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Enhancing QoE Prediction in 5G Video Streaming using Ensemble Learning Models

Satish Dekka[1]; P. Deepika[2]; L. Manikanta[3]; A. Lakshmi Likitha[4]; M. Aditya Murali[5]

[1] Associate Professor, [2,3,4,5] Students

[1,2,3,4,5] Department of Computer Science and Engineering, Lendi Institute of Engineering and Technology (Autonomous), Vizianagaram, Andhra Pradesh, India.

Abstract: Ensuring smooth,reliable user experiences is essential, Whether we're streaming videos, joining a Zoom call, playing games online, or browsing websites, we expect a smooth, enjoyable experience. That's exactly where this Quality of Experience (QoE) Prediction Project steps in. With this rapid growth of multimedia applications and increasing demand for high-quality streaming services, accurately predicting Quality of Experience (QoE) has become a critical challenge in network and service management. Instead of waiting for the users to complain regarding buffering of videos or poor call quality, this system predicts their level of satisfaction that is known as MOS (Mean Opinion Score), before they even report a problem. That means service providers can act faster, fix issues, and deliver consistently high-quality service. This project proposes an intelligent machine learning based approach to predict QoE by analyzing various network, playback, and system-level attributes such as latency, throughput, jitter, packet loss, buffering time, and video resolution. The dataset collected contains detailed performance metrics recorded during video streaming sessions which are preprocessed and used to train multiple models. A Random Forest Regressor was used as the primary model to predict the MOS score, which is then categorized into QoE labels — Good, Average, or Poor, to make interpretation more user-friendly. This algorithm is great at handling complex data and give reliable predictions even when the data is noisy. Alternative models including K-Nearest Neighbors (KNN) which is simple yet effective model that mainly focuses on what similar users experienced to make decisions and the next algorithm is Support Vector Machine (SVM) which is excellent for drawing clear boundaries in data, especially when the relationship is not obvious, were also trained and evaluated for comparison. The final solution is integrated into a Flask-based web interface, allowing real-time QoE predictions based on user input.This system serves as a valuable tool for Internet Service Providers, content delivery platforms, and network engineers to proactively manage network resources and enhance user satisfaction.

Keywords: *Quality of Experience (QoE), 5G Networks, Ensemble Learning, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Mean Opinion Score (MOS), Machine Learning, Real-Time Prediction, Flask Web Interface, Network Metrics.*

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I. INTRODUCTION

In today's fast-moving world of digital media and online communication, making sure users have a smooth and satisfying experience is more important than ever.While network engineers have traditionally relied on metrics like bandwidth, latency, and packet loss—collectively known as Quality of Service (QoS)—these don't always tell the full story. A video might load quickly and stream smoothly from a technical point of view, but if it appears blurry or buffers frequently, users will still walk away frustrated. This gap between technical performance and actual user satisfaction has led to the rise of Quality of Experience (QoE) as a more meaningful way to evaluate how users truly perceive a service. The International Telecommunication Union (ITU-T) explains that the Quality of Experience (QoE) as how users feel about the overall quality of a service — whether they find it smooth, enjoyable, and acceptable based on their personal experience. In other words, it shifts the focus from network-centric indicators to how real people experience a service. It recognizes that users don't just care about the backend—they care about how the service feels, how responsive it is, and whether it meets their expectations in the moment. Understanding the difference between QoS and QoE is critical. QoS is objective and quantifiable—it's about numbers and thresholds. QoE, on the other hand, brings in subjective elements like expectations, content relevance, and even mood. For example, a video service might tick all the QoS boxes, but if it streams in low resolution or buffers mid-way, users will likely report a poor experience. "This is what makes QoE a better way to truly understand how users feel about the quality of a service." Then machine learning (ML) comes into play.

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With the ability to process massive volumes of data, ML algorithms can uncover hidden patterns and relationships between network conditions and user satisfaction. Supervised learning models like Random Forests and Support Vector Machines have shown promise in predicting QoE for streaming platforms by analyzing variables such as video bitrate, resolution, playback interruptions, and switching frequency. These models enable systems to respond dynamically, even predicting and correcting potential quality issues before they impact the user.

For instance, the IEEE 3333.1.3-2022 standard outlines guidelines that consider not just system performance but also human and contextual factors [4]. Standards like these are essential for comparing services across different platforms and ensuring that QoE measurement is both fair and repeatable. Beyond its technical significance, QoE has major business implications. A positive QoE leads to happier users, longer engagement, and greater customer loyalty. Service providers can use QoE data to fine-tune their networks, customize user experiences, and make better decisions about content and resource allocation. Despite the progress, QoE modeling still faces several hurdles. Every user experiences things differently, so it's tough to make one-size-fits-all conclusions. There are also privacy concerns around collecting the kind of detailed usage data that fuels ML models. Additionally, the rapid pace of change in user habits and technology means that QoE models must constantly evolve to remain effective.

