Addis Ababa University
Addis Ababa Institute of Technology
Telecommunication Engineering Graduate Program

Machine Learning for Improved Root Cause Analysis of LTE Network Accessibility and Integrity Degradation

By
Fikreaddis Tazeb

Advisor
Dr. -Ing. Dereje Hailemariam

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Telecommunication Network Engineering

October 4, 2023
Addis Ababa, Ethiopia

Addis Ababa University
Addis Ababa Institute of Technology
Telecommunication Engineering Graduate Program

Machine Learning for Improved Root Cause Analysis of LTE Network Accessibility and Integrity Degradation

By
Fikreaddis Tazeb

Dr. Bisrat Derebssa ______________
Dean, School of Electrical and Computer Engineering Signature

Dr. -Ing. Dereje Hailemariam ______________
Advisor Signature

Dr. Beneyam Berehanu ______________
Internal Examiner Signature

Dr. Tsegamlak Terefe ______________
External Examiner Signature

Declaration

I, Fikreaddis Tazeb, hereby declare that this thesis is my original work conducted under the guidance and supervision of Dr. -Ing. Dereje Hailemariam. Any materials, data, or information sourced from others have been properly acknowledged.

Fikreaddis Tazeb
Name

Signature

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

Dr. -Ing. Dereje Hailemariam
Advisor

Signature

Abstract

Long Term Evolution (LTE) networks are essential for enabling high-speed, reliable communication and data transmission. However, the accessibility and integrity of LTE networks can degrade due to a variety of factors, such as congestion, coverage, and configuration problems. Root cause analysis (RCA) is a process for identifying the underlying causes of degradation. However, RCA can be time-consuming and labor-intensive. Machine learning can be used to enhance RCA by identifying patterns and trends in data that can be used to identify the root causes of problems. Limited work exists on machine learning-enabled RCA for LTE networks.

This thesis proposes a machine learning-enabled approach, specifically Convolutional Neural Network (CNN) and SHapley Additive exPlanations (SHAP), for RCA of LTE network performance degradation. The approach was evaluated using key performance indicators (KPIs) and counters data collected from LTE network of ethio telecom, a major operator in Ethiopia.

The main causes of reduced network accessibility are failure caused by the Mobility Management Entity (MME), the average number of users, and handover failures. Similarly, the underlying causes of degraded accessibility at the cell level are failure caused by MME, control channel element (CCE) utilization, and paging utilization. For network integrity, which is measured by user throughput, the main causes of degradation are the high number of active users, high downlink Physical Resource Block (PRB) utilization, poor Channel Quality Indicator (CQI), and coverage issues. At the cell level, the main factors are downlink PRB utilization, unfavorable CQI values, and high downlink block error rate.

For the given data, the model's sensitivity for network accessibility and integrity at the cell level is 82.8% and 95.5%, respectively. These results demonstrate the potential of the proposed approach to accurately identify degradation instances. The proposed approach using deep learning and SHAP offers reusability, high-dimensionality support, geographic scalability, and time resolution for improved performance analysis in networks of all sizes. Network operators can improve network performance by identifying and addressing the root causes of degradation.

Keywords: Accessibility, CNN, Integrity, LTE, Root Cause Analysis, SHAP

Acknowledgments

Firstly, I would like to thank God for blessing me with the strength, knowledge, and inspiration to complete this thesis. A special word of thanks goes to my advisor, Dr.-Ing. Dereje Hailemariam, for his guidance and support. From the very beginning, he played a crucial role in shaping the title of this thesis and continued to provide valuable insights and feedback until its completion. I am incredibly grateful for his unwavering dedication and encouragement throughout this thesis journey.

I am grateful to ethio telecom for providing the sponsorship that made this research possible. I thank Mr. Anley Tadesse and Mr. Redamichael Jemberu for their expert advice and help in collecting the data. I would also like to thank my examiners, Dr. Beneyam Berehanu and Dr. Tsegamlak Terefe, for their direction and valuable comments throughout the progress of this thesis.

Last but certainly not least, I would like to thank my family, especially my beloved Mom, and Zee for their love and support. They have been my constant source of encouragement.

Dedication

To my dearest mom, Emebet Tadesse, the most loving and kind person I know.

Contents

List of Figures

List of Tables

List of Acronyms

1D One-dimensional

1G First Generation

2G Second Generation

2D Two-dimensional

3D Three-dimensional

3G Third Generation

3GPP Third Generation Partnership Project

4G Fourth Generation

Adam Adaptive moment estimation

AI Artificial Intelligence

AMPS Advanced Mobile Phone System

ANN Artificial Neural Networks

AS Access Stratum

BCCH Broadcast Channel

CCE Control Channel Element

CDMA Code Division Multiple Access

CDMA2000 Code Division Multiple Access 2000

CNN Convolutional Neural Network

CSFB Circuit Switched Fallback

CQI Channel Quality Indicator

DNN Deep Neural Networks

DRBs Data Radio Bearers

EDGE Enhanced Data Rates for Global Evolution

eGTP-C GPRS Tunneling Protocol - Control Plane

E-UTRAN Evolved Universal Terrestrial Radio Access Network

E-RAB E-UTRAN Radio Access Bearer

EPS Evolved Packet System

EPC Evolved Packet Core

eNodeB Evolved NodeB

FDMA Frequency Division Multiple Access

GBR Guaranteed Bit Rate

GPRS General Packet Radio System

GSM Global System for Mobile Communication

HARQ Hybrid-automatic Repeat Request

HLR Home Location Register

HSS Home Subscriber Server

IMT International Mobile Telecommunications

IMT2000 International Mobile Telecommunications

IP Internet Protocol

KPI key performance indicator

KPIs key performance indicators

LIME Local interpretable model-agnostic explanations

LSTM Long short-term memory networks

LTE Long Term Evolution

MAC Medium Access Control

MCS Modulation and Coding Scheme

MIMO Multiple Input Multiple Output

MLP Multilayer Perceptron

MME Mobility Management Entity

NMS Network Management System

NAS Non-access stratum

OFDM Orthogonal Frequency Division Multiplexing

PDCP Packet Data Convergence Protocol

PDN Packet Data Networks

PDU Protocol Data Unit

P-GW PDN Gateway

PHY Physical Layer

PLMN Public Land Mobile Network

PRB Physical Resource Block

QoE Quality of Experience

QoS Quality of experience

QCI QoS Class Identifier

RAN Radio Access Networks

RACH Random Access Channel

ReLU Rectified Linear Unit

RCA Root cause analysis

RF Radio frequency

RRC Radio Resource Control

RLC Radio Link Control

ROC Receiver Operating Characteristic

RNN Recurrent Neural Networks

RSRP Reference Signal Received Power

SAE System Architecture Evolution

SRBs Signaling Radio Bearers

SHAP SHapley Additive exPlanations

SINR Signal to Noise and Interference Ratio

SMS Short Message Service

SMOTE Synthetic Minority Oversampling Technique

S-GW Serving Gateway

SDUs Service Data Units

TA Time Advance

TD-SCDMA Time Division-Synchronous Code Division Multiple Access

TDMA Time Division Multiple Access

TTI Transmission Time Interval

UE User Equipment

UMTS Universal Mobile Telecommunications Service

VoIP Voice over Internet Protocol

WiMAX Worldwide Interoperability for Microwave Access

WCDMA Wide-band Code Division Multiple Access

1 Introduction

This chapter introduces the main objective of this thesis, which is to develop a machine learning-based root cause analysis approach to improve accessibility and integrity of Long Term Evolution (LTE) networks. The chapter provides a review of relevant literature and an overview of the thesis structure. It also identifies research gaps and delineates the scope, limitations, contributions, and organization of the thesis.

1.1 Background

The Third Generation Partnership Project (3GPP) standard introduced the Fourth Generation (4G) LTE standard as an advanced technology to meet the increasing demand for high data rates in mobile cellular networks [1]. It operates over a data network using all Internet Protocol (IP), eliminating the need for a circuit-switched communication system. The key advantages of LTE are high data rates and spectrum efficiency as well as reduced data latency, signaling load, and energy consumption. As a result, LTE has been widely deployed by operators worldwide, thanks to its numerous advantages. However, the benefits come with the drawback of increased system complexity in managing and optimizing the network [15].

To ensure Quality of experience (QoS) and enhance customers' satisfaction, mobile network operators install a centralized Network Management System (NMS) to monitor the performance of their Radio Access Networks (RAN) and core networks. The NMS is a software platform that monitors, controls, and manages the network's overall performance. It helps network operators efficiently administer their networks, optimize performance, troubleshoot issues, and ensure high-quality service delivery. The NMS in LTE networks provides the necessary tools for smooth operation, optimization, and maintenance of the network infrastructure, enabling network operators to deliver high-quality services to end-users.

NMS also provides real-time data monitoring, analysis, reporting, and visualization of key performance indicators (KPIs) and counters related to the LTE network. KPIs are high-level metrics that measure the the network's overall health. According to 3GPP these KPIs are categorized into accessibility, retainability, integrity, availability, and mobility [3]. These KPIs are typically derived from counters and operators monitor them at regular intervals (hourly, daily, weekly, or monthly) to identify performance degradation, failures, problems, outages, or unusual events that might significantly impact service delivery and end-user experience. Counters, on the other hand, are low-level metrics that measure specific aspects of the network and keep track of various network events and activities. These counters provide detailed information about network traffic, resource allocation, and usage. For example, counters can monitor the number of dropped calls, network congestion, resource utilization, signaling messages, etc. KPIs and counters are related in that KPIs are typically derived from counters.

In the event of any performance issue, network engineers conduct troubleshooting activities. Root cause analysis (RCA) is an essential part of network troubleshooting as it enables engineers to identify and rectify the fundamental causes of the problem rather than just addressing the symptoms. By identifying and resolving the root causes, network operators can enhance network performance, minimize downtime, and elevate mobile service delivery quality [42].

This thesis focuses on the accessibility and integrity of LTE network. Accessibility key performance indicator (KPI) is utilized to determine if users can efficiently access the network and obtain services. This can be assessed through the analysis of Radio Resource Control (RRC), S1, and E-UTRAN Radio Access Bearer (E-RAB) setup success rates. Similarly, integrity KPI is used to ensure that high-quality services are provided to users without degradation. It can be analyzed through throughput (data rates), and latency statistics [3].

This thesis proposes a method to analyze the causes for accessibility and integrity performance degradation in LTE network based on real network data collected from ethio telecom's NMS. LTE network was chosen for examination because it is a live network with real data, making it an ideal platform for studying and improving network performance. The method employs machine learning models to analyze the data and pinpoint the specific reasons behind any performance degradation. This can help operators to improve the accessibility and integrity of their LTE networks, which can lead to increased customer satisfaction and revenue.

1.2 Statement of the Problem

Network performance can be degraded by various factors such as congestion, insufficient coverage, device failures, improper parameter settings, impaired link quality, and power supply issues [45]. If network operators fail to identify, evaluate, and even forecast the underlying causes of degradation, it can lead to customer dissatisfaction and revenue loss. Therefore, operators need to understand the causes of network performance degradation so that they can take corrective measures promptly and proactively optimize the network to prevent future degradation [37, 36].

ethio telecom, a major telecom service provider in Ethiopia, utilizes NMS to effectively monitor the performance of its network. The NMS provides comprehensive data on various aspects of the network, including network accessibility, integrity, and other performance metrics. In case of significant deviations in network performance, such as decreased accessibility or other issues, the responsibility to solve the problem lies with the optimization team's experienced engineers. The optimization team carefully analyzes the performance report generated by the NMS to identify the causes of degradation. However, this approach heavily relies on expert knowledge, which can limit its effectiveness. Moreover, the traditional approach to cause analysis is becoming outdated due to the increasing flexibility of LTE networks. This makes it challenging to assess the causes of reduced network accessibility and integrity, as it can be caused by several issues that impact multiple metrics simultaneously.

Fortunately, the presence of sufficient data at the NMS allows for a systematic and data-driven method of identifying the causes of network performance degradation. From a research standpoint, there are various RCA methodologies available, each with different degrees of complexity, performance, and applicability. However, the number of studies conducted in the domain of 4G LTE mobile networks, specifically focusing on accessibility and integrity, is limited.

Previous research on LTE accessibility has used a limited number of input features and has not considered counters that directly indicate the causes of accessibility problems. Additionally, to the best of our knowledge, there is no prior work that has investigated LTE network integrity using the advantage of deep learning for RCA. Therefore, it is important to investigate appropriate RCA methods and determine the causes of low network performance degradation.

1.3 Objective

1.3.1 General Objective

The primary goal of this thesis is to develop a machine learning based RCA method for two essential LTE network performance KPIs: network accessibility and integrity. This will be achieved by implementing a Convolutional Neural Network (CNN) combined with the SHapley Additive exPlanations (SHAP) method.

1.3.2 Specific Objectives

The main objective of the thesis is achieved by implementing the following tasks.

- Exploring LTE networks: architecture, protocols, and performance metrics.
- Conduct a comprehensive review of the literature to identify and examine previous works that are relevant and closely related to the current study.
- Investigating various RCA techniques and identifying the effective ones.
- Identify the potential factors contributing to performance degradation in LTE network.

- Gather relevant KPIs and counters that can be measured or observed to assess the impact of these causes.
- Prepare and preprocess data for the model.
- Design, evaluate, and validate a Deep Neural Networks (DNN) model, specifically a CNN classification model, for predicting accessibility and integrity.
- Assess the impact of input features on predicting low network accessibility and throughput by incorporating the CNN model with SHAP.
- Analyze the obtained results, draw conclusions based on the analysis, and provide relevant recommendations for improvement.

1.4 Literature Review

The increasing complexity of cellular networks poses challenges for operation and maintenance. [22] proposed an automatic diagnosis system for LTE networks based on unsupervised techniques. The system can identify LTE network problems and provide a diagnosis based on the impact of those causes on the KPIs. However, it can only provide a diagnosis for a single cause and may not be able to identify multiple root causes. The RCA procedure is performed statistically by human interaction.

Diago et al. [19] addressed the possible causes of low network accessibility in 4G networks by investigating KPIs and their evolution over time. They collected one-month data for various KPIs and used interpretable machine learning models with feature importance technique to assess the contribution of each KPIs towards decreasing network accessibility. The feature importance of the best model was calculated to evaluate which features were most important in predicting low accessibility at both aggregated network and individual cell levels. The results showed that certain KPIs have a greater impact on network accessibility than others. For example, the number of failure handovers, phone calls, and Short Message Service (SMS)s in the network and the overall download volume are the main causes of reduced accessibility in the overall network. At the cell level, the number of users in a cell and its download volume are the main causes of reduced accessibility. However, the authors' approach for determining feature importance is algorithm-dependent and does not take deep learning algorithms into account.

Maluambanzila et al. [36] proposed deep learning model for RCA of poor throughput in mobile 3G networks. The model takes both radio and core network performance indicators as input. The authors collected data from an actual mobile network operator's Iub and Gn interfaces, preprocessed it, and stored it on the Hadoop platform. The data was classified as "BAD" (throughput less than 500 kbps) or "GOOD" (throughput greater than 500 kbps) based on user perception. The proposed DNN model was trained and tested using the data, and various evaluation metrics, including accuracy, area under the Receiver Operating Characteristic (ROC) curve, and F1 score, were used to assess the model's performance. RCA was performed using Local interpretable model-agnostic explanations (LIME) technique to identify the reasons for poor Quality of Experience (QoE). The results of the study show that the deep neural network model developed in this study can accurately predict poor data throughput, with an accuracy of 95.5%. The RCA result identified the top four features that influenced poor data throughput, which was used to outline the influence of predictors focusing on the output response "BAD" for poor data throughput. Following this methodology [6], study RCA in Universal Mobile Telecommunications Service (UMTS) of low user throughput in Bahir Dar City. [6], utilize Multilayer Perceptron (MLP) neural network and LIME for RCA by providing feature importance.

Motivated by the challenges of identifying and resolving performance issues in fog computing environments, different works were done. Chetan B. and Mahantesh [11] proposed an approach for RCA that utilizes statistical methods and machine learning algorithms. They used a combination of data-driven and knowledge-driven techniques to identify anomalies and their root causes. Long short-term memory networks (LSTM) autoencoder is trained to identify anomalous data and pass anomalous data to a RCA model that uses SHAP. The SHAP algorithm calculates each feature's marginal contribution and identifies high marginal values as the root cause of the anomaly. The performance metrics of precision, recall, and F1-score were used to evaluate the anomaly detection model. Their result shows the proposed model improves anomaly detection and RCA accuracy compared to existing models.

According to the above-mentioned literature, several machine-learning models are proposed based on their fit for the specific task as well as their performance and complexity. Machine-learning-based models, particularly deep learning models, appear to be the way to go. Other papers investigate the Bayesian network for RCA and other applications. Recognizing the availability of numerous possibilities, this thesis proposes DNN, specifically CNN, paired with SHAP as the RCA model for low 4G network accessibility and integrity.

1.5 Methodology

In this thesis, the methodology employed for the research involved an extensive literature review to gain a comprehensive understanding of the current research papers related to low network accessibility and integrity RCA. The purpose of this review was to establish a strong foundation of background knowledge on the subject matter. Following the literature review, state-of-the-art solutions were identified for the identified problems and solutions. To select appropriate tools and algorithms, a careful evaluation was conducted.

To identify the possible causes of low accessibility and integrity, several methods of data collection were employed. Hourly KPI and counter data were collected from the NMS tool for the designated ethio telecom cells. Subsequently, data preprocessing was conducted to clean and prepare the collected data for analysis. The next phase involved the development of a causal DNN model. This model was designed to establish a causal relationship between various factors and the low accessibility and integrity issues. Finally, the model was evaluated to assess its performance and effectiveness in addressing the research problem. Using the developed model the feature importance is computed for RCA.

1.6 Scope and Limitations

1.6.1 Scope

The scope is to explore and construct a RCA model for low accessibility and integrity in the LTE network on chosen cells in the city of Addis Ababa. The CNN classification model is used for predicting accessibility and integrity, while SHAP values of input features are used for RCA. The model only considers the E-RAB setup success rate and downlink average user throughput as metrics for accessibility and integrity.

1.6.2 Limitations

- The research considers only accessibility and integrity, two of the most important LTE network performance indicators. However, the approach is generalizable when investigating other performance indicators.
- The input parameters are only collected from the RAN because this is where the majority of the performance data is generated. The dataset can be enriched with counters from the core network.

1.7 Contributions

This thesis proposes a novel approach to analyzing the causes of network performance degradation in LTE networks, focusing on accessibility and integrity. The proposed approach leverages the power of DNN with SHAP to analyze the otherwise less utilized KPIs and counters data extract from the operator's NMS. This allows for a better understanding of network health and the identification of underlying causes at various network levels, including groups of Evolved NodeB (eNodeB)s, individual eNodeB, and cell levels. The main contributions of this thesis are summarized as follows.

- The proposed approach is the first to use DNNs with SHAP to analyze the causes of network performance degradation in LTE networks.
- The approach is able to identify underlying causes at various network levels, which is not possible with traditional methods.
- The approach is evaluated using real-world data from a mobile network operator, and the results show that it can identify the causes of network performance degradation with high accuracy.

1.8 Thesis Structure

This thesis structure includes an overview and understanding of LTE networks in Chapter 2. It explores their components, architecture, performance indicators, and RCA. Chapter 3 covers the machine learning models and techniques used. Chapter 4 introduces a machine learning model for RCA in LTE networks, explaining the system model and setups. Chapter 5 presents and examines the results obtained from the application of the model. It analyzes its performance in identifying and addressing root causes. Finally, Chapter 6 concludes the study, summarizes the findings, and outlines potential future works.

2 Overview of LTE Network and Performance

The fundamental concepts and principles of LTE networks are discussed in this chapter. The chapter will provide a thorough understanding of LTE network design, protocols, and operation. In addition, critical performance indicators and metrics relating to accessibility and integrity degradation are discussed.

2.1 Overview of LTE Network

The evolution of cellular mobile networks has brought significant advancements over the years. The first networks, known as First Generation (1G) systems, relied on analog technology, with Advanced Mobile Phone System (AMPS) being the first commercial cellular network.

With the introduction of Second Generation (2G) systems, digital multiple access technologies like Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA) were introduced, and networks like Global System for Mobile Communication (GSM) and CDMA became prominent. In addition to being digital, 2G systems improved capacity, enhanced security, and offered additional services such as SMS and circuit-switched data. As 2G technology progressed, variations like General Packet Radio System (GPRS) and Enhanced Data Rates for Global Evolution (EDGE) emerged to support packet data services and higher data rates [33][15].

Third Generation (3G) systems were defined by the International Mobile Telecommunications (IMT2000) standard and offered higher transmission rates and improved capacity [33]. The main technologies associated with 3G are:

- Code Division Multiple Access 2000 (CDMA2000): It is based on CDMA technology, offering high-speed data and voice communication.
- Wide-band Code Division Multiple Access (WCDMA): This technology uses a wider frequency band to achieve higher data transfer rates and improved capacity.
- Time Division-Synchronous Code Division Multiple Access (TD-SCDMA): This technology combines time division and synchronous code division access techniques.

Following the advancement of 3G, 4G cellular wireless systems were introduced, representing a significant advancement in speed, capacity, and features [32]. Key factors driving the advancement of 4G architecture include [32, 33]:

- All-IP based: 4G systems are built on an all-IP infrastructure, which facilitates efficient data transmission and convergence of diverse communication technologies.
- Cost reduction: 4G systems aim to optimize network resources and minimize operational costs.
- Reduced data latency and signaling load: 4G systems prioritize the reduction of data transfer delays (latency) to enhance real-time communication and improve overall user experience.
- Inter-working mobility across different access networks: 4G systems enable seamless mobility management, allowing smooth handovers between various access networks.
- Always-on user experience with flexible QoS support: 4G systems ensure an "always-on" connectivity experience and offer flexible QoS mechanisms to cater to diverse traffic types.
- Worldwide roaming capability: 4G systems facilitate global roaming, enabling users to access services while traveling across different countries and operator networks.

4G systems use different access technologies, providing coverage and support for various devices. The commonly used access technologies in 4G systems are [15, 41]:

- **LTE and LTE-Advanced:** LTE is widely used in 4G systems. Although the initial release did not meet all the requirements for International Mobile Telecommunications (IMT) Advanced, subsequent releases like LTE-Advanced were designed specifically to meet 4G requirements.
- **Worldwide Interoperability for Microwave Access (WiMAX):** It offers high-speed wireless connectivity over long distances and can be used in areas with limited LTE coverage. However, WiMAX has seen limited deployment compared to LTE and is not as prevalent in most.

The LTE air interface is standardized by 3GPP. It uses Orthogonal Frequency Division Multiplexing (OFDM) in the downlink and single carrier Frequency Division Multiple Access (FDMA) in the uplink. LTE also uses various modulation techniques, multiplexing, scheduling, link adaptation, Hybrid-automatic Repeat Request (HARQ), Multiple Input Multiple Output (MIMO), and transmit diversity [1, 32].

2.2 LTE Architecture and Protocols

LTE was introduced in 2004 with the goal of implementing a new radio access technology focused on packet-switched data. The entire 3GPP network design, known as System Architecture Evolution (SAE), has been evolving in parallel with LTE. SAE includes both the LTE radio access network and the EPC network. LTE and Evolved Packet Core (EPC) are combined to form the Evolved Packet System (EPS), in which both the core network and the radio access are completely packet-switched [5, 29]. Figure 2.1 depicts the overall network architecture.

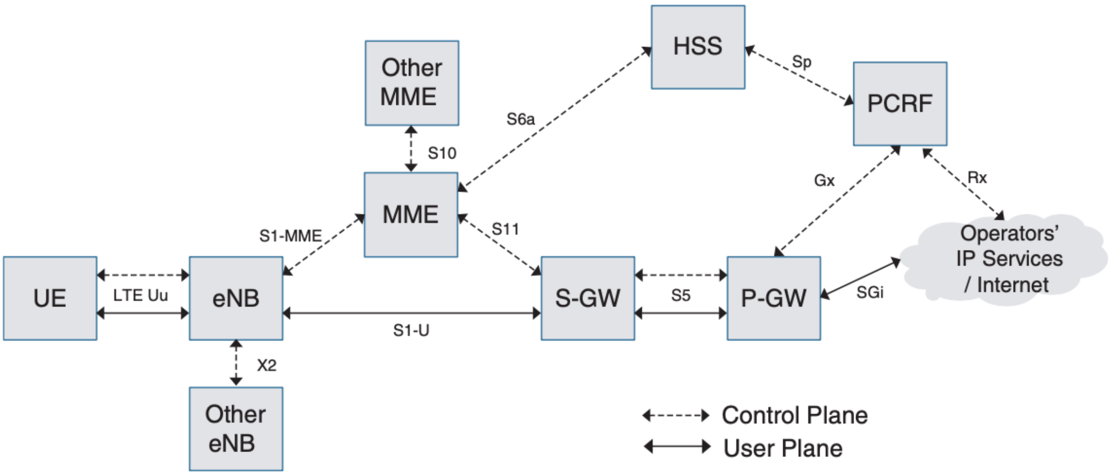


Figure 2.1: Basic EPS entities and interfaces [15].

The LTE system is made up of two main parts: the access network and the core network (EPC). Each element is connected together using standardized interfaces. The core network is responsible for routing data traffic and managing sessions. The access network is responsible for transmitting and receiving data between the User Equipment (UE) and the core network.

2.2.1 The Access Network

The LTE radio access network is flat, meaning that there is no central controller. Instead, all eNodeBs are equal and communicate with each other directly. This allows for faster and more efficient communication.

The eNodeBs communicate with each other using the X2 interface and with the EPC using the S1 interface. The X2 interface is used for handovers, while the S1 interface is used for data transmission and control signaling. The eNodeBs also communicate with the UEs using the Access Stratum (AS) protocols. The eNodeB is responsible for all radio-related functions [29]:

- Radio Resource Management: It comprises resource allocation in uplink and downlink as well as scheduling, radio bearer control, radio admission control, and radio mobility control.

- Header Compression: This performed in Packet Data Convergence Protocol (PDCP) to compress IP packet headers, which helps in the efficient utilization of radio resources, particularly for small packets such as Voice over Internet Protocol (VoIP).

- Routing of User Plane data towards Serving Gateway;

- Connectivity to the EPC: includes signaling to the Mobility Management Entity (MME) and the bearer path to the Serving Gateway (S-GW).

- Scheduling and transmission of broadcast information
- Security: Encrypt the data transmitted over the radio interface

2.2.2 The Core Network

The EPC is a significant advancement over the GSM core network and only supports access to the packet-switched domain [5]. It is composed of different types of nodes.

- **Mobility Management Entity**

  The MME is a control node in the EPC that manages user access, resources, and mobility. It controls all control-plane functions for subscribers and sessions. It tracks UE in idle mode, activates/deactivates bearers, selects S-GW, authenticates users, terminates Non-access stratum (NAS) signaling, generates temporary identities, and checks authorization to camp on the Public Land Mobile Network (PLMN) [40][4].

