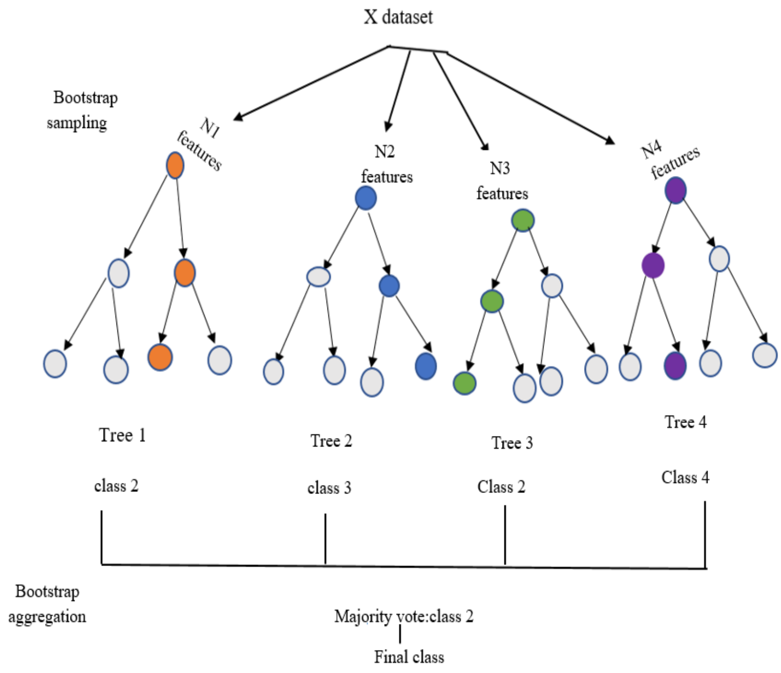


Figure 3. 2 Random forest tree [54].

As shown in Figure 3.2, for this particular example, the number of decision trees to create this forest are four, which are tree 1, tree 2, tree 3, and tree 4. And each tree is created by applying the bootstrapping process. The trees have their own data sets that are extracted from the original training datasets. Then, the trees are trained independently and predict their predictions, and the majority vote will be selected, and that will be the final prediction value.

3.3.1. Random Forest Hyperparameters

The random forest algorithm has a number of user-adjustable hyperparameters that can be used to enhance the model's performance.

Some of these are n_estimators, max depth, min samples split, min samples leaf, max features, and max leaf nodes [59] [60].

- **number of trees:** It refers to the number of decision trees in the forest. As we add more trees, our model might become more comprehensive at the expense of training time.

- **Max depth:** It is the most important hyperparameter in a random forest technique for preventing overfitting. As the tree's depth increases, the model learns every detail of information during the training phase, and we can't generalize in the testing model.
- **Min samples split:** The minimal number of samples required to divide an internal node is specified by the min sample split parameter, which is determined by the trade-off between overfitting and underfitting. We can reduce overfitting by using a large number of samples; however, using too many samples can result in underfitting.
- **Min sample leaf:** This is the minimum number of samples needed to form a leaf node (without any more splits).
- **Max Features:** This indicates the total number of features to take into consideration when determining the best split. For each split, the maximum number of features can be specified, or a fraction can be used to indicate the percentage of features that will be taken into consideration. We also have options such as sqrt, log2, none, and auto.
- **Criterion:** There are certain essential splitting parameters on decision nodes, namely Shannon entropy and the Gini index that are used to calculate information gain. Gini looks at Gini impurity, which measures the frequency with which a randomly chosen element would be labelled incorrectly. Whereas entropy looks at information gain, which gauges the purity (impurity) of a node or the disorder of a grouping [60] [61]. The lower the entropy, the higher the information gain, and thus a node has the same group (pure node). In addition, entropy and gini can be calculated as shown below in Eqs. 3.1 and 3.2, respectively.

$$Information\ Gain = 1 - Entropy$$

$$E = -\sum_{i=1}^{k} Pi * log2(pi) \quad (3.1)$$

Where pi is the probability of randomly selecting an example in class i.

$$Gini\ Impurity = 1 - Gini$$

$$G = -\sum_{i=1}^{k} pi^2 \quad (3.2)$$

Where k represents the number of classes in the target variable and Pi represents the ratio of the number of observations in the node.

3.3.2. Random Forest Hyperparameters Optimization

In the ML model, there are two types of parameters:hyperparameters and model parameters. Hyperparameters are parameters whose values control the learning process and arbitrary settings made by the users even before the model is trained. These are adjustable parameters used to obtain the optimal model. While the model parameters are learned during training.

HPO is a technique that involves searching for the best hyperparameter values to achieve the best performance on a given dataset. These design parameters could directly influence the training outcome, which is a significant challenge when dealing with ML problems. Determining the optimal hyperparameters requires a lot of time, particularly when the objective functions are difficult to compute or there are many parameters that need to be tuned. Grid and random search CV techniques are two of the best approaches for fine-tuning the hyperparameters in random forest methods. These techniques have some advantages and disadvantages over others. Grid search has proven to be a useful method for fine-tuning hyperparameters, but it has certain limitations, including the tendency to try too many different combinations and performing poorly when tuning many variables together [62].

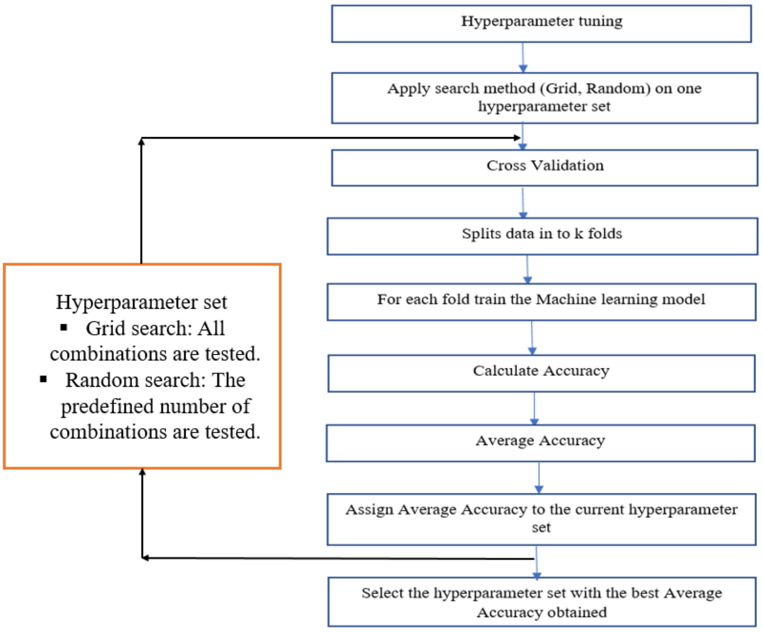


Figure 3. 3 Hyperparameter tuning architecture [63]

One better approach for increasing the accuracy of ML systems is parameter optimization [64]. In order to perform hyperparameter optimization, we have to first create a parameter space or parameter grid that contains a range of potential hyperparameter values that can be employed when building the model [59].

In this work, the random and grid search methods are employed for parameter tuning to improve the random forest classifier's accuracy. Before addressing grid and random search approaches, it is essential to explain CV, which is regarded as a vital phase in the hyperparameter tuning process. A statistical technique called CV is used to gauge how accurate ML models are. We are unsure of how well the model will perform once it has been trained on data that has never been used before. A guarantee is required for the model's performance in terms of prediction accuracy. A ML model must be tested with some unobserved data in order to assess its performance. We can assess if a model is underfitting, overfitting, or well generalized based on how it performs on unobserved data.

When the data in hand is limited, CV seems to be a highly helpful strategy for evaluating how good a ML model is. A portion of the data should be set aside for testing and validating in CV; this fraction won't be used to train the model but will be kept for later use. One of the most popular CV approaches is the K-fold, and we used this method to validate our model. In k-fold CV, the available learning set is split into k separate subsets that are similar in size. Fold refers to the number of splitting groups. The parameter K in K-fold CV represents the number of folds or sections into which a given dataset is divided. This partitioning is carried out by randomly selecting instances from the training set without replacement [63].

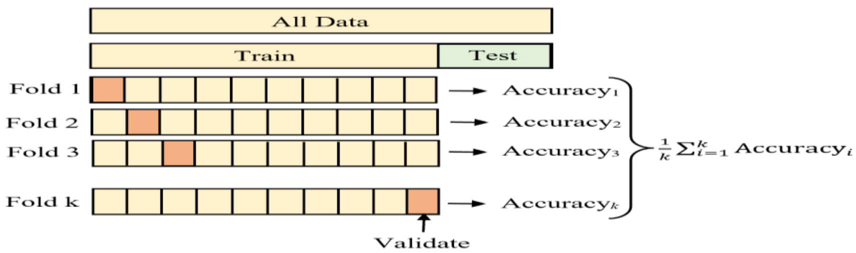


Figure 3. 4 Cross-validation [63]

The training set is made up of k-1 subsets, which in combination form the training set, and the model is applied to the remaining subset, known as the validation set, and the model accuracy will be evaluated. Repeat this process until all k subsets have served as validation sets [64]. For example, if k = 5, i.e., 5-fold CV means the model is trained 5 times iteratively, in the first iteration our model will be fit from the first to the fourth folds, and the fifth folds will be treated as validation. In the next iteration, the fifth fold will become part of the training, the first fold will become validation, and so on; this process occurs repeatedly k times.

- Grid search CV

In the grid search approach, the user sets a grid of hyperparameters and places these hyperparameters in a matrix form. The model is trained to consider every possible combination of hyperparameters in order to select the optimal parameter values, and the top-performing model is then chosen [62].

It is a technique used to find the best classifier parameters that will enable a model to correctly predict certain unlabeled data. CV, or training the model on many folds with various hyperparameter combinations to discover more accurate results, is a typical improvement to grid search [58]. Some hyperparameters that cannot be directly learned from the training phase are tuned using the grid search. Finding the best combination of the various hyperparameters in the classification model is challenging [58]. The main drawback of grid search is its high complexity when we have a huge amount of data or many hyperparameter combinations to tune. It is the best method when there are a few hyperparameters to be tuned [62]. In low-dimensional spaces, grid search is reliable, while in high-dimensional spaces, random search outperforms grid search [65].

- Random search CV

Random search is a basic improvement on grid search. It denotes a randomized search over probable parameter values for hyperparameters from specific distributions. The search procedure is carried out indefinitely until the desired accuracy is achieved. This technique is the most straightforward stochastic optimization method, and it works well for issues like a small search space and quick simulation. In order to train the algorithm, it selects random combinations of hyper-parameter values [62]. In this technique, rather than performing an exhaustive search, it will select certain hyperparameter values at random and attempt to identify which parameters have high values from that group of parameters in order to evaluate the accuracy of all possible combinations of the values for the hyperparameters.

3.3.3. Evaluation Random Forest Classifier

After training the model, the next step is to choose the right model evaluation metrics. The confusion matrix, accuracy, precision, recall, f1-score, and AUC are well-known evaluation metrics that help to measure the classifier's model performance [66].

- **Confusion Matrix:** In the confusion matrix for a binary classifier (Table 3.1), actual values are denoted as True (1) and False (0), while predicted values are Positive (1) and Negative (0). Estimates of classification model possibilities are obtained using the confusion matrix's expressions TP, TN, FP, and FN [66] [67].