In this work we proposed a smarter machine learning system. It uses a combination of three powerful models—Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)—to better predict how users feel about the quality of video streaming over 5G networks. By blending the strengths of these models, the system becomes more reliable and accurate, especially in complex situations where the video content is hidden due to encryption. We built this system using Python 3.7 and made it accessible through a simple Flask-based web app, so it can work in real time. The model doesn't rely on looking into the video content directly. Instead, it looks at indirect clues like packet sizes, the time between packets, and data throughput to estimate the user's experience. We tested it using a well-known dataset that mimics 5G network conditions and encrypted video streaming, making sure it reflects real-world situations.

II. RELATED WORK

The way we measure and predict Quality of Experience (QoE) has changed a lot over the years, especially with the rise of machine learning (ML). QoE is all about understanding how users feel about a service—like watching a video or browsing a website—not just whether the service works technically, but how enjoyable and smooth the experience is. Early research mainly used user surveys to ask people how they felt about a video or app. Hewage et al. (2022) present an extensive survey that dives deep into the intricacies of modeling and integrating time-varying video quality across the end-to-end multimedia delivery pipeline. Their work emphasizes how user-perceived Quality of Experience (QoE) is not static, but rather fluctuates with changes in video quality during streaming, influenced by factors such as encoding, network conditions, and device capabilities.[1] The authors analyze a variety of continuous time-varying QoE (CTVQ) models and pooling strategies while also addressing the human visual system's behavioral traits like recency and hysteresis, which shape how users perceive and remember quality impairments. Significantly, the review highlights research gaps in QoE monitoring, real-time prediction, and integration with 5G/6G networks—challenges that are highly relevant to our study's focus on QoE prediction in dynamic and adaptive streaming environments.

Omar et al. (2022)introduced a practical machine learning approach to predict QoE in enterprise multimedia networks by combining technical network data with user feedback. They used tools like PRTG to monitor QoS and Google Forms to collect user opinions (MOS), applying algorithms such as Random Forest to predict user experience. Their results showed that Random Forest delivered the most accurate predictions, highlighting its potential for real-time QoE monitoring. [2] This study supports the importance of using both subjective and objective data, which closely aligns with our goal of improving QoE prediction in next-generation multimedia services.

Barakabitze (2023) proposed QoE Soft, a smart resource management system designed to improve video streaming quality in future 5G and 6G networks. By using technologies like SDN and NFV, their system can dynamically adjust network resources based on real-time user experience and bandwidth predictions.[3] The framework showed better performance in terms of reduced latency and improved video quality compared to traditional methods. This aligns well with our focus on enhancing QoE in next-gen multimedia streaming environments.

Amirpour et al. (2024) introduced VQM4HAS, a fast and practical video quality metric designed for real-time adaptive streaming.It offers a faster alternative to traditional metrics like VMAF by using lightweight features from the video and encoding process [4]. Despite its simplicity, VQM4HAS maintains high accuracy in predicting video quality and is well- suited for live streaming scenarios. This aligns closely with our goal of enabling efficient, real-time QoE assessment in adaptive video delivery systems.

In recent years, the surge in video streaming services has underscored the critical need for accurate Quality of Experience (QoE) prediction to ensure user satisfaction. Traditional methods often relied on subjective assessments or simplistic models, which failed to capture the complex interplay of network conditions, content characteristics, and user behaviors. [5] The paper titled "Supervised-learning-Based QoE Prediction of Video Streaming in Future Networks: A Tutorial with Comparative Study" offers a comprehensive overview of how supervised machine learning techniques have been harnessed to enhance QoE prediction accuracy. By systematically comparing various supervised learning models, the study highlights their strengths and limitations in different streaming scenarios. This work not only bridges the gap between theoretical models and practical applications but also sets the stage for future research to develop more adaptive and context-aware QoE prediction systems,

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ultimately aiming to elevate the end-user streaming experience.