  Furthermore, it handles ciphering/integrity protection, security key management, and even lawful interception. It's responsible for mobility between LTE and 2G/3G, with the S3 interface terminating at the MME. The NAS protocols facilitate control-plane communication between the UE and the MME. They handle UE mobility, session management, and IP connectivity with the PDN Gatewa (P-GW). They also define rules for mapping parameters during mobility across different access networks. Most importantly, they provide NAS security through integrity protection and ciphering of signaling messages [4].

- **Serving Gateway**

  The S-GW is a user-plane element that manages user-plane mobility and acts as a demarcation point between the radio access and core networks. It maintains data paths between eNodeBs and the P-GW [16]. The S-GW routes and forwards user data packets, acting as the mobility anchor for the user plane during inter-eNodeB handovers and as the anchor for mobility between LTE and other radio access technologies. For idle mode UEs, the S-GW terminates the downlink data path and triggers paging when downlink data arrives for a UE. It also performs replication of the user traffic in case of lawful interception [16, 32].

- **Packet Data Network Gateway**

  The P-GW is the termination point of the packet data interface toward the Packet Data Networks (PDN). It supports policy enforcement (such as applying operator-defined rules for resource allocation and usage), packet filtering (such as packet inspection), and charging. P-GW provides connectivity from the UE to external packet data networks and acts as the anchor for mobility between 3GPP and non-3GPP technologies [16, 32].

- **Home Subscriber Server**

The Home Subscriber Server (HSS) is a central database that contains user and subscription related information. The functions of the HSS include mobility management, call and session establishment support, user authentication, and access authorization. The HSS is based on legacy Home Location Register (HLR) and authentication center functions in previous 3GPP releases [32].

2.2.3 Interfaces and Protocols of LTE

The LTE interfaces define points of interaction between various network elements or entities. They allow the interchange of control signaling, data, and management information [13]. Here are some of the most important LTE interfaces and protocols [13, 41]:

- S1 Interface: The S1-MME interface is the main interface between the eNodeB and the MME in the LTE core network. It carries control plane signaling messages such as initial attach, handover, paging, and session management. S1-U establishes a connection between eNodeB and S-GW for user traffic.
- X2 Interface: It allows communication between eNodeBs in the same LTE network. It supports handover coordination, neighbor cell information exchange, load balancing, interference coordination, and synchronization.
- S11 Interface: The S11 interface connects the S-GW and the P-GW. It is responsible for managing user-plane data during handover and provides connectivity to external networks such as the internet.
- S6a interface: The S6a interface connects the MME to the LTE core network's HSS. It facilitates authentication, authorization, and subscriber-related activities by allowing the MME to retrieve subscriber data from the HSS.
- S5/S8 Interface: The S5/S8 interface is used in the LTE core network for interaction between the MME and the S-GW. It enables mobility-related functions such as authentication, bearer management, and policy enforcement for user traffic.
- S-Gi Interface: The S-Gi interface links the P-GW to external packet data networks such as the Internet or private IP networks. It acts as a point of entry and exit for user data, ensuring connectivity between LTE and external networks.

In LTE, various protocols are used to establish and maintain communication links, manage mobility, handle signaling messages, and transport user data. Through the interfaces between UE and EPS, protocols are divided into AS and NAS [15]. The AS protocols are responsible for managing the radio interface and handling the transmission and reception of data over the air interface between the UE and eNodeB. They consist of the following layers:

- The Physical Layer (PHY) layer is in charge of signal coding/decoding, modulation/demodulation, multi-antenna processing, and signal mapping to the appropriate physical time-frequency resources. It is also in charge of mapping transport channels to physical channels.

- The Medium Access Control (MAC) layer is in charge of multiplexing data from several radio bearers, HARQ retransmission, and uplink and downlink scheduling. Each UE has just one MAC entity.

- The Radio Link Control (RLC) layer is responsible for segmentation, concatenation, retransmission, and in sequence delivery to higher levels. If the RLC Protocol Data Unit (PDU)s are received out of sequence as a result of the MAC layer's HARQ operation, the RLC reorders them. Each radio bearer that is set up for a terminal has one RLC entity [15].

- RRC layer is in charge of controlling the establishment, maintenance, and release of radio bearers between the UE and the eNodeB. It operates in the control plane.

- PDCP located above the RLC layer. It provides direct data transport for control plane messages (RRC and NAS) and for user plane packets.

The NAS protocols are responsible for handling the signaling and control procedures related to the establishment, maintenance, and release of the connection between the UE and EPC. They operate above the AS and handle the signaling protocols and procedures required for network registration, authentication, security, session management, and mobility [13].

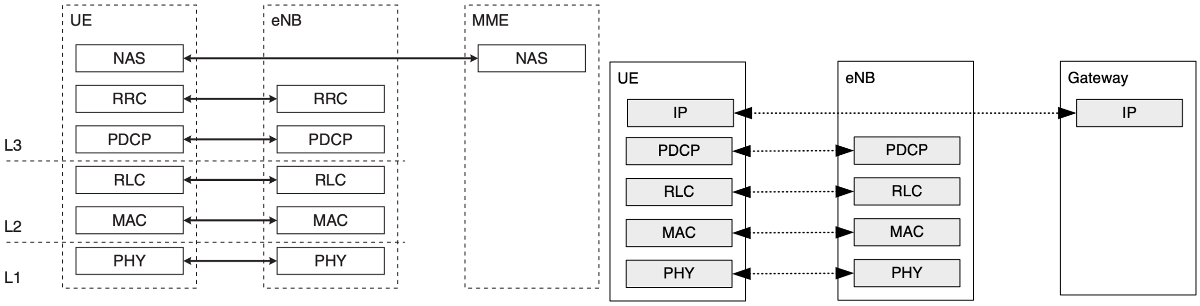
The LTE protocol stack consists of the control plane and the user plane protocols. The control plane is responsible for managing and controlling network functions in LTE. It handles signaling, authentication, mobility management, and session establishment. It also facilitates the establishment and maintenance of connections between the UE and the core network elements. When the UE is in LTE coverage, two control planes are configured to carry signaling messages between the EPS and the UE. The first is given by RRC and is used to communicate between the UE and the eNodeB. The second is responsible for transporting NAS signaling messages between the UE and the MME [12]. Figure 2.2a shows the protocol stack for the control-plane [1]:

- RLC and MAC sublayers perform the functions such as: scheduling and HARQ

- PDCP sublayer performs the control plan functions such as; ciphering and integrity protection

- RRC performs the functions: broadcast, paging, RRC connection management, radio bearer control, mobility functions and UE measurement reporting

- NAS control protocol performs: EPS bearer management; authentication, security control for the signaling for user plane, paging origination



(a) Control plane protocol stack.

(b) User plane protocol.

Figure 2.2: LTE radio interface [1].

The user plane transports user data packets between the UE and the core network elements, such as the P-GW. It ensures efficient and reliable transport of user traffic [13].

- RLC and MAC perform the same functions as for control plan
- PDCP sublayer performs for user plane the function such as: header compression, integrity protection, and ciphering

2.2.4 LTE Bearer Architecture

LTE uses bearers for QoS control instead of circuits. A bearer is a logical path or channel between the UE and the network. It allows for the transmission of user data, control signals, and other information [29]. Multiple applications can operate concurrently in a UE, each with different QoS requirements. For example, a UE can be engaged in a VoIP call while also browsing the internet or downloading a file. VoIP has stricter QoS requirements in terms of latency and delay jitter than web browsing and downloading, but the latter has a far lower packet loss rate. Separate bearers are configured within EPS to fulfill these requirements [12].

There are two types of EPS bearers in LTE: default and dedicated. The default bearer is established during the initial attach procedure and has no specified QoS. The dedicated EPS bearer is typically established during a call setup after transitioning from idle mode, does not allocate any additional IP addresses to the UE, and is linked to a given default EPS bearer. However, it has a defined and usually guaranteed QoS [50].

EPS bearers can be Guaranteed Bit Rate (GBR) or non-GBR bearers. In GBR dedicated network resources connected to a GBR value associated with the EPS bearer are permanently allocated during bearer establishment or modification. Otherwise, it is referred to as a non-GBR bearer. A dedicated bearer can be either a GBR or non-GBR bearer, whereas a default bearer is a non-GBR bearer [50].

- GBR bearers: GBR bearers are set up to support real-time or delay-sensitive services that demand a minimum guaranteed level of bandwidth and service quality [50]. They ensure that particular resources, such as bandwidth and network capacity, are reserved for these services. GBR bearers are typically used for applications such as VoIP calls, video streaming, online gaming, and other time-critical services [50][29].

- Non-GBR bearers: Non-GBR bearers are best suited for non-real-time services that do not require a guaranteed bandwidth level. They are built for applications that can tolerate variations in network conditions and do not have stringent latency or throughput requirements [50].. Web browsing, email, file downloads, social networking applications, and background data transfers are all examples of services that use non-GBR bearers [50][12].

End-to-end bearers in LTE are created using EPS bearers. The EPS bearer architecture (Figure 2.3) is a combination of several underlying bearers that work together to ensure seamless connectivity and efficient data transfer throughout the LTE network [1].

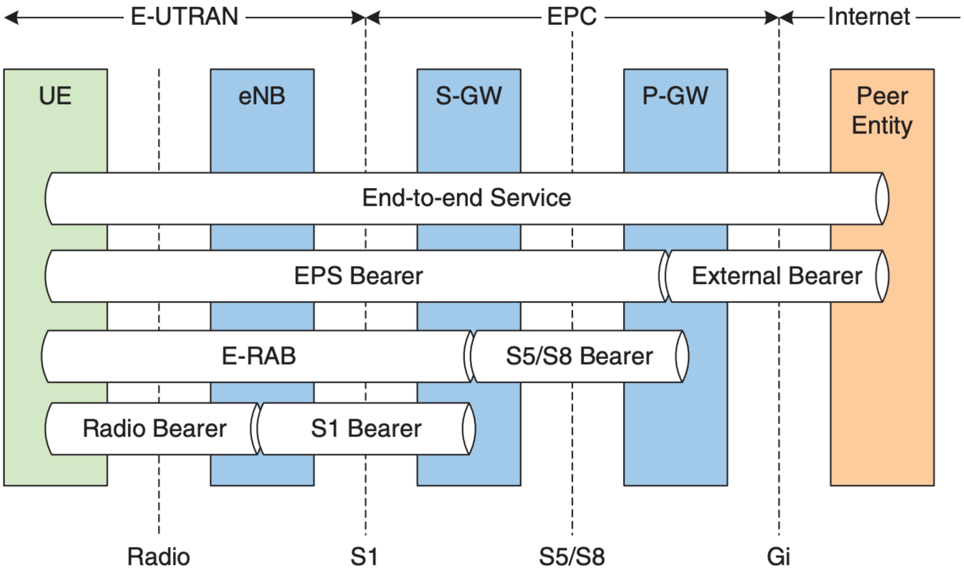


Figure 2.3: LTE bearer services architecture. [1].

- Radio Bearers: Radio bearers are established between the mobile device and the eNodeB. They carry user data and control information over the radio interface, ensuring reliable communication between the device and the network. Radio bearers handle tasks such as modulation, error correction, and encryption/decryption of data.

- S1 Bearers: S1 bearers connect the eNodeB with the EPC through the S1 interface. They transport user and control plane traffic between the radio access network and the core network elements.

- S5/S8 Bearers: S5/S8 bearers are established between the S-GW and the P-GW of the EPC. They facilitate the transfer of user and control plane data between the eNodeB and the external PDNs, such as the internet or private networks.

The UE requires dedicated Signaling Radio Bearers (SRBs) and Data Radio Bearers (DRBs) to exchange data and messages with the network. SRBs are established for the transfer of NAS messages, while DRBs are used to transport user-plane application data [41]. SRBs are established during the initial connection setup between the UE and the eNodeB and are used to exchange control information necessary for the establishment, maintenance, and release of data bearers (such as DRBs) that carry user data. The SRBs are established before DRBs. DRBs are used to transport user-plane application data, such as voice, video, and internet data [1].

An E-RAB uniquely identifies the concatenation of an S1 bearer and the corresponding DRBs. Each E-RAB corresponds to a specific EPS bearer, which defines the end-to-end connectivity and QoS requirements. In LTE, a single UE can support multiple end-to-end services, each of which has its own distinct bearer. Evolved Universal Terrestrial Radio Access Network (E-UTRAN) protocols can address up to 256 unique E-RABs for a single UE [32]. 3GPP has established a set of QoS Class Identifier (QCI) to standardize QoS handling. There are four classes that have a GBR and five classes with non-GBR.

2.3 LTE Network Performance Measurements

LTE Network is a collection of measurable events, parameters, and measurements used to compare performance in terms of meeting mobile networks' strategic and operational goals [15]. The service experienced by end users is measured by using a number of performance indicators that are aggregated to form a KPIs.

KPIs can be mainly grouped as Radio frequency (RF) KPI, Service KPI and Operation KPI. Each KPI category has its own objectives for different purposes of use. RF KPIs is required during the phase of network planning, network roll-out and initial optimization to measure actual values against planned values. On the other hand, service KPIs are used to measure the quality of service experienced by end users, such as the call drop rate and data throughput. They are used during the optimization and commercial introduction of the network, and for debugging specific problems. Lately, operation KPI is continuously collected and analyzed to set the performance and behaviour for further optimization process during all network optimization stages [15]. According to the 3GPP standard, service and operation KPIs are related to six main categories: accessibility, retainability, mobility, integrity, utilization, and availability [3]. It is important to monitor and manage these KPIs to ensure that the LTE network is performing at its best and providing a high-quality experience for end users.

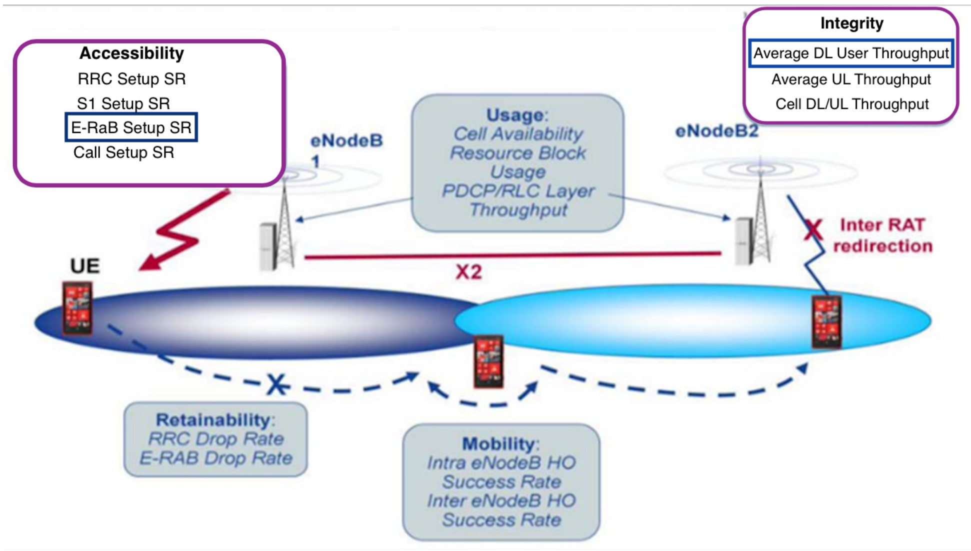


Figure 2.4: LTE performance indicators [49].

2.3.1 Accessibility

Accessibility KPIs identify issues at the EPS attach procedures, call setup, or during tracking area updating as part of LTE mobility. The main procedures whose performance is measured by accessibility KPIs are RRC connection setups, S1 setups, and E-RAB setups. To understand the setup success rates, let's discuss how setups are established in an LTE network taking into account the request by the UE-generated data services..

In LTE, the radio connection between the UE and the network can be either active (RRC_CONNECTED) or not active (RRC_IDLE). In the RRC_IDLE state, the radio connection is inactive. The network has no control over UE mobility, and the UE does not need to provide any measurement reports for updates. However, the UE performs neighbor cell measurement for cell (re)selection. The UE also monitors the Paging Channel for incoming calls as well as system information broadcast on the Broadcast Channel (BCCH) [13, 32]. In the RRC_CONNECTED state, the UE can send and receive data in both the uplink and downlink directions. It measures the downlink radio quality of neighboring cells and delivers RRC measurement reports based on the measurement configuration obtained from the MME. The UE continues to scan the Paging Channel for incoming calls [13, 32]. The service request procedure in LTE ensures the establishment of dedicated bearer resources and the activation of the necessary connections between the UE, eNodeB, MME, S-GW, and P-GW. The steps involved in the service request procedure are as follows [41]:

1. The UE establishes an RRC connection with the eNodeB
2. The UE sends a service request message to the MME to request dedicated bearer resources by including the bearer resource allocation request. The eNodeB establishes an S1 logical connection with the MME for this UE.
3. After authentication and security mode procedures, the MME initiates activation of the default bearer with the S-GW/P-GW by sending the GPRS Tunneling Pro-

tocol - Control Plane (eGTP-C) modify bearer request message to the S-GW. The S-GW activates the required resources and forwards the modify bearer request to the P-GW.

4. The P-GW processes the modified bearer request message and activates the required resources. It responds to the S-GW with the modify bearer response message, which is then forwarded to the MME.

5. The MME initiates the dedicated bearer establishment procedure by sending the eGTP-C bearer resource command to the S-GW. The S-GW processes the bearer resource command and forwards it to the P-GW.

6. The MME sends the E-RAB setup request to the eNodeB to set up the bearer between the eNodeB and the S-GW. It also piggybacks the NAS activate dedicated EPS-bearer context request to the UE.

7. The eNodeB allocates the resources for the radio bearers using an RRC connection reconfiguration request message to the UE and includes the received NAS message. The UE establishes the radio bearers and responds with an RRC connection reconfiguration complete message to the eNodeB.

8. The eNodeB sends the E-RAB setup response to the MME, indicating that the radio bearers are established between the eNodeB and the UE. The UE sends the activate dedicated EPS bearer context accept NAS message the MME via the eNodeB.

9. The MME sends a create bearer response to the S-GW to complete the dedicated bearer activation. The S-GW then forwards the message the P-GW.

From the above description, step 1 is the RRC setup, step 2 is the S1 setup, and steps 3-9 are the E-RAB setups. These steps are used to calculate network performance measurements, such as the network accessibility KPIs. Network accessibility KPIs assess the likelihood of a user accessing the network and requesting services under specific operating conditions [1]. This includes measuring the success rate of the RRC, S1, and E-RAB setups.

1. RRC Setup Success Rate

The RRC protocol exists at IP level (layer 3) between UE and eNodeB. The major functions of the RRC protocol include connection establishment and release functions, broadcast of system information, radio bearer establishment, reconfiguration/release, RRC connection mobility procedures, paging notification and outer loop power control [13].

The RRC connection establishment is used to make the transition from RRC Idle mode to RRC Connected mode. The UE must make the transition to RRC Connected mode before transferring any application data, or completing any signaling procedures. However, it must first be synchronized in the uplink. This is accomplished by sending a Random Access Channel (RACH) preamble (Message 1) to the eNodeB, to which the eNodeB answers with a random access response also called Message 2. The RRC connection establishment procedure is always initiated by the UE but can be triggered by either the UE or the network by different causes [3].

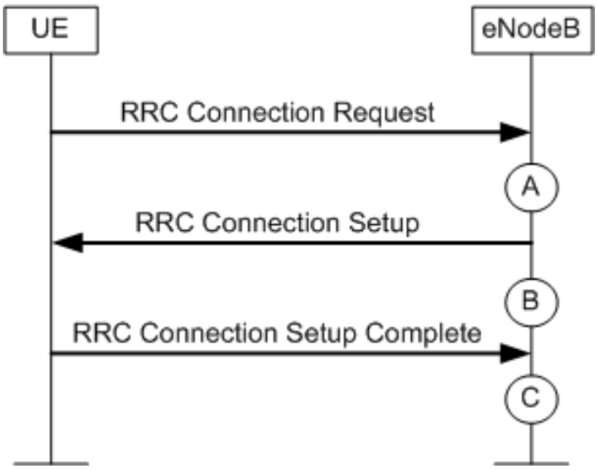


Figure 2.5: RRC connection setup procedure [3].

After the UE has done initial cell selection and determined the best suited cell for radio access, it sends an RRC connection request message also known as Message 3, to the eNodeB. This RRC connection request message, in addition to the UE identity, contains an establishment cause that allows distinguishing between mobile-originating signaling (most commonly observed for tracking area units and Attach messages), mobile-originating data calls, mobile-terminating (idle UE responds to a paging message) connections (all data calls), emergency calls, and high-priority access calls [41].

After the RRC connection request message is received, the eNodeB should reply by sending an RRC connection setup message. This RRC Connection setup contain SRBs 1 and some basic radio parameters like power control and Channel Quality Indicator (CQI) periodicity. Before this, the UE uses SRBs 0 to send the RRC message. If the RRC connection is successfully established, the UE will send an RRC connection setup complete message to the eNodeB. If the UE desires to send it, this message also contains the NAS information. At this moment, the RRC setup is completed and SRBs 1 is also setup [3, 41].

The RRC setup success rate KPI is calculated by analyzing counters measured at the eNodeB when receives an RRC Connection Request message from the UE shown in Figure 2.5. The eNodeB counts the number of RRC connection attempts at measurement point A and the number of successful RRC connections at measurement point C. Using an equation, the RRC connection setup success rate RRC_{SSR} can be computed per cell as follows:

$$RRC_{SSR} = \frac{RRC_{Success}}{RRC_{Attempt}} x100\% \tag{2.1}$$

Where $RRC_{Success}$ number of times the RRC connection was successfully established and $RRC_{Attempt}$ is number of RRC connection was attempted.

However, instead of sending the RRC connection setup message, the eNodeB may reject the UE's connection request by sending RRC Connection Reject. RRC setup success rate represents the effectiveness of the initial radio connection establishing procedure. A high RRC setup success rate indicates greater accessibility, fewer call setup errors, and a better user experience.

2. **S-1 Setup Success Rate**

   After the UE has completed the RRC Connection which has been explained in the above, the eNodeB initiates S1 Initial UE message to the MME indicating the purpose of the UE (attach, tracking area update, Circuit Switched Fallback (CSFB), service request etc) and its credentials. It also contains the NAS configuration information related to users, based on which the MME sets up S1 signaling connections for UE. Once the MME receives this message, the first S1 message sent by the MME may be Initial Context Setup Request, Downlink NAS transport, or UE Context release Command. Receiving any of these messages indicates that the S1 signaling connection is set up successfully [26].

$$S1_{SSR} = \frac{S1_{Success}}{S1_{Attempt}} x100\% \tag{2.2}$$

   Where $S1_{Success}$ is number of times the S1 signaling connection was successfully established and $S1_{Attempt}$ attempted.

   S1 Interface success rate reflects the effectiveness of the S1 interface, which directly impacts mobility management, handover success, and overall network accessibility. Higher success rates ensure seamless connectivity during handovers and reliable communication between network elements [40].

3. **E-RAB Setup Success Rate**

   An E-RAB is a logical link between the UE and the EPC that enables data transmission. It is part of the EPS bearer and allows the flow of user data and signaling information between the UE and the network, which includes the MME and the S-GW. The E-RAB setup is part of the radio interface establishment process in LTE networks. It involves the establishment of bearers for data transmission between the UE and the network [33].

   The E-RAB setup procedure follows the initial radio connection establishment and authentication processes. After the RRC connection is established, the eNodeB sends the Initial UE message to the MME. The MME may respond with an S1 Initial Context Setup Request message, which contains the E-RAB ID and QCI that must be configured for the UE. It also contains the maximum bit rate configuration of the bearer, which specifies the maximum data rate allowed for communication on that particular E-RAB [26, 40].

The eNodeB then reconfigured the UE using an RRC Connection Reconfiguration message, which adds the SRBs 2 and DRBs based on the QCI requirement. The eNodeB also sends a Security Mode Command to the UE to configure the security context. Once these steps are completed, the eNodeB responds to the MME with an S1 Initial Context Setup Response, indicating a successful E-RAB setup.

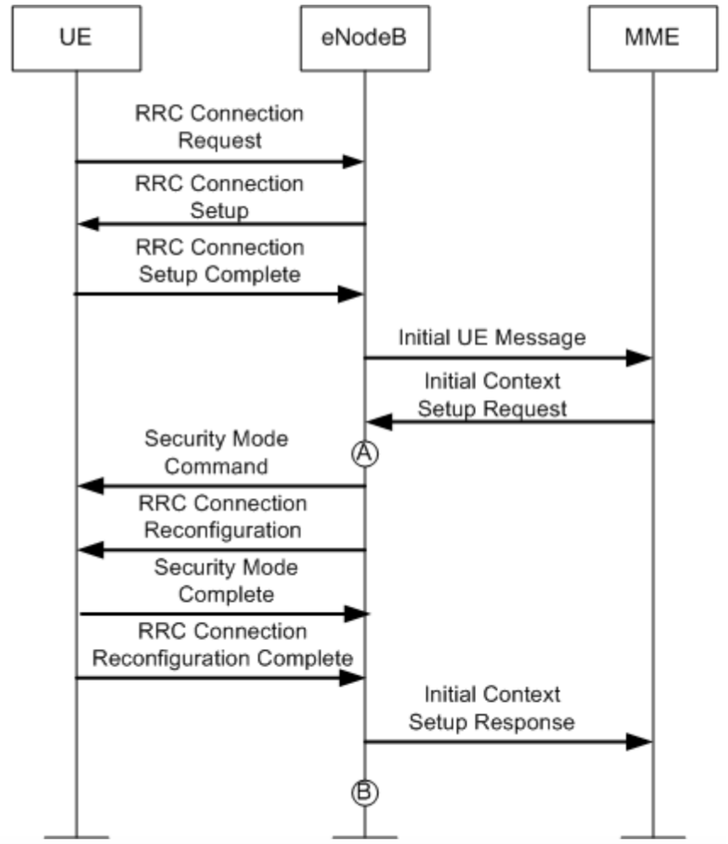


Figure 2.6: Measurement points for UE-triggered E-RAB setup [26].

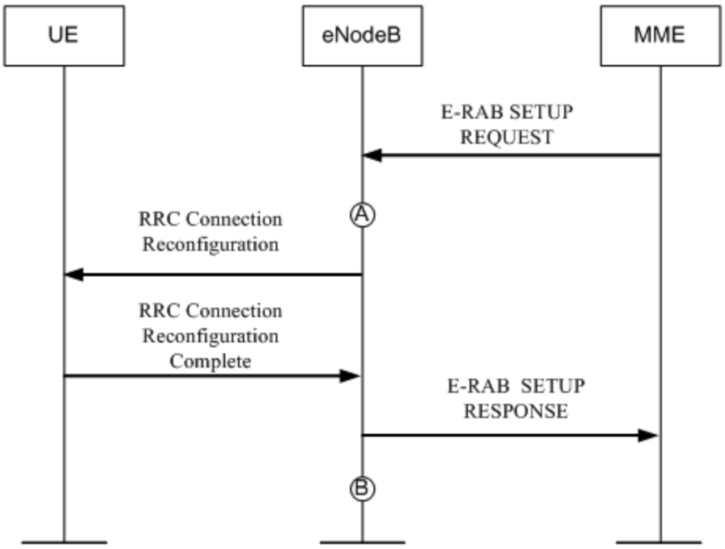


Figure 2.7: Measurement point for MME-initiated E-RAB setup [26]

The E-RAB setup success rate KPI represents the success rate of E-RAB setup for all services, including VoIP, within a specific cell or radio network. This KPI is calculated using two counters measured at the eNodeB: the E-RAB connection setup attempts (all) counter and the successful E-RAB setup (all) counter.

