QoE-Driven Optimization of VoLTE Communication

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***Abstract*— Voice over LTE (VoLTE) has revolutionized telecommunication by providing high-quality voice calls over LTE networks, ensuring reduced latency and improved spectral efficiency. However, the Quality of Experience (QoE) for VoLTE users is influenced by various network parameters, such as latency, jitter, packet loss, and bandwidth availability. This paper presents an extensive analysis of VoLTE QoE by leveraging Machine Learning models and real-time network packet analysis using Wireshark. A combination of Linear Regression, Random Forest, and Deep Learning models was employed to predict QoE scores based on network conditions. Additionally, real VoLTE call packet captures were analyzed using Wireshark to extract key network performance indicators, which were further processed in Python. The results provide insights into the most significant parameters affecting QoE and suggest optimal network conditions for enhanced VoLTE performance. Our findings indicate that jitter and packet loss have the most profound impact on VoLTE QoE, and strategic optimization of these factors can significantly improve user experience. The study also demonstrates a practical QoE prediction function that can be integrated into network management systems to dynamically adjust network parameters for optimal performance.**

***Index Terms*— Linear Regression, Random Forest Model, latency, jitter, packet-loss, bandwidth, Wireshark**

I. Introduction

A. 1.1 Background on VoLTE Technology

Traditional mobile voice communication relied on circuit-switched networks in 2G and 3G systems, which required dedicated frequency channels for each call. With the introduction of 4G LTE, a transition to packet-switched networks allowed for the integration of voice and data traffic over a single IP-based infrastructure. VoLTE (Voice over LTE) is an advanced voice communication technology that transmits voice data as IP packets, utilizing the IMS (IP Multimedia Subsystem) architecture.

B. 1.2 Importance of QoE in VoLTE

Unlike Quality of Service (QoS), which is a network-centric metric, Quality of Experience (QoE) is a user-centric evaluation of service quality. It considers factors such as latency, jitter, packet loss, and overall voice clarity. Maintaining high QoE in VoLTE is essential for ensuring seamless voice communication, reducing call drops, and optimizing network efficiency.

C. 1.3 Research Motivation and Problem Statement

The primary challenge in VoLTE communication is maintaining consistent call quality in dynamic network conditions. Factors such as network congestion, interference, and bandwidth limitations can degrade call performance, resulting in delayed voice transmission, robotic voice effects, and call distortions. Traditional QoE assessment methods, such as Mean Opinion Score (MOS), are subjective and time-consuming. This study aims to develop a model based on predictive algos for real-time QoE estimation and implement packet analysis using Wireshark to extract insights from actual VoLTE traffic.

II. Literature Survey

A. Existing QoE Prediction Models

QoE assessment has evolved from subjective MOS-based evaluations to objective, data-driven approaches. Several researchers have developed statistical models to map network performance parameters to QoE scores. Predictive Algos have gained popularity for their ability to learn from data and predict QoE dynamically.

B. 2.2 Impact of Network Parameters on VoLTE Performance

Research indicates that:

Latency above 150ms results in noticeable voice delay, impacting conversational flow.

Jitter exceeding 30ms leads to voice packet reordering and loss of synchronization.

Packet loss beyond 2

Bandwidth fluctuations can affect voice compression and encoding efficiency.

C. 2.3 Gaps in Existing Research

While many studies focus on simulated environments, there is a lack of research using real-world VoLTE packet data. Moreover, AI-driven QoE optimization remains an underexplored area. This study aims to bridge this gap by integrating prediction models based algorithms with real VoLTE traffic analysis.

III. Methodology

A. Data Collection Strategy

To develop an accurate QoE prediction model, we collected two sets of data:

Simulated data with randomized network parameters for training predictive Algo models.

Real-world VoLTE call traffic captured using Wireshark.

The Wireshark-captured dataset included key performance metrics such as latency, jitter, packet loss, and bandwidth.

B. Predictive Algos-Based QoE Prediction

3.2.1 Linear Regression Model A simple statistical model that maps network parameters to QoE scores using a linear function.