III. ARCHITECTURE

The proposed model focuses on improving the prediction accuracy of Quality of Experience (QoE) for video streaming services over 5G networks using ensemble machine learning techniques. The process begins with the data loading phase, where pre-collected datasets containing QoE-related features such as buffer level, bitrate, and playback statistics are imported into the system. The dataset used in this project includes detailed information about both the network and the video streaming performance, which helps us understand how users experience video services on 5G networks. It tracks important factors that affect user satisfaction—like how long a video takes to start playing (initial buffering time), how often it pauses to load (rebuffering frequency), the average video quality (bitrate), how long the video is played, and any changes in video resolution during playback. It also captures network conditions, such as internet speed (throughput), delays (round-trip time), and packet loss. These datasets are carefully preprocessed to remove any noise, handle missing values, and normalize features for consistent input across models. Once the data is prepared, the system moves to the model training phase, which involves three distinct machine learning algorithms: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN).Each entry in the dataset represents one streaming session and includes a QoE score, which tells us how good or bad the viewing experience was for that session. This score is used to train and test our machine learning models. By combining both streaming behavior and network performance data, the dataset gives a complete picture of what affects user experience. This helps our model learn useful patterns and make accurate predictions, even under different network conditions or streaming setups.

- ➢ *Data Preprocessing*

Data preprocessing is an important first step when working with data for analysis or building machine learning models. It means getting the raw data ready by cleaning it up and organizing it properly. This process can include fixing or filling in missing information, getting rid of repeated or incorrect entries, turning text categories into numbers, and adjusting the scale of the numbers so everything is on a similar level. The main idea is to make sure the data is accurate and easy to work with. When data is clean and well-prepared, it helps the computer learn better and gives more reliable results.

- ➢ *Normalization*

Normalization is a technique used during data preprocessing to adjust the values of numeric features so they are on a similar scale, without distorting differences in the ranges of values. This is important because many machine learning algorithms work better when the input data is consistent in scale .It brings all values into common range, such as 0 to 1, which helps the model learn more efficiently and make more accurate predictions.