As shown in Figure 2.6 eNodeB collects the number of E-RAB connection setup attempts at measurement point A, and the number of successful E-RAB connections is counted at measurement point B [3, 26]. By comparing these two counters, the E-RAB setup success rate (All) can be calculated as:

$$ERAB_{SSR} = \frac{ERAB_{Success}}{ERAB_{Attempt}} x100\% \tag{2.3}$$

Where $ERAB_{Success}$ successful E-RAB setups and $ERAB_{Attempt}$ is E-RAB connection setup attempts.

This indicates the effectiveness of establishing data bearers. A high E-RAB setup success rate indicates that the network is capable of quickly and reliably establishing data bearers, allowing for smooth data transmission and minimizing service disruptions. Efficient data transfer is crucial for providing a seamless user experience and ensuring that services can be accessed without interruptions or delays. On the other hand, a low E-RAB setup success rate may indicate issues with network performance, congestion, or other factors that can lead to data-related failures and reduced network accessibility [1, 15, 41].

2.3.2 Integrity

To evaluate network performance, the 3GPP defines integrity as one of the basic categories for KPIs [3]. It attempts to measure how the RAN impacts the service quality provided to the users. The integrity KPIs indicate service quality provided for UEs in an

E-UTRAN. Within this category, two different types of metrics are commonly defined: latency and throughput.

In the downlink, the latency is related to the delay experienced by the users, measured as the time from the reception of data in the eNodeB to the transmission of the first packet over the radio interface. The throughput is the data rate experienced by the users, measured as the data volume per elapsed time unit on the radio interface [3]. Some of the integrity KPIs are discussed as follows:

1. **Average User Throughput**

   Average user throughput refers to the measurement of data transfer speed achieved by an individual user within a particular cell or network. It is calculated using the formula:

   $$Throughput_{User} = \frac{PDCP_{Vol}}{Time}[Mbps] \tag{2.4}$$

   Where $PDCP_{Vol}$ represents the total volume of PDCP Service Data Units (SDUs) transferred per cell and reporting output period, excluding data transferred in the Transmission Time Interval (TTI) emptying the buffer (referred to as 'last TTIs'), and $Time$ is the time used to send the information excluding last TTIs [2]. Both $PDCP_{Vol}$ and $Time$ are aggregated measurements of all users in a cell. The purpose of excluding data transferred during certain time intervals, known as "last TTIs," is to eliminate any non utilized periods and create a measurement that is independent of the file size being transferred. This allows for a more accurate representation of the actual throughput experienced by users in the cell [2]. This definitions are valid for downlink and uplink channels.

2. **Cell Downlink Average Throughput**

   The cell downlink average throughput is a measure of the capacity and efficiency of the network in delivering data to the end users in a cell. It is calculated as the total PDCP data volume transferred in a cell and reporting output period considering all TTIs divided by the scheduler activity time [2, 26].

   $$Throughput_{cell} = \frac{PDCP_{vol}}{Time_{sch}}[Mbps] \tag{2.5}$$

   Where $PDCP_{vol}$ is the total PDCP SDUs data volume transferred in a cell and ROP considering all TTIs, and $Time_{sch}$ is the scheduler activity time. $Time_{sch}$ is incremented by 1 milliseconds is every TTI with data to be scheduled. Therefore, $Throughput_{cell}$ is the aggregated user throughput in a cell when resource are being scheduled [2].

   A higher cell downlink average throughput indicates a network with better capacity to handle data traffic and deliver faster download speeds to users, resulting in a better user experience. Conversely, a lower cell downlink average throughput suggests that the network may be congested or experiencing limitations in delivering data efficiently [2, 26].

As part of their network performance management activities, telecom operators monitor and optimize the network performance indicators. By analyzing this parameter, they may discover areas for improvement, optimize network setups, and fix any issues that may affect overall service quality [2, 26].

2.4 Root Cause Analysis in Cellular Networks

2.4.1 Network Troubleshooting

Network troubleshooting is the process of identifying and resolving problems with a network. It is a critical part of network management and optimization. The goal of network troubleshooting is to restore service to users as quickly as possible and to prevent future problems from occurring [33]. In the context of cellular networks, network troubleshooting can be used to identify and resolve events that has an impact on the network. This could include problems such as network outages, network degradation, and problems with specific users. Here are key terms related to network troubleshooting:

- **Degradation:** is a decrease in the quality of service provided by a network. This could manifest itself in a number of ways, such as increased latency, decreased throughput, increased packet loss or dropped calls. Network degradation can be caused by a number of factors, such as overloading the network, interference, or environmental conditions.
- **Outage:** is a complete loss of service in a network. This can be caused by a number of factors, such as a power outage, a hardware failure, or a software bug.
- **Problem:** an issue that affects a specific user or group of users, but does not result in a complete loss of service.
- **Failure:** is a complete loss of functionality of a network component.
- **Fault:** is a problem with a network component that causes the network to malfunction.

There are two approaches to identifying and resolving network problems: active and proactive network troubleshooting [37]. Active network troubleshooting is the process of actively searching for network problems. This may involve monitoring network traffic, running diagnostic tools, or simply being on the lookout for any signs of trouble. It is often used in response to a specific problem that has been detected by a monitoring system or reported by users. On the other hand, proactive network troubleshooting is the process of taking steps to prevent network problems from occurring in the first place. This may involve things like regularly checking for software updates, implementing security measures, and monitoring network performance. Proactive network troubleshooting can help to avoid costly downtime and improve the overall reliability of a network [53].

By following the steps outlined below, network engineers can identify and resolve problems quickly and efficiently, ensuring that the network remains available and reliable for users. Network troubleshooting can be divided into three main phases [54, 42]:

1. **Fault detection**

   This process involves identifying a network-wide fault, which may be observed by users or devices. It could manifest as an anomaly or issue affecting the network's performance, connectivity, or services. Fault detection techniques and tools are used to identify the presence of a fault, but they do not necessarily provide information about the underlying causes.

2. **Fault localization**

   Once a network-wide fault is detected, the next step is to localize and pinpoint the specific locations and types of faults associated with the observed issue. This process aims to narrow down the scope of the problem and identify where exactly the faults are occurring within the network infrastructure. Various diagnostic techniques and tools are used to gather data and analyze the affected components, such as routers, switches, or communication links.

3. **Root cause analysis**

   Once the fault has been detected and localized, the RCA process can be used to identify the underlying cause of degradation and problem. The RCA process has been utilized in many sectors and is usually focused with determining the root causes of events that have safety, health, environmental, quality, reliability, production, and performance impacts. RCA is a systematic approach to identifying the underlying causes of a problem [44]. RCA can be used to improve the reliability and performance of a system by identifying and addressing the root causes of problems. It is typically used after an incident has occurred to identify the underlying causes of the problem and to develop corrective actions to prevent it from happening again.

   This can help to prevent future degradation and problems from happening and to improve the reliability and performance of the network. The RCA process typically involves the following main steps [46, 44]:

   - **Data collection:** gather as much information as possible about the event or the problem. This may include data from network logs, monitoring tools, and interviews with affected users. The goal is to create a detailed timeline of the event and identify any potential contributing factors.
   - **Determining potential causal factors:** Once the data has been collected, it can be used to create a causal factor chart. This will shows the sequence of events that led to the occurrence. The chart can be used to identify the root cause of the event, as well as any other factors that may have contributed to it.

- **Root cause/s identification:** using available RCA tools or techniques to discover the root causes of each causal factor. Where the root cause of an event is the underlying factor that made it happen. Once the root cause has been identified, it can be addressed to prevent the event or problem from happening again.
- **Recommendation generation and implementation:** recommendations can be made to prevent the event from happening again. These recommendations may include changes to policies, procedures, or network configurations. It is important to implement the recommendations promptly to ensure that the event does not happen again.

2.4.2 Techniques of Root Cause Analysis

Many RCA techniques have been presented in recent years, which can be classified into three main types: knowledge-based, data-driven and hybrid techniques.

1. **Knowledge-based Techniques**

   Knowledge-based techniques construct cause-and-effect relationship maps based on a prior understanding of information flow. These techniques rely on expert knowledge to identify the root causes of problems. This knowledge is typically captured in a knowledge base, which is a repository of information about the system being analyzed. Knowledge-based techniques are typically used when the problem is well-understood and there is a wealth of expert knowledge available [39]. Some examples of knowledge-based RCA techniques include [46]:

   - **Expert rules:** Expert rules are rules that are created by experts in the field of network management. The rules specify the conditions that must be met for a problem to occur. For example, an expert rule might state that ”if a router is overloaded, then it will experience packet loss.”
   - **Fault trees:** Fault trees are graphical models that show the sequence of events that can lead to a problem. Fault trees can be used to identify the root cause of a problem by tracing back through the sequence of events. For example, a fault tree for a network outage might show that the outage could be caused by a power outage, a hardware failure, or a software bug.
   - **Fish-bone diagrams:** Fish-bone diagrams are a type of diagram that is used to organize the causes of a problem into categories. The categories are typically represented by the bones of the fish, and the causes are represented by the branches of the bones. Fish-bone diagrams can be used to identify the root causes of problems by helping to visualize the relationships between different causes.

2. **Data-driven Techniques**

Data-driven techniques entail creating cause-and-effect relationship maps exclusively from data without the use of domain knowledge. These methodologies are distinguished by intensive field research activities. Data-driven techniques can be used to identify patterns in data that may not be obvious to humans. This can be helpful for identifying problems that are not well-understood or for which there is limited expert knowledge [46]. Some examples of data-driven RCA techniques include

a) **Statistical approaches:** Statistical approaches use a variety of statistical techniques to determine the fundamental cause of observed anomalies at the population level from data samples [46]. Granger causality, transfer entropy, and dynamic time warping are examples of statistical techniques.

b) **Metric-based approaches:** Based on rationale and assumptions, metric-based techniques build nodes and edges in a graph and find the root cause using graph-based metrics such as centrality and shortest distance [46]. For example, a metric-based technique might find the root cause of a network outage by identifying the node in the network with the highest degree of centrality.

c) **Machine learning approaches:** Machine learning approaches learn a model from input and output data in order to discover the root cause. For example, a machine learning approach might be trained on a dataset of network outages and their root causes. Once the model is trained, it can be used to predict the root cause of new outages.

3. **Hybrid Techniques**

   Hybrid techniques combine the benefits of both knowledge-based and data-driven approaches by creating qualitative causality maps from domain knowledge and then quantifying the degree of cause and effect from data [46]. Hybrid techniques can be used to take advantage of the strengths of both approaches. For example, a hybrid technique could use expert knowledge to identify a set of potential root causes, and then use data to narrow down the list of potential causes.

2.4.3 Benefits of RCA in Cellular Networks

As discussed above, RCA refers to the process of examining and identifying the underlying reasons for network problems or failures. It assists the telecom operator and network engineers in understanding why problems (degradation, failure) occur and developing effective ways to prevent their recurrence.

RCA in cellular networks includes investigating different components such as network infrastructure, equipment, software, protocols, configuration settings, and operating procedures. By identifying the root causes, network operators can take corrective actions to improve network performance, reliability, and user experience [33]. RCA is important in cellular networks as it provides various advantages [53, 57, 24].

- **Reduced downtime and service disruptions:** RCA helps to reduce downtime and service disruptions by detecting the root causes of network problems. By understanding the root causes, telecom operators can take proactive steps to avoid future occurrences and provide uninterrupted services to their customers.
- **Improved network reliability and performance:** RCA increases network reliability and performance by addressing the root causes of system degradation. This enables telecom companies to optimize their network architecture, improve stability, and consistently deliver high-quality services.
- **Improved customer satisfaction and loyalty:** RCA helps to improve customer satisfaction and loyalty. Telecom companies can build trust with their customers by quickly resolving issues and limiting their recurrence, resulting in higher satisfaction and long-term loyalty.
- **Optimized resource allocation and reduced costs:** RCA enables telecom operators to optimize resource allocation while reducing their expenses. By identifying the root causes of inefficiencies and bottlenecks, they can make informed decisions on resource planning, deployment, and maintenance, resulting in cost savings and enhanced operational efficiency.

3 Fundamentals of CNN and SHAP

This chapter will discuss the machine learning models and algorithms used in this thesis work to predict or classify the degradation of LTE networks. SHAP method is also discussed which is used to interpret the prediction model and give high score values for the root causes of degradation.

3.1 Machine Learning

New advancements in mathematics and computer science provide opportunities to organize and analyze vast amounts of (complex) data automatically. In particular, the different machine Learning approaches promise fast and reliable results [20]. Machine learning is a branch of artificial intelligence that focuses on algorithms that can discover patterns automatically and make predictions or decisions based on data. Artificial Intelligence (AI) is a discipline of computer science focused on developing systems that can accomplish activities that normally require human intelligence. These tasks may involve speech recognition, decision-making, problem-solving, and others [17].

Machine learning algorithms are commonly categorized into supervised learning, unsupervised learning, and reinforcement learning. Supervised learning makes use of labeled data to find function approximations from the input data to the target. It is called supervised since the labels of the dataset provide the correct output to each of its inputs. In other words, the computer needs a teacher or a supervisor who tells it the correct answer to learn. On the contrary, unsupervised learning methods use unlabeled data and let the models find patterns in it independently. These models are commonly used for exploratory data analysis. In reinforcement learning agents learn from interactions with their environment. By successively exploring the state space the agent learns the behavior that optimizes some predefined reward function [47, 20].

An important finding in machine learning is that no single machine learning model is optimal or appropriate for all problems [38]. The performance of machine learning models depends on several factors, including the data, the problem definition, and the use case. The data that is used to train a machine learning model is essential. The model will only be as good as the data that it is trained on. The problem definition also plays a role in the performance of a machine learning model. If the problem is not well-defined, the model will not be able to learn effectively. The problem definition should be clear and concise, and it should specify the desired output of the model. Also, the number of input features can affect the complexity of the model and the amount of data that the model needs to learn. For example, a model with 10 input features will need more data to learn than a model with 5 input features [38]. The best machine learning model for a particular problem will depend on the specific factors of the problem. It is important to evaluate different models and compare their performance to find the best fit for the problem.

3.1.1 Deep Learning

Deep learning, also known as DNN or deep neural learning, is a type of machine learning that uses artificial neural networks to learn from data. Deep learning models are trained on large datasets, and they can learn to identify patterns in data that are too complex for traditional machine learning algorithms to recognize [9, 17].

Artificial Neural Networks (ANN)

The essential building blocks of deep learning are ANN. ANN are inspired by the structure and function of the human brain, and they are made up of interconnected nodes, or artificial neurons, that are structured in layers [55]. An input layer, one or more hidden layers, and an output layer are common components of ANN.

- **Input layer:** The input layer is the first layer of an ANN, and it receives the input data.
- **Hidden layers:** The hidden layers are the intermediate layers of an ANN, and they are responsible for learning the features of the input data.
- **Output layer:** The output layer is the final layer of an ANN, and it produces the output of the network.

In the human brain, biological neurons take input from other neurons, form an action potential, and then output signals to subsequent neurons via synapses. Likewise, information flows through the network in ANN, from the input to the output layer. Each neuron in a layer receives inputs from the neurons in the previous layer and then passes its output to the neurons in the next layer. This process is repeated until the final result is provided by the output layer [9].

In ANN network every connection has a weight. Weights are important in learning because they determine the strength of the link between neurons. When a neuron receives an input, it multiplies the input by the weight of the connection and then applies an activation function to the result. The activation function determines how the neuron responds to the input.

Activation Function

The activation function is a mathematical function that is applied to the weighted sum of the inputs to a neuron. The activation function determines how the neuron responds to the input. Some common non-linear activation functions include the sigmoid function, the tanh function, and the Rectified Linear Unit (ReLU) function.

- Sigmoid function: takes real numbers as its input and binds the output to a value between 0 and 1. The sigmoid function has a ’S’ shaped curve. The mathematical formula for sigmoid is:

$$\phi(x) = \frac{1}{1+e^{-x}} \tag{3.1}$$

- ReLU function: is used to convert all of the input values to positive numbers. Output 0 if the input is less than 0, and the input itself if the input is greater than or equal to 0. The mathematical representation of ReLU is:

$$\phi(x) = max(0, x) \tag{3.2}$$

- Hyperbolic tangent (tanh) function: is used to keep the input values (real numbers) to a range between [-1, 1]. Tanh’s mathematical representation is:

$$\phi(x) = \frac{e^{2x}-1}{e^{2x}+1} \tag{3.3}$$

The activation function is important because it allows the network to learn non-linear relationships between the input and output data. Without the activation function, the network would only be able to learn linear relationships [21].

Optimizers

The optimizer function plays a critical role in training a neural network. It is a mathematical algorithm that calculates how much the loss function will change when making a small adjustment to the weights of the neurons [8]. The optimizer function aims to find the best set of weights that minimize the loss function and improve the performance of the neural network during training.

Different optimizers use various techniques to update the weights of the neural network. Some common optimizers include Stochastic Gradient Descent, Adaptive moment estimation (Adam), and AdaGrad [8]. Each optimizer has its advantages and disadvantages, and the choice of optimizer depends on the specific problem and data being used. Among these optimizers, Adam is widely used in deep learning.

Adam optimizer uses adaptive learning rates to update model parameters, taking into account both the gradient mean and variance. This enhances the optimization process and helps in achieving faster convergence in training deep neural networks compared to fixed learning rate methods like SGD [23].

Hyperparameters

Hyperparameters are crucial settings that determine the behavior and performance of a machine learning model. Unlike model parameters, which are learned from training data, hyperparameters are set manually or through optimization techniques [38, 23]. In this thesis, the following hyperparameters were considered:

- **Number of layers and Number of neurons in a layer:** The structure of an ANN is determined by the number of layers it has, as well as the number of neurons in each layer. The depth of the network refers to the number of layers in an ANN. The complexity of the problem being solved typically determines the number of neurons in each layer [55]. "Deep" learning refers to the depth of these networks. DNN often have multiple hidden layers, enabling them to learn complex patterns in the data. The compositional nature of DNN allows them to represent complex functions as compositions of simpler functions, thus facilitating the learning of more intricate patterns in the data [9].
- **Number of epochs:** An epoch refers to a complete pass through the entire training dataset by the learning algorithm. The number of epochs defines how many times the training process iterates over the entire dataset. Choosing an appropriate number is crucial to balance convergence and overfitting. Too few epochs may result in an under-trained model, whereas too many epochs can lead to excessive training time or overfitting.
- **Batch size:** During training, instead of using the entire dataset, it is common to divide it into smaller subsets called batches. The batch size hyperparameter determines the number of training samples processed at once before updating the model's parameters. Selecting an optimal batch size can impact training time, memory requirements, and convergence speed. Smaller batch sizes may lead to noise in gradient estimation, while larger batch sizes might require more memory.
- **Learning rate:** The learning rate controls the step size at which a model's parameters are updated during the optimization process. It determines how quickly the model adapts to new data. Selecting an appropriate learning rate is crucial for efficient convergence. A high learning rate may cause instability, preventing convergence, while a low learning rate might slow down the training process significantly.

In summary, choosing the right hyperparameters for a model is a challenging task that impacts its performance and behavior. Properly fine-tuning hyperparameters using various techniques, such as grid search, random search, or Bayesian optimization, is essential to achieve optimal model performance [23]. In this thesis, the hyperparameters were fine-tuned using grid search to achieve the best possible performance.

Type of DNN Architecture

There are many different types of deep learning architectures, but some of the most common include MLP, CNN, and Recurrent Neural Networks (RNN). They all consist of interconnected neurons that are organized in layers

- **MLP:** MLPs are the simplest type of ANN, consisting of one or more hidden layers of fully connected neurons. MLPs are typically used for classification tasks, such as image recognition and natural language processing [8, 23]
- **RNN:** RNN are a type of DNN that are designed for processing sequential data, such as time series or text. RNN have a feedback loop, which allows them to learn long-term dependencies in the data. RNN can be used for tasks such as speech recognition, language translation, and music generation.

  However, basic RNN can suffer from the vanishing gradient problem, which means that the gradients can become very small as they propagate through the network. This can make it difficult for the network to learn long-term dependencies [23]. To address this problem, variants of basic RNN have been developed, such as LSTM and gated recurrent unit. These variants use gates to control the flow of information through the network, which helps to prevent the vanishing gradient problem. LSTM has two gates, while gated recurrent units have a single gate. Both LSTM and gated recurrent units are effective at learning long-term dependencies in data, but LSTMs are typically more complex and difficult to train [23].
- **CNN:** is a type of feedforward neural network that are commonly used for image classification and object detection. Feedforward neural networks is a type of neural network that processes data in a linear fashion, from the input layer to the output layer.

3.1.2 Convolutional Neural Networks

CNN introduced by LeCun [34] for achieving handwritten digit recognition. CNN is a type of deep learning algorithm that is well-suited for processing data with spatial structure, such as images and video [23]. CNN has a hierarchical architecture, with each layer learning to extract different features from the input data. This makes them ideal for identifying patterns in network performance data, which is often represented as a multidimensional array. The name ”convolutional” refers to the network’s use of a mathematical technique known as convolution. Convolution is a subset of linear operations. Convolutional networks are simple neural networks with at least one layer that employs convolution rather than general matrix multiplication [31].

CNN is made up of neurons, where each neuron has a learnable weight and bias. It contains an input layer, an output layer, and multiple hidden layers, where the hidden layer consists of convolutional layers, a pooling layer, fully connected layers, and various normalization layers.

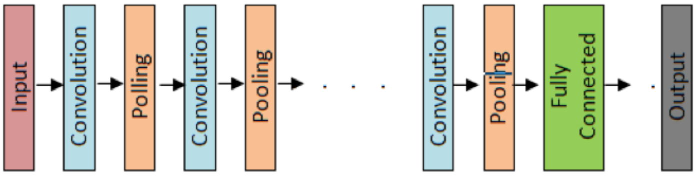


Figure 3.1: Conceptual architecture of CNN [49].

Convolution layer

Convolutional layers are a type of neural network layers that are used to extract features from the input data. They are the most important component of any CNN architecture, and they are responsible for learning the low-level features of the data. A convolutional layer works by applying a kernel to the input data. The kernel is a grid of weights that are adjusted during training to extract meaningful features from the data. The output of the kernel is a feature map, which is a smaller version of the input data that contains information about the features that have been extracted by the kernel [30, 51]. The convolution operation is typically denoted with an asterisk:

$$s(t) = (I * K)(t) \tag{3.4}$$

In CNN terminology, the function I referred to as the input data, the function K is the kernel, and the output s(t) is referred to as the feature map. The discrete convolution operation of CNN can be defined as follows:

$$s(i, j) = (K * I)(i, j) = \sum_{m} \sum_{n} I(i - m, j - n)K(m, n) \tag{3.5}$$

Here, i and j represent the coordinates of the output feature map, while m and n represent the size of the kernel. The value of the output feature map at position (i, j) (represented by S(i, j)) is obtained by sliding the kernel over the input matrix and taking the dot product of the kernel with the corresponding submatrix of the input data.

The size of the kernel determines the size of the feature map. A larger kernel will extract larger features from the input data, while a smaller kernel will extract smaller features. The stride determines how the kernel is applied to the input data. A larger stride will move the kernel over the input data more quickly, while a smaller stride will move the kernel over the input data more slowly. The padding determines how the input data is padded before the kernel is applied. Padding can be used to ensure that the output feature map has the same size as the input data [30, 51]. When working with data on a network performance system, time is typically discretized. This means that the NMS provides data at regular intervals, such as once per hour. If so, the discrete convolution will expressive more for this thesis.

Non-linearity layer

Non-linearity layers are used to add non-linearity to the CNN. This is important because it allows the CNN to learn more complex relationships between the input data and the output. By transforming the input signal to the output signal, the non-linearity layer introduces non-linearities, which helps the network to model complex relationships between the input and output [51]. Some popular types of non-linearity layers include sigmoid, tanh, ReLU. The ReLU is the most commonly used activation function in CNN. When compared to others, ReLU has the advantage of requiring a minimal computing load [49].

Pooling layer

The pooling layer is another important component of CNN that can have local or global subsampling layers. The pooling layer adds the outputs of a neuron at one layer into an individual neuron in the following layer. Its main task is to scale down the spatial size of the representation to diminish the number of parameters and calculations in the model [51]. It not only speeds up the calculations but also prevents the problem of overfitting. The most common form of pooling layer is the max pooling, which selects the maximum value from each patch of the feature map. The pooling layer helps to reduce the dimensionality of the feature maps and to extract the most salient features of the input data [56, 51].

Fully connected layers

The fully connected layer is a standard deep neural network that seeks to build predictions from the activations to be used for classification or regression. It has a similar principle as the conventional MLP. This layer acquires full connections to each activation in the previous layer, and the activations can be calculated by using matrix multiplication followed by a bias offset.

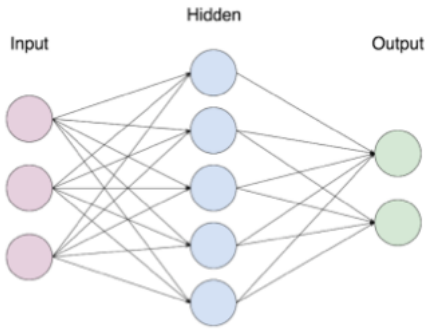


Figure 3.2: Fully connected layer [49].

The fully connected layer is usually placed after the convolutional and pooling layers and is responsible for making the final prediction based on the learned features [51]. A

CNN contained at least one convolutional layer and after that pursued by at least one fully connected layer as in a standard multi-layer neural network.

There are three main types of CNN [49]: One-dimensional (1D), Two-dimensional (2D), and Three-dimensional (3D). They are all used to extract features from data, but the difference between the three types of CNN is the dimensionality of the data that they are used to process.

- 1D CNN are used to process 1D data, such as time series data. The convolutional layers in a 1D CNN have a single spatial dimension, and they are typically used to extract features from the data along the temporal dimension.

- 2D CNN are used to process 2D data, such as image data. The convolutional layers in a 2D CNN have two spatial dimensions, and they are typically used to extract features from the data along the height and width dimensions.

- 3D CNN are used to process 3D data, such as volumetric data. The convolutional layers in a 3D CNN have three spatial dimensions, and they are typically used to extract features from the data along the height, width, and depth dimensions.

3.2 SHapley Additive exPlanations

As machine learning models become more intricate and sophisticated, they often operate as ”black boxes,” meaning that it becomes challenging to comprehend the underlying logic behind their predictions [35, 43]. Machine learning interpretability is the process of understanding and explaining how machine learning models arrive at their predictions or decisions. The growing emphasis on interpretability and explainability stems from the need for transparency and accountability in machine learning systems [43, 48]. It is crucial to understand why a particular prediction was made to ensure fairness, avoid bias, and build trust. Interpretability methods can be classified based on several attributes, including model-specific vs. model-agnostic methods, intrinsic vs. post-hoc interpretability, and global vs. local interpretability [35].