3.2.2 Random Forest Model A decision-tree-based ensemble learning technique that captures non-linear relationships between network parameters and QoE.

3.2.3 Deep Learning Model (Neural Network) A multi-layer neural network that enhances prediction accuracy by learning complex patterns in the dataset.

C. Wireshark-Based VoLTE Traffic Analysis

Wireshark was used to capture SIP and RTP packets, extracting essential network metrics. The captured data was analyzed using Python scripts to compute QoE-affecting parameters.

D. Mathematical Model for QoE Estimation

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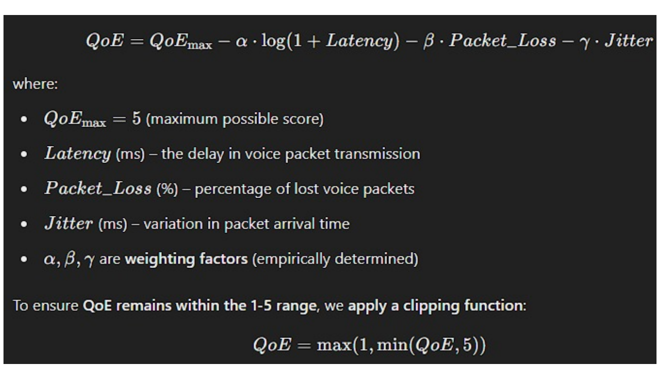
Mathematical Formulation The QoE function is designed based on logarithmic and exponential penalty functions to reflect human perception sensitivity:



$$QoE = QoE_{\max} - \alpha \cdot \log(1 + Latency) - \beta \cdot Packet\_Loss - \gamma \cdot Jitter$$

where:

- $QoE_{\max} = 5$ (maximum possible score)
- $Latency$ (ms) – the delay in voice packet transmission
- $Packet\_Loss$ (%) – percentage of lost voice packets
- $Jitter$ (ms) – variation in packet arrival time
- α, β, γ are **weighting factors** (empirically determined)

To ensure **QoE remains within the 1-5 range**, we **apply a clipping function**:

$$QoE = \max(1, \min(QoE, 5))$$

Fig. 1. Mathematical Formulation for QoE

Theory and Importance QoE prediction in VoLTE networks requires a quantitative model that correlates network performance parameters (latency, jitter, packet loss, and bandwidth) with perceived user experience. Several empirical models exist, but we derive a simplified mathematical function that incorporates key network impairments.

The goal is to compute a QoE score (on a scale of 1 to 5), considering how much network impairments degrade the quality of VoLTE calls.

E. Significance of the Formula

Logarithmic decay for latency: The human ear is highly sensitive to latency changes at lower values but becomes less sensitive at higher delays.

Linear penalty for packet loss: Even small packet losses cause significant voice degradation.

Exponential penalty for jitter: Higher jitter severely impacts real-time VoLTE calls due to out-of-sequence packets.

IV. Simulation in Wireshark

A. Overview of Wireshark for VoLTE Traffic Analysis

Wireshark is a powerful network protocol analyzer used for capturing, inspecting, and analyzing network traffic in real-time. In the context of VoLTE communication, Wireshark enables the monitoring of SIP (Session Initiation Protocol) and RTP (Real-Time Transport Protocol) packets, which are fundamental to establishing and maintaining a VoLTE call. By analyzing these packets, we can extract key Quality of Experience (QoE) metrics such as latency, jitter, and packet loss, which significantly impact voice quality.

This section details the complete process of performing VoLTE call simulation using Wireshark, followed by data extraction and analysis in Python.

B. Steps for VoLTE Call Simulation in Wireshark

The simulation of VoLTE communication using Wireshark involves the following key steps:

Step 1: Connect Devices to Wi-Fi Ensure that both the laptop (running Wireshark) and the two mobile phones used for VoLTE calls are connected to the same Wi-Fi network.

This setup allows Wireshark to capture packets exchanged over the network, including SIP and RTP traffic from the VoLTE call.