Table 3. 1 Confusion matrix

Actual class	Predicted class	
	Positive Class (1)	Negative Class (0)
True Class (1)	TP	FN
False Class (0)	FP	TN

- **True Positive (TP):** The confusion matrix's data point is TP when a positive result is predicted and what actually happens is the same.
- **False Positive (FP):** The data point in the confusion matrix is regarded as FP when a positive outcome is predicted and what happens is a negative outcome.
- **False Negative (FN**): The confusion matrix's data point is FN when a negative outcome is predicted and what happens is a positive outcome.
- **True Negative (TN):** In the confusion matrix, a data point is designated as TN when a negative outcome is predicted and what happens is the same.

For four-class classification, a confusion matrix is shown above in Figure 3.7 for the four-class classification problem of classifying instances into four classes [68].

Actual value →

Predicted value ↓

	A	B	C	D
A	100	0	0	0
B	80	9	1	1
C	10	0	8	0
D	10	1	1	9

Figure 3. 5 Confusion matrix for the four-class classification [68]

- **Accuracy:** The accuracy metric measures the proportion of correct predictions to the total number of evaluated cases.

$$ACC = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FN+FP}} \quad (3.3)$$

- **Precision:** It is determined which positive patterns are correctly predicted from the total predicted patterns in a positive class.

$$PREC = \frac{TP}{TP+FP} \quad (3.4)$$

- **Recall:** It is determined as the ratio of correct positive predictions (TP) to all positive predictions (P), known as the true positive rate or sensitivity.

$$REC = \frac{TP}{TP+FN} \quad (3.5)$$

- **F1-measure or F1-score:** It is a measure of the accuracy of the test and the harmonic mean of precision and recall.

$$F1\ Score = \frac{2*precision*recall}{precision*recall} \quad (3.6)$$

- **AUC**: It shows how well the classifier can differentiate between positive and negative classifications. It accepts values in the range of 0 and 1. Performance is better when the AUC is larger. The AUC of a random model is 0.5, while the AUC of a perfect model is 1. An AUC of 0.0 indicates a model with 100% incorrect predictions.

Chapter 4

4. Experimentation

To successfully carry out this task, it needed to define the study area, thresholds, coverage classes, and system models, as stated in the following sections.

4.1 Area Selection

The data collection was conducted on 324 eNodeBs with 1208 cells in the cluster 20 area, which includes 7 locations (from Meseket Square, Wello Sefer, Airport Road, Edna Mall, Atlas, Golagol, and Urael) as illustrated in Figure 4.1 with geographic coordinate ranges of (38.72454E–38.86114E, 8.8668385N–9.0665395N) longitude and latitude, respectively. Table 4.1 shows that the selected LTE eNodeBs. Typically, it shows the distribution of all Addis Ababa LTE eNodeBs as well as the selected area's eNodeB count and distribution on a Google map. Information such as site ID, cell ID, and location information (latitude and longitude) are gathered based on the selected area. In this work, UEs MR parameters, including RSRP, RSEQ, and SINR, are also captured with the help of this geographic data.

Figure 4. 1 The selected area

Table 4. 1 Geographical coordinates of available sites and the selected LTE eNodeBs

	LTE eNodeBs sites in Addis Ababa	Selected eNodeBs
Longitude	38.76772-38.887913	38.72454-38.86114
Latitude	8.81866-9.075676	8.8668385-9.0665395
Total no of sites	1110	324
Total no of cells	7268	1208

4.2. Threshold and Target Coverage Class Definition

As mentioned before, in LTE networks, the RSRP, RSRQ, and SINR are important characteristics to assess signal coverage level. When a mobile device moves between cells and executes cell selection, reselection, or handover, a modem can use it to uniformly evaluate the state of the connection to a particular neighboring tower. The modem selects the tower with the highest RSRP out of all the neighboring towers RSRP values, but the modem bases its decision on RSRQ when the RSRP values of two towers are the same signal strength or the strength is weak to call. The signal level thresholds denote that, in order to provide a good service, the signal quality and strength must be greater than the specified thresholds. The RSRP parameter measures the desired signal strength and is typically stated in dBm, whereas the RSRQ and SINR parameters measure signal quality, and both are given in dB. SINR [69] is vendor-specific. In this study, the network coverage is divided into four classes depending on thresholds. It considers the combination of the RSRP, RSRQ, and SINR threshold values and classifies them as "excellent", ”good", "medium", and "weak," including the network coverage situation in between the thresholds.

Table 4. 2 Target coverage class based on RSRP, RSRQ, and SINR levels

Signal level	RF	Target

RSRP	RSRQ	SINR	connectivity	coverage class
> = -80	> = -10	> = 20	Excellent	3
-80 to - 90	-10 to -15	13 to 20	Good	2
-90 to -100	-15 to -20	0 to 13	Medium	1
< = -100	< = -20	< = 0	Weak	0

4.3. System Model

This section discusses the system model for this study. Data collection comes first, followed by data pre-processing (data cleaning and transformation), and then model building (split into training and testing models). We provide 80% of the data for the training model and 20% for the testing. Then grid and random search are used for HPO after the random forest algorithm learns from this training dataset. As a result, we obtain the predicted value, and then we verify our model using the prediction and the true test dataset. Finally, we visualize the predicted coverage classes on Google Earth Pro.

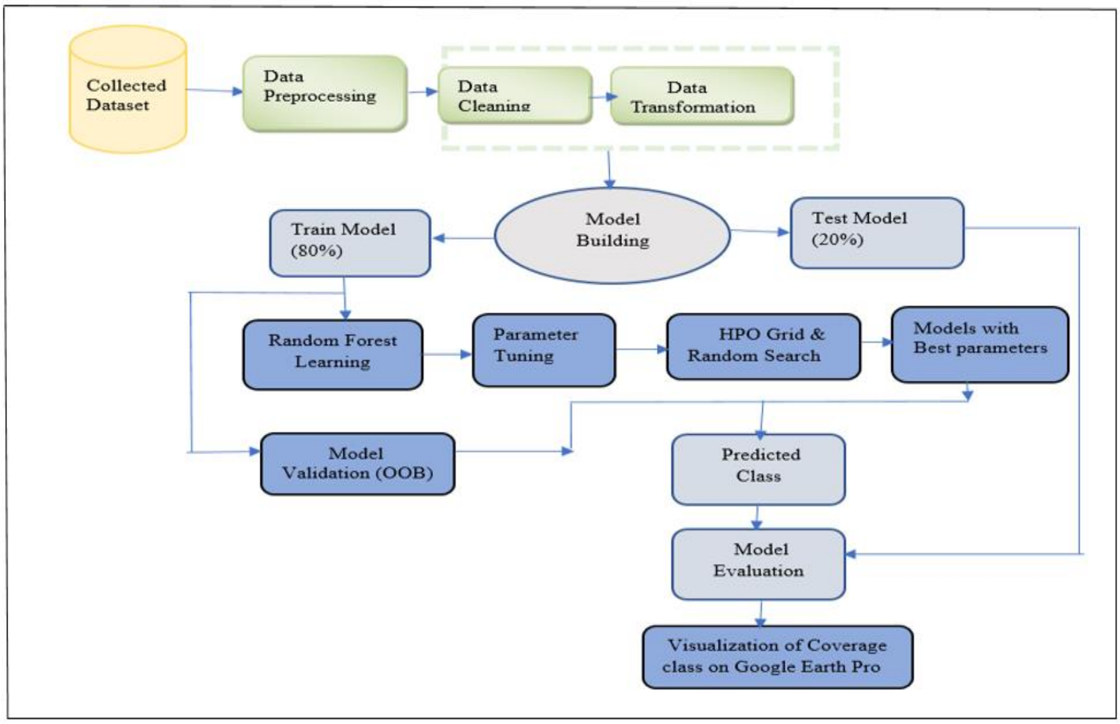


Figure 4. 2 System model of the thesis

- **Data collection**: This study is focused on offering a solution that uses UE MR data via the MDT functionality. The UE MR is collected using the mentor tool in order to create an initial database. For the analysis, RSRP, RSRQ, and SINR parameters are collected, as well as serving cell IDs and event locations (latitude and longitude). The data used for this study was collected for one week because the menor tool could not store the data for more than one week.

- **Data preprocessing:** The representation and quality of the instance data are primarily responsible for increasing the model's accuracy, decreasing the time and resources required to train the model, avoiding overfitting, and making it easier to understand. If there is a lot of redundant information present, then it will be difficult to acquire knowledge during the training phase. It is well understood that steps for preparing and filtering data take a considerable amount of time to process in ML problems. Data pre-processing includes data cleaning, normalization, transformation, feature extraction and selection, etc. For the final training set, the result of data pre-processing is used [70]. However, for this task, only data cleaning and data transformation needed to be performed.

- **Data Cleaning**: In order to prepare data for analysis, it must be cleaned up, meaning that any missing, inconsistent, duplicate, or noisy data must be removed or modified. Therefore, there is no null (missing) value in this procedure [70]. Additionally, we may look at the correlation heat map to see how input features are related. A correlation heat map is used to show the linear relationship between three independent variables, as shown below in Figure 4.3.

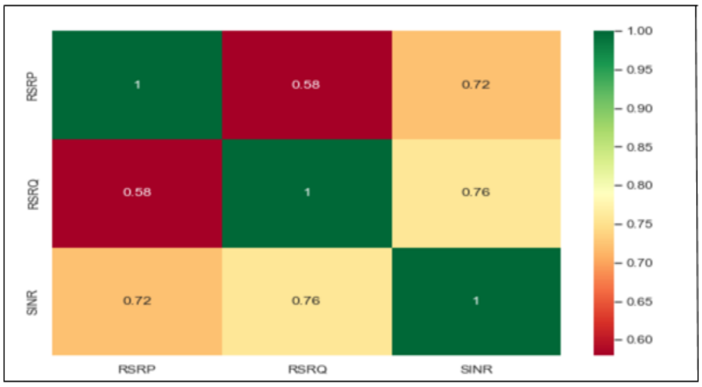


Figure 4. 3 Correlation between the three inputs

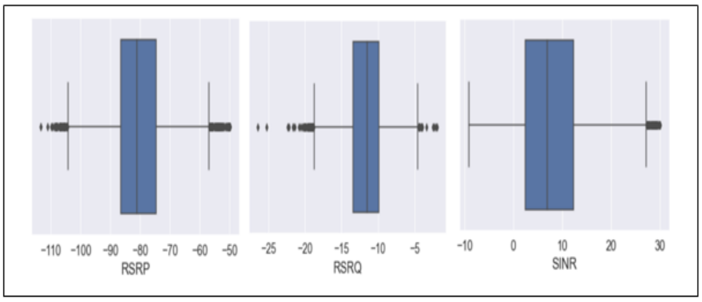


Figure 4. 4 Outlier found on each independent

As shown in Figure 4.4, an outlier is found in our dataset for each independent variable. Hence, we applied a well-known method, the interquartile range (IQR), to treat outliers, as can be seen in Figure 4.5 below. The IQR is the range between the first and third quartiles, namely Q1 and Q3. IQR = Q3 – Q1. Outliers are those data values that are either below or above the Q1–1.5 IQR or Q3 + 1.5 IQR, respectively [71].