- **Model-specific vs. Model-agnostic:** Model-specific methods are those that can only be applied to a certain class of models, while model-agnostic methods are applicable to any machine learning model in general [43, 48].

- **Intrinsic vs. Post-hoc:** Intrinsic interpretability approaches explain a model's behavior starting from the input of the model and going through the model parameter by parameter. In contrast, post-hoc techniques involve explainability into a model from its outcome, such as marking what part of the input data is responsible for the final decision. Intrinsic methods are built into the model itself, while post-hoc methods are added to the model after it has been trained [43, 48].

- **Global vs. Local:** Global interpretability methods explain the whole logic of a model and the reasoning behind all possible outcomes [35]. They provide a summarized explanation of the model's behavior for each feature regardless of its value. Global model interpretability explains a model through the most important rules learned from the training data and represents the explanation through the model's structure and parameters. The whole system can be explained, and the logic can be followed from the input to every possible outcome. Local interpretability methods explain model characteristics and the impact of input features for a specific prediction. The model can be explained only for each single prediction. These methods are optimized for individual samples, but they may not provide a complete picture of the model's behavior [35].

SHAP [35] is a popular post-hoc interpretability method that can be used to explain both the global and local behavior of machine learning models. It provides a way to explain the contribution of each feature to the final prediction made by the model.

The basic idea behind SHAP is to use game theory, to apportion the model's prediction among the input features [35]. The Shapley value is a method for distributing the value of game among its players. In the context of machine learning, the players are the input features, and the value being distributed is the difference between the prediction made by the model and the average prediction across the dataset. The SHAP framework provides a unified measure of importance called the shap value to explain the contribution of each feature to the final prediction. The general formula to compute the Shap value for a feature is as follows:

$$\phi_i = \sum_{S \subseteq F} \frac{|S|!(|F| - |S| - 1)!}{|F|!} f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S) \tag{3.6}$$

where:

- ϕ_i is the Shap value of feature i
- $\frac{|S|!(|F|-|S|-1)!}{|F|!}$ is the number of ways to choose set S from the set of all features F, excluding feature i.
- $f_{S \cup i}(x_{S \cup i}) - f_S(x_S)$, is the difference between the model's prediction when feature i is included in the set S and the model's prediction when feature i is excluded from the set S.
- S is a subset of features in F that does not include feature i
- |F|! is the total number of ways to choose a subset of features from F, used to normalize the Shap values

SHAP uses a local approach to interpretability by calculating the shap values for each feature for a specific prediction. Calculated by taking the sum of the difference between the model's prediction with and without the feature, for all possible subsets of features that do not include the feature. The weight of each subset is determined by the number of features in the subset. It also provides a global approach to interpretability by summarizing the SHAP values across all predictions to identify the most important features of the model. This is calculated by averaging the local SHAP values across all inputs [35]. The SHAP framework can be used for a wide range of machine learning models, making it a powerful tool for model interpretability.

SHAP values can be calculated using different methods, including explainer, tree, kernel, and deep approaches [35]:

a. **Explainer SHAP**: This method uses simple linear models like linear regression or Lasso regression to compute SHAP values. It is computationally efficient but may not be suitable for complex models or those with non-linear relationships.

b. **Tree SHAP**: This approach uses a modified version of the Game Theory Shapley value. Instead of generating all possible feature orders, it averages over feature orderings based on the tree structure of a decision tree. It works well for tree-based models such as random forests.

c. **Kernel SHAP**: This method uses a LIME to explain the output of a machine learning model. It is versatile and can be applied to a variety of models, both linear and non-linear.

d. **Deep SHAP**: Deep SHAP is an extension of the SHAP method that can be applied to deep learning models. To compute the Shapley values, Deep SHAP uses a modified version of the model that includes a baseline input, which is used as a reference point for computing the contribution of each feature. The method then computes the difference between the model's output for the actual input and the baseline input, and uses this difference to compute the Shapley values. To calculate SHAP values in Deep SHAP, the following steps are taken [35]:

   - **Generate a background dataset:** A background dataset is generated to serve as a reference for the model. This dataset should be representative of the data that the model will be applied to.
   - **Sample a subset of the background dataset:** A subset of the background dataset is selected to create a set of reference points for the SHAP values.
   - **Generate a model output:** The model is used to generate an output for each reference point in the subset.
   - **Compute the contribution of each feature:** The contribution of each feature to the output is computed by comparing the output of the model with and without the feature present. This is done for each reference point in the subset.
   - **Compute the SHAP value:** The contribution of each feature is averaged across all reference points, and this average is used to compute the SHAP value for that feature.

- **Sum up the SHAP values:** The SHAP values for each feature are summed up to obtain the overall importance of each feature in the model.

4 Proposed Root Cause Analysis Model

This chapter proposes RCA model that uses CNN and SHAP to identify the root causes of accessibility and integrity degradation problems. The chapter begins by discussing the metrics of accessibility and integrity. It then introduces the proposed RCA framework, which is based on CNN and SHAP. The experimental setup is then described, including data collection, preprocessing, and CNN model development. Finally, the metrics used for model evaluation are presented.

4.1 The Proposed RCA Framework

LTE networks are prone to accessibility and integrity degradation, which can affect network performance and the user experience. As defined earlier chapter, accessibility degradation is the diminished ability of users to access the network or specific services. In this thesis, the E-RAB setup success rate is chosen as a metric to evaluate the accessibility of the LTE network. This metric offers valuable insights into the network's performance in establishing bearers to fulfill user service requests. A high E-RAB setup success rate indicates that a substantial number of connection requests from UEs are being successfully established, indicating good accessibility and efficient network operations. Conversely, if the E-RAB setup success rate is degraded, it implies that the UE's request has not been successful, leading to user dissatisfaction.

In addition to accessibility, network integrity is another important aspect to consider. Integrity degradation is the corruption or loss of data during transmission. In the context of data services, average user throughput is commonly used by operators to verify the integrity of the network. Average user throughput measures the average data transfer rate experienced by users over a certain time. It helps assess the network's capacity to deliver data efficiently to users. Higher average user throughput generally indicates better network integrity and performance, as users are able to receive data at faster speeds, and vice versa.

The proposed RCA method for addressing E-RAB setup success degradation and user throughput degradation in LTE networks integrates the use of CNN and SHAP. The CNN model is specifically designed to handle one-dimensional input data and extract important features from it, for this reason, a 1D CNN type is used.

A 1D CNN model is a type of deep learning model that is particularly effective for analyzing sequential data or time series data, which is often encountered in telecommu-

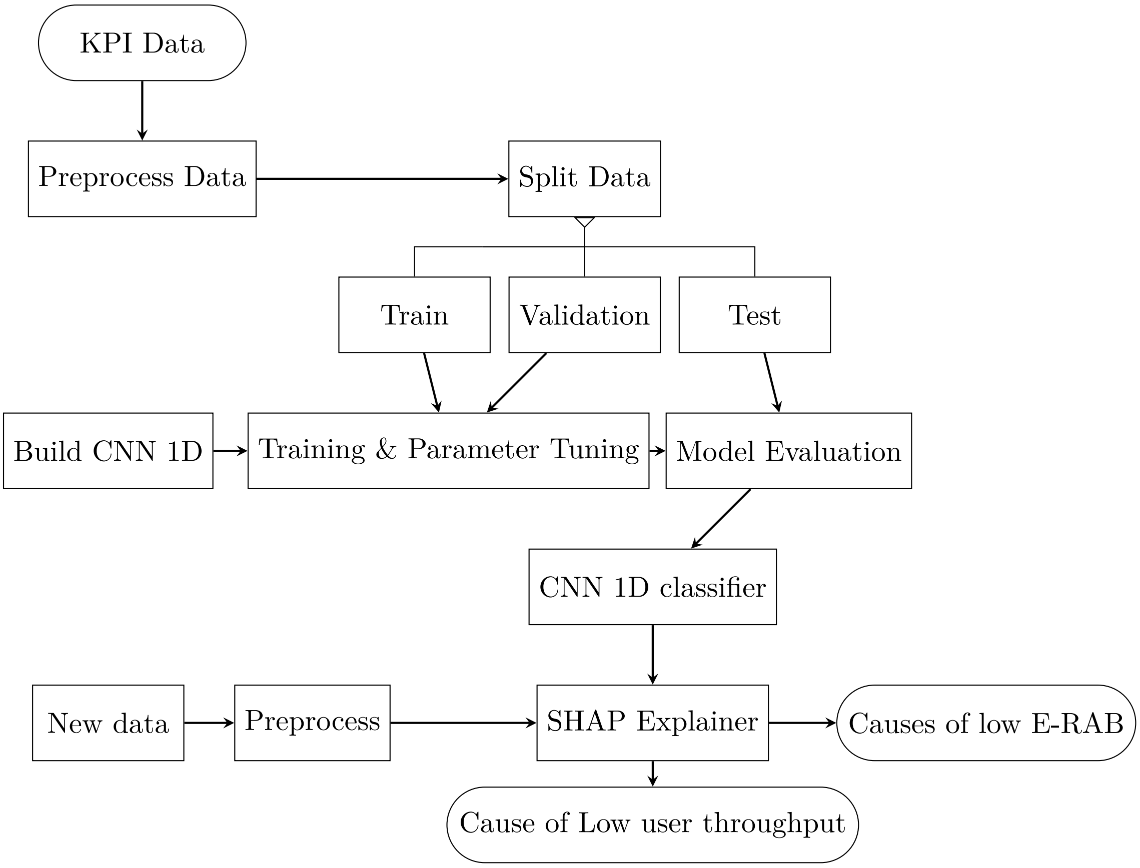


Figure 4.1: Proposed approach for low user throughput and E-RAB setup success RCA.

nication networks. Once the 1D CNN model predicts the degradation instances, SHAP is utilized to interpret the prediction model and provide a high score value for the root causes of the degradation. By applying SHAP, the proposed method can identify the key factors or inputs that contribute the most to the degradation of E-RAB setup success rate and user throughput.

4.2 Experiment setup

4.2.1 Data Collection

When conducting RCA of LTE low user throughput and low E-RAB setup success, several factors need to be considered. These include analyzing radio conditions, signaling flows, logging messages, and cell loading to determine the underlying causes for the low throughput and network accessibility issues [45]. In this particular study, data was collected from the ethio telecom LTE network.

The first step in the data collection process was to identify the reasons or causes why E-RAB setup success and user throughput were degrading. These reasons needed to be understandable to humans so that they could be addressed. By pinpointing these causes, it becomes easier to identify the relevant parameters measured on the NMS. To gather the necessary data, the following tasks were performed:

1. **Identification of Human-Understandable Causes:** The first task involved identifying causes that can be easily understood by humans and are typically associated with the degradation of E-RAB setup success and user throughput. Examples of such causes may include signal interference, high network congestion, hardware failures, software glitches, or configuration issues.

2. **Measurement Parameter Identification:** Once the human-understandable causes were identified, the next step was to determine the specific parameters that can be measured on the NMS. These parameters are directly related to the identified causes and provide insights into the performance of the LTE network. Examples of measurement parameters may include signal strength, intera frequency handover failure, resource usage, number of active users, etc.

The dataset consists of 42 features that act as causal factors for two outcomes: low user throughput and E-RAB setup success. These outcomes are predicted by a CNN 1D classifier model. The input parameters for the model are derived from the Performance Report System (PRS) and include various counters and KPIs, which are potential causes for user throughput and E-RAB setup success. The following KPIs and counters serve as input parameters for the model:

- **Reference Signal Received Power (RSRP):** RSRP is defined as the average power of resource elements that carry cell-specific reference signals over the entire bandwidth. RSRP levels typically range from around −75 dBm (close to an eNodeB) to −120 dBm (at the cell edge). In the uplink, the information is taken from a trace event that reports the number of transport blocks on the MAC level that are scheduled in the uplink, distinguishing between two cases.

- **Physical Resource Block (PRB) Utilization:** In LTE each cellular tower has a fixed number of Physical PRB defined in time and frequency. When a user requests a certain type of service or E-RAB, the LTE scheduler at a cell site will allocate a certain number of PRB depending on the request. PRB utilization refers to the percentage or proportion of PRBs that are actively used for data transmission at a given time. It indicates the efficiency of resource allocation and utilization within the system. Higher PRB utilization suggests that a larger portion of the available resources is being utilized for data transmission.

- **Control Channel Element (CCE) utilization:** Is an indicator used in wireless communication networks to measure the efficiency of allocated control channel resources. These control channels are responsible for transmitting signaling information between the network and user devices. When CCE utilization is high, it means that a large percentage of the available control channel resources are being utilized. This can indicate a high demand for signaling information in the network. However, a high CCE utilization can have negative effects on user throughput and E-RAB setup success.

- **Paging utilization:** Paging is a mechanism used to notify a UE about incoming calls, messages, or other events when the UE is in idle mode. The paging utilization counter measures the frequency at which the network initiates paging for idle UEs. A higher paging utilization counter indicates a higher number of paging requests sent by the network.

  If the paging utilization is high, it means that a large number of devices need to be paged frequently, which can overload the system's capacity and resources. This increased demand for paging can lead to delays in setting up E-RAB. Additionally, it reduces the available resources for carrying user data. As a result, the average user throughput in the cell can decrease, impacting the overall network performance.

- **CQI:** Its purpose is to provide the eNodeB with information about the link adaptation parameters and the maximum achievable data rate that can be successfully received by the UE. The CQI value received at the eNodeB serves as an indication of the current channel conditions. Based on this value, the eNodeB can determine and select the appropriate modulation and coding scheme to be used for the downlink. transmission. The modulation scheme influences how the data is encoded onto the radio waves, while the coding scheme controls the amount of error correction applied to the transmitted data. The selection of the optimal modulation and coding scheme based on the CQI helps to maximize the data rate and overall system performance while ensuring reliable communication between the eNodeB and the UE.

- **Intra frequency handover failure:** Is an indicator of the unsuccessful handover or transfer of a mobile device from one eNodeB to another within the same frequency. When a handover fails, the user's connection is not seamlessly transferred to the new eNodeB, resulting in disruptions or even dropped calls. This can lead to deteriorated user experience, decreased throughput, and reduced data or voice service quality.

  Low user throughput can occur because of failed handovers, as the mobile device may struggle to connect to a stronger or less congested eNodeB, resulting in slower data speeds. Failed handovers can also prevent the successful setup of bearers, leading to reduced data rates and lower overall network performance.

- **L.Traffic.ActiveUser.Avg:** This counter represents the average number of active users in the network over a specific period. Active users are those who are currently using data services, making calls, or engaged in any network activity. When the number of active users increases, the available network resources get divided among a larger number of users. This can result in decreased throughput for each user, meaning that the data transfer rate experienced by individual users may decrease. With limited network resources, the network may struggle to handle the increased traffic, resulting in lower user throughput. Also, the network may face capacity issues, and as a result, it might fail to set up the required bearers for all the users successfully.

- **L.Traffic.User.Avg:** Refers to the average number of users in the network over a specific time. It includes both active and inactive users. Inactive users refer to those who are connected to the network but not actively involved in any activity, such as idle or standby users.

- **Circuit Switched Fallback (CSFB) failure times:** Refer to instances where the CSFB procedure fails during a voice call in an LTE network. If a device fails to fall back to the circuit-switched network properly, it may struggle to establish a successful E-RAB connection.

- **L.HHO.PingPongHo:** Ping Pong Ho events occur in LTE when a mobile device rapidly switches between two cells due to signal strength fluctuations. This situation typically happens when a mobile device is moving within the overlapping coverage areas of two cells. When ping-ponging handovers occur frequently, there is a higher chance of an E-RAB setup failure due to timing issues and increased signaling congestion. Also, each handover involves signaling procedures and radio resource allocation, causing delays and interruptions in data transmission.

- **Transport Network layer fault:** The transport network layer is responsible for providing the transport and routing functions for user data within the LTE network [1]. It ensures that the data packets are properly delivered between the UE and the network through the core network. The counter L.E-RAB.FailEst.TNL specifically counts the number of times the establishment of the E-RAB fails at the transport network layer. This counter helps to monitor the performance and identify any potential issues or bottlenecks in the transport network layer.

- **Failure caused by MME:** This can be determined by examining the counters L.E-RAB. FailEst.MME and L.E-RAB.AbnormRel.MME. The counter L.E-RAB.FailEst.MME indicates the number of E-RAB setup failures that have been initiated by the MME. On the other hand, the counter L.E-RAB.AbnormRel. MME indicates abnormal E-RAB releases caused by the MME.

Cause symptom mapping for the input parameters is presented in Table 4.1. These parameters are the same for both the E-RAB setup and for low average user throughput. It's important to note that some of these counters may overlap and could indicate multiple types of problems. For example, high congestion can lead to resource problems and affect handover performance. Therefore, network operators need to analyze these counters together and take appropriate measures to optimize the network performance.

Table 4.1: Cause-symptom mapping for E-RAB setup and user throughput.

Causes Class	**Observable Features**
Traffic	L.Traffic.User.Avg L.Traffic.ActiveUser.Avg 4G_DL Data Volume (MB)
Handover	Intra_fre_HO_failure Inter_fre_HO_failure L.E-RAB.AbnormRel.HOFailure
Resource	DL PRB Utilization L.E-RAB.AbnormRel.Radio L.E-RAB.FailEst.NoRadioRes
Coverage and Interference	TA(>1.95KM) DL BLER Rate Rank1 Rate L.UL.Interference.Avg RSRP <-120dBm Percentage -120dBm <= RSRP< -115dBm L.RRCRedirection.E2W.Coverage
Congestion	CCE Utilization Paging utilization RRC Congestion Ratio E-RAB Congestion Ratio
Configuration	L.HHO.PingPongHo
Core Network	L.E-RAB.FailEst.MME L.E-RAB.AbnormRel.MME
Transmission Network	L.E-RAB.AbnormRel.TNL
Power Outage, Hardware faults	Cell unavailability

4.2.2 Data Preprocessing

Data Preprocessing is a crucial step in machine learning that involves preparing the data for analysis to improve the accuracy and effectiveness of the chosen method. Several important tasks need to be performed during data preprocessing.

- **Data cleaning:** is the process of handling and correcting any errors, inconsistencies, or outliers present in the dataset. During data cleaning, certain procedures are carried out such as removing irrelevant data, fixing formatting issues, and addressing missing or duplicate values. Clean data ensures that the subsequent analysis and modeling are accurate and reliable.

  One common challenge is dealing with missing values, which occur when the cell is not available or out of service. In this particular dataset, interpolation techniques cannot be applied to address missing values. Counters like PRB utilization, active user, and average user should be zero when the cell is out of service. Additionally, removing these instances is not an option as the model needs to learn about cell unavailability. To handle the missing values in this dataset, a solution is to replace them with zero.

- **Data normalization:** Machine learning algorithms can face difficulties when processing features that have widely differing scales or ranges. As a solution, normalization is employed as a data preprocessing technique to bring these features to a common scale. This is done to enhance model performance and training stability. Specifically in this thesis, the input parameters consist of KPIs and counters that are derived from an LTE network, but these parameters are frequently impacted by outliers. To handle this issue, Robust scaling is being considered as the approach for this research. It scales the data based on the interquartile range instead of the mean and standard deviation. The interquartile range is a measure of the spread of the data that is less sensitive to outliers than the mean and standard deviation [38].

  $$\frac{x_i - Q_1(x)}{Q_3(x) - Q_1(x)} \tag{4.1}$$

  Where Q_1 is the 1st quartile, and Q_3 is the third quartile.

- **Data discretization:** is the process of converting continuous data into categorical data by dividing it into predefined categories. In this particular case, the targets of interest are the E-RAB setup success and average user throughput, which are continuous values. To analyze this data, it needs to be grouped into a binary classification.

  For the binary classification, class 0 represents low user throughput, while class 1 represents not low user throughput. Similarly, class 0 represents low E-RAB setup success, and class 1 represents acceptable E-RAB setup success. In LTE, user throughput is considered low if it falls below 3Mbps. Additionally, low E-RAB setup success is defined as E-RAB setup success below 99%.

4.2.3 Software

To implement the RCA, several different software tools have been utilized. All of them are available through open-source licenses for educational purposes.

Pyhton: Anaconda Distribution

Anaconda is a custom Python distribution. It provides access to a great variety of Python packages that facilitate data science tasks. Some of the packages [18, 27] used in this thesis are:

- **NumPy:** The fundamental package for scientific computing in Python. It provides multidimensional array support, as well as support for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, basic linear algebra, statistical operations, random simulation, etc. This thesis makes use of this library throughout the whole implementation, as the data and methods developed in this thesis make use of multidimensional tabular data stored in arrays.

- **Scikit-learn:** A Python library that provides tools for data analysis and machine learning.
- **Pandas:** A Python library providing fast, flexible, and expressive data structures designed to make working with ”relational” or ”labeled” data both easy and intuitive. It allows the manipulation and processing of tabular data in an efficient way, and it is used in this project during the parsing and cleaning phases of the data preprocessing.
- **Keras and TensorFlow:** Keras and TensorFlow are two powerful libraries used for developing deep learning models, including CNN. Keras is a high-level neural network API that can run on top of other libraries like TensorFlow. It simplifies the process of building and training neural networks by providing a user-friendly interface and high-level abstractions. TensorFlow, on the other hand, is an open-source deep learning framework developed by Google. It provides a more low-level and flexible approach to building neural networks, allowing users to have greater control over the model architecture and training process. Used in this thesis to train and deploy a CNN 1D neural neural network to classify the degradation.

4.2.4 CNN 1D Model Development

A 1D CNN model for binary classification is presented, where the goal is to classify whether a cell's performance is degraded (class 0) or not degraded (class 1). The model has several layers, including two convolutional layers, a dropout layer, a max pooling layer, a flatten layer, and two dense layers.

The model is created using the Sequential API from Keras. Conv1D layers are added to perform convolution operations. The first layer added to the model is a 1D convolutional layer (conv1d) with 128 filters, a kernel size of 3, and a ReLU activation function. The input_shape parameter specifies the shape of the input data, with *x_train.shape[1],1* represent the number of features in data and a single dimension (1) for the hourly interval measurement, where *x_train* is the training data. This layer learns to extract features from the input data. The second convolutional conv1d layer is added with the same configuration as the previous one.

A dropout layer with a dropout rate of 0.5 is incorporated to prevent overfitting by randomly dropping out some of the neurons. The max pooling layer with a pooling size of 2 reduces the dimensionality of the output from the convolutional layers. The flatten layer converts the output from the convolutional and max pooling layers into a one-dimensional array to be compatible with dense layers.

The first and second dense layers with 64 units and a ReLU activation function is used, serving as the hidden layer. These layers learn to classify the input data into two classes. The final dense layer with 1 unit and a sigmoid activation is included for the output, representing the binary classification.

The model is compiled with the binary cross-entropy loss function, the Adam optimizer, and accuracy as a metric. This means that the model will be trained to minimize the binary cross-entropy loss, which is a measure of the difference between the predicted and actual labels. The Adam optimizer will be used to train the model, and the accuracy metric will be used to evaluate the model's performance.

4.3 Model Evaluation

Model evaluation metrics are used to assess the performance of a classification model. They help in understanding how well the model can correctly predict the classes of the input data. In the case of a 1D CNN classification model for classifying user throughput/E-RAB setup susses as degraded (class 0) or not degraded (class 1), the following evaluation metrics can be used:

- **Confusion Matrix:** A confusion matrix shows the count of true positive (TP, correctly identified positive instances), false positive (FP), false negative (FN, instances misclassified as negative), and true negative (TN) predictions. It helps visualize the performance of the model in terms of correct and incorrect predictions.
- **Sensitivity:** One important metric derived from the Confusion Matrix is Sensitivity. Sensitivity is a measure used to evaluate the performance of a classification. It assesses the model's ability to correctly identify positive (degraded) instances in a dataset. To compute sensitivity, the number of true positives is divided by the sum of true positives and false negatives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4.2}$$

- **Precision:** Precision measures the model's ability to correctly classify positive instances out of all the instances it classified as positive. It is calculated by dividing the number of true positives by the sum of true positives and false positives.

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

  A high precision score indicates that the model has a low rate of incorrectly classifying negative instances as positive.

- **Specificity:** Specificity is also known as the True Negative Rate. Specificity evaluates the model's ability to accurately identify negative cases (class 1 or normal instances) among all the true negative instances in the dataset. It focuses on minimizing false positive errors, thus aiming to avoid classifying normal instances as degraded or abnormal.

$$Specificity = \frac{TN}{TN + FP} \tag{4.4}$$

  A high specificity score suggests that the model is capable of correctly identifying normal instances while minimizing false alarms.

It is critical to find an optimal balance between specificity and sensitivity when designing a successful binary classification model. While specificity indicates that normal performance is recognized correctly, sensitivity ensures that performance degradation is detected correctly. The optimal balance is determined by the application and the costs or repercussions of false positives and false negatives.

- **F1-Score:** The F1-Score combines both precision and recall by taking their harmonic mean. It provides a balanced evaluation of a model's performance by considering both its ability to avoid false positives and its ability to detect all positive instances.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.5}$$

- **Accuracy:** Accuracy is another metric that measures the overall correctness of the model's predictions. It represents the ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.6}$$

5 Results and Discussions

The evaluation and analysis of the machine learning model built in the previous chapter will be the focus of Chapter 5. A detailed performance evaluation will be carried out to examine the models' accuracy, efficiency, and reliability. In addition, the results of the model for real-world LTE network data will be investigated and discussed.

In this study, a dataset spanning 62 days was utilized to analyze 4G KPIs and counters. The data was obtained from a specific area, with measurements taken hourly for each KPI. This resulted in 24 values for each KPI and counters, making a total of 1501 measurements for each cell. The selection of the network area was carried out in collaboration with experts from the Engineering team, who employed the NMS network tool. This tool helps to identify an area that frequently experiences lower throughput issues.

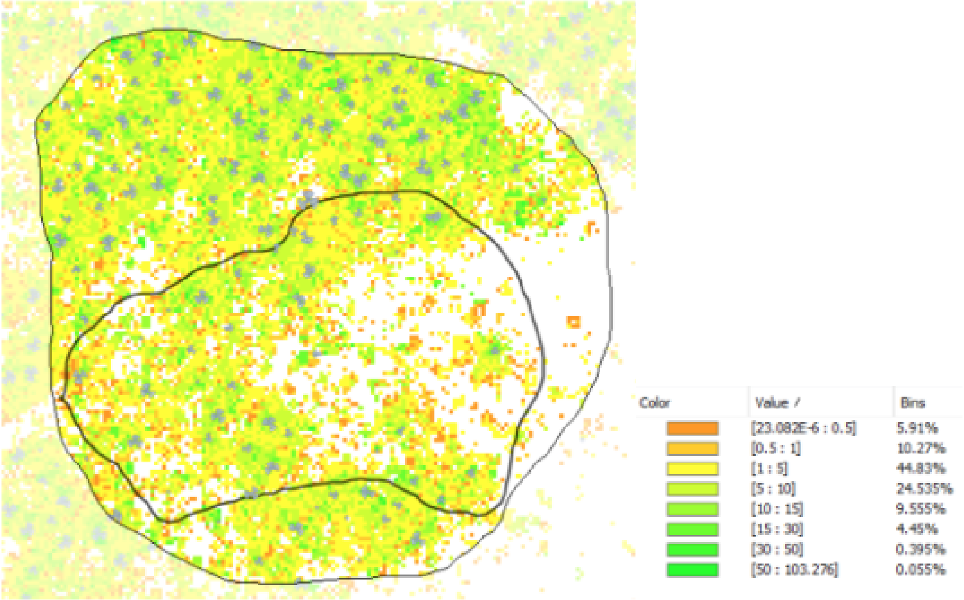


Figure 5.1: Selected network area for the analysis.