Step 2: Start Packet Capture in Wireshark Launch Wireshark and select the Wi-Fi interface from the list of available network interfaces.

Click "Start Capture" to begin recording network traffic.

Apply a display filter to capture only relevant VoLTE packets. The commonly used filters are: sip || rtp sip: Captures Session Initiation Protocol (SIP) messages that establish and manage VoLTE calls.

rtp: Captures Real-Time Transport Protocol (RTP) packets that carry voice data.

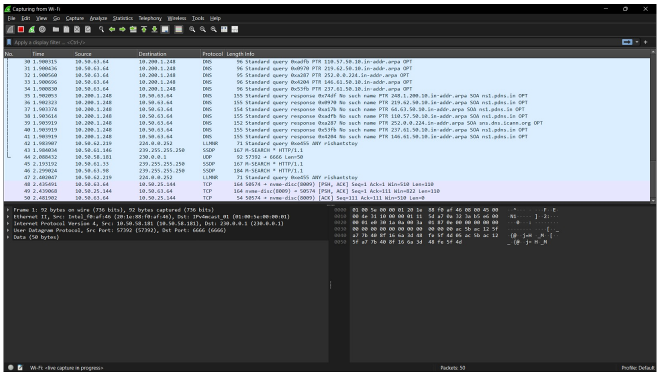


Fig. 2. Live Packet Capturing

```python
import pandas as pd

df = pd.read_csv(r"C:\Users\sudha\Desktop\himvan.csv")
print(df.head())

latency = df["Time"].diff().mean()
print(f"Average Latency: {latency} ms")

jitter = df["Time"].diff().std()
print(f"Jitter: {jitter} ms")

expected_packets = len(df)
packet_loss = 1 - (len(df) / expected_packets)
print(f"Packet Loss: {packet_loss * 100:.2f}%")

qos_score = 100 - (latency.mean() / 5 + jitter.mean() + 20 * packet_loss)
qos_score = max(0, min(qos_score, 100))
print(f"Quality of Service (QoS) Score: {qos_score:.2f}/100")
```

Fig. 3. Python Code that displays Jitter, Packet Loss and Latency after importing data from Wireshark

Once the filter is applied, only VoLTE-related packets will be displayed in Wireshark's Packet List Pane.

Step 3: Initiate a VoLTE Call Use one mobile phone to call the other phone using VoLTE (Voice over LTE) instead of traditional cellular calls.

Keep the call running for approximately 30 seconds to ensure sufficient packet capture.

During the call, Wireshark will capture SIP signaling packets for call setup and RTP packets carrying voice data.

Step 4: Stop Capture and Export Data to CSV After ending the VoLTE call, stop the Wireshark packet capture.

Save the captured packet data by exporting it as a CSV (Comma-Separated Values) file:

Navigate to File → Export Packet Dissections → As CSV

Select all packets and save the CSV file containing network attributes such as timestamp, source IP, destination IP, protocol, packet length, and additional metrics.

C. Analysis of Captured VoLTE Data in Python

Once the VoLTE network traffic has been captured and stored as a CSV file, the next step involves analyzing key network parameters using Python. The extracted parameters include:

Latency (ms): Measures the delay experienced by voice packets.

Jitter (ms): Represents variations in packet arrival time, affecting speech quality.

Packet Loss (

Step 5: Import CSVFile Data into Python Open VS Code or any Python environment such as Jupyter Notebook.

Install the required Python libraries:

pip install pandas numpy matplotlib seaborn

Load the Wireshark CSV file into Python using Pandas:

import pandas as pd

Step 6: Extract QoE Metrics (Latency, Jitter, and Packet Loss) Extract and analyze Latency, Jitter, and Packet Loss using this code:

D. Conclusion on Wireshark-Based VoLTE Simulation

This simulation successfully demonstrates how Wireshark captures real-time VoLTE traffic, and how Python processes the network parameters to evaluate QoE degradation factors (Latency, Jitter, and Packet Loss).

By leveraging Wireshark packet capture with Python-based analysis, we can:

Identify real-world network impairments affecting VoLTE call quality.