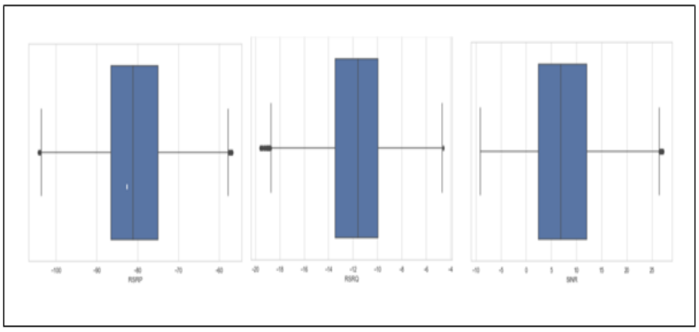


Figure 4. 5 Outliers are cleared from the three features

- **Data Normalization**: The process of normalization involves "scaling down" the features. Within a feature, there is often a large difference between the maximum and minimum values, e.g., 0.01 and 1000. The magnitudes of the values are scaled to noticeably low values after normalization [70]. The most common methods are z-score and min-max normalization, and in this study, we use the min-max normalization method.

Table 4. 3 Input dataset sample

Index	Data	Sector	Long	Lati	RSRP	RSRQ	SINR
1	1/6/2023	x	x	x	-65.7	-9.35	14.3
2	1/6/2023	x	x	x	-64.3	-9.65	15.13
3	1/6/2023	x	x	x	-64.1	-10.35	15.93
----	----	----	----	----	----	----	----
7677	7/6/2023	x	x	x	-67.65	-7.85	26.1
7678	7/6/2023	x	x	x	-63.4	-4.6	24.63

- **Model Building:** Following the pre-processing stage, the random forest algorithm was applied to the data for classification. The dataset used for classification has 7678 instances and 3 features. These datasets are divided into two parts: the training set covers 80% of the randomly chosen data samples, while the testing set contains the remaining 20%.

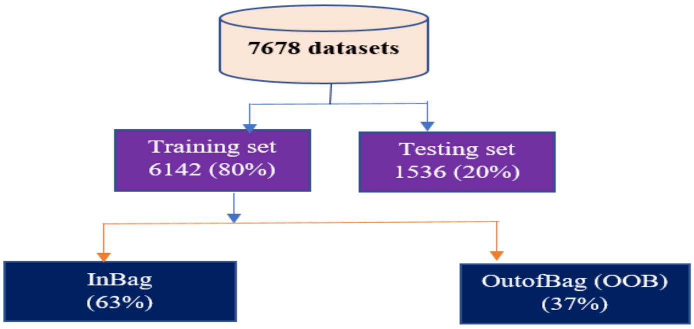


Figure 4. 6 Data splitting process

Table 4. 4 Data sample after prediction

Index	Sector	Long	Lati	RSRP	RSRQ	SINR	Predicted Class
1	x	x	x	-77.85	-11.15	10.5	1
2	x	x	x	-91.3	-13	2.2	1
2	x	x	x	-80.6	-10.8	1.85	1
---	x	x	x	---	---	---	---
1535	x	x	x	-67.45	-8.25	21.65	3
1536	x	x	x	-92.65	-10.75	9.55	1

Random forest creates different independent decision trees; as illustrated below in Figure 4.7, the applied number of trees were three, and each tree has its own data set that is the same size as the initial training data set, which is 6142. The trees are extracted from the original training datasets by using the bootstrapping process. However, when using the bootstrap process, only 63% of this data is taken, and 37% of the dataset has been filled by replacement and duplication. In addition, the data that are not selected by bootstrapping process are OOB, which is 37% of the training dataset that is not used for training the model but is used for model validation purposes.

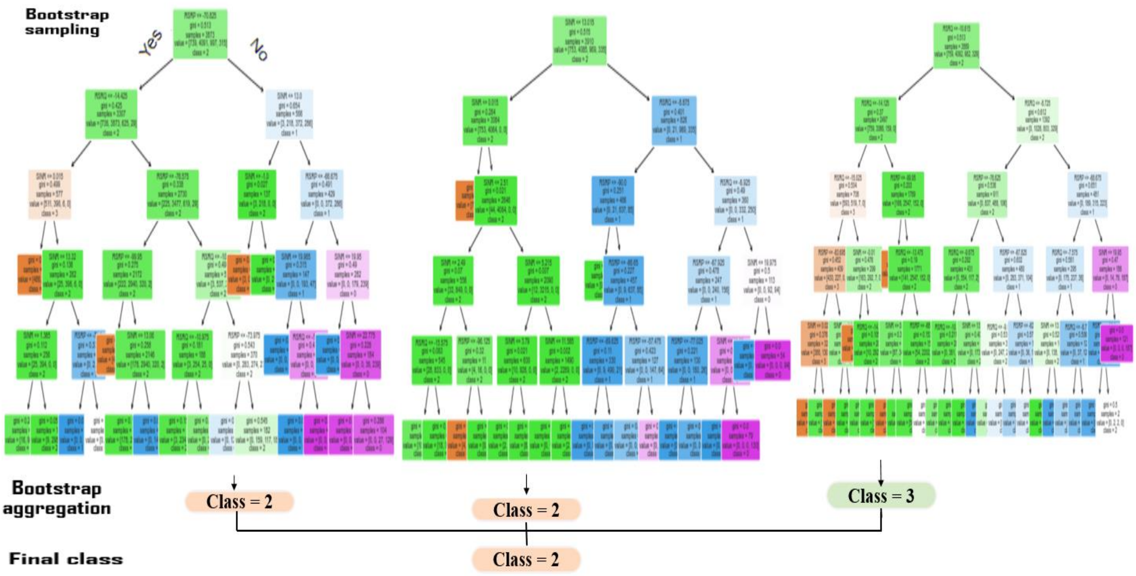


Figure 4. 7 Random forest classifier trees

In a random forest, the depth of the tree is one of the key parameters to avoid overfitting. In this algorithm, we don't need to increase the growth of the tree. Because the more splits a tree has, the more information it collects about the data, and the model learns every detail, including the errors. As a result, overfitting happened, and the model failed to generalize to the new data. Hence, we should limit the maximum depth of the trees, and to do so, each tree becomes a weak learner in the training phase, but at the end, the trees are able to predict its value, and as a committee, we get an accurate prediction.

- **Hyperparameter optimization:** The random search hyperparameter space is depicted in Figure 4.8a. Using this method we can select the number of iterations our model will go through. In our case, we fix n iterations 50 times and choose cv = 5 at random, producing 250 candidate models that are ready for fitting. The best model with the best hyperparameters will also be selected. In addition, the random search CV approach is a highly useful technique when dealing with a big dataset.

```
from scipy.stats import randint
np.random.seed(42)

rs_space={'max_depth':np.arange(2, 4,10),
              'n_estimators':np.arange(10, 500, step=50),
              'max_features':randint(1,7),
              'criterion':['gini','entropy'],
              'min_samples_leaf':randint(1,4),
              'min_samples_split':np.arange(2, 10, step=2),

         }
```

a) Random search

```
np.random.seed(42)
param_grid = {
    'n_estimators': [25, 50, 75, 100, 150, 200],
    'max_features': ['auto','sqrt', 'log2'],
    'max_depth': [3, 4, 5],
    'max_leaf_nodes': [3, 6, 9],
    'criterion' : ['gini', 'entropy'],
    }
```

b) Grid search

Figure 4. 8 Hyperparameter optimization parameter space

As we can see in Figure 4.8b, we have 324 combinations of candidate models in our grid space, and with a CV value of 5, we have a total of 1620 models that are ready for fitting. The best model with the best hyperparameter values will then be selected. If the dataset has become large and the grid contains many parameters, there are probably many different combinations, making it impossible to check the values of each of the hyperparameters because the training model is going to take a very long time. It may be computationally expensive, but when we have a smaller dataset, grid search is quite accurate.

Chapter 5

5. Results and Discussion

This chapter of the thesis presents the predicted coverage class on Google Earth Pro, results from the examination of the random forest algorithm, random forest with grid and random search approaches, and the results of model evaluation.

5.1. Qualitative and Quantitative Results

This section displays the predicted coverage class on Google Earth Pro. The cells are denoted by different colors based on their signal strength at the time they served the specified area.

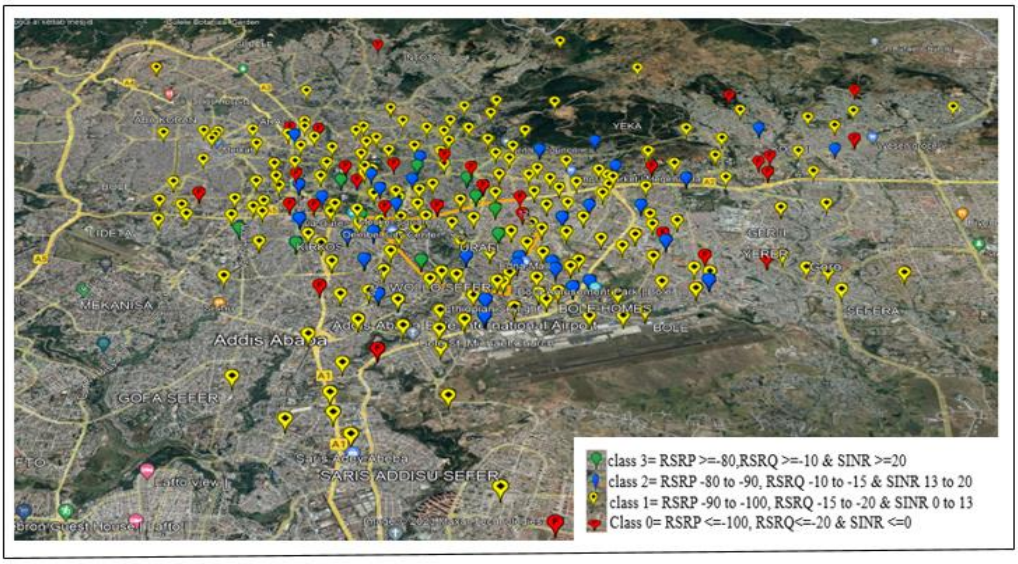
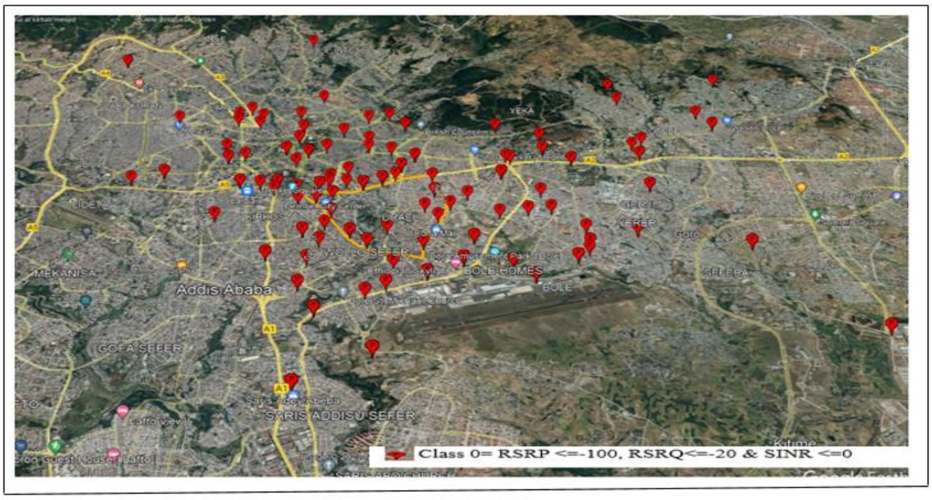
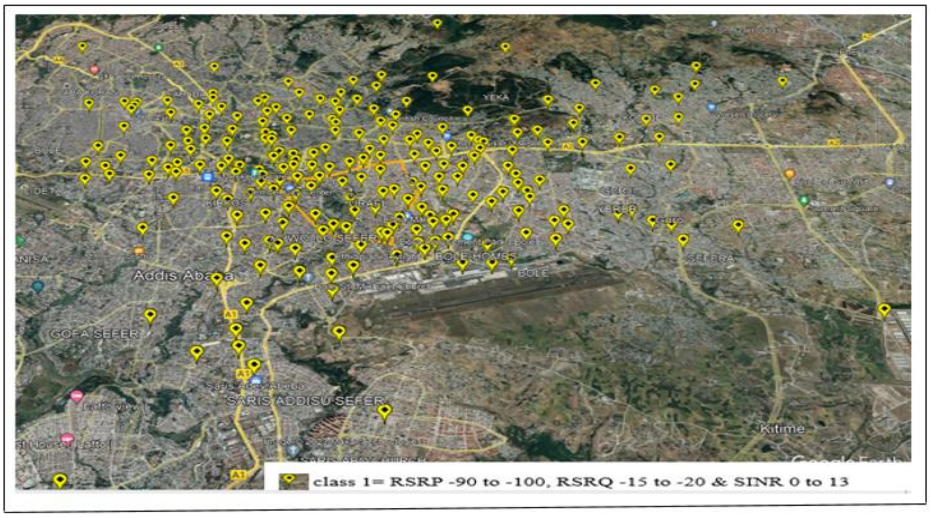