The chosen network area for analysis is depicted in Figure 5.1, with the specific area marked within the small circle. The orange color highlights the region with decreased user throughput. The eNodeB analysis focused on one particular eNodeB in this network, consisting of 9 cells. A total of 13509 samples were collected from this selected eNodeB for analysis. Furthermore, for the network-level analysis, a broader range of data was included, amounting to 362,095 samples in total. These rich datasets enabled a comprehensive network performance assessment.

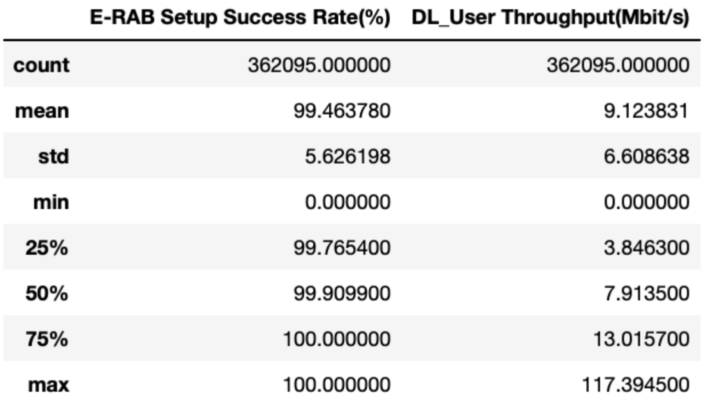
5.1 Dataset Visualization

As described in the previous chapter, the raw data contains an invalid (null) character when the cell is out of service. This indicates that there was no measured value for those counters. Other than that, there are no missing values in the dataset. In this case, handling the missing values using techniques like imputation or deleting the raw data is not an option. If null values are deleted, the model will not learn the condition when the cell is not out of service, thus missing important causes. The option being considered here is to replace the null values with zero, which will indicate that there was no measurement value for those counters.

A. **Visualize Targets Variables**

In the aggregated network, the dataset includes 362,095 observations for each variable. The E-RAB Setup success rate has a mean of 99.46%, indicating a high overall success rate. The standard deviation is 5.626, suggesting relatively low variability in the data. The lowest E-RAB Setup success rate recorded is 0%, while the highest is 100%.

Analyzing the quartiles, observe that 25% of the data has an E-RAB Setup success rate below 99.76%. The median (50%) for this variable is approximately 99.9%. As for the upper quartile, it is 100%, showing that 75% of the data falls within this range.



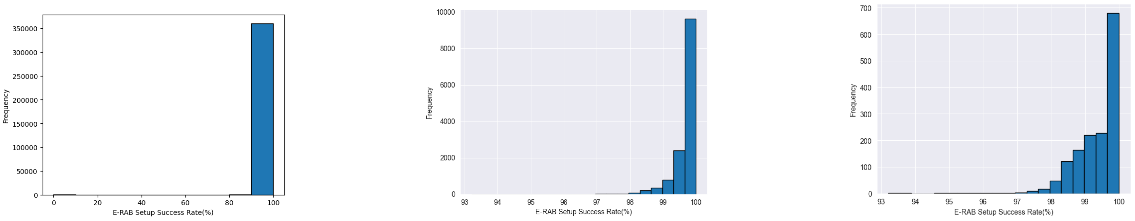
	E-RAB Setup Success Rate(%)	DL_User Throughput(Mbit/s)
count	362095.000000	362095.000000
mean	99.463780	9.123831
std	5.626198	6.608638
min	0.000000	0.000000
25%	99.765400	3.846300
50%	99.909900	7.913500
75%	100.000000	13.015700
max	100.000000	117.394500

Figure 5.2: Statistical results for E-RAB setup success and user throughput.

Similarly, for the downlink user throughput variable in the aggregated network, the mean throughput is 9.12 Mbit/s, with a standard deviation of 6.6. The minimum throughput observed is 0.0 Mbit/s, while the maximum is 117.3 Mbit/s. Examining the quartiles for downlink user throughput, 25% of the data falls below 3.8 Mbit/s, the median is 7.9 Mbit/s, and the upper quartile is 13.01 Mbit/s.

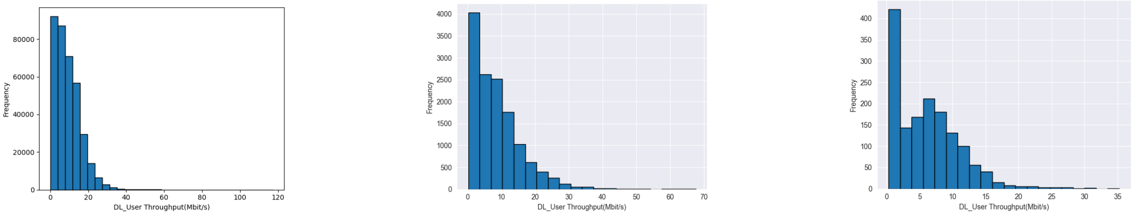
Now, let’s consider the dataset at the cell level, which consists of 1,501 observations for each variable. The mean E-RAB Setup success rate is 99.19%, indicating a high overall success rate. The standard deviation is 0.88, suggesting relatively low variability in the data. The minimum value for E-RAB Setup Success Rate is 91.062%, while the maximum value is 100%. The quartiles reveal that 25% of the data falls below 98.59% for E-RAB setup success, and the median is approximately 99.45%. The upper quartile is 100%, indicating that 75% of the data falls within this range.

For downlink user throughput at the cell level, the mean throughput is 6.287216 Mbit/s, with a standard deviation of 4.704356. The minimum throughput observed is 0.3359 Mbit/s, while the maximum is 26.8045 Mbit/s. The quartiles show that 25% of the data is below 2.102450 Mbit/s, the median is 5.7781 Mbit/s, and the upper quartile is 9.0782 Mbit/s. Overall, the distribution of the target variables is shown below at the network, eNodeB, and cell levels.



(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.3: E-RAB setup success distribution using histogram.

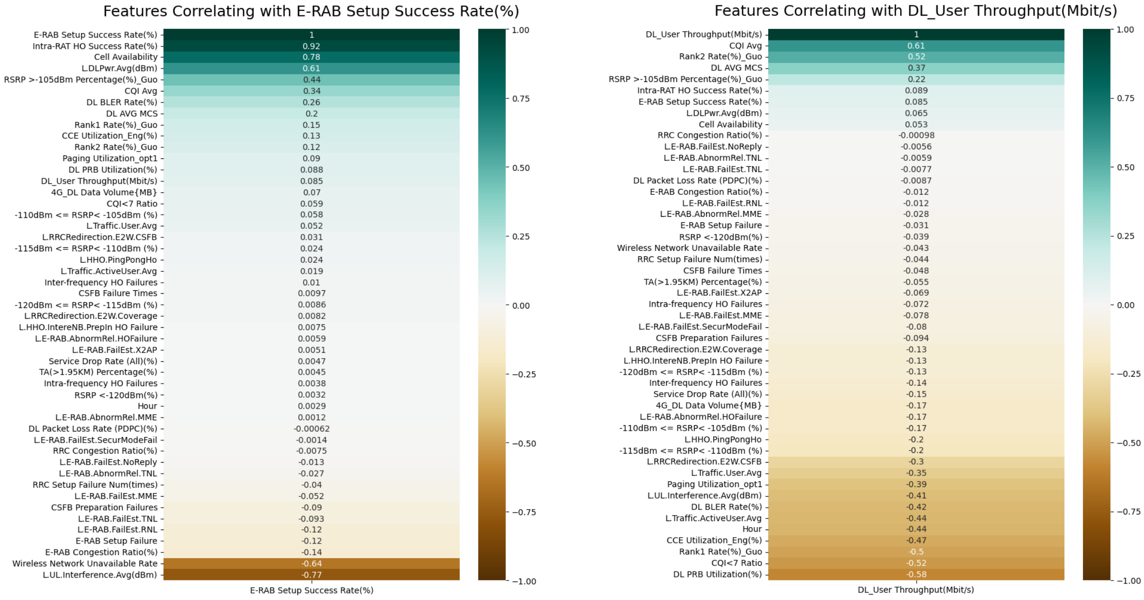


(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.4: Downlink user throughput distribution using a histogram.

B. **Feature Correlation**

To visualize the relationship between the input parameters and the target components, we are using Pearson correlation. Figure 5.5 shows the linear relationship of the input parameters with the target variables. A linear relationship means that there is a consistent change in one variable with respect to another. In Pearson correlation, a positive correlation indicates a direct relationship where both variables increase or decrease together, while a negative correlation indicates an inverse relationship where one variable increases while the other decreases.



(a) E-RAB setup success with other features

(b) User throughput with other features

Figure 5.5: Correlation between features and the targets.

Figure 5.5a demonstrates that the KPIs such as frequency handover setup success, CQI Avg, DL AVG MCS, and L.DLPwr.Avg(dBm) has a high positive correlation with E-RAB setup success. Conversely, E-RAB Congestion Ratio(%), E-RAB setup failure, L.UL.Interference.Avg (dBm), Wireless Network Unavailable Rate, and paging utilization have a negative relationship with E-RAB setup success.

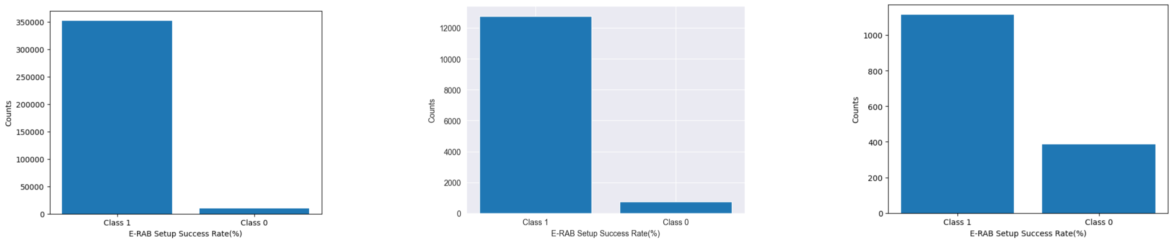
Figure 5.5b indicates that CQI avg, E-RAB setup success, DL AVG MCS, Intra-RAT HO Success Rate(%), high RSRP, and cell availability have a positive correlation with DL user throughput. In contrast, CCE utilization, DL PRB utilization,L.Traffic.ActiveUser.Avg, CQI<7 Ratio, DL BLER rate, and L.UL.Interference has a negative relationship with average user throughput. These features will be used for further analysis to identify the root causes of low E-RAB setup success and low user throughput.

5.2 Evaluation Results

This subsection discusses the performance of the DNN model on the test dataset. It would also discuss the hyperparameters that were used to train the model and how they affected the performance.

5.2.1 Determining Model Inputs and Outputs

After analyzing the data, a threshold value was set for the binary classification. For E-RAB setup success rate, a value less than 99% is considered low or degraded (Class 0), while a value greater than 99% is considered normal or not degraded (Class 1). This threshold value was chosen because it is the point at which the percentage of declined E-RAB setup requests begins to increase significantly.

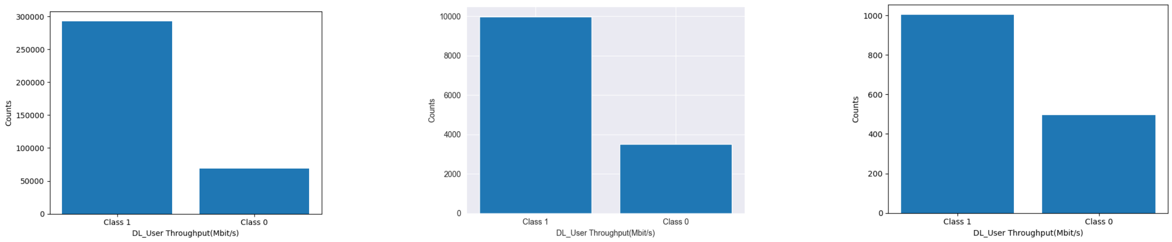


(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.6: E-RAB setup success classes

When E-RAB setup success rate is less than 99%, it indicates that 1% of the E-RAB requests for service were declined. This suggests that there may be issues with the network performance or capacity that are affecting the ability of cells to establish logical connections with UE. This leads to dropped calls, slower data speeds, and other problems.

For user throughput, a value of greater than 3 Mbps was considered as good (Class 1), and a value less than 3 Mbps is considered as low or degraded (Class 0). This threshold value was chosen because it is the point at which users begin to experience noticeable degradation in performance. When the user throughput is less than 3 Mbps, users may experience slower data speeds, buffering while streaming, or delay in page loading.



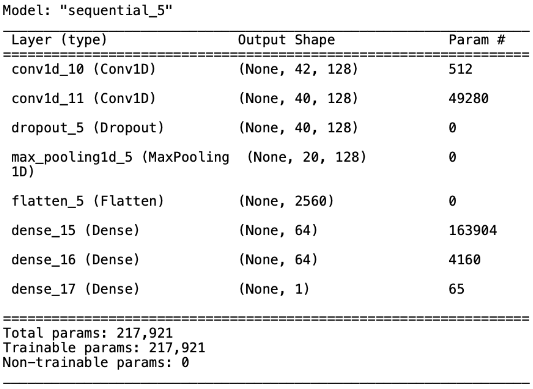
(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.7: Downlink user throughput classes

5.2.2 Developed Model

To construct the 1D CNN binary classification model, GridSearch method [23] was utilized to fine-tune the hyperparameters. GridSearch is a method that systematically explores different combinations of hyperparameters to find the optimal configuration for model performance. Due to limitations in processing devices and time constraints, the GridSearch was conducted exclusively using the data at the eNodeB level. The tuned hyperparameters include the number of convolutional layers, filter size, kernel size, dense layer, and the number of neurons in the dense layer.

After hyperparameter tuning, using GridSearch, the developed model summary for network level data is presented in Figure 5.8. The model is sequential, meaning the layers are stacked sequentially in order. The layers in the model are as follows:



```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_10 (Conv1D)          (None, 42, 128)           512

 conv1d_11 (Conv1D)          (None, 40, 128)           49280

 dropout_5 (Dropout)         (None, 40, 128)           0

 max_pooling1d_5 (MaxPooling  (None, 20, 128)          0
 1D)

 flatten_5 (Flatten)         (None, 2560)              0

 dense_15 (Dense)            (None, 64)                163904

 dense_16 (Dense)            (None, 64)                4160

 dense_17 (Dense)            (None, 1)                 65

=================================================================
Total params: 217,921
Trainable params: 217,921
Non-trainable params: 0
_________________________________________________________________
```

Figure 5.8: Summary of the proposed 1D CNN model

Trainable parameters are the weights and biases in a model that are updated during the training process. These parameters are learned from the input data to make predictions and optimize the model's performance. The proposed architecture, as shown in Figure 5.9, consists of two convolutional layers, a dropout layer, pooling layers, and three dense layers.

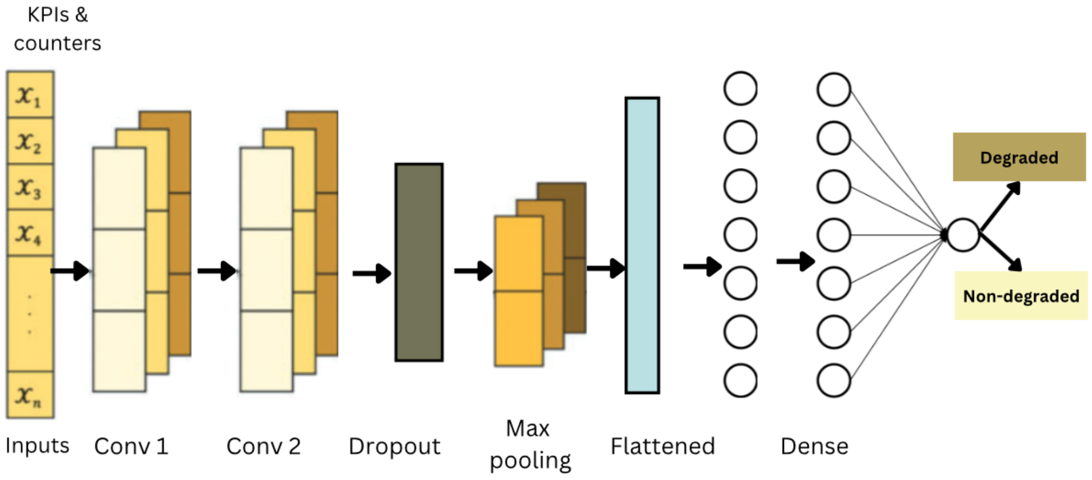


Figure 5.9: The architecture of the proposed 1D-CNN model.

- Input layer: Receive input of n number of features (counters and KPIs). The value of n depends on the number of features in each dataset. For this analysis, the input layer receives 42 counters and KPIs.
- The first Conv1D layer takes input data and performs a 1D convolution operation with 128 filters a kernel size of 3, and ReLU activation function, producing an output shape of (None, 42, 128). This indicates 'None' for the batch size, 42 for the features, and 128 for the number of filters. It has 512 trainable parameters.
- The second convolutional layer has the same configuration as the previous layer and produces an output shape of (None, 40, 128). It has 49,280 trainable parameters.
- A Dropout layer with a rate of 0.5 is added. Dropout randomly sets a fraction of

input units to 0 during training, which helps prevent overfitting. The output shape remains the same: (none, 40, 128). It has no trainable parameters as it does not learn any weights.

- A MaxPooling1D layer with a pool size of 2 is added. Max pooling reduces the dimensionality of the input by taking the maximum value within a defined pool size. This layer has an output shape of (none, 20, 128) and 0 trainable parameters.
- Flatten layer: Reshapes the tensor from (none, 20, 128) to (none, 2560), flattening the input tensor for the subsequent dense layers.
- Dense layer: This layer is a fully connected layer with 64 neurons and ReLU activation function. It receives the flattened input and produces an output of shape (none, 64). It has 163904 trainable parameters.
- Dense layer: Another fully connected layer with 64 neurons and ReLU activation function producing an output shape of (none, 64). This layer contains 4,160 parameters.
- Output layer: The final dense layer with 1 unit/neuron and sigmoid activation function for binary classification. It has 65 parameters. The sigmoid activation function outputs values between 0 and 1, representing the probability of the input being in either class.

The model is compiled with the *binary_crossentropy* loss function, Adam optimizer, and accuracy as the evaluation metric.

As shown in the above section, there exists an imbalance between the positive and negative classes, with the degraded (positive) classes having a lower count than the not-degraded classes. This imbalance introduces potential bias in the model and can result in false predictions for the degraded class. Both oversampling and under-sampling techniques are not applicable in this study. Oversampling might introduce synthetic data while under-sampling may lead to a loss of crucial information in the data [38]. To overcome this issue, a stratified K-fold cross-validation method was utilized. This method ensures that each training fold maintains a balanced class distribution [38]. The proposed 1D CNN classification hyperparameters are presented in Table 5.1.

Table 5.1: Proposed 1D CNN Model Overall Hyperparameters'

Parameter	**Value**
Optimizer	Adam
Learning rate	0.001
Loss	Binary Cross-entropy
Stratified Cross validation Fold size	5
Epochs	50
Batch size	32

5.2.3 Developed Model Performance

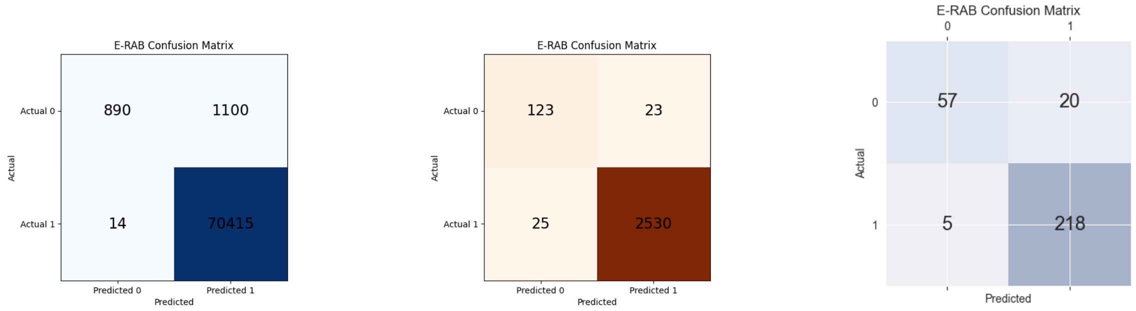
Once the model is developed, it is trained using the same input data to predict both low throughput and E-RAB setup success. The target variable is modified accordingly for each prediction. For E-RAB analysis, the input parameters are based on those described in Chapter 4, including downlink user throughput. The output of this analysis is the E-RAB setup success rate. Likewise, for throughput analysis, the input parameters consist of KPIs and counters discussed in Chapter 4, while the output is the downlink user throughput.

After developing the 1D CNN model, stratified k-fold cross-validation with 5 splits was used to evaluate the performance of the model. Within each fold, the model is trained on the training data using the *fit()* function. Then, predictions are made on the test data using the *predict()* function. The accuracy, precision, sensitivity, F1 score, and F2 score are calculated and stored for each fold. The confusion matrices for each fold are also calculated and an average confusion matrix is computed by summing the confusion matrices on each fold and dividing by the number of folds.

A. Model performance for E-RAB Prediction

Figure 5.10 shows the confusion matrix results of the model in predicting E-RAB setup success on test data on the last fold. The x-axis represents the predicted class, while the y-axis represents the actual class of the test data. The II and the IV quadrants contain the samples that the model predicted accurately, while the I and the III quadrants contain incorrectly classified classes.

In the network level analysis of E-RAB setup success, the model correctly predicted samples amount to 71,305, which is the sum of 890 and 70,415. The total number of incorrectly classified instances is 1,114, which is the sum of 14 and 1,100.



(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.10: Model performance for E-RAB setup analysis

For eNodeB level analysis, the model correctly predicted 2,653 classes, which is the sum of 123 and 2,530. The number of incorrectly predicted classes is $25 + 23 = 48$. In the cell level analysis, a total of 275 instants were correctly classified on the fold 5, which is the sum of 57 and 218. The number of incorrectly classified instants is $5 + 20 = 25$.

Table 5.2 presents the average model performance for E-RAB prediction. It includes the accuracy, precision, sensitivity, F1-score, and F2-score for different levels of analysis (cell, eNodeB, and network).

Table 5.2: Model performance for E-RAB prediction

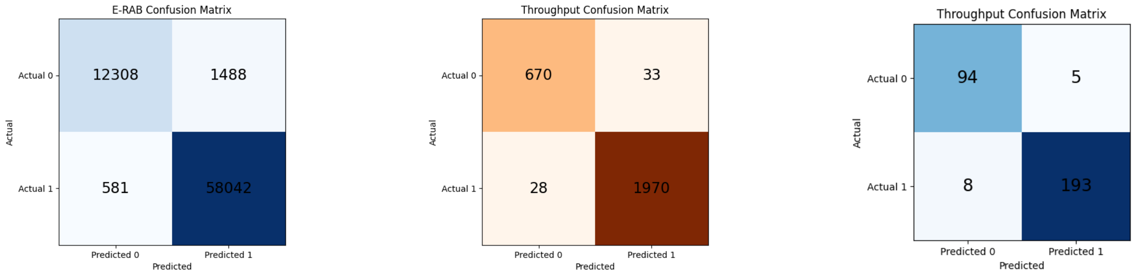
	Accuracy	**Precision**	**Sensitivity**	**F1-score**	**Specificity**
Cell level	93.4	90.9	82.8	86.6	97.1
eNodeB level	98.3	86.1	82.1	83.8	99.2
Network	98.3	75.04	44.8	55.68	99

B. Model performance for User Throughput prediction

The proposed classification model performance on downlink user throughput prediction is presented as follows. Figure 5.11 displays the confusion matrix results on the last fold. The x-axis represents the predicted class, while the y-axis represents the actual class of the test data. The II and IV quadrants contain the samples that the model predicted accurately, while the I and III quadrants contain incorrectly predicted classes.

In the network level analysis of user throughput (Figure 5.11), the model correctly predicted a total of $12308+58042 = 70,350$ instances. The total incorrectly classified samples amount to 2,069.

For eNodeB analysis, the model correctly predicted 2,653 samples, while 48 samples were incorrectly predicted. In the cell-level analysis, a total of 287 samples were correctly predicted, and 13 samples were predicted incorrectly.



(a) Network level (b) eNodeB level (c) Cell Level

Figure 5.11: Model performance for throughput analysis

Table 5.3: Model performance for throughput prediction

	Accuracy	**Precision**	**Sensitivity**	**F1-score**	**Specificity**
Cell level	97.2	96.1	95.5	95.7	98
eNodeB level	97.6	96	94.7	95.3	98
Network	97.1	95.4	89.2	92.2	90.8

Table 5.3 presents the average model performance for user throughput prediction, including the accuracy, precision, sensitivity, F1-score, and F2-score for different levels of

analysis (cell, eNodeB, and network).

5.3 Results

This section focuses on analyzing key KPIs and counters that are important for predicting the low E-RAB setup success and low downlink user throughput. This analysis is conducted both on a group level and for individual instances.

To perform this, a SHAP Deepexplainer object was created using a trained CNN model and the reshaped training data. This Deepexplainer object will enable the computation of SHAP values, indicating the contribution of each feature to the model's output. The Deepexplainer object is used to calculate SHAP values for the first 200 or more samples of the reshaped testing data. To provide a visual representation of feature importance, the SHAP values were graphically displayed using the shap.summary_plot() function. This plot aids in comprehending the KPIs and counters that greatly influence the model's output. The SHAP values for all features were computed specifically for the identified degraded class. The shap python library was utilized for these calculations.

Additionally, for single instance analysis, a KernelExplainer object is created to compute SHAP values for a single prediction. The *shap.force_plot()* function was then used to create a force plot that visualizes the contributions of each feature to the predicted output for that specific sample.

5.3.1 E-RAB Setup Success Analysis

In this section, the results for the E-RAB setup success will be presented. For the analysis, the most important KPIs and counters for predicting if the E-RAB setup success is below a threshold are presented. This includes different levels of analysis like network, eNodeB, and cell level.

i. Network Level

   The figure representing the KPIs and counters for predicting if the E-RAB setup success falls below a certain threshold in an aggregated network test is shown in Figure 5.12. The model used for prediction demonstrates a sensitivity of 44.8% and an F1-score of 55.68%.