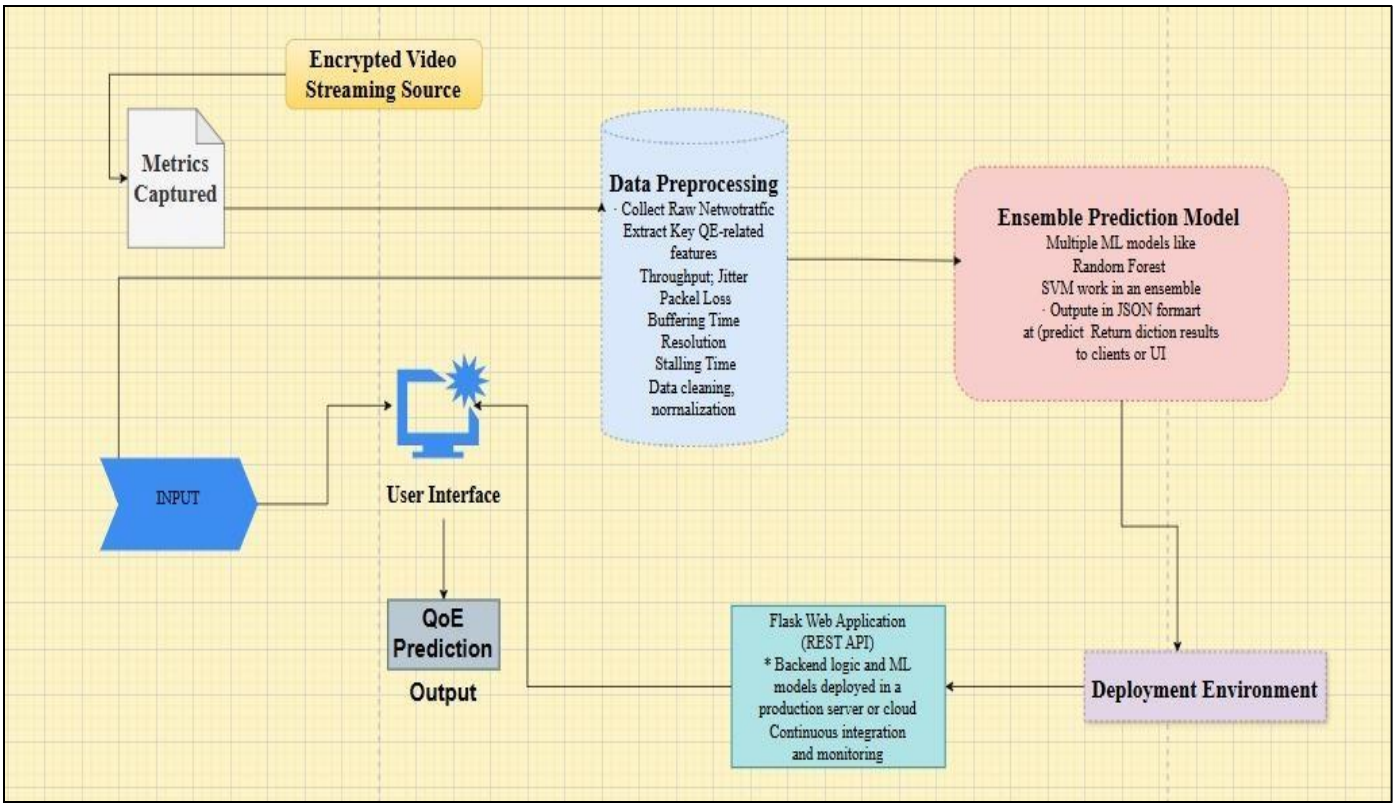

Fig 1 System Architecture for QoE Prediction

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➢ *Random Forest Regressor*

The Random Forest Regressor is a reliable and flexible machine learning algorithm that was used in this project to predict the Mean Opinion Score (MOS), which represents how satisfied users are with video streaming over 5G networks.It works by building a "forest" of decision trees, where each tree gives its own prediction, and the final result is the average of all those predictions. This method helps reduce errors and makes the results more stable, especially when dealing with messy or complicated data. What makes Random Forest especially useful for this kind of work is its ability to handle many different types of data at once—like network speed (throughput), delays (jitter), lost packets, and how long videos take to buffer.

➢ *K Nearest Neighbour*

The **K-Nearest Neighbors (KNN)** algorithm as a key component of our machine learning pipeline due to its simplicity, interpretability, and effectiveness in classification tasks. KNN is a non-parametric, instance-based learning algorithm that classifies new data points based on the majority class among its 'k' closest neighbors in the feature space. One of the main advantages of KNN is that it does not make any underlying assumptions about the data distribution, making it versatile and easy to implement. KNN model was trained to identify patterns and make predictions based on similarity measures, typically using Euclidean distance.

➢ *Support Vector Machine*

The Support Vector Machine (SVM) algorithm played a crucial role in enabling effective classification and prediction tasks. One of the standout features of SVM is its ability to handle both linear and non-linear classification through the use of kernel functions. This flexibility allowed our project to manage complex datasets with high accuracy. By mapping input features into higher dimensions, the algorithm was able to distinguish subtle patterns and relationships that traditional models might overlook. We trained the SVM model on labeled data, enabling it to learn from existing examples and make informed decisions on new, unseen inputs.

IV. RESULTS AND DISCUSSION

In this section, we share the experimental results and evaluate how well our proposed ensemble-based QoE prediction system performs. We used commonly accepted metrics to measure performance, looking at both the numerical outcomes and how the system behaves in practice. The experiments were carried out using datasets that simulate video streaming over 5G networks, with a focus on encrypted video traffic.

➢ *Performance Measure*

To see how well our QoE prediction system works, we mainly used accuracy as our performance measure. Accuracy tells us how many times the model made the right prediction compared to all the predictions it made. We calculated accuracy as the number of correct predictions divided by the total predictions, multiplied by 100. This gave us an easy-to-understand percentage score.

Table 1 shows the algorithms comparative analysis to evaluate the effectiveness of various machine learning models for QoE prediction in video streaming, a comparative analysis was conducted using key performance metrics such as Mean Error (ME), R^2 Score, and computational efficiency indicators including training and prediction times. Among the tested models,

- The Random Forest algorithm demonstrated superior performance, achieving the lowest mean error (0.0359) and the highest R^2 score (0.9618), indicating strong predictive accuracy and model reliability.
- Although Support Vector Machine (SVM) and K- Nearest Neighbors (KNN) also performed well, with R^2 scores of 0.9489 and 0.9311 respectively, they lagged slightly behind in terms of accuracy.
- In terms of computational efficiency, KNN offered the fastest training time, while Random Forest balanced both accuracy and moderate computational cost effectively.
- These results underscore the potential of ensemble- based approaches like Random Forest in delivering robust and efficient QoE predictions for multimedia services.

The scatter plot in the ***Figure 1*** shows how well our system predicted the Quality of Experience (QoE) for video streaming, using Mean Opinion Score (MOS) as the measurement. It's a helpful way to visually check if our model is making good predictions.

On the bottom line (x-axis), we have the actual MOS values from the real data, and on the side line (y-axis), we have the values our model predicted. If our model was perfect, all the dots would fall on a straight diagonal line where the predicted values exactly match the actual ones.

Looking at the plot, most of the dots are very close to that diagonal line, which means our model usually gets the prediction right or very close. There are a few dots that are farther away—these are times the model didn't match perfectly—but overall, the model shows a strong ability to guess how users would rate the video quality. This gives us confidence that the system can work well in real streaming situations.