Figure 5. 1 Distribution of coverage situations on Google Earth Pro

As illustrated in Figure 5.1, the target coverage classes, such as class 0, class 1, class 2, and class 3, are represented by the colors red, yellow, blue, and green, respectively. These colors show the signal level of various cells. What we have learned from this figure is that certain cells that are located far from the target area still have good cellular coverage in terms of quality and/or strength. On the contrary, the particular cells that are located closest to the targeted area do not offer adequate cellular coverage.



a) Class 0



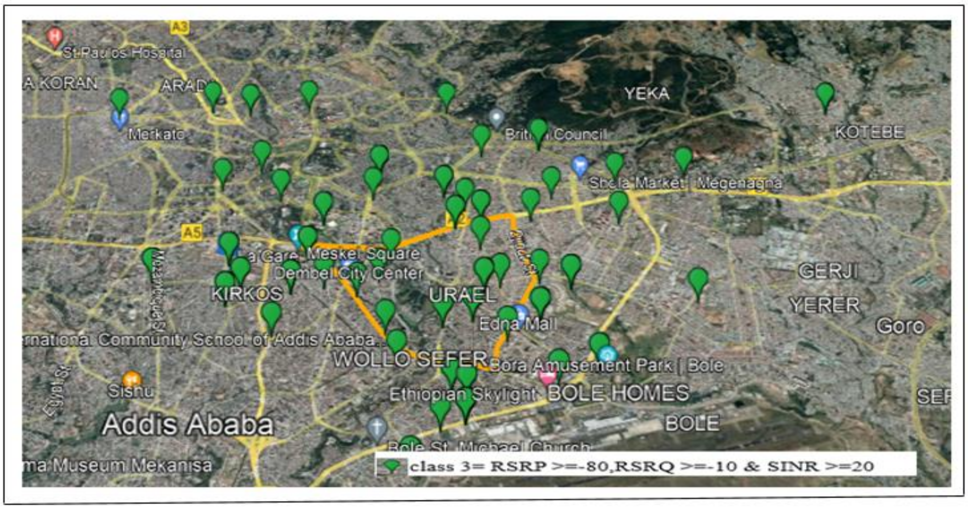
b) Class 1

Figure 5. 2 Distribution of coverage situations of class 0 and class 1

- **Class zero:** The red color in Figure 5.2a shows the areas where mobile terminals detect reference signals at the required RSRP and RSRQ levels. It is the area where RF RSRP, RSRQ, and SINR are below the threshold. It denotes that the respective RF values are less than -100 dBm, -20 dB, and 0 dB, respectively. This indicated that there is a coverage hole problem in the area due to bad signal strength and quality (interference), including SINR. When the SINR signal level is low, it usually implies that interference levels are high, which means RSRP and RSRQ are poor. The other possible reason for getting a low RSRP value is that the user is far from the serving cell or there are obstructions in their path (between the user and eNodeB). From a quality point of view, many users using the same eNodeB (high eNodeB utilization) could be contributing to the low RSRQ value. This class is referred to as weak coverage, which implies that the signal strength and quality of areas have a serious problem with coverage.

- **Class one:** Figure 5.2b shows the distribution of coverage situation on class 1, which is colored in yellow and shows the area where RF RSRP, RSRQ, and SINR are in the ranges between -90 to -100 dBm, -15 to -20 dB, and 0 to 13 dB, respectively. In this figure, the majority (65%) of the areas covered by medium (class 1) signal strength and quality. In comparison to class zero, this suggests that the area has strong signal quality and strength. As we have learned from Figures 5.6a and b, there are typically cells that are close to the target (selected) area but nevertheless provide weaker coverage in terms of quality and strength. In this case, the potential causes from the perspective of coverage strength are barriers, which might lead to a low RSRP, although cellular coverage is limited despite the large distance between users and cells.
- **Class two:** Shows the distribution of coverage in class 2, which is colored blue. This class, known as strong coverage, designates the area where the RF RSRP, RSRQ, and SINR are between -80 and -90 dBm, -10 to -15 dB, and 13 to 20 dB, respectively. In comparison to class 1, it suggests that the locations have strong coverage in terms of signal strength and quality, as illustrated in Figure 5.3a below.

a) Class 2



b) Class3

Figure 5. 3 Distribution of coverage situations of class 2 and class 3

- **Class three:** Figure 5.3b shows the distribution of coverage in class 3, which is colored green. That is also referred to as excellent coverage, and denotes the areas where the RF RSRP, RSRQ, and SINR are above or equal to the threshold values of -80 dBm, -10 dB, and 20 dB, respectively. It suggests that the region has very high signal strength, quality, and SINR values. In this figure, only 6% of the areas are covered by excellent signal strength and quality. As we have learned from Figures 5.3a and b, there are cells that travel far and serve the target area with outstanding coverage strength and quality. In these circumstances, there may be no barriers between a user and the eNodeB or low cell utilization.

Figure 5.4 shows that the target classes of coverage situations share a percentage of the testing dataset. In this figure, the majority of target classes are covered by medium RF signal conditions in terms of strength and quality, which is class 1 and accounts for 65% of the testing data. While the area with good coverage (class 2) shared 15% of the whole area, the other two situations, class 0 for weak coverage and class 3 for excellent coverage, shared 11% and 5%, respectively. Additionally, 4% of the entire testing dataset was incorrectly classified.

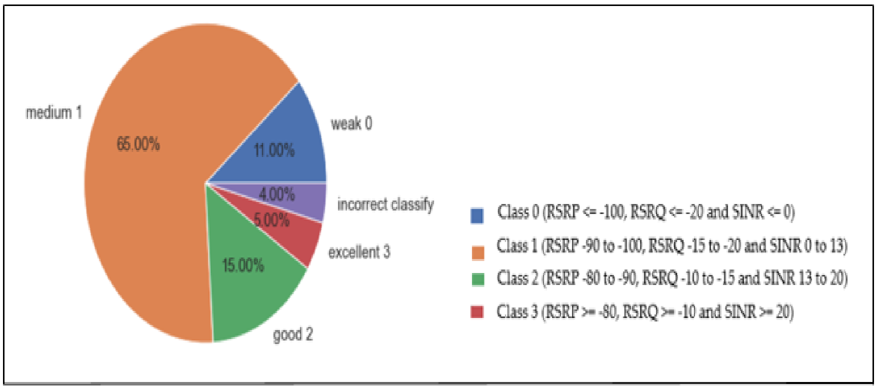


Figure 5. 4 Coverage situations share (%) testing dataset

While using grid and random search, as shown below in Figures 5.5 and 5.6, the majority of the target class is also covered by class 1, which accounts for 65% of the testing data in both cases. Figure 5.5 shows that the area with good coverage (class 2) shared 15% of the whole area, and the other two situations, class 0 for weak coverage and class 3 for excellent coverage, shared 11% and 7%, respectively. Additionally, 2% of the entire testing dataset was incorrectly classified. As we have learned from this figure, the HPO with random search decreased the incorrect classification from 4% to 2%.

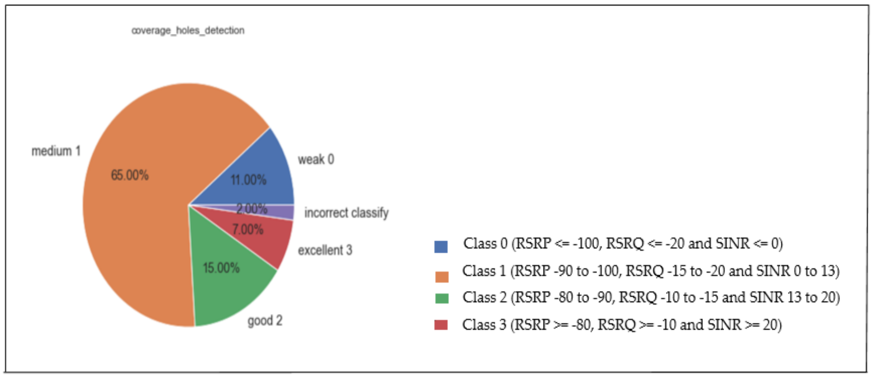


Figure 5. 5 Coverage situations share (%) testing dataset of random search

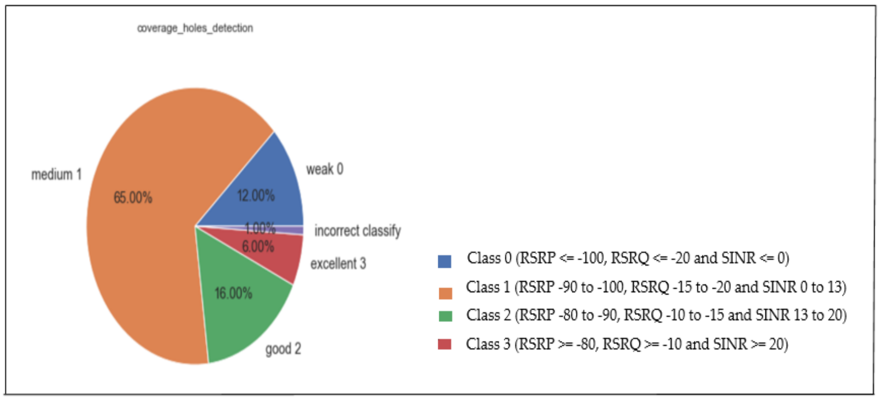


Figure 5. 6 Coverage situations share (%) testing dataset of grid search

Whereas Figure 5.6 illustrates that the area with good coverage (class 2) shared 16% of the whole area, the other two situations, class 0 for weak coverage and class 3 for excellent coverage, shared 12% and 6%, respectively, and 1% of the entire testing dataset was incorrectly classified. This figure indicates that as we applied the HPO with grid search, the incorrect classification decreased from 4% to 1%. This indicates that our model will be an excellent classifier with great accuracy.