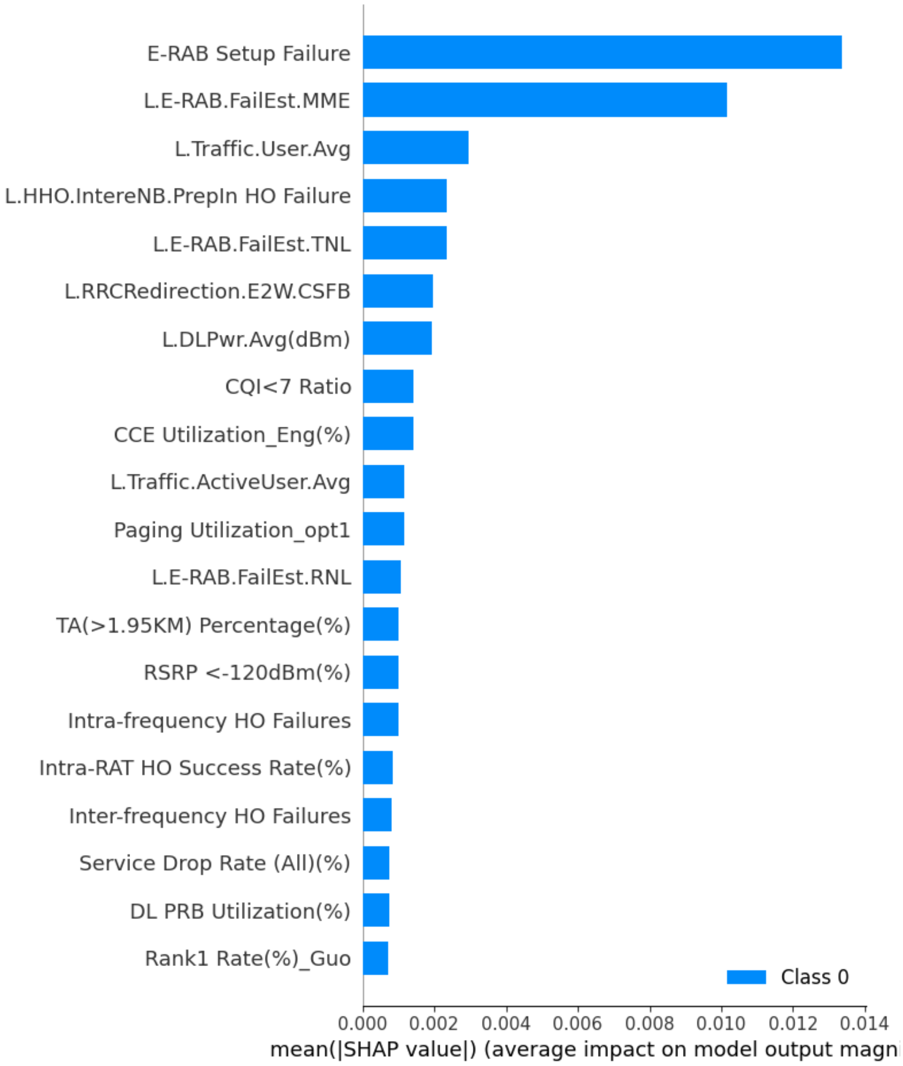


Figure 5.12: Root causes for lower E-RAB setup success at the network level.

The summary plot illustrated in Figure 5.12 merges feature importance with feature effects, presenting a comprehensive overview. The x-axis corresponds to the SHAP values, while the y-axis corresponds to the degraded instance features. The ordering of the features is based on their significance. It reveals that the number of E-RAB setup failures has the most significant impact on predicting low E-RAB setup success. This is followed by the failure of E-RAB setup caused by the MME. The third notable counter is the average number of users in the network. The fourth and fifth most important counters are the handover failure between the eNodeBs and the E-RAB setup failure due to transport network problem. Other contributors to predicting low E-RAB setup failure include CSFB, CQI values below seven, CCE utilization, average number of active users, and setup failure due to insufficient radio resources.

ii. eNodeB Level

Figure 5.13 illustrates the most crucial KPIs and counters for predicting E-RAB setup success below the threshold at the eNodeB level. The model's performance for prediction achieves a sensitivity of 82.1% and an F1-score of 83.8%.

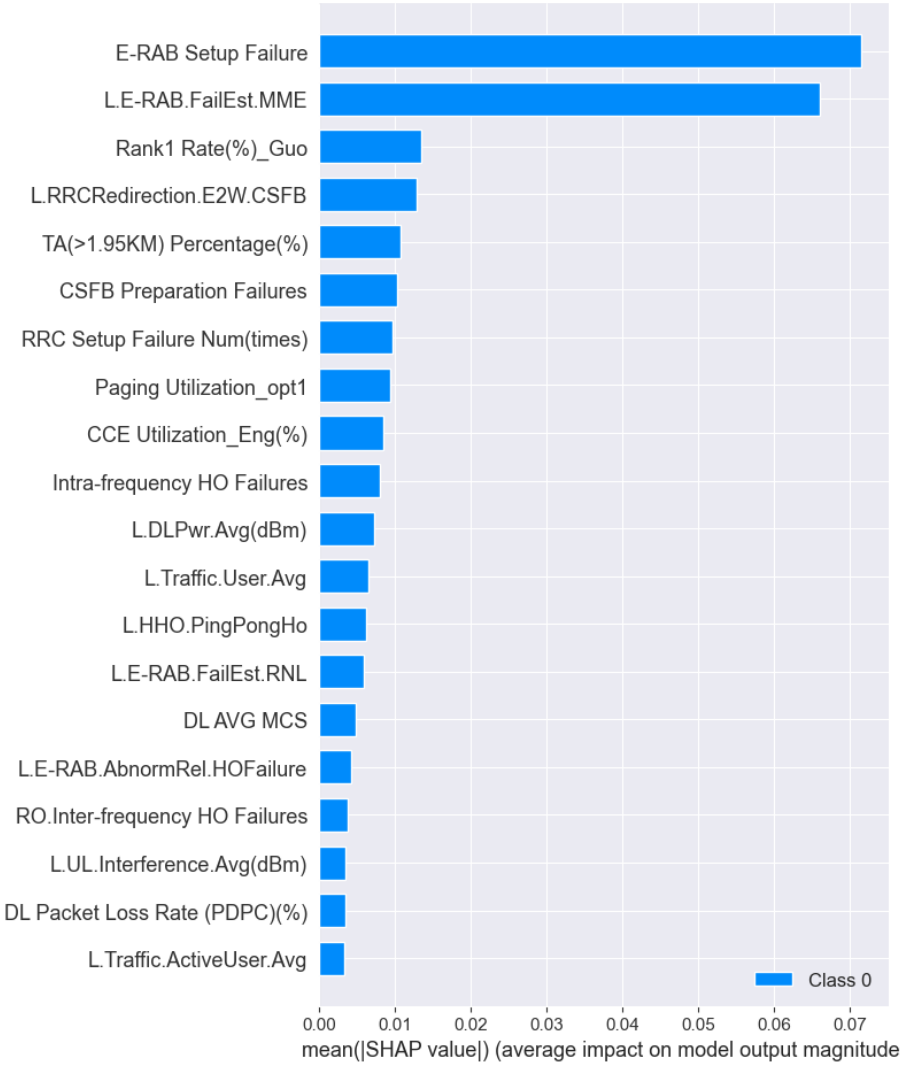


Figure 5.13: Root causes for lower E-RAB setup success at the eNodeB level.

The same as in the network level analysis, the number of E-RAB failures and E-RAB failures due to MME are the most important counters. Furthermore, the Rank 1 rate and CSFB redirection are also essential metrics in this prediction. Moreover, the time advance, number of CSFB preparation failures, and number of RRC setup failures are crucial counters in predicting lower E-RAB setup success. The paging utilization, CCE utilization, and inter-frequency handover failure are also significant KPIs in prediction E-RAB setup success below the threshold.

iii. Cell Level

The results for the single cell are presented here. The model's performance for prediction achieves a sensitivity of 86.6% and an F1-score of 82.8%. Figure 5.14 displays KPIs and counters that are most important for predicting low E-RAB setup success.

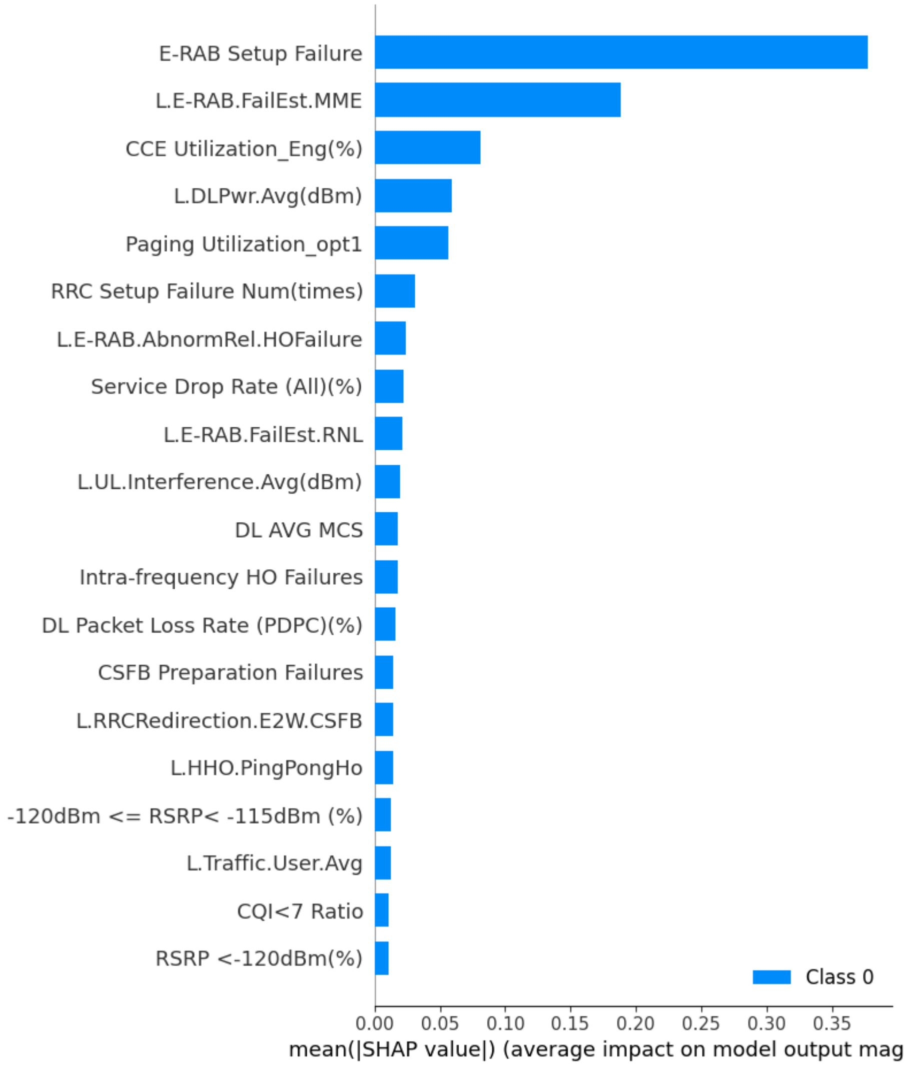


Figure 5.14: Root causes for lower E-RAB setup success at the cell level.

The same as the above two analyses, the number of E-RAB setup failures and E-RAB setup failures due to MME are the first and the second most significant counters in predicting low E-RAB setup success. Following this, CCE utilization, paging utilization, and number of RRC setup failures are significant for the prediction. Additionally, abnormal E-RAB release due to handover failure, E-RAB failure due to resource problems, and interference are also important counters.

iv. Individual Instance Analysis

The analysis mentioned above was conducted on aggregated samples from the test data. To identify the most significant KPIs for predicting low E-RAB setup success in individual instances, a force plot is utilized. This force plot visually presents the positive or negative contribution of each feature towards the final prediction, relative to a base value.The base value that shown in the *shap.force_plot* plot, depicts the expected output of the model. By examining the force plot, we can understand how the SHAP values influence the model's prediction, shifting it from the base value to the actual prediction for the selected instance.

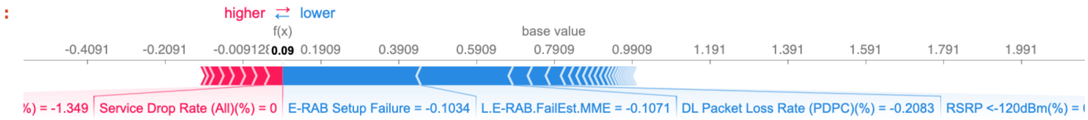


Figure 5.15: Root causes for lower E-RAB setup success in a single instance.

Figure 5.15 illustrates the Shap force plot for the 10th sample in the test set. The plot shows the computed SHAP values for the input dataset, indicating the contribution of each feature towards the final prediction for the given sample.

The length of the bars in the plot indicates the level of impact on the prediction, with longer bars signifying a higher impact and shorter bars representing a lower impact. Specifically, for the sample, the factors that play an important role in predicting a base value of 0.09 (which indicates a lower E-RAB setup success) are a number of E-RAB failures, E-RAB failure due to MME and RSRP less than $-120dBm$ percentage. These three features influence the prediction the most in this scenario.

5.3.2 Downlink User Throughput Analysis

The results for low user throughput in the downlink will be presented. The analysis includes KPIs and counters at various levels: network, eNodeB, and cell.

i. Network Level

Figure 5.16 showcases the important KPIs and counters for predicting low downlink user throughput in an aggregated network test. The model's performance for prediction achieves a sensitivity of 89.2% and an F1-score of 92.2%. Among the factors, the average number of active users is considered to be the most important factor for predicting low user throughput (Figure 5.16). The second important factor is downlink PRB utilization. The third factor is the ratio of CQI values less than 7. Another significant factor is the number of redirections to WCDMA due to coverage issues.

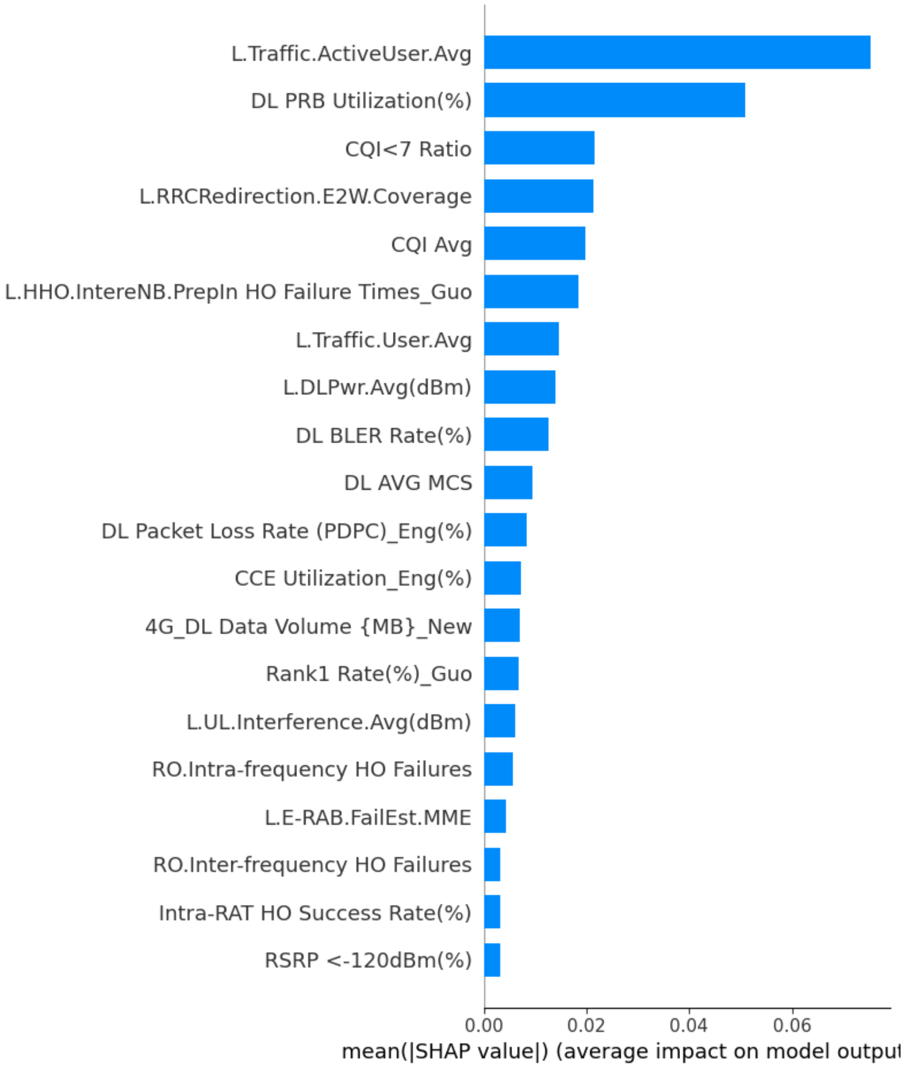


Figure 5.16: Root causes for lower user throughput at the network level.

Additionally, KPIs such as CQI average, inter eNodeB handover failure, average traffic user, and downlink block error also contribute significantly to the prediction.

ii. eNodeB Level

Figure 5.17 analyzes the KPIs that contribute to predicting low user throughput at the eNodeB level. The model's performance for prediction achieves a sensitivity of 94.7% and an F1-score of 95.3%. The primary counter is the average active user number, which has the highest impact on predicting low user throughput. The second most important KPI is the downlink PRB utilization, followed by the CCE utilization ratio, which represents the third factor. The fourth significant KPI is the average user number, while the fifth factor is the ratio of CQI values less than seven. Additional KPIs that significantly contribute to the prediction include E-RAB setup failure, time advance greater than 1.95km percentage, and downlink block error rate. These variables also play a vital role in determining the likelihood of low user throughput.

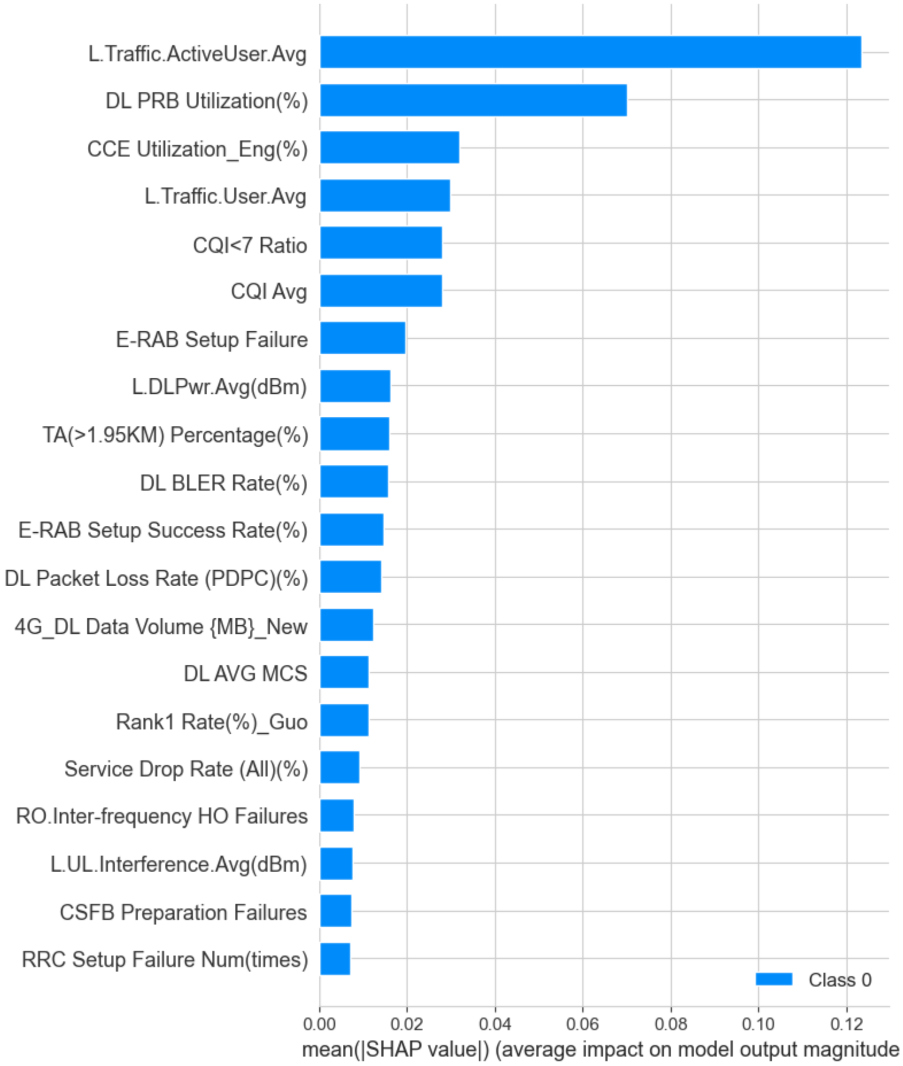


Figure 5.17: Root causes for lower user throughput at the eNodeB level.

iii. Cell Level

At the cell level, Figure 5.18 presents the most important KPIs for predicting low user throughput. The model's performance for prediction achieves a sensitivity of 95.5% and an F1-score of 95.7%. Downlink PRB utilization plays the most significant role in determining low user throughput at the cell level. The second most important KPI is the ratio of CQI values less than seven. Additionally, downlink packet loss rate and inter eNodeB handover failures are the fourth and fifth significant KPIs for prediction purposes.

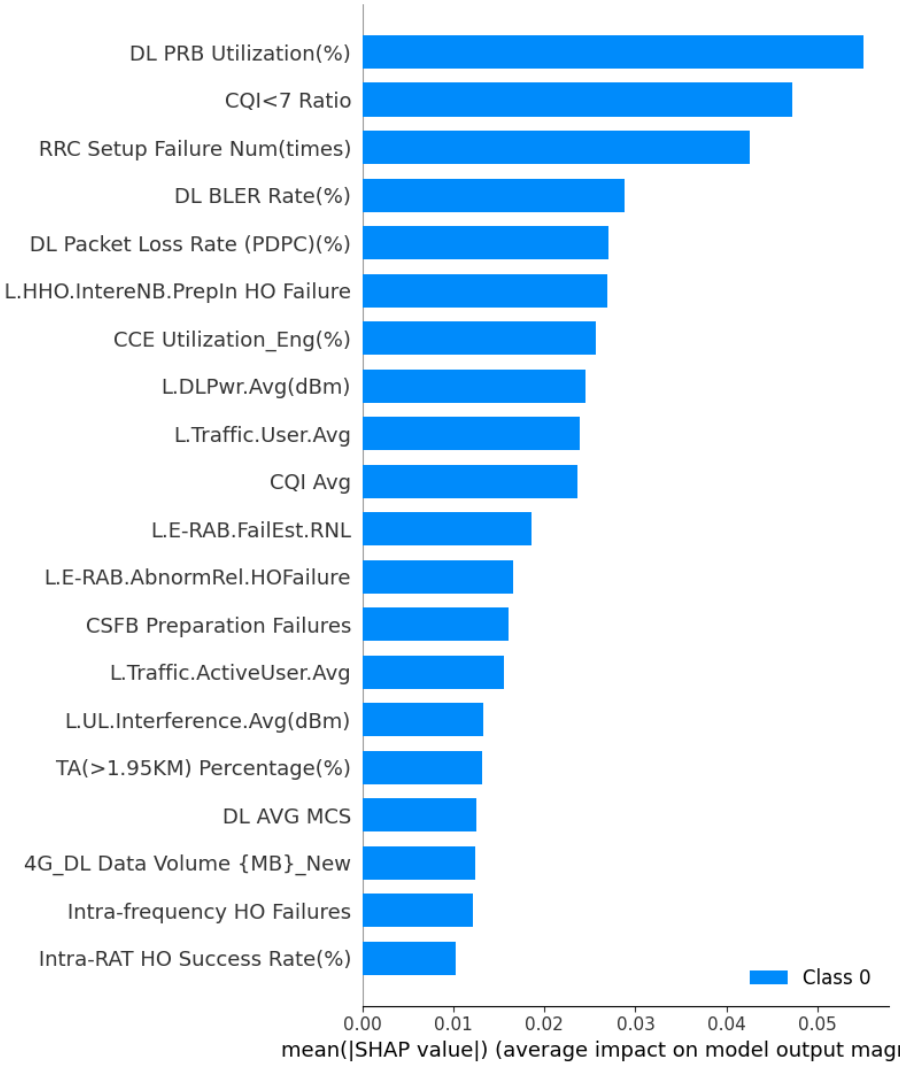


Figure 5.18: Root causes for lower user throughput at the cell level.

CCE utilization, downlink average power, average number of users, and E-RAB failures due to insufficient radio resources also significantly contribute to the prediction of low user throughput in LTE cells.

iv. Individual instance Analysis

The shape force plot for the 50^{th} sample in the test data is displayed in Figure 5.19. The model's prediction output of $f(x) = 0.2$ suggests a low user throughput. The plot indicates that the downlink PRB utilization, number of RRC setup failures, and downlink block error rate are the most significant KPIs for this prediction.

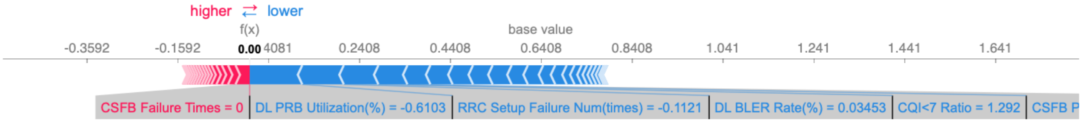


Figure 5.19: Root causes for lower user throughput in a single instance.

5.4 Discussion of the Results

Based on the results obtained from the analysis, several important KPIs and counters have been identified for predicting low E-RAB setup success and low downlink user throughput at different levels of the network.

5.4.1 Result Discussions Of Accessibility

The E-RAB setup success rate network accessibility is a metric that measures the percentage of successfully established E-RABs out of the total attempted E-RAB setup requests. This success rate reflects the efficiency of the network in establishing the necessary connections between the UE and the LTE network.

The analysis of low E-RAB setup success identified important KPIs and counters at the network, eNodeB, and cell levels. At the network level, the most significant factors were the count of E-RAB setup failures, E-RAB failures due to MME, number of user traffic, handover failure, failure caused by transmission network, and CSFB redirection. At the eNodeB level, the number of E-RAB setup failures, E-RAB failures due to MME, Rank 1 rate, CSFB redirection, high time advance, CSFB preparation failures, number of RRC setup failures, paging utilization, CCE utilization, and inter-frequency handover failures played a crucial role. In the cell-level analysis, the number of E-RAB setup failures, E-RAB failures due to MME, CCE utilization, paging utilization, RRC setup failures, handover failures, and interference were identified as causes for low E-RAB setup success.

Interpreting the KPIs and counters, the results achieved are according to the intuition about lower network accessibility.

- E-RAB setup Failure counter refers to the total count of unsuccessful attempts to establish an E-RAB connection between the UE and the network. A high E-RAB setup failure counter contributes to a lower E-RAB setup success rate which is a crucial metric for network accessibility.

- L.E-RAB.FailEst.MME (E-RAB failures due to MME): If this counter consistently increases or its value is high, which indicates a potential problem with the MME, which can negatively impact the E-RAB setup success rate and overall network accessibility. Examples of such errors may include MME overload, resource allocation failure, or signaling issues.