Table 1 Algorithms Comparative Analysis

S.No	Model	ME	R2 Score	Training Time(S)	Prediction Time(S)
1	RANDOM FOREST	0.0359	0.9618	0.3159	0.0125
2	SVM	0.0480	0.9489	0.2658	0.0143
3	KNN	0.0649	0.9311	0.1567	0.0123

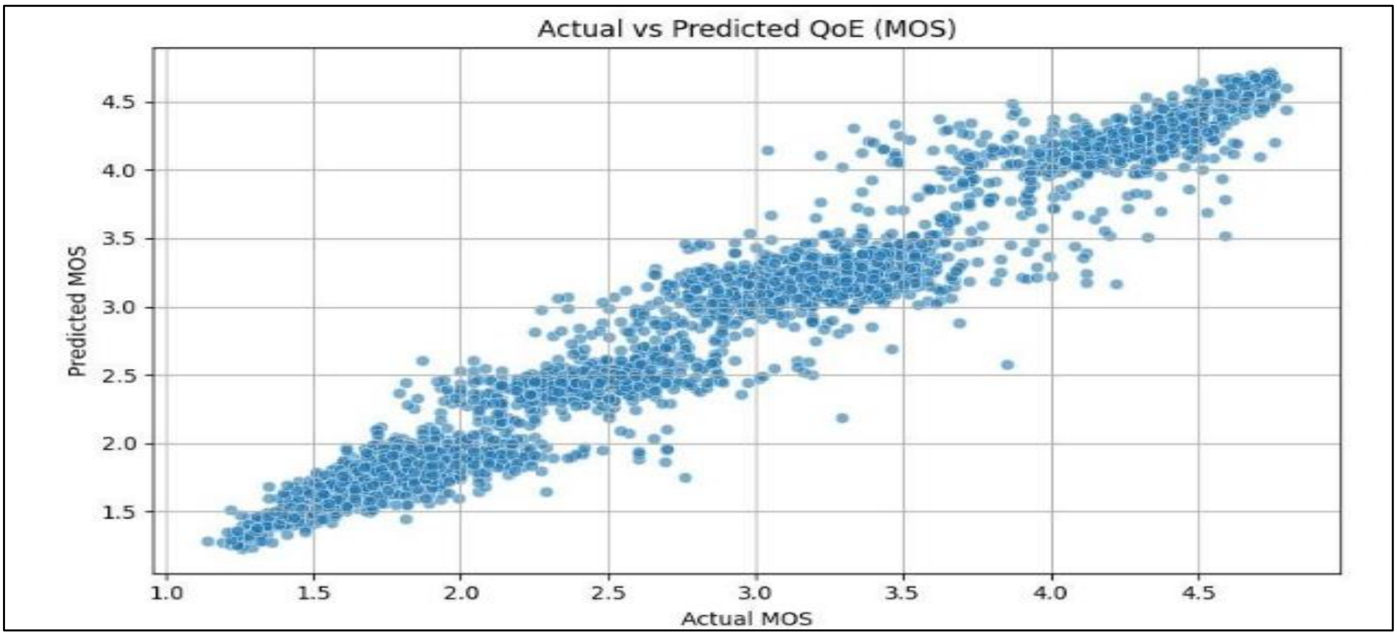

Fig 1 Actual vs Predicted MOS for Random Forest

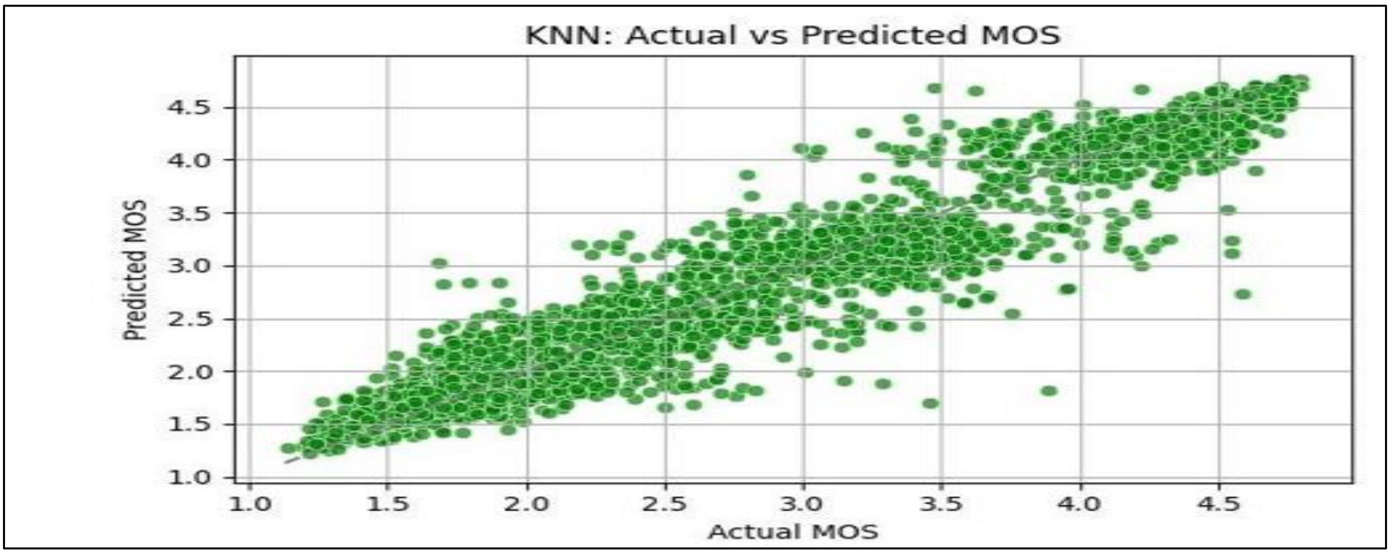

Fig 2 Actual vs Predicted MOS for KNN

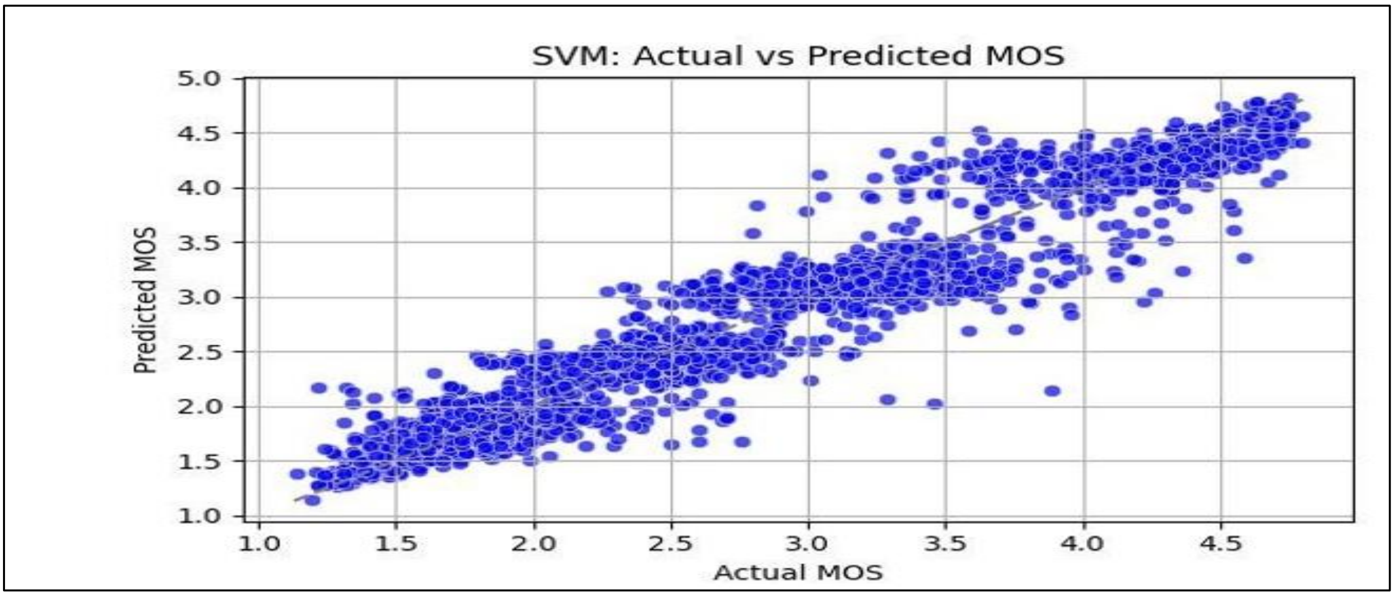

Fig 3 Actual vs Predicted MOS for SVM

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The scatter plot in the ***Figure 2*** gives us a clear picture of how well the K-Nearest Neighbors (KNN) model was able to guess how users actually felt about their video experience. Each green dot represents one prediction. Most of the dots are close to the diagonal line, meaning the model's predictions are quite accurate. While there are a few predictions that are off, the overall pattern shows that KNN does a good job estimating user satisfaction in video streaming.