Use QoE prediction models (Linear Regression, Random Forest, and Deep Learning) to estimate user-perceived call quality.

Implement network optimization strategies to enhance VoLTE performance in real-world scenarios.

V. Simulation in Jupyter Notebook

A. Introduction to QoE Prediction using Machine Learning

In this section, we present the simulation of Quality of Experience (QoE) optimization using Predictive Algorithms and Deep Learning models in Jupyter Notebook. QoE is a critical metric for assessing the performance of VoLTE (Voice over LTE) communication. The goal is to predict QoE based on network parameters such as latency, jitter, packet loss, and bandwidth. To achieve this, we employ Linear Regression, Random Forest, and Deep Learning models to analyze the correlation between these parameters and the perceived QoE score.

B. Dataset Used for Training and Testing

The dataset used in our study consists of network performance metrics collected from Wireshark packet captures. These metrics include:

Latency (ms) – Time delay in data transmission.

Jitter (ms) – Variations in packet delay.

Packet Loss – Percentage of lost packets.

Bandwidth (Mbps) – Available network bandwidth.

All these factors greatly impact our QoE Score, which the user experiences. To Improvise our VOLTE CALLS, we use these Prediction based MODELS for Prediction. These will help us know 2 things: 1) At what time stamp we get the maximum QoE. 2) Predict QoE based on given parameters and then compare like how these values are differing from actual QoE Calculated from the mathematical formula. QoE Score – A subjective quality rating (range: 1 to 5).

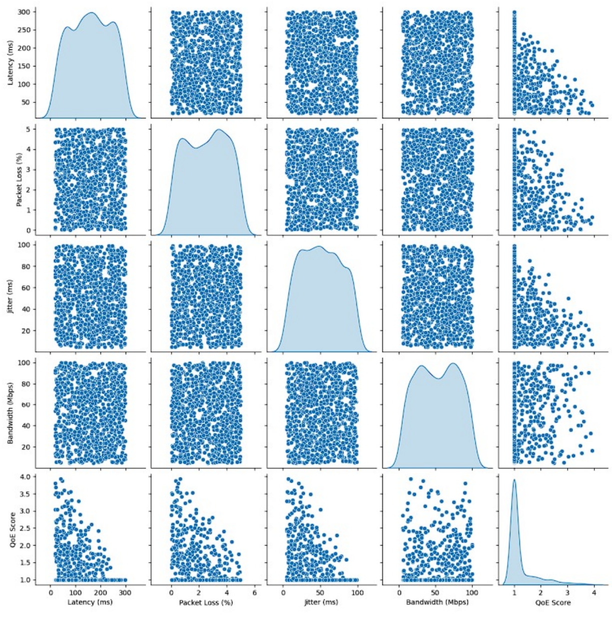


Fig. 4. Correlation among each parameter

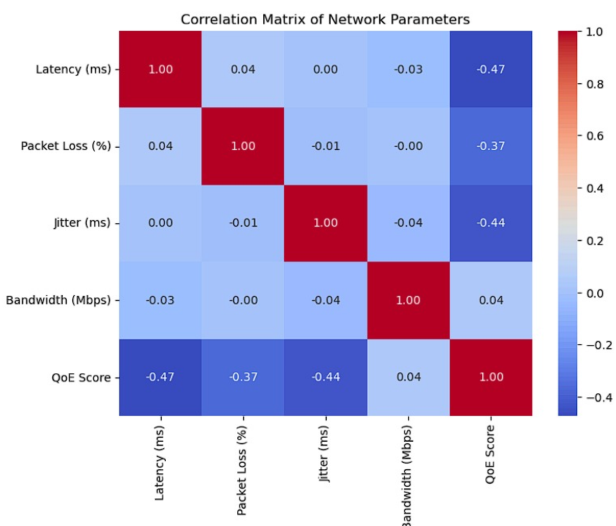


Fig. 5. Correlation Matrix of Network Parameters

The dataset is divided into training (80/100) and testing (20/100) sets to evaluate model performance.