- CSFB redirection (L.RRCRedirection.E2W.CSFB): This counter was found to have a substantial influence on network accessibility. CSFB technology allows circuit-switched calls over a 4G network that doesn't support LTE. A higher value of this counter indicated more instances that the number of phone calls and SMS messages has affected network accessibility.

- CCE utilization refers to the usage of resources on the Control Channel, which is responsible for transmitting control information. If the CCEs are highly utilized, indicating control channel congestion, the resources available for establishing and maintaining connections may be limited. This can result in an increased probability of unsuccessful E-RAB setups which leads to low network accessibility.

- The Rank indicator refers to the number of transmit antennas being used by the eNodeB for communication with a particular UE. The Rank 1 rate (%) indicates the percentage of UEs with a rank value of 1. If the Rank 1 rate is higher than the other ranks, it means that the network is transmitting data using a single antenna most of the time. This can potentially lead to a lower E-RAB setup success.
- Handover failures: When the number of failure handovers is high, the cells are crowded with user sessions and cannot accept any more sessions, which leads to lower network accessibility.
- The high number of RRC setup failures indicates there is a failure to establish the RRC connection between the UE and the network, preventing the E-RAB setup success.
- The Time Advance (TA) counter is used to measure the propagation delay between the eNodeB and UE. A potentially higher TA (>1.95km) percentage means that a significant number of UEs are located relatively far away from the eNodeB, resulting in weaker signal reception. This can degrade network accessibility, as the UE might struggle to establish a reliable connection due to poor signal quality.
- The counter L.E-RABFailEst.RNL (L.E-RAB.FailEst.NoRadioRes) counter represents the number of failed E-RAB establishment attempts due to the lack of radio resources, which indicates poor network accessibility. Insufficient radio resources can occur because of reasons, such as high network congestion and limited available spectrum,
- Paging utilization refers to the amount of paging resources being used to deliver paging messages to UE. The network sends Paging messages to notify a specific device of incoming calls, messages, or other network events. When network resources are heavily utilized for paging, there may not be enough available resources to handle the E-RAB setup requests, leading to delays or failures in setting up the connections and ultimately affecting network accessibility.

Overall, the results of the analysis show that there are root causes that contribute to low E-RAB setup success. By identifying and addressing these factors, operators can improve network accessibility and provide a better experience for their users.

5.4.2 Result Discussion Of Integrity

In this thesis, user downlink average throughput was utilized as a measure to assess the integrity of the network, defined as the extent to which network services are delivered without substantial issues after being acquired. Significant KPIs and counters were identified at the network, eNodeB, and cell levels for predicting low downlink user throughput.

The analysis found that at the network level, the causes of low downlink average throughput in the selected network area were the number of active users (L.Traffic.ActiveUser.Avg), high downlink PRB utilization, poor CQI, redirections to WCDMA due to coverage issues, handover failure, and average number of user and block errors. Network congestion, indicated by both the number of active users and high PRB utilization, was the main cause of lower throughput in the analysis. Poor CQI, which indicates low SINR, also contributed to throughput degradation. In LTE, a lower CQI results in a lower Signal to Noise and Interference Ratio (SINR) value and consequently, a lower Modulation and Coding Scheme (MCS) index, leading to lower throughput. The results also suggest that a coverage issue is contributing to lower throughput in the selected network area.

At the eNodeB level, the average number of active users, downlink PRB utilization, CCE utilization ratio, average user number, poor CQI values, number of E-RAB setup failure, time advance (>1.95km), and block error rate were identified as crucial factors for low user throughput. In the cell-level analysis, significant factors for lower throughput included downlink PRB utilization, poor CQI, number of RRC setup failure, downlink block error rate, handover failures, CCE utilization, and average number of user.

Both the L.Traffic.ActiveUser.Avg counter and downlink PRB utilization significantly contribute to low user throughput at both the network and eNodeB levels. L.Traffic.ActiveUser.Avg indicates the average number of subscribers actively using the network, providing an indication of overall user traffic activity. On the other hand, downlink PRB utilization measures the proportion of available radio resources used for downlink data transmission. Furthermore, PRB utilization has become a leading cause of low throughput at the cell level.

Increased congestion often occurs as the number of active users rises, leading to a decrease in downlink user throughput. High PRB utilization indicates that the network is operating at or near its maximum capacity, leading to even more congestion. Consequently, congestion becomes the root cause of low user throughput in the network, eNodeB, and cell levels. Besides the congestion, coverage and handover failures are additional causes for low throughput in the network level analysis. Downlink user throughput at the eNodeB level is also affected by control channel congestion (CCE utilization) and the average number of users (both active and inactive) over a specific time period. Downlink user throughput at the cell-level also affected by block error rate and lack of radio resource.

For individual instances, force plots were used to visualize the contribution of each feature to the prediction, helping to understand which features had the most significant impact on the predicted output. In the analysis of E-RAB setup success for an individual instance, features such as the number of E-RAB failures, E-RAB failures caused by core network (MME), and RSRP less than $-120dBm$ percentage were found to have a high impact on the prediction which are the root causes. For low downlink user throughput, features such as downlink PRB utilization, number of RRC setup failures, and downlink block error rate were identified as significant contributors to the prediction.

These findings provide valuable insights for network operators to optimize network resources and improve network performance, leading to better customer satisfaction and increased revenue.

6 Conclusion and Future Work

This chapter summarizes the main findings of the thesis and proposes extensions of this work as future research. It also discusses the limitations of the current work and how they could be addressed in future studies.

6.1 Conclusion

This research proposes a CNN-SHAP approach for RCA of LTE network accessibility and integrity degradation. The 1D CNN is used to detect instances of decreased network accessibility and integrity by analyzing historical LTE network data. The three analyses at the network, eNodeB, and cell levels considered the factors that contribute to decreased accessibility and integrity at these levels. However, the model's prediction performance in the network-level analysis was lower than in the other two analyses due to the significant imbalance between the degraded and non-degraded classes. This imbalance can negatively affect the model's ability to accurately classify the degraded class. To address this challenge, a stratified cross-validation method was chosen, instead of employing upsampling techniques such as Borderline Synthetic Minority Oversampling Technique (SMOTE), which introduces additional synthetic data and increases computational time.

The SHAP algorithm was employed for RCA, calculating the average impact of each feature on the model's output and identifying high marginal values as the root causes of low accessibility and integrity. The SHAP algorithm is computationally efficient and quickly identifies the most influential feature for degraded instances.

The proposed approach leveraged the advantages of deep learning and SHAP. This results in a number of advantages over traditional RCA methods, including:

- **Reusability:** The same approach can be used to analyze different performance indicators by simply changing the target variable.
- **High-dimensionality support:** The proposed approach can handle a large number of network features for improved performance analysis. This is important because network performance can be affected by a wide range of factors.
- **Geographic scalability:** The proposed approach can be scaled from single cells to large networks with minimal performance loss, making it suitable for use in networks of all sizes.

- **Time resolution:** The proposed approach can provide analysis results on a single cell with a resolution as low as one hour.

By understanding the root causes of these problems, network operators can make informed adjustments to network resources, thus preventing such occurrences in the future. The proposed CNN-SHAP approach offers an effective method for RCA in 4G networks, and can help network operators to improve network performance and customer satisfaction by identifying and resolving issues related to decreased accessibility and integrity.

6.2 Future Work

The proposed approach can be further improved in the following ways.

- Use additional data sources, such as drive test data, network alarms, and network logs, for the RCA. It would be interesting to investigate how these data sources compare to historical data in terms of their effectiveness for RCA.
- Extend the study to other types of networks, such as fifth-generation networks. This would help to understand the general principles of RCA for network performance problems.
- Analysis of other performance indicators, such as retainability, or mobility can also affect the overall user experience. Future work can expand the analysis to include these metrics and investigate their impact on network degradation. This can provide a more comprehensive understanding of the factors affecting network performance.

Reference

[1] 3GPP. *Evolved Universal Terrestrial Radio Access (E-UTRA) and Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Overall description;* Technical Specification (TS) 36.300 V14.0.0. Version 13. 3rd Generation Partnership Project (3GPP), Sept. 2016.

[2] 3GPP. *Key Performance Indicators (KPI) for Evolved Universal Terrestrial Radio Access Network (E-UTRAN): Definitions.* Technical Specification (TS) 32.450. Version 17.0. 3rd Generation Partnership Project (3GPP), Apr. 2022.

[3] 3GPP. *Key Performance Indicators (KPI) for Evolved Universal Terrestrial Radio Access Network (EUTRAN); Requirements.* Technical Specification (TS) 32.451. Version 13. 3rd Generation Partnership Project (3GPP), Apr. 2016.

[4] Sassan Ahmadi. *LTE-Advanced A Practical Systems Approach to Understanding 3GPP LTE Releases 10 and 11 Radio Access Technologies.* Elsevier Inc, 2013.

[5] Alcatel.Lucent. *Strategic White Paper, The LTE Network Architecture.* 2009.

[6] Yonas Alemayehu. "Root Cause Analysis of Unsatisfactory User Throughput in UMTS for Bahir Dar City". MA thesis. Addis Ababa, Ethiopia: Addis Ababa Univ. Dept. of Electrical. Eng, 2021.

[7] R Barco et al. "Analysis of Throughput Performance Statistics for Benchmarking LTE Networks". In: *EURASIP Journal on Wireless Communications and Networking* 2017.130 (2017). DOI: `https://doi.org/10.1186/s13638-017-0914-3`.

[8] Yoshua Bengio, Yann Lecun, and Geoffrey Hinton. "Deep learning for AI". In: *Communications of the ACM* 64.7 (2021), pp. 58–65.

[9] Yoshua and Bengio. "Deep learning". In: *Nature* 521.7553 (2015), pp. 436–444.

[10] V. Buenestado et al. "Analysis of Throughput Performance Statistics for Benchmarking LTE Networks". In: *IEEE Communications Letters* 18.9 (2014), pp. 1607–1610. DOI: `10.1109/LCOMM.2014.2337876`.

[11] Chetan M Bulla and Mahantesh N Birje. "Improved data-driven root cause analysis in a fog computing environment". In: *Int. J. Intell. Inf. Technol.* 18.1 (Apr. 2022), pp. 1–28.

[12] SM Chadchan and CB Akki. "3gpp lte/sae: an overview". In: *International Journal of Computer and Electrical Engineering* 2.5 (2010), p. 806.

[13] Erik Dahlman, Stefan Parkvall, and Johan Sköld. "Chapter 8 - Radio-Interface Architecture". In: *4G: LTE/LTE-Advanced for Mobile Broadband (Second Edition).* Ed. by Erik Dahlman, Stefan Parkvall, and Johan Sköld. Second Edition. Oxford: Academic Press, 2014, pp. 121–139. ISBN: 978-0-12-419985-9. DOI: `https://doi.org/10.1016/B978-0-12-419985-9.00008-8`.

[14] Anamika Dhillon and Gyanendra K Verma. "Convolutional neural network: a review of models, methodologies and applications to object detection". In: *Progress in Artificial Intelligence* 9.2 (2020), pp. 85–112.

[15] Ayman ElNashar, Mohamed A. El-saidny, and Mahmoud Sherif. *Design, Deployment and Performance of 4G-LTE Networks: A Practical Approach.* John Wiley Sons, 2014.

[16] Ayman ElNashar, Mohamed A. El-saidny, and Mahmoud Sherif. "LTE Network Architecture and Protocols". In: *Design, Deployment and Performance of 4G-LTE Networks: A Practical Approach.* 2014, pp. 1–45. DOI: `10.1002/9781118703434.ch1`.

[17] Alpaydın Ethem. *Introduction to Machine Learning, Fourth Edition.* The MIT Press, 2020.

[18] Pedregosa Fabian et al. "Scikit-learn: Machine Learning in Python". In: *Journal of Machine Learning Research* 12.85 (2011), pp. 2825–2830. URL: `http://jmlr.org/papers/v12/pedregosa11a.html`.

[19] Diogo Ferreira et al. "Prediction of low accessibility in 4G networks". In: *Annals of Telecommunication* 77.10 (2022), pp. 421–435.

[20] A. Géron. *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems.* O'Reilly Media, Incorporated, 2019. ISBN: 9781492032649. URL: `https://books.google.com.et/books?id=OCS1twEACAAJ`.

[21] Anirudha Ghosh et al. "Fundamental Concepts of Convolutional Neural Network". In: *Recent Trends and Advances in Artificial Intelligence and Internet of Things.* Cham: Springer International Publishing, 2020, pp. 519–567.

[22] Ana Gómez-Andrades et al. "Automatic Root Cause Analysis for LTE Networks Based on Unsupervised Techniques". In: *IEEE Transactions on Vehicular Technology* 65.4 (2016), pp. 2369–2386. DOI: `10.1109/TVT.2015.2431742`.

[23] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning.* `http://www.deeplearningbook.org`. MIT Press, 2016.

[24] Inayatul Haq et al. "Impact of 3G and 4G Technology Performance on Customer Satisfaction in the Telecommunication Industry". In: *Electronics* 12.7 (2023). ISSN: 2079-9292. DOI: `10.3390/electronics12071697`. URL: `https://www.mdpi.com/2079-9292/12/7/1697`.

[25] Hendrawan Hendrawan. "Accessibility Degradation Prediction on LTE/SAE Network Using Discrete Time Markov Chain (DTMC) Model". In: *Journal of ICT Research and Applications* 13.1 (2019), pp. 1–18. DOI: `10.5614/itbj.ict.res.appl.2019.13.1.1`.

[26] Huawei. *eRAN7.0 KPI Reference.* Technical Report (TR) V100R009C00. 01. Huawei, Apr. 2016.

[27] Eric Jones, Travis Oliphant, and Pearu Peterson. *SciPy: Open Source Scientific Tools for Python*. 2001. URL: http://www.scipy.org.

[28] Junichi Kawasaki, Genichi Mouri, and Yusuke Suzuki. "Comparative Analysis of Network Fault Classification Using Machine Learning". In: *NOMS 2020 - 2020 IEEE/IFIP Network Operations and Management Symposium*. 2020, pp. 1–6. DOI: 10.1109/NOMS47738.2020.9110454.

[29] Farooq Khan. "Network architecture and protocols". In: *LTE for 4G Mobile Broadband: Air Interface Technologies and Performance*. Cambridge University Press, 2009, pp. 5–19. DOI: 10.1017/CBO9780511810336.003.

[30] Yoon Kim. *Convolutional Neural Networks for Sentence Classification*. 2014. arXiv: 1408.5882 [cs.CL].

[31] Jayanth Koushik. *Understanding Convolutional Neural Networks*. 2016. arXiv: 1605.09081 [stat.OT].

[32] Alexander Kukushkin. "4G-Long Term Evolution (LTE) System". In: (2018).

[33] Alexander Kukushkin. *4G-Long Term Evolution (LTE) System*. 2018, pp. 205–291. DOI: 10.1002/9781119484196.ch11.

[34] Y. Le Cun et al. "Handwritten digit recognition: applications of neural network chips and automatic learning". In: *IEEE Communications Magazine* 27.11 (1989), pp. 41–46. DOI: 10.1109/35.41400.

[35] Scott M Lundberg and Su-In Lee. "A Unified Approach to Interpreting Model Predictions". In: *Advances in Neural Information Processing Systems*. Ed. by I. Guyon et al. Vol. 30. Curran Associates, Inc., 2017.

[36] Maluambanzila Minerve Mampaka and Mbuyu Sumbwanyambe. "Poor Data Throughput Root Cause Analysis in Mobile Networks using Deep Neural Network". In: *IEEE 2nd Wireless Africa Conference (WAC)*. 2019, pp. 1–6. DOI: 10.1109/AFRICA.2019.8843409.

[37] Maha Mdini. "Anomaly detection and root cause diagnosis in cellular networks". Theses. Ecole nationale supérieure Mines-Télécom Atlantique, Sept. 2019. URL: https://theses.hal.science/tel-02304602.

[38] Thomas Rincy N and Roopam Gupta. "A Survey on Machine Learning Approaches and Its Techniques:" in: *2020 IEEE International Students' Conference on Electrical,Electronics and Computer Science (SCEECS)*. 2020, pp. 1–6. DOI: 10.1109/SCEECS48394.2020.190.

[39] Konstantinos Papageorgiou et al. "A systematic review on machine learning methods for root cause analysis towards zero-defect manufacturing". In: *Frontiers in Manufacturing Technology* 2 (Oct. 2022), p. 972712. DOI: 10.3389/fmtec.2022.972712.

[40] André Perez. "Mobile Network Signaling Protocols". In: *Implementing IP and Ethernet on the 4G Mobile Network*. Elsevier, 2017, pp. 15–44. ISBN: 978-1-78548-238-0. DOI: https://doi.org/10.1016/B978-1-78548-238-0.50002-9.

[41] V Srinivasa Rao and Rambabu Gajula. “Protocol signaling procedures in LTE”. In: *White Paper, Radisys Corporation* (2011).

[42] Jussi Reunanen, Jari Salo, and Riku Luostari. “LTE Key Performance Indicator Optimization”. In: *LTE Small Cell Optimization*. John Wiley Sons, Ltd, 2015. Chap. 12, pp. 195–248. ISBN: 9781118912560. DOI: https://doi.org/10.1002/9781118912560.ch12.

[43] Marco Túlio Ribeiro, Sameer Singh, and Carlos Guestrin. “”Why Should I Trust You?”: Explaining the Predictions of Any Classifier”. In: *CoRR* abs/1602.04938 (2016). arXiv: 1602.04938. URL: http://arxiv.org/abs/1602.04938.

[44] James J Rooney and Lee N Vanden Heuvel. “Root cause analysis for beginners”. In: *Quality progress* 37.7 (2004), pp. 45–56.

[45] E. Rozaki. “Automated Network Optimisation Using Data Mining as Support for Economic Decision Systems”. PhD thesis. 2019. URL: https://books.google.com.et/books?id=3e1ZzQEACAAJ.

[46] Haniyeh Seyed Alinezhad, Mohammad Hossein Roohi, and Tongwen Chen. “A review of alarm root cause analysis in process industries: Common methods, recent research status and challenges”. In: *Chemical Engineering Research and Design* 188 (2022), pp. 846–860. ISSN: 0263-8762. DOI: https://doi.org/10.1016/j.cherd.2022.10.041.

[47] Chirag Shah. *A Hands-On Introduction to Machine Learning*. Cambridge University Press, 2022. DOI: 10.1017/9781009122092.

[48] Yi-Han Sheu. “Illuminating the Black Box: Interpreting Deep Neural Network Models for Psychiatric Research”. In: *Frontiers in psychiatry* 11 (2020), p. 551299. ISSN: 1664-0640. DOI: 10.3389/fpsyt.2020.551299.

[49] Farhana Sultana, Abu Sufian, and Paramartha Dutta. “Advancements in Image Classification using Convolutional Neural Network”. In: *2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*. IEEE, Nov. 2018.

[50] Huang Tao, Zhang Zhijiang, and Liu Yunjie. “QoS Mechanism in EPS”. In: *ZTE Communications* 7.1 (2020), pp. 49–53.

[51] Jonas Teuwen and Nikita Moriakov. “Chapter 20 - Convolutional neural networks”. In: *Handbook of Medical Image Computing and Computer Assisted Intervention*. Ed. by S. Kevin Zhou, Daniel Rueckert, and Gabor Fichtinger. The Elsevier and MICCAI Society Book Series. Academic Press, 2020, pp. 481–501. ISBN: 978-0-12-816176-0. DOI: https://doi.org/10.1016/B978-0-12-816176-0.00025-9.

[52] Van Tong et al. “Machine Learning based Root Cause Analysis for SDN Network”. In: *IEEE Global Communications Conference (GLOBECOM)*. 2021, pp. 1–6. DOI: 10.1109/GLOBECOM46510.2021.9685185.

[53] Yannan Yuan et al. “Anomaly Detection and Root Cause Analysis Enabled by Artificial Intelligence”. In: *2020 IEEE Globecom Workshops (GC Wkshps*. 2020, pp. 1–6. DOI: 10.1109/GCWkshps50303.2020.9367508.

[54] Xincheng Zhang. Wiley-IEEE Press, 2018. DOI: 10.1002/9781119158981.ch2.

[55] Yu Zhang et al. “A Survey on Neural Network Interpretability”. In: *IEEE Transactions on Emerging Topics in Computational Intelligence* 5.5 (2021), pp. 726–742. DOI: 10.1109/TETCI.2021.3100641.

[56] Nan Zheng and Pinaki Mazumder. “Fundamentals and Learning of Artificial Neural Networks”. In: *Learning in Energy-Efficient Neuromorphic Computing: Algorithm and Architecture Co-Design*. 2020, pp. 11–60. DOI: 10.1002/9781119507369.ch2.

[57] ZTE. *uSmart RNIA White Paper*. ZTE Corporation, . China. 2022. URL: https://www.zte.com.cn/content/dam/zte-site/res-www-zte-com-cn/mediares/zte/files/newsolution/wireless/ran/white_paper/Operation_EN40.pdf.

Machine Learning for Improved Root Cause Analysis of LTE Network Accessibility and Integrity Degradation

Fikreaddis Tazeb, *AAiT,* and Dr. -Ing. Dereje Hailemariam *AAiT*

October 4, 2023

***Abstract*—Long Term Evolution (LTE) networks are essential for enabling high-speed, reliable communication and data transmission. However, the accessibility and integrity of LTE networks can degrade due to a variety of factors, such as congestion, coverage, and configuration problems. Cause analysis is a process for identifying the underlying causes of degradation. However, cause analysis can be time-consuming and labor-intensive. Machine learning can be used to enhance cause analysis by identifying patterns and trends in data that can be used to identify the root causes of problems. Limited work exists on machine learning-enabled cause analysis for LTE networks.**

This thesis proposes a machine learning-enabled approach, specifically Convolutional Neural Network (CNN) and SHapley Additive exPlanations (SHAP), for cause analysis of LTE network performance degradation. The approach was evaluated using key performance indicators (KPIs) and counters data collected from LTE network of ethio telecom, a major operator in Ethiopia.

The main causes of reduced network accessibility are failure caused by the Mobility Management Entity (MME), the average number of users, and handover failures. Similarly, the underlying causes of degraded accessibility at the cell level are failure caused by MME, control channel element (CCE) utilization, and paging utilization. For the case of network integrity, which is measured by user throughput, the main causes of degradation are the high number of active users, high downlink Physical Resource Block (PRB) utilization, poor Channel Quality Indicator (CQI), and coverage issues. At the cell level, the main factors are downlink PRB utilization, unfavorable CQI values, and high downlink block error rate.

For the given data, the model's sensitivity for network accessibility and integrity at the cell level is 82.8% and 95.5%, respectively. These results demonstrate the potential of the proposed approach to accurately identify degradation instances. Network operators can mitigate degradation by understanding root causes and optimizing resources.

***Index Terms*—Accessibility, CNN, Integrity, LTE, Root Cause Analysis, SHAP.**

I. INTRODUCTION

LTE networks offer high data rates, spectrum efficiency, and reduced latency, signaling load, and energy consumption. However, their increased complexity makes them challenging to manage and optimize [1].

To ensure QoS and enhance customer satisfaction, mobile network operators install centralized network management systems (NMS) to monitor, control, and manage the performance of their RAN and core networks. NMS provide real-time data monitoring, analysis, reporting, and visualization of key performance indicators (KPIs) and counters related to the LTE network. KPIs are high-level metrics that measure the overall health of the network, while counters are low-level metrics that measure specific aspects of the network [2]. KPIs are typically derived from counters and are used to identify performance degradation, failures, problems, outages, or unusual events that might significantly impact service delivery and end-user experience. Counters provide detailed information about network traffic, resource allocation, and usage [3].

In the event of any performance issue, network engineers conduct troubleshooting activities. Root cause analysis (RCA) is an essential part of network troubleshooting as it enables engineers to identify and rectify the fundamental causes of the problem rather than just addressing the symptoms. Through the identification and resolution of the root causes, network operators can enhance network performance, minimize downtime, and elevate mobile service delivery quality. This thesis focuses on the accessibility and integrity of LTE networks.Accessibility is the ability of users to access the network and obtain services, while integrity is the ability of the network to provide high-quality services without degradation.

This thesis aims to develop a machine learning based RCA method, implementing CNN with SHAP, for two essential LTE network performance KPIs: network accessibility and integrity by exploring LTE Networks, conducting a comprehensive review of literature, investigating various RCA techniques, identifying potential factors contributing to performance degradation, gathering relevant KPIs and counters, designing, evaluating and validating a DNN model, assessing the impact of input features through CNN and SHAP, analyzing obtained results, drawing conclusions, and providing relevant recommendations for improvement. The specific objectives of the thesis include exploring LTE Networks: architecture, protocols, and performance metrics, identifying effective RCA techniques, preparing and preprocessing data for the model, and analyzing the obtained results. The thesis concludes with relevant recommendations for improvement.

The main contributions of this thesis are:

- The proposed approach is the first to use DNNs with SHAP to analyze the causes of network performance degradation in LTE networks.
- The approach is able to identify underlying causes at various network levels, which is not possible with traditional methods.
- The approach is evaluated using real-world data from a mobile network operator, and the results show that it

is able to identify the causes of network performance degradation with high accuracy.

A. Accessibility

Accessibility is a measure of how easily and reliably users can access the network and obtain services. Network accessibility is typically assessed through the analysis of the following metrics: RRC setup success rate, S1 setup success rate, and E-RAB setups, which are part of the service request procedure, starting with RRC setup, followed by S1 setup, and E-RAB setup, respectively [4], [5].

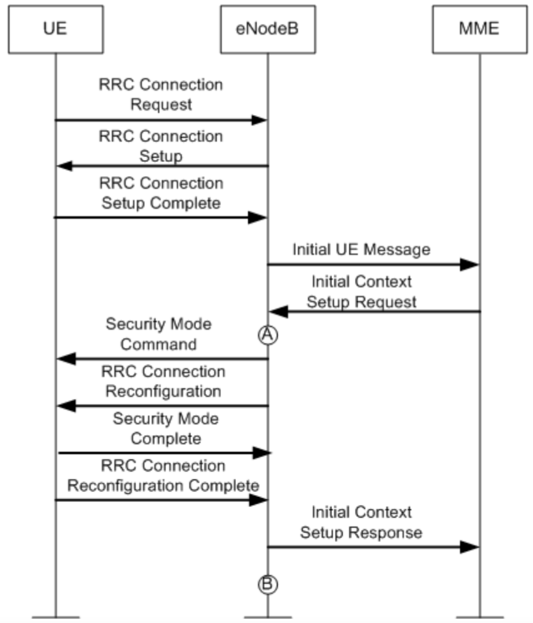


Fig. 1. Measurement points for UE-triggered E-RAB setup [6].

1) **RRC setup success rate:** The RRC setup success rate reflects the effectiveness of the initial radio connection establishment procedure, calculated using counters measured at the eNodeB, and a high RRC setup success rate indicates greater accessibility and fewer call setup errors.
2) **S1 setup success rate:** The S1 setup success rate reflects the effectiveness of the S1 interface, which directly impacts mobility management, handover success, and overall network accessibility, calculated using counters measured at the eNodeB, and a higher success rate ensures seamless connectivity during handovers and reliable communication between network elements.
3) **E-RAB setup success rate:** The E-RAB setup success rate represents the success rate of E-RAB setup request for all services within a specific cell or radio network, calculated using counters measured at the eNodeB, and a high E-RAB setup success rate indicates that the network is capable of quickly and reliably establishing data bearers, allowing for smooth data transmission and minimizing service disruptions

B. Integrity

The 3GPP defines integrity as a category for network performance KPIs, which includes latency and throughput metrics [2].