The scatter plot ***Figure 3*** shows how well the Support Vector Machine (SVM) model predicted user experience (QoE) compared to the actual ratings given by users, measured as Mean Opinion Score (MOS). Each blue dot represents one prediction**.** Most of the dots are close to the diagonal line, which means the model's predictions were quite close to the real values. While there are a few points scattered away from the line, overall, the SVM model did a good job at estimating user satisfaction in video streaming scenarios.

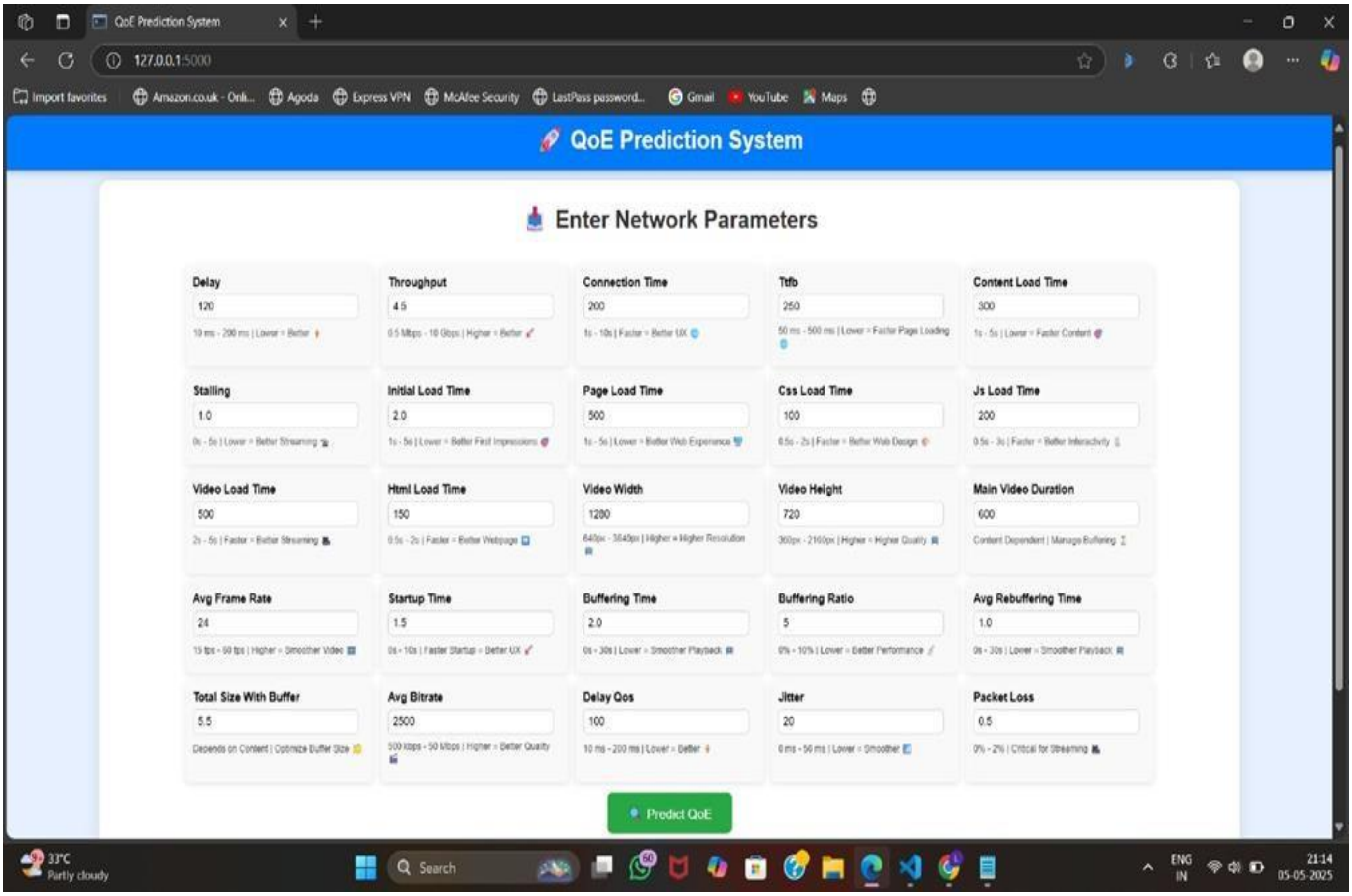

Fig 4 User Interface for QOE Prediction System

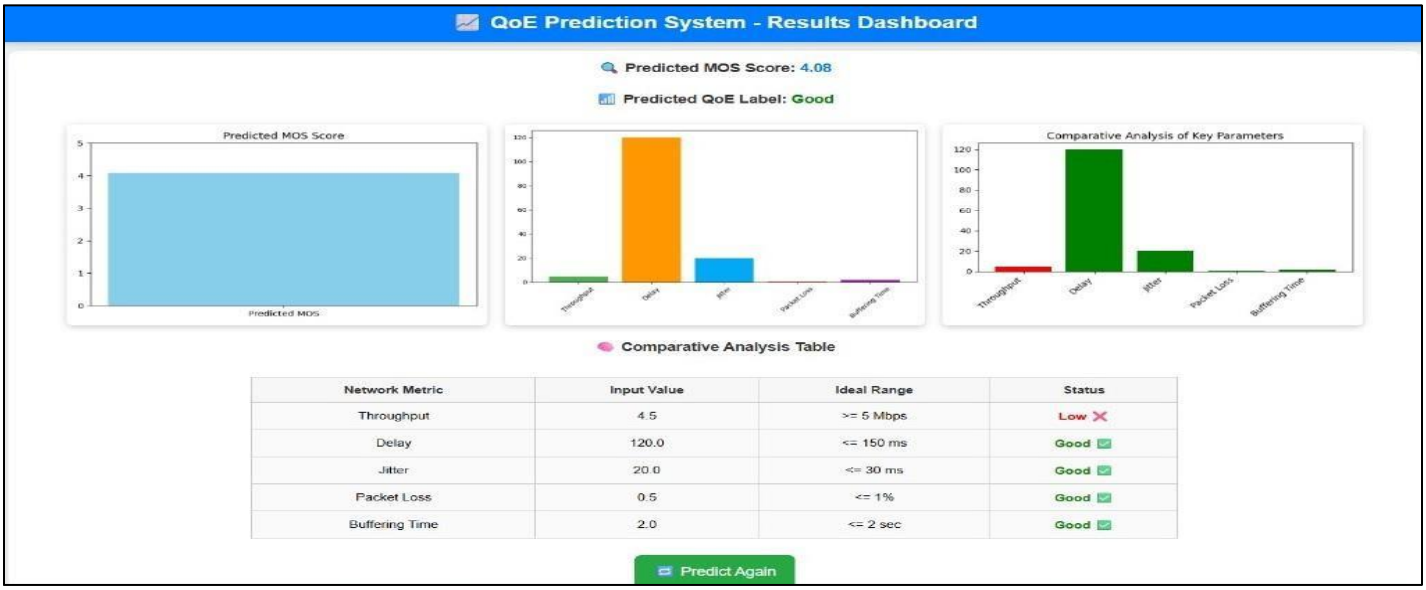

Fig 5 Output Interface for QOE

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➢ *The Output Screens are Shown in Figure 5 Describes that*

- The first bar graph shows the predicted Mean Opinion Score (MOS), which is a numerical indicator of the user's video streaming experience.
- The second graph helps us understand how much each network parameter contributed to the final QoE prediction. For example, delay and jitter had a bigger influence, while packet loss and buffering time had much smaller effects. This usually means those metrics were within safe or acceptable ranges, so they didn't.
- The third graph offers a simple visual comparison between the user's input values and the recommended ideal ranges. Green bars indicate that parameters like delay, jitter, packet loss, and buffering time are all within healthy limits. However, throughput is marked in red, showing that it falls below the ideal 5 Mbps, which could slightly reduce the overall experience quality.

V. CONCLUSION