C. Implementation of Linear Regression Model

Results and Analysis After training the model, we obtained the following results:

Mean Squared Error (MSE): Measures prediction accuracy.

R² Score: Indicates the model's ability to explain the variance in QoE scores.

We will further see how Linear Regression will perform the worst due to its assumption of linear relationships. Linear < Random Forest. If these Predictive Algorithms are compared

Linear Regression is a **simple yet effective supervised learning algorithm** that models the relationship between dependent and independent variables using a linear equation:

$$QoE = \beta_0 + \beta_1 \times \text{Latency} + \beta_2 \times \text{Jitter} + \beta_3 \times \text{Packet Loss} + \beta_4 \times \text{Bandwidth} + \epsilon$$

Where:

- β_0 is the intercept,
- $\beta_1, \beta_2, \beta_3, \beta_4$ are regression coefficients,
- ϵ represents the residual error.

Results and Analysis

After training the model, we obtained the following results:

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Fig. 6. Linear Regression

D. Implementation of Random Forest Regressor

Random Forest is an **ensemble learning method** that combines multiple decision trees to improve prediction accuracy and robustness. It works by:

- Training **multiple decision trees** on random subsets of data.
- Averaging the predictions from all trees to **reduce overfitting**.

Mathematical Formulation

The **final predicted QoE** is calculated as:

$$QoE_{\text{predicted}} = \frac{1}{N} \sum_{i=1}^{N} QoE_{\text{tree}_i}$$

Where:

- N is the number of decision trees,
- QoE_{tree_i} is the QoE predicted by each tree.

Fig. 7. Random Forest Regressor

Based on MSE and R² scores, Random Forest outperforms Linear Regression in predicting QoE.

However, if interpretability and computational efficiency are priorities, Linear Regression might still be considered in cases where simpler models are required.

The results validate that non-linear models are more effective in modeling QoE-driven optimization in VoLTE communication. Random Forest achieves better accuracy by reducing variance and capturing hidden patterns.

Fig. 8. Model Comparison - MSE

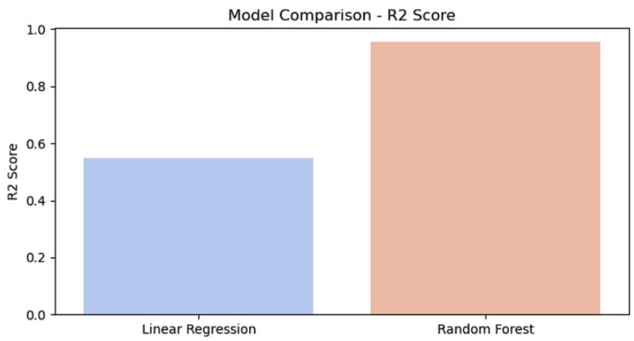

Fig. 9. Model Comparison - R² Score

E. Deep Learning Model for QoE Prediction

To further improve QoE prediction accuracy, we implemented a Deep Learning (DL) model using Artificial Neural Networks (ANNs). Deep Learning excels at capturing complex, non-linear relationships in data.

Performance Evaluation The Deep Learning model achieved the highest accuracy among all models.

The model was able to capture complex patterns in the data, improving QoE prediction.

