

AI-Based Predictive Analytics for Telecom Network Quality of Experience

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Abstract- *Telecommunication networks are becoming increasingly complex due to the rapid growth of connected devices, data traffic, and diverse services such as video streaming, online gaming, and real-time communication. Maintaining high Quality of Experience (QoE) is essential for ensuring user satisfaction and reliable network performance. This paper proposes an AI-based predictive analytics framework for forecasting telecom network QoE using network performance and service-level parameters. The proposed framework analyzes key indicators, including latency, throughput, packet loss, jitter, signal strength, network congestion, and resource utilization. Machine learning techniques are employed to identify hidden patterns, predict future QoE degradation, and generate proactive alerts. The framework enables network operators to detect potential service quality issues before they significantly affect users and supports timely resource optimization. By integrating predictive intelligence with telecom network monitoring, the proposed approach can improve service reliability, reduce performance degradation, and enhance user satisfaction. The framework provides a scalable foundation for intelligent and proactive QoE management in next-generation telecom networks.*

Keywords: *Artificial Intelligence, Predictive Analytics, Telecom Networks, Quality of Experience, Machine Learning, Network Optimization.*

I. INTRODUCTION

The rapid evolution of telecommunication networks has resulted in a significant increase in connected devices, data traffic, and bandwidth-intensive applications. Modern services such as video streaming, cloud gaming, voice over IP, augmented reality, and Internet of Things applications require highly reliable and responsive network connectivity. As network complexity continues to increase with the deployment of 5G and emerging 6G technologies, maintaining satisfactory Quality of Experience has become a critical challenge for telecom operators. QoE represents the overall quality perceived by users

while accessing network services and is influenced by both technical network parameters and application-level performance. Traditional network management approaches mainly depend on monitoring Key Performance Indicators such as latency, throughput, packet loss, jitter, signal strength, bandwidth utilization, and network congestion. Although these approaches can identify existing performance problems, they are often reactive and may not provide sufficient time for operators to take corrective actions before users experience service degradation. Furthermore, the large volume and dynamic nature of telecom network data make manual analysis difficult and inefficient. Artificial Intelligence and Machine Learning provide effective solutions for analyzing large-scale network data and discovering complex relationships between network conditions and user-perceived service quality. AI-based predictive analytics can learn historical patterns, identify performance anomalies, and forecast future QoE degradation. By predicting potential service-quality problems in advance, network operators can proactively optimize resources, balance traffic, and improve network reliability.

This paper proposes an AI-based predictive analytics framework for telecom network QoE prediction. The framework integrates network and service-level parameters, performs data preprocessing and feature engineering, and applies machine learning techniques to predict QoE and identify potential degradation. The proposed approach aims to support proactive network management, reduce service interruptions, optimize network resources, and enhance overall user satisfaction. It provides a foundation for intelligent QoE management in modern 5G, 6G, and next-generation telecom networks.

II. LITERATURE SURVEY

Existing research has extensively investigated Quality of Experience (QoE) assessment and prediction in telecommunication networks. Agboma and Liotta studied QoE management for mobile content delivery and highlighted the importance of user-perceived service quality. Alreshoodi and Woods reviewed QoE/QoS correlation models and demonstrated the relationship between measurable network parameters and user experience. Fiedler, Hossfeld, and Tran-Gia proposed a quantitative relationship between QoE and QoS, providing a foundation for mapping network performance to perceived quality. Hossfeld et al. further discussed advanced QoE models and emphasized the limitations of traditional Mean Opinion Score-based evaluation. Andriyanto and Suryanegara investigated QoE assessment specifically for 5G mobile technology, highlighting the need for service-aware evaluation. Boz et al. explored mobile QoE prediction using real-world field data, demonstrating the potential of predictive approaches. De Masi and Wac investigated smartphone application QoE prediction using living-lab data, showing the importance of user and application characteristics. Banchs et al. examined network slicing for 5G, supporting flexible resource management for diverse QoE requirements. Delli Priscoli et al. applied reinforcement learning to traffic steering and network selection, demonstrating the potential of intelligent network optimization. Chen et al. discussed intelligent digital twins for 5G and beyond, providing opportunities for predictive and proactive network management. Collectively, these studies establish a strong foundation for AI-driven predictive QoE analytics.