Generally, Figures 5.4, 5.5, and 5.6 indicate that there are high shares of medium (class 1) coverage and quality, which are critically served by poor signal strength and quality throughout the test period. Although the percentages of incorrect classification for normal random forest classifier and random forest classifier with random and grid searches are 4%, 2%, and 1%, respectively, this indicates that hyperparameter tuning is a very important method to minimize incorrect classification and increase the accuracy of the model.

5.2. Evaluation of the Detection Algorithm

Figure 5.7 displays the predicted class results against the true class in terms of the classification of the four coverage classes as a confusion matrix. The figure showed us that there are points not located on the diagonal line, and they stand in for instances that were improperly classified. The datasets are clearly identified as belonging to their respective classes by the points on the diagonal line.

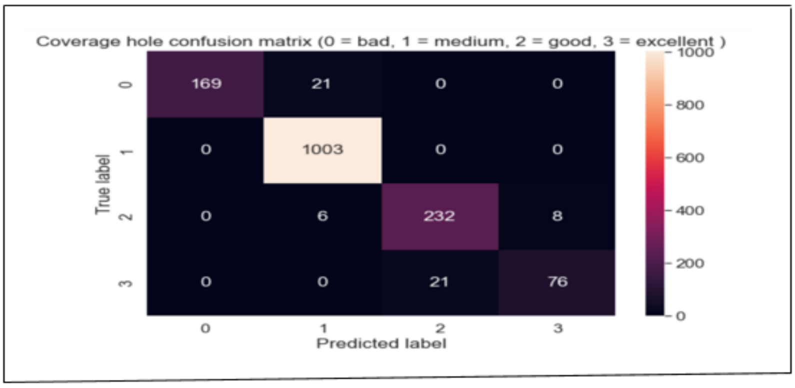


Figure 5. 7 Generated test result in confusion matrix form

The accuracy performance measure is then determined using the corresponding formula shown in Eq. 3.3. The algorithm, according to the confusion matrix in the figure, incorrectly identified only 56 of the 1536 test instances. This results in a 96.3% accuracy rate, as seen in Figure 5.8, which needs to be improved. The above figure demonstrates that there are four different classes of coverage situations, including class 0, class 1, class 2, and class 3. The diagonal line is denoted by TP0, TP1, TP2, and TP3, with values of 169, 1003, 232, and 76, respectively.

```
Classification Report:  precision    recall  f1-score

           0       1.00      0.89      0.94
           1       0.97      1.00      0.99
           2       0.92      0.94      0.93
           3       0.90      0.78      0.84

    accuracy                           0.96
   macro avg       0.95      0.90      0.92
weighted avg       0.96      0.96      0.96

Accuracy: 96.35416666666666
Accuracy traning: 96.66232497557799
Accuracy test: 96.35416666666666
```

```
print(model.oob_score_)
0.7338000651253663
```

Figure 5. 8 Classification report of accuracy, precision, recall and f1-score

Figure 5.8 shows that the performance measurements of the random forest classifier, which are precision, recall, and f1-score, are calculated as per the corresponding formulas presented in Eqs. (3.4), (3.5), and (3.6), respectively. Furthermore, the results, including the OOB score, suggested that the model needed optimization.

The confusion matrix of random search in Figure 5.9 illustrates that out of 1536 test instances, the algorithm identified 34 incorrectly. This resulted in an accuracy of 97.7%, as illustrated in Figure 5.10, which is good given that accuracy improved from 96.3 to 97.7% following the HPO random search. The diagonal line of the four classes of coverage situations is represented by TP0, TP1, TP2, and TP3, which are 172, 1002, 231, and 97, respectively.

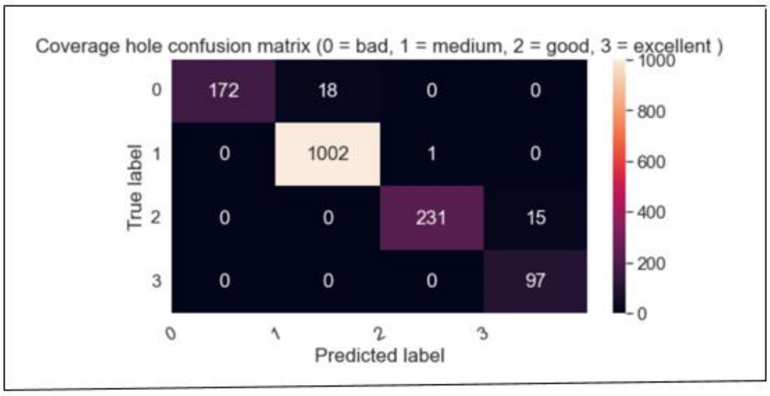


Figure 5. 9 Generated test result in confusion matrix form of random search

Classification Report:	precision	recall	f1-score
0	0.91	1.00	0.95
1	1.00	0.98	0.99
2	0.94	1.00	0.97
3	1.00	0.87	0.93

```
Accuracy: 97.78645833333334
Accuracy test: 97.78645833333334
Accuracy traning: 98.09508303484206
```

Figure 5. 10 Classification report of accuracy, precision, recall and f1-score of random Search

Figure 5.10 shows the performance measurements of the random search, which are precision, recall, and f1-score, are calculated as per the corresponding formulas presented in Eqs. (3.4), (3.5), and (3.6), respectively.

The confusion matrix of grid search in Figure 5.11 shows that, out of 1536 test instances, only 12 of them were misclassified and detected by the algorithm. As shown in Figure 5.12, this resulted in an accuracy of 99.2%, which is a significant improvement from 96.6 to 99.2% following the HPO grid search. The diagonal line is represented by TP0, TP1, TP2, and TP3 with values of 189, 1002, 246, and 87, respectively.

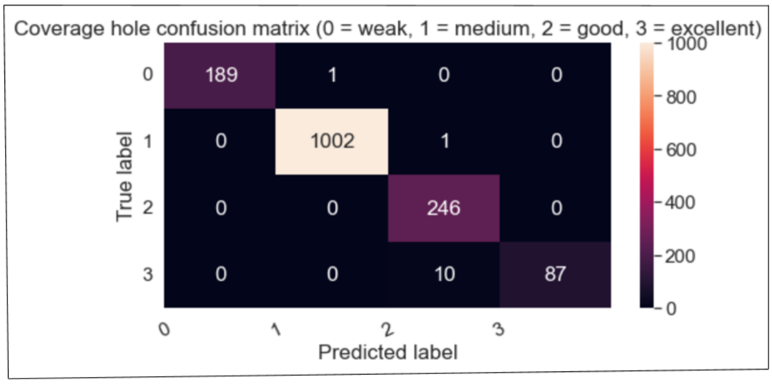


Figure 5. 11 Generated test result in confusion matrix form of grid search

```
Classification Report: precision    recall  f1-score
                     0       0.99      1.00      1.00
                     1       1.00      1.00      1.00
                     2       1.00      0.96      0.98
                     3       0.90      1.00      0.95

              accuracy                           0.99
             macro avg       0.97      0.99      0.98
          weighted avg       0.99      0.99      0.99

          Accuracy: 99.21875
          Accuracy test: 99.21875
          Accuracy traning: 99.54412243568869
```

Figure 5. 12 Classification report of accuracy, precision, recall, and f1-score of grid search

Figure 5.12 shows the performance measurements of the grid search, which are precision, recall, and f1-score, are calculated as per the corresponding formulas presented in Eqs. (3.4), (3.5), and (3.6), respectively.

```
roc_auc_score(y_test,y_score,multi_class='ovr')

0.9999941224761817
```

Figure 5.13 AUC value of one-vs.-rest for grid search

AUC used the one-vs.-rest technique for evaluating multiclass models by contrasting each class with all the others simultaneously. In this case, we choose one class and think of it as our positive class, while the others are thought of as our negative class. This converts the multiclass classification output into a binary classification output, allowing all of the established binary classification metrics to be used to assess the situation. For a dataset with four classes, we must repeat this for every class that is present, resulting in four distinct one-vs.-rest scores. To arrive at a final one-vs.-rest model score, we can finally average them. The range of the AUC values is 0 to 1. Performance is better when the AUC is larger. Figure 5.13 illustrates that the average value of the four AUC classes, with an AUC value of 0.99, is close to 1, which indicates that the detection model is an excellent classifier.

Chapter 6

6. Conclusion and Future Works

6.1. Conclusion

This thesis has presented the idea of network coverage hole detection and the challenges associated with using conventional coverage hole detection techniques. The UE MR data from the ethio telecom LTE network, which are RSRP, RSRQ, and SINR, have been considered for the investigation. These data were used to build a model that classifies different coverage situations, such as "weak coverage," "medium coverage," "good coverage," and "excellent coverage."

MDT can be applicable to all technology networks, and it uses cost-effective mobile devices for measuring the data, which helps to minimize operational effort, enhance the quality and performance of the network while reducing operator maintenance expenses. Also, it has the capacity to record all coverage data, including UE-generated traffic from indoor areas, from every geographic region.

Data has been collected and preprocessed, and tests have been carried out to evaluate the proposed detection algorithms. The experiments have shown that the original random forest classifier and the optimizing with grid and random search detection algorithms can be applied to coverage hole detection. As a result, both grid and random search significantly improve the original random forest classifier's performance, with grid search having the best results. In addition, the confusion matrix, accuracy, precision, recall, f1-score, and AUC were used in order to assess the performance of the detection methods. Finally, the applied approach is also expected to be used for other technologies to find coverage holes.

6.2. Future Works

This thesis considered only the detection of LTE network coverage holes using the random forest algorithm. This research could be expanded in the future to include the mitigation of the coverage holes and the diagnosis of their root causes. In addition, it may be possible to explore how traffic dynamics affect coverage holes by taking into account both busy and off-peak traffic hours.

References

[1] S. K. Jha, R. Rokaya, A. Bhagat, A. R. Khan, and L. Aryal, "LTE Network: Coverage and Capacity Planning — 4G Cellular Network Planning around Banepa," in *2017 International Conference on Networking and Network Applications (NaNA)*, IEEE, Oct. 2017, pp. 180–185. doi: 10.1109/NaNA.2017.23.

[2] A. M. Miyim and A. Wakili, "Performance Evaluation of LTE Networks," in *2019 15th International Conference on Electronics, Computer and Computation, ICECCO 2019*, Institute of Electrical and Electronics Engineers Inc., Dec. 2019. doi: 10.1109/ICECCO48375.2019.9043271.