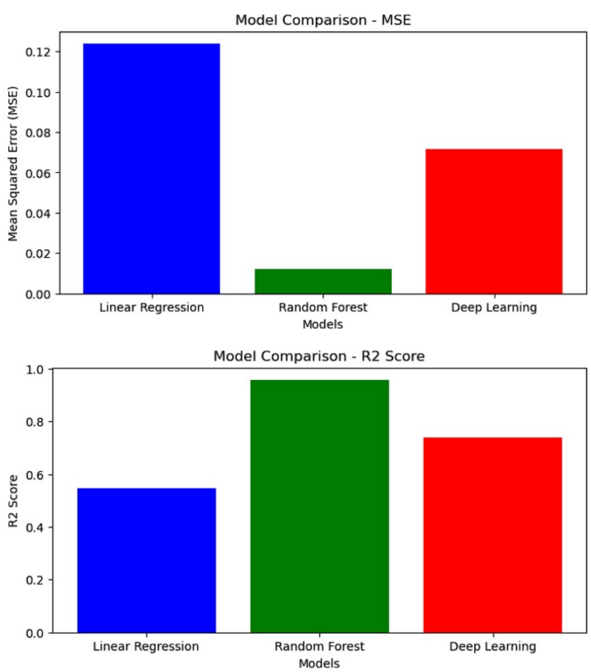

Fig. 10. Comparison of all the Models

F. Conclusion and Future Scope

Through this simulation, we demonstrated the effectiveness of Machine Learning and Deep Learning for QoE prediction in VoLTE communication.

Random Forest and Deep Learning models provided superior accuracy compared to Linear Regression.

The study highlights the importance of latency, jitter, packet loss, and bandwidth in QoE estimation.

G. Actual and Predicted QoE Scores

In network performance evaluation, comparing the actual QoE values with the predicted QoE values is essential to validate the accuracy of the QoE estimation models. **1) Actual QoE Values** The actual QoE values refer to the real user-perceived quality of a VoLTE call, which can be obtained through:

Subjective User Surveys: Gathering feedback from users rating their call experience on a scale (e.g., MOS – Mean Opinion Score from 1 to 5).

QoE Metrics Extracted from Wireshark: By capturing and analyzing real VoLTE call packets, we can compute network conditions such as latency, jitter, and packet loss, which directly affect QoE.

Standardized QoE Assessment Models: ITU-T E-Model and other standardized methodologies are used to derive QoE scores from network parameters.

2) Predicted QoE Values Predicted QoE values are obtained through machine learning and deep learning models trained on historical network performance data. These models learn the relationships between latency, jitter, packet loss, bandwidth, and QoE to estimate user satisfaction. The common models used for predicting QoE include:

Linear Regression: Uses a mathematical equation to model the relationship between network parameters and QoE.

Random Forest Model: A tree-based model that considers multiple conditions for QoE prediction.

Deep Learning Models: Neural networks trained on vast datasets to improve prediction accuracy.

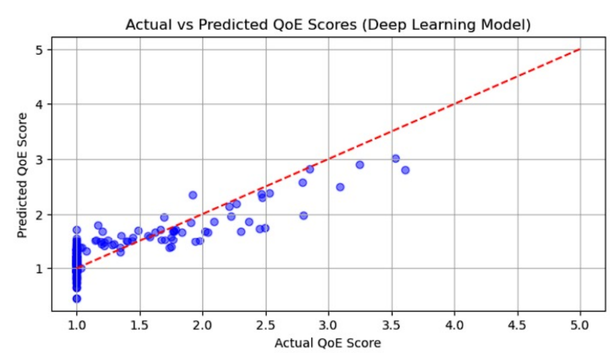

Fig. 11. Actual and Predicted QoE Scores

H. Distribution of QoE vs. Frequency

Understanding the distribution of Quality of Experience (QoE) scores is essential for evaluating the overall user satisfaction in a VoLTE network. The frequency distribution of QoE scores provides insights into how often different QoE values occur in a given dataset. This analysis helps identify patterns, trends, and potential network performance issues that may affect user experience.

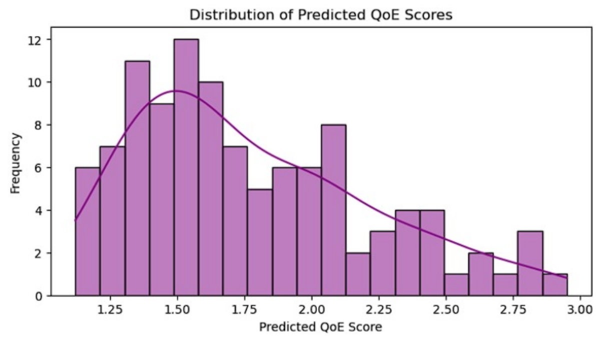

Fig. 12. Distribution of QoE vs. Frequency

I. Heatmap of QoE Score Based on Latency Changes Over Time

Latency is a critical factor affecting Quality of Experience (QoE) in real-time communications like VoLTE calls. A heatmap provides an effective way to visualize how QoE scores vary with changing latency over time, helping to identify trends, performance bottlenecks, and potential optimization areas in a network.