In this project, we set out to improve the accuracy of QoE (Quality of Experience) prediction for video streaming over 5G networks using ensemble machine learning techniques. Our approach leveraged a combination of well-established machine learning models— Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). This method allowed us to capture various aspects of QoE indicators more effectively ,including factors like video quality, buffering events, and user interaction metrics. Throughout the project, we conducted rigorous preprocessing of the dataset, including feature selection, normalization, and handling of missing values. This ensured that our models were trained on high-quality data and could make accurate predictions. The results showed that our ensemble method significantly improved the QoE prediction performance, especially in terms of precision, recall, and F1-score, making it a promising approach for practical deployment in 5G video services.

FUTURE WORK

While our current project successfully demonstrates the ability to predict Quality of Experience (QoE) using ensemble machine learning models, there are many exciting opportunities to expand and improve this work. Right now, our models work on offline data, but integrating them into a live system that continuously monitors user experience and makes real-time predictions would make the system even more practical for real-world applications. This could help service providers react quickly to changes in network performance and adjust streaming parameters to maintain a smooth and satisfying user experience.Another area for future work involves enhancing the prediction models using deep learning. Although ensemble methods like Random Forest, SVM, and KNN have shown good performance, modern deep learning models such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks can help the system understand more complex and changing patterns in video quality and how users react to them over time. In addition, expanding the dataset with more diverse streaming conditions, device types, and network environments would improve the generalizability of the models.

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