[3] "LTE Planning and dimensioning 1 ITU PITA Workshop on Mobile network planning and security."

[4] TSGS, "TS 128 627 - V13.1.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (3GPP TS 28.627 version 13.1.0 Release 13)," 2016. [Online]. Available: http://portal.etsi.org/tb/status/status.asp

[5] Y. Migdadi, "The Leading Practices of Green Mobile Telecommunication Base Station Design," *International Journal of Green Computing*, vol. 6, no. 2, pp. 43–52, Jul. 2015, doi: 10.4018/ijgc.2015070104.

[6] M. Yassin *et al.*, "A Novel Dynamic Inter-Cell Interference Coordination Technique for LTE Networks."

[7] TSGS, "TS 128 627 - V13.1.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (3GPP TS 28.627 version 13.1.0 Release 13)," 2016. [Online]. Available: http://portal.etsi.org/tb/status/status.asp

[8] A. Gómez-Andrades, R. Barco, and I. Serrano, "A method of assessment of LTE coverage holes," *EURASIP J Wirel Commun Netw*, vol. 2016, no. 1, Dec. 2016, doi: 10.1186/s13638-016-0733-y.

[9] G. Abdissa, W. Advisor, and Dr.-I. D. Hailemariam, "UMTS Network Coverage Hole Detection using Decision Tree Classifier Machine Learning Approach," 2020.

[10] C. K. Anjinappa and I. Guvenc, "Coverage Hole Detection for mmWave Networks: An Unsupervised Learning Approach," Aug. 2021, doi: 10.1109/LCOMM.2021.3106251.

[11] A. Bisrat, "Detecting Cell Outage by applying Density based Anomaly Detection Algorithm Using Machine Learning Technique: The Case of Ethio Telecom UMTS Network," 2020.

[12] B. Solomon Bekele Advisor Dr-Ing Dereje Hailemariam, "Cell Outage Detection Through Density-based Local Outlier Data Mining Approach: In case of Ethio telecom UMTS Network," 2018.

[13] D. Rai and A. Dwivedi, "LTE Theory to Practice-KPI Optimization (A 4G Wireless Technology) LTE Brings New Technologies like Multiple Input Multiple Output (MIMO) Transmission," International Journal of Innovative Technology and Exploring Engineering, 2018, [Online]. Available: www.ijitee.org

[14] H. Holma and Antti. Toskala, LTE for UMTS : evolution to LTE-Advanced. John Wiley & Sons, 2011.

[15] F. Krasniqi, A. Maraj, and E. Blaka, "Performance analysis of mobile 4G/LTE networks."

[16] P. Man Sainju, "LTE PERFORMANCE ANALYSIS ON 800 AND 1800 MHz BANDS."

[17] D. Kozma, G. Soos, D. Kozma, G. Soós, and P. Varga, "Supporting LTE Network and Service Management through Session Data Record Analysis MANTIS-Cyber Physical System based Proactive Collaborative Maintenance View project Supporting LTE Network and Service Management through Session Data Record Analysis." [Online]. Available: https://www.researchgate.net/publication/305999478

[18] H. Nashaat, O. Refaat, F. W. Zaki, and I. E. Shaalan, "Dragonfly-Based Joint Delay/Energy LTE Downlink Scheduling Algorithm," *IEEE Access*, vol. 8, pp. 35392–35402, 2020, doi: 10.1109/ACCESS.2020.2974856.

[19] F. Afroz, K. Sandrasegaran, and A. K. H, "Interference Management in Lte Downlink Networks," International Journal of Wireless & Mobile Networks, vol. 7, no. 1, pp. 91–106, Feb. 2015, doi: 10.5121/ijwmn.2015.7106.

[20] H. Ben Rekhissa, C. Belleudy, and P. Bessaguet, "Energy efficient resource allocation for M2M devices in LTE/LTE-A," Sensors (Switzerland), vol. 19, no. 24, Dec. 2019, doi: 10.3390/s19245337.

[21] Z. Shakir, A. Y. Mjhool, A. Al-Thaedan, A. Al-Sabbagh, and R. Alsabah, "Key performance indicators analysis for 4 G-LTE cellular networks based on real measurements," International Journal of Information Technology (Singapore), vol. 15, no. 3, pp. 1347–1355, Mar. 2023, doi: 10.1007/s41870-023-01210-0.

[22] K. Ervasti, "A Survey on Network Measurement: Concepts, Techniques, and Tools."

[23] TSGS, "TS 132 450 - V9.1.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Key Performance Indicators (KPI) for Evolved Universal Terrestrial Radio Access Network (E-UTRAN): Definitions (3GPP TS 32.450 version 9.1.0 Release 9)," 2010. [Online]. Available: http://portal.etsi.org/chaircor/ETSI_support.asp

[24] F. Krasniqi, L. Gavrilovska, and A. Maraj, "The analysis of key performance indicators (KPI) in 4G/LTE networks," in Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, *LNICST*, Springer, 2019, pp. 285–296. doi: 10.1007/978-3-030-23976-3_25.

[25] TSGS, "TS 132 455 - V15.0.0 - LTE; Telecommunication management; Key Performance Indicators (KPI) for the Evolved Packet Core (EPC); Definitions (3GPP TS 32.455 version 15.0.0 Release 15)," 2018. [Online]. Available: https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx

[26] Amour, L., & Dandoush, A. (2022). "Crowdsourcing Based Performance Analysis of Mobile User Heterogeneous Services,"*Electronics*, *11*(7), 1011. https://doi.org/10.3390/electronics11071011

[27] TSGS, "TS 128 667 - V13.0.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Radio Planning Tool Access (RPTA) Integration Reference Point (IRP); Requirements (3GPP TS 28.667 version 13.0.0 Release 13)," 2016. [Online]. Available: http://portal.etsi.org/tb/status/status.asp

[28] M. Elbagir Mohammed and K. Hamid Bilal, "LTE Radio Planning Using Atoll Radio Planning and Optimization Software," 2012. [Online]. Available: www.ijsr.net

[29] K. Goyal and A. K. Kar, "Determinants of Customer Satisfaction in Telecommunication," in *Lecture Notes in Electrical Engineering*, Springer, 2020, pp. 754–761. doi: 10.1007/978-3-030-30577-2_67.

[30] D. Baumann, "Minimization of Drive Tests (MDT) in Mobile Communication Networks," 2013, doi: 10.2313/NET-2014-03-1_02.

[31] TSGR, "TS 137 320 - V12.2.0 - Universal Mobile Telecommunications System (UMTS); LTE; Universal Terrestrial Radio Access (UTRA) and Evolved Universal Terrestrial Radio Access (E-UTRA); Radio measurement collection for Minimization of Drive Tests (MDT); Overall description; Stage 2 (3GPP TS 37.320 version 12.2.0 Release 12)," 2014. [Online]. Available: http://portal.etsi.org/chaircor/ETSI_support.asp

[32] R. Mondal, J. Turkka, T. Ristaniemi, and T. Henttonen, "Performance evaluation of MDT assisted LTE RF fingerprint framework," in *2014 7th International Conference on Mobile Computing and Ubiquitous Networking, ICMU 2014*, IEEE Computer Society, 2014, pp. 33–37. doi: 10.1109/ICMU.2014.6799054.

[33] TSGS, "TS 128 627 - V13.1.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (3GPP TS 28.627 version 13.1.0 Release 13)," 2016. [Online]. Available: http://portal.etsi.org/tb/status/status.asp

[34] TSGR, "TS 136 214 - V14.2.0 - LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer; Measurements (3GPP TS 36.214 version 14.2.0 Release 14)," 2017. [Online]. Available: https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx

[35] *2008 IEEE International Symposium on Wireless Communication Systems.* I E E E, 2008.

[36] R. Nofitasari and S. Haryadi, "Self-healing mechanism with RSRP measurement in LTE network," in *Proceedings - ICWT 2017: 3rd International Conference on Wireless and Telematics 2017*, Institute of Electrical and Electronics Engineers Inc., Feb. 2018, pp. 144–148. doi: 10.1109/ICWT.2017.8284156.

[37] G. Molla and Dr.-E. Y. Wondie, "Network by Using Coordinated Multipoint Transmission Technique: The Case of Addis Ababa, Ethiopia."

[38] M. Sousa, A. Martins, and P. Vieira, "Self-diagnosing low coverage and high interference in 3G/4G radio access networks based on automatic RF measurement extraction," in *ICETE 2016 - Proceedings of the 13th International Joint Conference on e-Business and Telecommunications*, SciTePress, 2016, pp. 31–39. doi: 10.5220/0005958300310039.

[39] M. M. El-Said, A. Kumar, and A. S. Elmaghraby, "Pilot Pollution Interference Reduction Using Multi-Carrier Interferometry," 2003.

[40] M. A. Ouamri and M. Azni, "Overshooting and cost minimization in LTE cellular network using non-dominate sorting genetic algorithm based on laplace crossover," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Jul. 2019. doi: 10.1145/3341325.3341997.

[41] R. H. H. Al-Hashemy and I. M. Saadoon, "An intelligent algorithm to reduce and eliminate coverage holes in the mobile network," *Journal of Intelligent Systems*, vol. 30, no. 1, pp. 920–930, Jan. 2021, doi: 10.1515/jisys-2021-0046.

[42] X. Zhao, X. Luo, T. Wu, and D. Xiao, "The prediction mathematical model for HO performance in LTE networks," in *Proceedings - 2013 IEEE 8th International Conference on Networking, Architecture and Storage, NAS 2013*, 2013, pp. 191–197. doi: 10.1109/NAS.2013.31.

[43] B. Davaasambuu, K. Yu, and T. Sato, "Self-optimization of handover parameters for long-term evolution with dual wireless mobile relay nodes," *Future Internet*, vol. 7, no. 2, pp. 196–213, 2015, doi: 10.3390/fi7020196.

[44] H. S. Park, Y. Lee, T. J. Kim, B. C. Kim, and J. Y. Lee, "Faster Recovery from Radio Link Failure during Handover," *IEEE Communications Letters*, vol. 24, no. 8, pp. 1835–1839, Aug. 2020, doi: 10.1109/LCOMM.2020.2994989.

[45] IEEE Staff and IEEE Staff, *2012 Australasian Telecommunication Networks and Applications Conference.*

[46] R. Kwan and C. Leung, "A survey of scheduling and interference mitigation in LTE," *Journal of Electrical and Computer Engineering*. 2010. doi: 10.1155/2010/273486.

[47] Q. WIDAYATI and R. AMALIA, "Call Drop Rate on Cellular Network Case Study of PT Indosat Tbk Palembang," Institute of Research Engineers and Doctors, LLC, Feb. 2018, pp. 37–40. doi: 10.15224/978-1-63248-144-3-27.

[48] A. Rusan and R. Vasiu, "Emulation of backhaul packet loss on the LTE S1-U interface and impact on end user throughput," in *Proceedings - 2015 IEEE 11th International Conference on Intelligent Computer Communication and Processing, ICCP 2015*, Institute of Electrical and Electronics Engineers Inc., Oct. 2015, pp. 529–536. doi: 10.1109/ICCP.2015.7312715.

[49] F. Livingston, "Implementation of Breiman's Random Forest Machine Learning Algorithm," 2005.