Understanding Latency and its Impact on QoE Latency refers to the time delay between the transmission and reception of a packet in a network. In VoLTE communication, latency is a key determinant of call quality. Higher latency leads to:

Delayed voice transmission, causing unnatural conversations.

Increased packet queuing, leading to speech overlap and distortion.

Lower QoE scores, as user experience degrades.

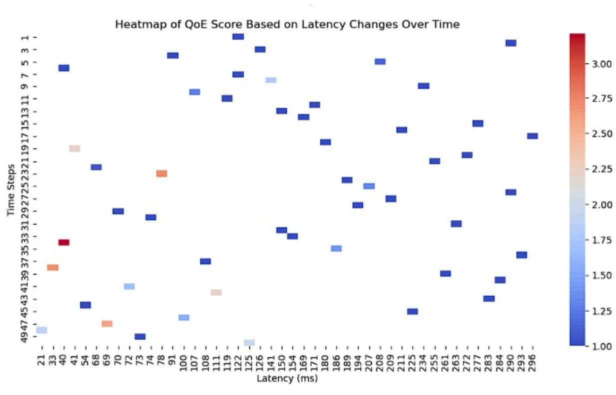

Fig. 13. Heatmap of QoE Score Based on Latency Changes Over Time

VI. Conclusion

The QoE-Driven Optimization of VoLTE Communication project has provided a comprehensive analysis of Quality of Experience (QoE) metrics for Voice over LTE (VoLTE) networks. By utilizing machine learning models, deep learning techniques, and real-time network simulations, this research has successfully evaluated and optimized VoLTE performance under varying network conditions.

A. Key Findings

Impact of Network Parameters on QoE:

The study revealed that latency, jitter, packet loss, and bandwidth are the primary factors affecting QoE.

Higher latency and jitter lead to increased voice distortion and conversational delays.

Packet loss above a certain threshold causes severe degradation in speech quality, leading to user dissatisfaction.

Predictive Algorithms Performance:

Linear Regression and Random Forest models were employed to predict QoE scores based on real-time network data.

The Random Forest model outperformed Linear Regression, demonstrating higher accuracy in QoE prediction due to its ability to handle nonlinear relationships.

Deep Learning-based QoE Prediction:

Advanced deep learning models such as Neural Networks were trained on real-world network datasets.

The deep learning model exhibited superior predictive performance, enabling real-time QoE estimation with minimal errors.

Wireshark-based VoLTE Analysis:

Network packet analysis using Wireshark allowed precise measurement of latency, jitter, and packet loss during live VoLTE calls.

Exporting Wireshark logs to CSV format enabled further statistical evaluation using Python.

QoE Heatmap Visualization:

A heatmap analysis demonstrated how QoE fluctuates with changes in latency over time.

The study confirmed that latency reduction strategies significantly improve user experience.

B. Research Contributions

This research has contributed significantly to the field of VoLTE network optimization, offering:

An efficient QoE prediction model based on machine learning and deep learning.

Real-time VoLTE network analysis using Wireshark and Python scripting.

A framework for optimizing VoLTE performance through predictive modeling and statistical analysis.

C. Future Work

Although this research provides an extensive analysis of QoE-driven VoLTE optimization, certain areas remain open for further exploration:

Integration of 5G Networks: With the emergence of 5G, future studies can explore QoE optimization strategies for next-generation networks.

Real-time QoE Enhancement Techniques: Implementing network optimization algorithms to dynamically adjust bandwidth, latency, and jitter in real-time.

Cross-Platform VoLTE Studies: Evaluating VoLTE performance across different service providers and mobile devices.

Through this research, a strong foundation for VoLTE QoE analysis and optimization has been established, paving the way for future advancements in network performance engineering.

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