- Average user throughput represents the measurement of data transfer speed achieved by an individual user within a cell or network, calculated as the total volume of PDCP SDUs transferred per cell and reporting output period divided by the time used to send the information, excluding last TTIs [7].
- Cell downlink average throughput is a measure of the capacity and efficiency of the network in delivering data to end-users in a cell, calculated as the total PDCP data volume transferred in a cell and reporting output period considering all TTIs divided by the scheduler activity time [7]. These metrics provide insight into the network's capacity to handle data traffic and deliver faster download speeds to users, allowing operators to optimize network setups and fix any issues affecting overall service quality.

This paper is organized as follows: Section II summarizes the proposed research methodology. Section III presents the model prediction performance and the implementation of the SHAP method. Section IV analyzes the SHAP method output to identify the most critical KPIs and counters used to generate SHAP plots. Finally, Section V presents the conclusions and research directions for future work.

II. RELATED WORKS

Diago et al. [8] investigated KPIs and their evolution over time to identify the possible causes of low network accessibility in 4G networks. They collected one-month data for various KPIs and used interpretable machine learning models to assess the contribution of each KPI towards decreasing network accessibility. The results showed that certain KPIs have a greater impact on network accessibility than others, such as the number of failure handovers, phone calls, and SMSs in the network, and the overall download volume. At the cell level, the number of users in a cell and its download volume are the main causes of reduced accessibility. However, their approach to determining feature importance is algorithm-dependent and does not take deep learning algorithms into account.

Maluambanzila et al. [9] proposed a deep learning model for root cause analysis (RCA) of poor throughput in mobile 3G networks. The model takes both radio and core network performance indicators as input. They collected data from an actual mobile network operator and trained a DNN model to predict poor data throughput. The RCA result identified the top four features that influenced poor data throughput. This methodology was followed in a study by [10] to investigate the root cause of low user throughput in UMTS networks in Bahir Dar City. They used a MLP neural network and LIME for RCA by providing feature importance.

Motivated by the challenges of identifying and resolving performance issues in fog computing environments, different works have been done using machine learning algorithms. Chetan B. and Mahantesh [11] proposed an approach for root cause analysis (RCA) that uses an LSTM autoencoder to identify anomalous data and then passes that data to a RCA model that uses SHAP. The SHAP algorithm calculates each feature's marginal contribution and identifies high marginal values as the root cause of the anomaly.

Several machine-learning models have been proposed based on their fit for the specific task as well as their performance and complexity. Machine-learning-based models, particularly deep learning models, appear to be the way to go. This thesis proposes a CNN paired with SHAP as the RCA model for low 4G network accessibility and integrity.

III. PROPOSED APPROACH

This work evaluates the accessibility of the LTE network using the E-RAB setup success rate, a metric that reflects the network's performance in establishing bearers to fulfill user service requests, while network integrity is assessed by average user throughput, which measures the average data transfer rate experienced by users over a certain period of time. The proposed RCA method for addressing E-RAB setup success degradation and user throughput degradation integrates the use of 1D CNN and SHAP to extract important features from one-dimensional input data. Once the 1D CNN model predicts the occurrence of degradation, SHAP is utilized to interpret the prediction model and provide a high score value for the root causes of the degradation. By applying SHAP, the proposed method can identify the key factors or inputs that contribute the most to the degradation of E-RAB setup success rate and user throughput.

A. Data Collection

To gather data for this study, human-understandable causes associated with the degradation of E-RAB setup success and user throughput, such as signal interference, high network congestion, hardware failures, software glitches, or configuration issues, were identified, followed by determining specific parameters that can be measured on the NMS, such as signal strength, inter-frequency handover failure, resource utilization, and number of active users. The input parameters for the model are derived from the Performance Report System (PRS) and include various counters and KPIs, which are potential causes for user throughput and E-RAB setup success.

B. Data Preprocessing

Data preprocessing is a crucial step in machine learning that involves preparing the data for analysis to improve the accuracy and effectiveness of the chosen method.

- Data cleaning is the process of handling and correcting any errors, inconsistencies, or outliers present in the dataset. In this particular dataset, we will replace missing values with zero.
- Data normalization is used to bring features to a common scale. In this thesis, we will use robust scaling, which is less sensitive to outliers.
- Data discretization is the process of converting continuous data into categorical data. In this particular case, we will discretize the targets of interest, E-RAB setup success and average user throughput, into binary classifications. Class 0 represents low user throughput while class 0 represents user throughput above the threshold. Similarly, class 0 represents low E-RAB setup success, and class 1 represents acceptable E-RAB setup success.

A threshold value was set for the binary classification based on the analysis of the data. For E-RAB setup success rate, a value less than 99% is considered as degraded (Class 0), while a value greater than 99% is considered as normal (Class 1), as this is the point at which declined E-RAB setup requests begin to increase significantly. For user throughput, a value of greater than 3 Mbps was considered as good (Class 1), and a value less than 3 Mbps is considered as degraded (Class 0), as this is the point at which users begin to experience noticeable degradation in performance.

C. Convolutional Neural Network

CNN is a type of deep learning algorithm well-suited for processing data with spatial structure, such as images and video. It has a hierarchical architecture with an input layer, output layer, and multiple hidden layers, including convolutional layers, non-linearity layers, pooling layers, and fully connected layers [12] [13]. Convolutional layers extract features from the input data, with a kernel applied to the input data to learn low-level features. Non-linearity layers add non-linearity to the CNN, while pooling layers reduce the dimensionality of the feature maps. Fully connected layers make the final prediction based on the learned features. There are three main types of CNN: 1D, 2D, and 3D, used to process 1D data, such as time series data, 2D data, such as image data, and 3D data, such as volumetric data [12] [14].

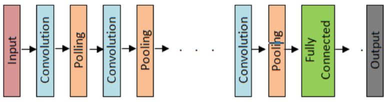


Fig. 2. Conceptual architecture of CNN [14].

D. SHapley Additive exPlanations

Machine learning interpretability is crucial for understanding and explaining how models arrive at their predictions. Interpretability methods can be classified based on several attributes, including model-specific vs. model-agnostic methods, intrinsic vs. post-hoc interpretability, and global vs. local interpretability. The SHAP framework is a popular post-hoc interpretability method that can be used to explain both the global and local behavior of machine learning models. It provides a way to explain the contribution of each feature to the final prediction made by the model using game theory to apportion the model's prediction among the input features [15].

SHAP values can be calculated using different methods, including explainer, tree, kernel, and deep approaches [15]. Explainer SHAP uses simple linear models to compute shap values. It is computationally efficient but may not be suitable for complex models or those with non-linear relationships. Tree SHAP uses a modified version of the Game Theory Shapley value. It works well for tree-based models such as random forests. Kernel SHAP is versatile and can be applied to a variety of models, both linear and non-linear.

Deep SHAP is an extension of the SHAP method that can be applied to deep learning models. It involves generating a background dataset, sampling a subset of the background dataset, generating a model output, computing the contribution of each feature, computing the SHAP value, and summing up the SHAP values to obtain the overall importance of each feature in the model [15].

E. Evaluation Metrics

To evaluate the proposed model, performance metrics precision, sensitivity, and F1-score. These metrics represent the accuracy and efficiency of the binary classification process. Sensitivity measures the percentage of correctly identified positive classes, while specificity measures the percentage of correctly identified negative classes. The following terms are used to define these measures: True Negative (TN) and True Positive (TP) indicate correctly predicted positive and negative classes. False Negative (FN) and False Positive (FP) represent incorrectly predicted negative and positive classes.

Precision measures the percentage of correctly predicted positive (degraded) samples.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Sensitivity measures the percentage of all positive samples that are correctly predicted.

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

F1-score is a harmonic mean of precision and recall, and it is used to evaluate the overall performance of a model.

$$F1_{score} = 2 * \frac{Precision}{Sensitivity} \tag{3}$$

Accuracy measures the overall correctness of the model's predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

IV. RESULTS

A. Model Performance

The 1D CNN model is trained using input data to predict both low throughput and E-RAB setup success, with modified target variables for each prediction. The model is evaluated using stratified k-fold cross-validation with 5 splits, where the model is trained on the training data and predictions are made on the test data to calculate accuracy, precision, sensitivity, F1 score, and F2 score for each fold. Confusion matrices are also calculated for each fold, and an average confusion matrix is computed by summing the confusion matrices on each fold and dividing by the number of folds.

TABLE I
MODEL PERFORMANCE FOR E-RAB PREDICTION

	Accuracy	**Precision**	**Sensitivity**	**F1-score**	**Specificity**
Cell	93.4	90.9	82.8	86.6	97.1
eNodeB	98.3	86.1	82.1	83.8	99.2
Network	98.3	75.04	44.8	55.68	99

TABLE II
MODEL PERFORMANCE FOR THROUGHPUT PREDICTION

	Accuracy	**Precision**	**Sensitivity**	**F1-score**	**Specificity**
Cell	97.2	96.1	95.5	95.7	98
eNodeB	97.6	96	94.7	95.3	98
Network	97.1	95.4	89.2	92.2	90.8

B. Root causes of low E-RAB Setup Success

For the analysis, the most important KPIs and counters for predicting if the E-RAB setup success is below a threshold are presented. This includes different levels of analysis like network, eNodeB, and cell level.

1) Network Level
Figure 3 representing the KPIs and counters for predicting if the E-RAB setup success falls below a certain threshold in an aggregated network test is shown in Figure 3. The model used for prediction demonstrates a sensitivity of 44.8% and an F1-score of 55.68%.

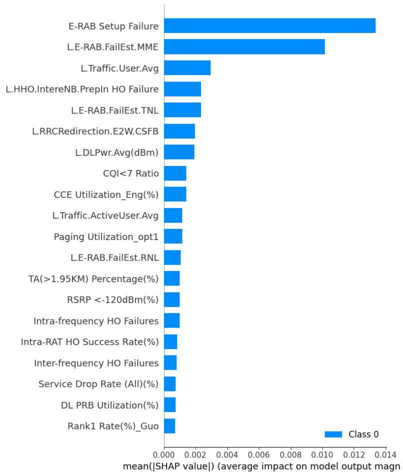


Fig. 3. Root causes for lower E-RAB setup success in Network level.

2) eNodeB Level
Figure 4 illustrates the most crucial KPIs and counters for predicting E-RAB setup success below the threshold at the eNodeB level. The model's performance for prediction achieves a sensitivity of 82.1% and an F1-score of 83.8%.

3) Cell Level
The results for the single cell are presented here. The model's performance for prediction achieves a sensitivity of 86.6% and an F1-score of 82.8%. Figure 5 displays KPIs and counters that are most important for predicting low E-RAB setup success.

4) Individual Instance Analysis

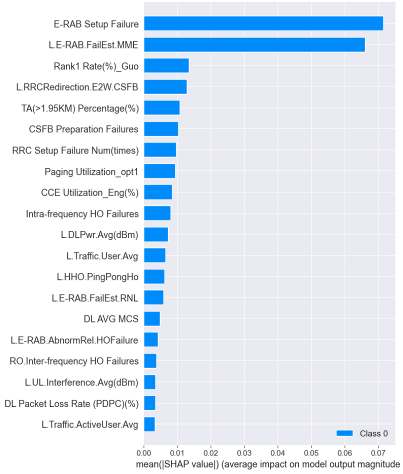


Fig. 4. Root causes for lower E-RAB setup success in eNodeB level.

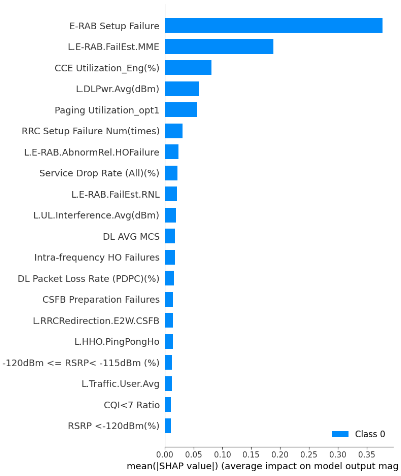


Fig. 5. Root causes for lower E-RAB setup success in cell level.

The analysis mentioned above was conducted on aggregated samples from the test data. To identify the most significant KPIs for predicting low E-RAB setup success in individual instances, a force plot is utilized. This force plot visually presents the positive or negative contribution of each feature towards the final prediction, relative to a base value.The base value that shown in the *shap.force_plot* plot Figure 6, depicts the expected output of the model. By examining the force plot, we can understand how the SHAP values influence the model's prediction, shifting it from the base value to the actual prediction for the selected instance.

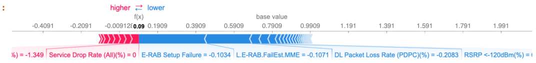


Fig. 6. Root causes for lower E-RAB setup success in a single instance.

C. Root Causes of Downlink User Throughput

1) Network Level

Figure 7 showcases the important KPIs and counters for predicting low downlink user throughput in an aggregated network test. The model's performance for prediction achieves a sensitivity of 89.2% and an F1-score of 92.2%. Among the factors, the average number of active users is considered to be the most important factor for predicting low user throughput (Figure 7).

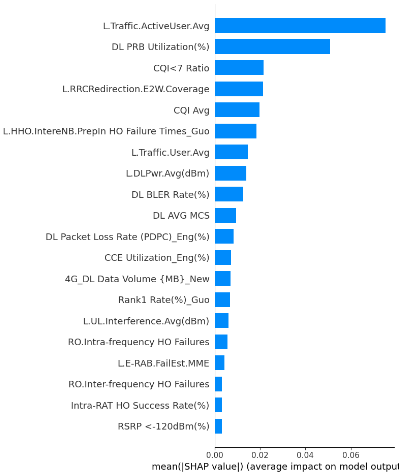


Fig. 7. Root causes for lower user throughput in the network level.

2) eNodeB Level

Figure 8 analyzes the KPIs that contribute to predicting low user throughput at the eNodeB level. The model's performance for prediction achieves a sensitivity of 94.7% and an F1-score of 95.3%. The primary counter is the average active user number, which has the highest impact on predicting low user throughput. The second most important KPI is the downlink PRB utilization, followed by the CCE utilization ratio, which represents the third factor. The fourth significant KPI is the average user number, while the fifth factor is the ratio of CQI values less than seven.

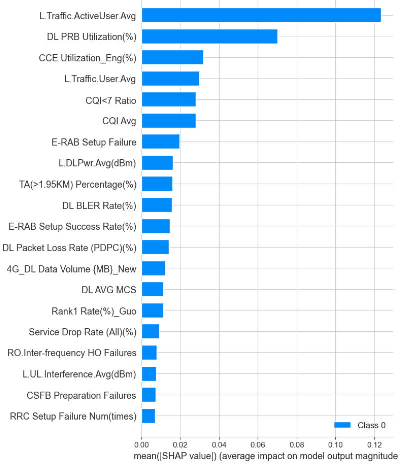


Fig. 8. Root causes for lower user throughput in eNodeB level.

3) Cell Level

At the cell level, Figure 9 presents the most important KPIs for predicting low user throughput. The model's performance for prediction achieves a sensitivity of 95.5% and an F1-score of 95.7%. Downlink PRB utilization plays the most significant role in determining low user throughput at the cell level. The second most important KPI is the ratio of CQI values less than seven. Additionally, downlink packet loss rate and inter eNodeB handover failures are the fourth and fifth significant KPIs for prediction purposes.

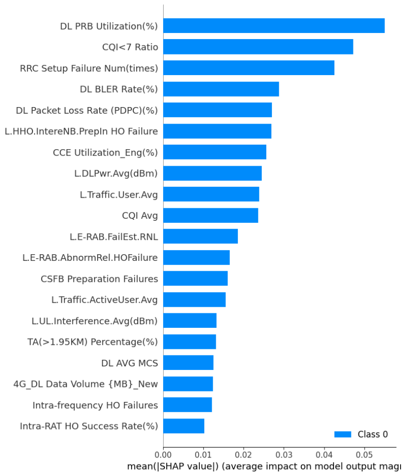


Fig. 9. Root causes for lower user throughput in cell level.

4) Individual instance Analysis
The shape force plot for the 50^{th} sample in the test data is displayed in Figure 10. The model's prediction output of $f(x) = 0.2$ suggests a low user throughput. The plot indicates that the downlink PRB utilization, number of RRC setup failures, and downlink block error rate are the most significant KPIs for this prediction.

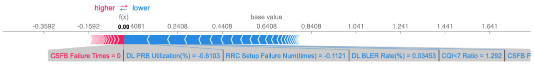


Fig. 10. Root causes for lower user throughput in a single instance.

D. Discussion

Important KPIs and counters have been identified at different levels of the network for predicting low E-RAB setup success and low downlink user throughput.

The analysis of low E-RAB setup success identified important KPIs and counters at the network, eNodeB, and cell levels. At the network level, the most significant factors were the count of E-RAB setup failures, E-RAB failures due to MME, number of user traffic, handover failure, failure caused by transmission network, and CSFB redirection. At the eNodeB level, the number of E-RAB setup failures, E-RAB failures due to MME, Rank 1 rate, CSFB redirection, high time advance, CSFB preparation failures, number of RRC setup failures, paging utilization, CCE utilization, and inter-frequency handover failures played a crucial role. In the cell-level analysis, the number of E-RAB setup failures, E-RAB failures due to MME, CCE utilization, paging utilization, RRC setup failures, handover failures, and interference were identified as causes for low E-RAB setup success.

The KPIs and counters analyzed in the study indicate that the following factors contribute to lower network accessibility:

- High E-RAB setup failure counter: This indicates that there is a problem with establishing E-RAB connections, which is essential for network access.
- High L.E-RAB.FailEst.MME counter: This indicates a problem with the MME, which can negatively impact network accessibility.
- High CSFB redirection counter: This indicates that there is a high number of circuit-switched calls over the 4G network, which can affect network accessibility.
- High CCE utilization: This indicates that the control channel is congested, which can make it difficult to establish and maintain connections.
- High Rank 1 rate: This indicates that the network is transmitting data using a single antenna most of the time, which can lead to lower E-RAB setup success.
- High handover failures: This indicates that the cells are crowded with user sessions and cannot accept any more sessions, which leads to lower network accessibility.
- High RRC setup failures: This indicates that there is a problem with establishing the RRC connection between the UE and the network, preventing the E-RAB setup success.
- High time advance (TA) counter: This indicates that a significant number of UEs are located relatively far away from the eNodeB, resulting in weaker signal reception, which can degrade network accessibility.
- High L.E-RABFailEst.RNL counter: This indicates a lack of radio resources, which can lead to poor network accessibility.
- High paging utilization: This indicates that the paging resources are heavily utilized, which can make it difficult to handle E-RAB setup requests, leading to delays or failures in setting up the connections and ultimately affecting network accessibility.

The other metric downlink average user throughput was utilized as a measure to assess the integrity of the network, defined as the extent to which network services are delivered without substantial issues after being acquired. Significant KPIs and counters were identified at the network, eNodeB, and cell levels for predicting low downlink user throughput.

The analysis found that at the network level, the causes of low downlink average throughput in the selected network area were the number of active users (L.Traffic.ActiveUser.Avg), high downlink PRB utilization, poor CQI, redirections to WCDMA due to coverage issues, handover failure, and average number of user and block errors. Network congestion, indicated by both the number of active users and high PRB utilization, was the main cause of lower throughput in the analysis. Poor CQI, which indicates low SINR, also contributed to throughput degradation. In LTE, a lower CQI results in a lower SINR value and consequently, a lower MCS index, leading to lower throughput. The results also suggest that a coverage issue is contributing to lower throughput in the selected network area.

At the eNodeB level, the average number of active users, downlink PRB utilization, CCE utilization ratio, average user number, poor CQI values, number of E-RAB setup failure, time advance (¿1.95km), and block error rate were identified as crucial factors for low user throughput. In the cell-level analysis, significant factors for lower throughput included downlink PRB utilization, poor CQI, number of RRC setup failure, downlink block error rate, handover failures, CCE utilization, and average number of user.

Both the L.Traffic.ActiveUser.Avg counter and downlink PRB utilization significantly contribute to low user throughput at both the network and eNodeB levels. L.Traffic.ActiveUser.Avg indicates the average number of subscribers actively using the network, providing an indication of overall user traffic activity. On the other hand, downlink PRB utilization measures the proportion of available radio resources used for downlink data transmission. Furthermore, PRB utilization has become a leading cause of low throughput at the cell level.

Increased congestion often occurs as the number of active users rises, leading to a decrease in downlink user throughput. High PRB utilization indicates that the network is operating at or near its maximum capacity, leading to even more congestion. Consequently, congestion becomes the root cause of low user throughput in the network, eNodeB, and cell levels. Besides the congestion, coverage and handover failures are additional causes for low throughput in the network level analysis. Downlink user throughput at the eNodeB level is also affected by control channel congestion (CCE utilization) and the average number of users (both active and inactive) over a specific time period. Downlink user throughput at the cell-level also affected by block error rate and lack of radio resource.

For individual instances, force plots were used to visualize the contribution of each feature to the prediction, helping to understand which features had the most significant impact on the predicted output. In the analysis of E-RAB setup success for an individual instance, features such as the number of E-RAB failures, E-RAB failures caused by core network (MME), and RSRP less than $-120dBm$ percentage were found to have a high impact on the prediction which are the root causes. For low downlink user throughput, features such as downlink PRB utilization, number of RRC setup failures, and downlink block error rate were identified as significant contributors to the prediction.

V. CONCLUSIOS AND FUTURE WORK

This paper proposes a CNN-SHAP approach for RCA of network accessibility and integrity degradation in LTE networks. The approach uses a 1D CNN to detect instances of degradation by analyzing historical data. The model achieved lower prediction performance at the network level than at the eNodeB and cell levels due to a class imbalance. To address this challenge, stratified cross-validation was used instead of upsampling techniques. The SHAP algorithm was used for RCA to calculate the average impact of each feature on the model's output and identify high marginal values as the root causes of degradation. The SHAP algorithm is computationally efficient and quickly identifies the most influential feature for degraded instances.

The proposed approach leverages the advantages of deep learning and SHAP, offering several advantages over traditional RCA methods, including reusability, high-dimensionality support, geographic scalability, and time resolution. By understanding the root causes of performance degradation, network operators can make informed adjustments to network resources and improve network performance and customer satisfaction.

The proposed approach for RCA can be further improved in the following ways. Firstly, additional data sources, such as drive test data, network alarms, and network logs, can be used to enhance the RCA process. It would be interesting to investigate how these data sources compare to historical data in terms of their effectiveness for RCA. Secondly, the study can be extended to other types of networks, such as fifth-generation networks, to understand the general principles of RCA for network performance problems. Thirdly, future work can expand the analysis to include other performance metrics, such as retainability or mobility, to investigate their impact on network degradation and provide a more comprehensive understanding of the factors affecting network performance. These improvements could enhance the accuracy and effectiveness of RCA in identifying and resolving network performance issues.

ACKNOWLEDGMENT

I expresses gratitude to God for blessing with strength, knowledge, and inspiration to complete this thesis. Special thanks to my advisor, Dr.-Ing. Dereje Hailemariam, for his invaluable guidance and support throughout the entire process. I am incredibly grateful for his unwavering dedication and encouragement throughout this thesis journey. I also thank ethio telecom for their sponsorship, and Mr. Anley Tadesse and Mr. Redamichael Jemberu for their expert advice and help in collecting the data. I am also grateful to my examiners, Dr. Beneyam Berehanu and Dr. Tsegamlak Terefe, for their direction and valuable comments. Finally, I express my deepest appreciation to my family, especially my mother and Zee, for their unwavering love and support.

REFERENCES

[1] A. ElNashar, M. A. El-saidny, and M. Sherif, *Design, Deployment and Performance of 4G-LTE Networks: A Practical Approach*. John Wiley Sons, 2014.

[2] 3GPP, "Key performance indicators (kpi) for evolved universal terrestrial radio access network (eutran); requirements," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 32.451, Apr. 2016, Version 13.

[3] J. Reunanen, J. Salo, and R. Luostari, “Lte key performance indicator optimization,” in *LTE Small Cell Optimization*. John Wiley Sons, Ltd, 2015, ch. 12, pp. 195–248, ISBN: 9781118912560. DOI: https://doi.org/10.1002/9781118912560.ch12.

[4] 3GPP, “Evolved universal terrestrial radio access (e-utra) and evolved universal terrestrial radio access network (e-utran); overall description;” 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 36.300 V14.0.0, Sep. 2016, Version 13.

[5] V. S. Rao and R. Gajula, “Protocol signaling procedures in lte,” *White Paper, Radisys Corporation*, 2011.

[6] Huawei, “Eran7.0 kpi reference,” Huawei, Technical Report (TR) V100R009C00, Apr. 2016, 01.

[7] 3GPP, “Key performance indicators (kpi) for evolved universal terrestrial radio access network (e-utran): Definitions,” 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 32.450, Apr. 2022, Version 17.0.

[8] A. Gómez-Andrades, P. Muñoz, I. Serrano, and R. Barco, “Automatic root cause analysis for lte networks based on unsupervised techniques,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 2369–2386, 2016. DOI: 10.1109/TVT.2015.2431742.

[9] D. Ferreira, C. Senna, P. Salvador, *et al.*, “Prediction of low accessibility in 4g networks,” *Annals of Telecommunication*, vol. 77, no. 10, pp. 421–435, 2022.

[10] Y. Alemayehu, “Root cause analysis of unsatisfactory user throughput in umts for bahir dar city,” M.S. thesis, Addis Ababa Univ. Dept. of Electrical. Eng, Addis Ababa, Ethiopia, 2021.

[11] C. M. Bulla and M. N. Birje, “Improved data-driven root cause analysis in a fog computing environment,” *Int. J. Intell. Inf. Technol.*, vol. 18, no. 1, pp. 1–28, Apr. 2022.

[12] N. Zheng and P. Mazumder, “Fundamentals and learning of artificial neural networks,” in *Learning in Energy-Efficient Neuromorphic Computing: Algorithm and Architecture Co-Design*. 2020, pp. 11–60. DOI: 10.1002/9781119507369.ch2.

[13] J. Teuwen and N. Moriakov, “Chapter 20 - convolutional neural networks,” in *Handbook of Medical Image Computing and Computer Assisted Intervention*, ser. The Elsevier and MICCAI Society Book Series, S. K. Zhou, D. Rueckert, and G. Fichtinger, Eds., Academic Press, 2020, pp. 481–501, ISBN: 978-0-12-816176-0. DOI: https://doi.org/10.1016/B978-0-12-816176-0.00025-9.

[14] F. Sultana, A. Sufian, and P. Dutta, “Advancements in image classification using convolutional neural network,” in *2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, IEEE, Nov. 2018.

[15] S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions,” in *Advances in Neural Information Processing Systems*, I. Guyon, U. V. Luxburg, S. Bengio, *et al.*, Eds., vol. 30, Curran Associates, Inc., 2017.