[50] A. Lindholm, N. Wahlström, F. Lindsten, and T. B. Schön, "Supervised Machine Learning Lecture notes for the Statistical Machine Learning course."

[51] Q. Liu and Y. Wu, "Supervised Learning," in *Encyclopedia of the Sciences of Learning*, Springer US, 2012, pp. 3243–3245. doi: 10.1007/978-1-4419-1428-6_451.

[52] V. Sharma, "Survey of Classification Algorithms and Various Model Selection Methods," 2000.

[53] B. Baykara and A. Uk, "Impact of Evaluation Methods on Decision Tree Accuracy CORE View metadata, citation and similar papers at core," 2015.

[54] L. Breiman, "Random Forests," 2001.

[55] G. (Gareth M. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning : with applications in R*.

[56] T.-H. Lee, A. Ullah, and R. Wang, "Bootstrap Aggregating and Random Forest."

[57] Y. Zhao and Y. Zhang, "Comparison of decision tree methods for finding active objects," *Advances in Space Research*, vol. 41, no. 12, pp. 1955–1959, 2008, doi: 10.1016/j.asr.2007.07.020.

[58] S. George and B. Sumathi, "Grid Search Tuning of Hyperparameters in Random Forest Classifier for Customer Feedback Sentiment Prediction," 2020. [Online]. Available: www.ijacsa.thesai.org

[59] P. Probst and A.-L. Boulesteix, "To tune or not to tune the number of trees in random forest?," May 2017, [Online]. Available: http://arxiv.org/abs/1705.05654

[60] D. Stamate, W. Alghamdi, D. Stahl, D. Logofatu, A. Zamyatin, and A. Z. Pidt: A, "Novel Decision Tree Algorithm Based on Parameterised Impurities and Statistical Pruning Approaches," pp. 273–284, 2018, doi: 10.1007/978-3-319-92007-8_24ï.

[61] T. Daniya, M. Geetha, and K. S. Kumar, "Classification and regression trees with gini index," *Advances in Mathematics: Scientific Journal*, vol. 9, no. 10, pp. 8237–8247, 2020, doi: 10.37418/amsj.9.10.53.

[62] R. Hossain and D. Timmer, "Machine Learning Model Optimization with Hyper Parameter Tuning Approach," 2021.

[63] E. Elgeldawi, A. Sayed, A. R. Galal, and A. M. Zaki, "Hyperparameter tuning for machine learning algorithms used for arabic sentiment analysis," *Informatics*, vol. 8, no. 4, Dec. 2021, doi: 10.3390/informatics8040079.

[64] M. M. RAMADHAN, I. S. SITANGGANG, F. R. NASUTION, and A. GHIFARI, "Parameter Tuning in Random Forest Based on Grid Search Method for Gender Classification Based on Voice Frequency," *DEStech Transactions on Computer Science and Engineering*, no. cece, Oct. 2017, doi: 10.12783/dtcse/cece2017/14611.

[65] J. Bergstra, J. B. Ca, and Y. B. Ca, "Random Search for Hyper-Parameter Optimization Yoshua Bengio," 2012. [Online]. Available: http://scikit-learn.sourceforge.net.

[66] Ž. Vujović, "Classification Model Evaluation Metrics," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, pp. 599–606, 2021, doi: 10.14569/IJACSA.2021.0120670.

[67] H. M and S. M.N, "A Review on Evaluation Metrics for Data Classification Evaluations," *International Journal of Data Mining & Knowledge Management Process*, vol. 5, no. 2, pp. 01–11, Mar. 2015, doi: 10.5121/ijdkp.2015.5201.

[68] Ž. Vujović, "A case study of the application of WEKA software to solve the problem of liver inamation," 2021, doi: 10.21203/rs.3.rs-464435/v1.

[69] F. Afroz, R. Subramanian, R. Heidary, K. Sandrasegaran, and S. Ahmed, "SINR, RSRP, RSSI and RSRQ Measurements in Long Term Evolution Networks," *International Journal of Wireless & Mobile Networks*, vol. 7, no. 4, pp. 113–123, Aug. 2015, doi: 10.5121/ijwmn.2015.7409.

[70] S. Kotsiantis, D. Kanellopoulos, and P. E. Pintelas, "Data Preprocessing for Supervised Learning Semi-supervised regression View project Time-series forecasting View project," 2014. [Online]. Available: https://www.researchgate.net/publication/228084519

[71] "Detecting Data Outliers with Machine Learning," *Al-Salam Journal for Engineering and Technology*, pp. 152–164, May 2023, doi: 10.55145/ajest.2023.02.02.018.

APPENDIX

LTE Network Coverage Hole Detection Technique using Random Forest Classifier Machine Learning Algorithm

Serkadis Bahiru
Addis Ababa Institute of Technology
School of Electrical and Computer Engineering
Addis Ababa University
serkserk763@gmail.com

Dr.–Eng. Yihenew Wondie
Addis Ababa Institute of Technology
School of Electrical and Computer Engineering
Addis Ababa University
yihenew.wondie@aait.edu.et

Abstract — The most significant phases for the mobile operator are the performance of cellular networks and the evaluation of quality of service (QoS). Hence, Long-Term Evolution (LTE) network monitoring and measuring are necessary in determining mobile network statistics to optimize the performance of the network in a particular area. Measuring networks is an effective way to qualify and quantify how networks are being used and how they are behaving, and it helps to find voids or uncovered areas that are coverage holes in the LTE network.

A coverage hole is defined as a client's being unable to receive a wireless network signal. Traditionally, it is detected through drive tests, but it costs resources and time. In order to identify coverage holes in the LTE network, this study proposed a random forest classifier Machine Learning (ML) approach.

The data was gathered from the User Equipment (UE) via minimization drive test (MDT) functionality with low cost, which measures Reference Signal Receive Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal to Interference and Noise Ratio (SINR). The RSRP and RSRQ measure the strength and quality of the reference signal received at the device's antenna, whereas SINR is a metric that assesses the relationship between the targeted signal strength and the total power of all interfering signals and noise.

The results obtained show that the employed model's accuracy was 96.3%. However, we could use the hyperparameter optimization (HPO) technique to enhance the model's performance, namely random and grid search cross validation (CV), which increased the model's accuracy to 97.7% and 99.2%, respectively.

Keywords: Coverage hole, Random forest classifier, Hyper parameter optimization, minimization drive test, RSRP, RSRQ, SINR

I. INTRODUCTION

Cellular communication has advanced significantly, with advancements in voice and data streaming. The 4G technology supports high-speed voice and data access, while LTE networks are being developed by the 3GPP to meet growing mobile data usage and new applications. Network planning aims to achieve maximum capacity without compromising service quality, considering future growth and expansion [1]. Users benefit financially from wise spectrum reuse and strategic site placement. During the radio-planning phase, the primary considerations include installing base stations and setting up them, ensuring signal strength in the service area, and determining the radio resources available for each cell. Coverage planning ensures the percentage of the area covered by cellular service, while capacity planning determines the number of calls handled in a specific area and the likelihood of users being blocked due to lack of radio channels. The self-organized network (SON) function is used to optimize both coverage and capacity. The telecommunications industry's rapid growth has prompted mobile phone providers to compete to provide the best services to customers [2].

Mobile operators face challenges in cellular networks, such as coverage holes, where pilot signal strength is below a threshold required for access. These holes are often caused by physical obstructions, unsuitable antenna parameters, or inadequate radio frequency planning. They can lead to call drop and radio link failure. To address these issues, cutting-edge equipment is used to gather field performance data, including measurements of pedestrians in indoor and outdoor environments. Detecting coverage holes helps identify voids or uncovered areas in the LTE network, ensuring reliability and minimizing data loss [3]. This approach reduces costs and enhances performance.

II. STATEMENT OF THE PROBLEM

There are various challenges in telecommunications; one of the problems that researchers are working hard to solve is the coverage hole. RF transmissions from outdoor macrocarrier towers can have difficulty providing indoor coverage, which is one of the drawbacks of radio-based cellular systems. Concrete, glass, steel, and other building materials may block the signals. In the modern digital world, weak coverage is a challenge, particularly for large establishments and businesses like airports, transit hubs, stadiums, hospitals, retail, office buildings, and manufacturing sites. In order to improve network performance, ethio telecom planned indoor and outdoor network coverage using the urban propagation model; however, there are still call drops and handover failures due to coverage outages. This shows that there is an undetectable coverage hole in the planning tool. Data accuracy declines because transmission links are disconnected due to a coverage hole in the network, and effectively enhancing network service quality requires the prompt discovery of coverage outages. When users enter a coverage hole, they will experience call loss and handover failure. A call drop occurs when a connection is suddenly disconnected before the user's desired service is finished. The bad thing that could happen for the user is that they completely lose their connection, leading to customer displeasure. As a result, users complain endlessly about call drop, handover failure, and poor performance in locations with LTE coverage holes.

Currently, coverage holes have been detected through drive tests in the case of ethio telecom. However, it has two significant drawbacks. First, manual drive testing involves a lot of resources, including time, specialized tools, and the engagement of highly skilled engineers; this results in high operating expenses (OPEX). Second, given that the majority of UE-generated traffic from indoor areas and since manual drive testing tends to be limited to on-road testing, it is challenging to adequately evaluate coverage across all regions. This makes drive testing an expensive task with practical limitations due to cost and accessibility issues.

So far, many research has been done on the detection of network coverage holes using approaches like decision trees, density-based anomaly detection, and data mining. One of the research was to develop a decision tree for detecting coverage holes, but the problem is that we can’t generalize the model, which leads to overfitting.

Therefore, the proposed approach develop a coverage hole detection technique based on the random forest classifier algorithm using Measurement Report (MR) data via MDT functionality. In order to minimize overfitting, random forest create numerous trees and train each tree (model) separately using a variety of data sets. The outcome is then predicted by each model, and the final prediction will be decided by the majority vote and the model offers a high degree of accuracy.

III. RELATED WORK

Many studies have been done on applying ML algorithms in the domain of telecommunications and detecting network coverage holes. Within this section, related studies that highlight coverage detection and optimization application cases are mentioned.

Gomez-Andrades, Barco, and Serrano [4] developed a method for assessing LTE network coverage holes, identifying cells with holes, determining their type and severity, and evaluating their effects on LTE and RAT consumers. However, the study only considered heterogeneous deployment situations. Abdissa G. [5] used decision tree classifier-supervised ML algorithms to detect coverage holes in the Universal Mobile Telecommunications System (UMTS). The approach uses Nastar tool to measure received signal code power and energy per chip. The study's limitation is model overfitting, a common issue in decision tree training.

Chethan K. Anjinappa and Ismail G. Uvenc [6] have developed an unsupervised learning method for detecting coverage holes in mmWave networks using uniform manifold approximation and projection. Their method, tested on a deep MIMO dataset, successfully learns data structure and provides visual holes. Bisrat A. [7] and Bekele S. [8] developed a cell outage detection technique using handover information and density-based anomaly detection methods. They used traffic data and incoming handover data to detect outages in the UMTS network environment.

IV. SYSTEM MODEL

Data collection: This study aims to provide a solution using UE MR data via MDT functionality, using the mentor tool to create an initial database. Data was collected for one week due to Menor's storage limitations.

Data preprocessing: The quality and representation of instance data significantly impact model accuracy, training time, and resource efficiency. Reducing redundant information during training can hinder knowledge acquisition. Data pre-processing, including cleaning, normalization, transformation, and feature extraction, takes time and is used in the final training set.

Model Building: The random forest algorithm was applied to a classification dataset with 7678 instances and 3 features. The dataset was divided into a training and testing set. Three independent decision trees were created, each with a 6142-size data set. The bootstrapping process extracted 63% of the data, filling 37% with replacement and duplication. The depth of a random forest tree is crucial to prevent overfitting, as excessive splits can lead to overfitting. To prevent this, the maximum depth of trees should be limited, allowing each tree to become a weak learner in the training phase.

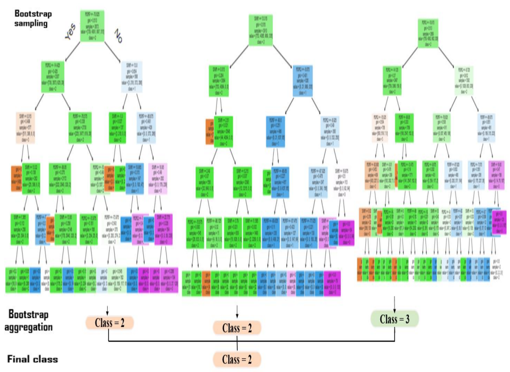


Fig 1. Random forest classifier trees

Hyperparameter optimization: Figure 2a illustrates the random search hyperparameter space, allowing for n iterations and cv = 5 random selection, producing 250 model candidates with optimal hyperparameters, a useful technique for large datasets. Figure 2b shows

324 candidate models in a grid space, with 1620 ready for fitting. The best model with the best hyperparameter values is selected. Large datasets may have many combinations, making it difficult to check hyperparameter values. Grid search is accurate for smaller datasets.

```python
from scipy.stats import randint
np.random.seed(42)

rs_space={'max_depth':np.arange(2, 4,10),
              'n_estimators':np.arange(10, 500, step=50),
              'max_features':randint(1,7),
              'criterion':['gini','entropy'],
              'min_samples_leaf':randint(1,4),
              'min_samples_split':np.arange(2, 10, step=2),

        }
```

a) Random search

```python
np.random.seed(42)
param_grid = {
    'n_estimators': [25, 50, 75, 100, 150, 200],
    'max_features': ['auto','sqrt', 'log2'],
    'max_depth': [3, 4, 5],
    'max_leaf_nodes': [3, 6, 9],
    'criterion' : ['gini', 'entropy'],
    }
```

b) Grid search

Figure 2. Hyperparameter optimization parameter space

V. RESULTS AND DISCUSSION

The section displays predicted coverage classes on Google Earth Pro, with cells colored based on signal strength at the time they served the specified area.

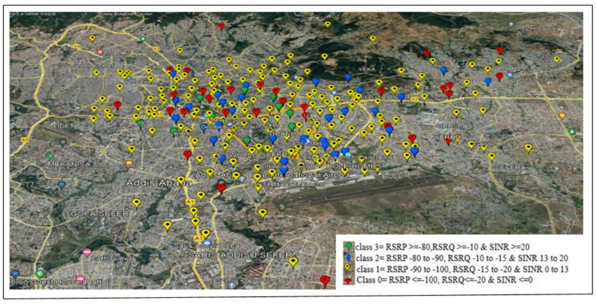


Figure 3. Distribution of coverage situations on Google Earth Pro

Figure 3 shows target coverage classes, represented by colors red, yellow, blue, and green, indicating signal levels of cells. It reveals that cells far from the target area have good coverage, while those closest offer inadequate coverage.

a) Class 0: The red color shows areas where mobile terminals detect reference signals below the required RSRP and RSRQ levels. These areas have low RF RSRP, RSRQ, and SINR, indicating a coverage hole problem due to poor signal strength and quality, including interference. Low SINR signals often indicate high interference levels, poor RSRP and RSRQ, and weak coverage, indicating serious issues with signal strength and quality.
b) Class 1: The yellow color shows coverage situation in class 1, with 65% of areas covered by medium signal strength and quality. However, cells close to the target area provide weaker coverage due to potential barriers, leading to low RSRP and limited cellular coverage despite the large distance between users and cells.
c) Class 2: The blue-colored shows strong coverage, with RF RSRP, RSRQ, and SINR values between -80 and -90 dBm, -10 to -15 dB, and 13 to 20 dB, compared to class 1.
d) Class 3: The green colored shows excellent coverage where RF RSRP, RSRQ, and SINR are above or equal to threshold values. Only 6% of areas are covered by excellent signal strength and quality, suggesting no barriers between users and eNodeB or low cell utilization.

Evaluation of the Detection Algorithm: Figure 4 shows a confusion matrix comparing predicted class results against the true class classification of four coverage classes, with points on the diagonal line indicating improper classifications.

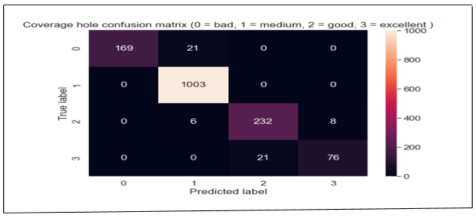


Figure 4. Generated test result in confusion matrix form

```
Classification Report:  precision    recall  f1-score

           0       1.00      0.89      0.94
           1       0.97      1.00      0.99
           2       0.92      0.94      0.93
           3       0.90      0.78      0.84

    accuracy                           0.96
   macro avg       0.95      0.90      0.92
weighted avg       0.96      0.96      0.96

Accuracy: 96.35416666666666
Accuracy traning: 96.66232497557799
Accuracy test: 96.35416666666666

print(model.oob_score_)
0.7338000651253663
```

Figure 5. Classification report of accuracy, precision, recall and f1-score

Figure 4 shows that the algorithm, based on a confusion matrix, identified only 56 out of 1536 test instances, resulting in a 96.3% accuracy rate, indicating a need for improvement. The figure shows four coverage situations and diagonal lines.

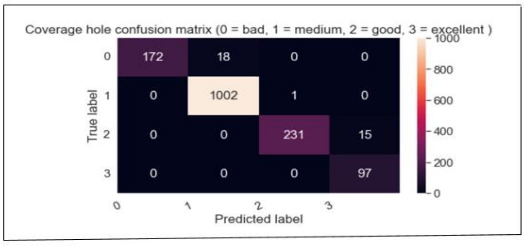


Figure 6. Generated test result in confusion matrix form of random search

```
Classification Report:    precision    recall  f1-score
                   0       0.91      1.00      0.95
                   1       1.00      0.98      0.99
                   2       0.94      1.00      0.97
                   3       1.00      0.87      0.93

        Accuracy: 97.78645833333334
        Accuracy test: 97.78645833333334
        Accuracy traning: 98.09508303484206
```

Figure 7. Classification report of accuracy, precision, recall and f1-score of random Search

Figure 6 shows that the algorithm identified 34 incorrect instances out of 1536 test instances, resulting in an accuracy of 97.7%. This improvement was observed after the HPO random search, indicating improved coverage situations.

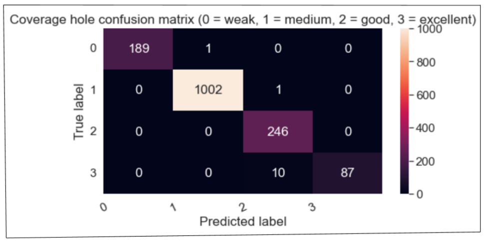


Figure 8. Generated test result in confusion matrix form of grid search

```
Classification Report: precision    recall  f1-score
                   0       0.99      1.00      1.00
                   1       1.00      1.00      1.00
                   2       1.00      0.96      0.98
                   3       0.90      1.00      0.95

            accuracy                           0.99
           macro avg       0.97      0.99      0.98
        weighted avg       0.99      0.99      0.99

        Accuracy: 99.21875
        Accuracy test: 99.21875
        Accuracy traning: 99.54412243568869
```

Figure 9. Classification report of accuracy, precision, recall, and f1-score of grid search

Figure 8 shows that the grid search algorithm successfully identified 12 out of 1536 test instances, resulting in an accuracy of 99.2%, a significant improvement from 96.6%, with diagonal lines representing TP0, TP1, TP2, and TP3.

```
roc_auc_score(y_test,y_score,multi_class='ovr')

0.9999941224761817
```

Figure 10. AUC value of one-vs.-rest for grid search

The AUC technique evaluates multiclass models by contrasting each class with all others simultaneously. This converts the multiclass output into a binary classification output, allowing for the use of binary classification metrics. Figure 10 shows that four distinct one-vs.-rest scores are repeated for each class, and the AUC ranges from 0 to 1, with a larger AUC indicating better performance.

VI. CONCLUSION

This thesis explores network coverage hole detection using UE MR data from Ethiopia telecom LTE network, focusing on challenges and developing a model to classify coverage situations.

MDT utilizes cost-effective mobile devices to measure data, improving network quality and performance, and recording coverage data from all geographic regions. The study evaluated the performance of the original random forest classifier and grid and random search detection algorithms for coverage hole detection, showing significant improvements. Grid search demonstrated the best results, and the approach is expected to be used for other coverage hole detection technologies.

REFERENCES

[1] S. K. Jha, R. Rokaya, A. Bhagat, A. R. Khan, and L. Aryal, "LTE Network: Coverage and Capacity Planning — 4G Cellular Network Planning around Banepa," in 2017 International Conference on Networking and Network Applications (NaNA), IEEE, Oct. 2017, pp. 180–185. doi: 10.1109/NaNA.2017.23.

[2] A. M. Miyim and A. Wakili, "Performance Evaluation of LTE Networks," in *2019 15th International Conference on Electronics, Computer and Computation, ICECCO 2019*, Institute of Electrical and Electronics Engineers Inc., Dec. 2019. doi: 10.1109/ICECCO48375.2019.9043271.

[3] TSGS, "TS 128 627 - V13.1.0 - Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (3GPP TS 28.627 version 13.1.0 Release 13)," 2016. [Online]. Available: http://portal.etsi.org/tb/status/status.asp

[4] A. Gómez-Andrades, R. Barco, and I. Serrano, "A method of assessment of LTE coverage holes," *EURASIP J Wirel Commun Netw*, vol. 2016, no. 1, Dec. 2016, doi: 10.1186/s13638-016-0733-y.

[5] G. Abdissa, W. Advisor, and Dr.-I. D. Hailemariam, "UMTS Network Coverage Hole Detection using Decision Tree Classifier Machine Learning Approach," 2020.

[6] C. K. Anjinappa and I. Guvenc, "Coverage Hole Detection for mmWave Networks: An Unsupervised Learning Approach," Aug. 2021, doi: 10.1109/LCOMM.2021.3106251.

[7] A. Bisrat, "Detecting Cell Outage by applying Density based Anomaly Detection Algorithm Using Machine Learning Technique: The Case of Ethio Telecom UMTS Network," 2020.

[8] B. Solomon Bekele Advisor Dr-Ing Dereje Hailemariam, "Cell Outage Detection Through Density-based Local Outlier Data Mining Approach: In case of Ethio telecom UMTS Network," 2018.