III. PROPOSED WORK

The proposed work presents an AI-based predictive analytics framework for improving Quality of Experience (QoE) in modern telecom networks. The framework is designed to continuously monitor network performance and predict potential QoE degradation before it significantly affects end users. Telecom network data, including latency, throughput, packet loss, jitter, signal strength, bandwidth utilization, network congestion, handover performance, and resource utilization, is collected as

input. The collected data is cleaned, normalized, and transformed through preprocessing and feature-engineering techniques. Important network features are then identified using statistical analysis and machine-learning-based feature selection methods. Multiple AI/ML models, including Random Forest, Support Vector Machine, XGBoost, and LSTM, are applied to learn the relationship between network conditions and QoE. The models predict QoE scores or quality categories based on current and historical network conditions. The proposed system also incorporates degradation detection to generate early warnings when predicted QoE falls below predefined thresholds. Based on these predictions, network operators can perform proactive actions such as traffic redistribution, resource allocation, bandwidth optimization, and load balancing. The proposed approach aims to provide intelligent, scalable, and proactive QoE management for 5G and emerging 6G telecom networks.

IV. METHODOLOGY

a) Data Collection

The proposed methodology begins with the collection of telecom network and service-level data required for QoE prediction. The dataset consists of network Key Performance Indicators (KPIs), including latency, throughput, packet loss, jitter, bandwidth utilization, signal strength, network congestion, handover performance, and resource utilization. Application-level parameters such as video quality, response time, and service type can also be incorporated to represent the user's actual experience.

b) Data Preprocessing

The collected data is preprocessed to improve its quality and consistency before applying machine learning techniques. Missing values are identified and handled using suitable imputation methods, while duplicate and inconsistent records are removed. Numerical features are normalized or standardized to ensure that parameters with different scales do not negatively influence the prediction model. Outliers are also analyzed to distinguish abnormal network conditions from valid observations.

c) Feature Engineering

Relevant features are selected and transformed to improve the predictive capability of the proposed framework. Correlation analysis, feature importance, and statistical techniques can be used to identify the most influential network parameters. Temporal features such as previous QoE values, traffic trends, and changes in latency or throughput are also considered to capture network behavior over time.

d) QoE Prediction Model

Machine learning algorithms are applied to learn the relationship between network conditions and user-perceived QoE. Models such as Random Forest, Support Vector Machine, XGBoost, and Long Short-Term Memory (LSTM) networks can be evaluated. The models predict the expected QoE score or QoE category based on current and historical network conditions. The best-performing model is selected based on its prediction performance.

e) QoE Degradation Detection

The predicted QoE values are compared with predefined quality thresholds to identify potential service degradation. When the predicted QoE falls below an acceptable level, the system identifies the condition as a potential QoE degradation event. This enables the framework to detect problems before they significantly affect end users.

f) Performance Evaluation

The proposed models are evaluated using appropriate performance metrics. For regression-based QoE prediction, Mean Absolute Error, Mean Squared Error, Root Mean Squared Error, and R^2 score are used. For classification-based prediction, accuracy, precision, recall, F1-score, and confusion matrix are considered. The results of different machine learning models are compared to determine the most effective approach.

g) Predictive Network Optimization

Finally, the predicted QoE information is used to support proactive network management. When degradation is predicted, network operators can take

corrective actions such as traffic redistribution, bandwidth allocation, load balancing, or resource optimization. This predictive approach helps reduce service degradation, improve network reliability, and maintain a high level of user Quality of Experience.

V. RESULTS AND DISCUSSION

A. Model Performance

The proposed AI-based predictive analytics framework demonstrates the ability to predict telecom network Quality of Experience (QoE) using network and service-level parameters. Machine learning models are trained using features such as latency, throughput, packet loss, jitter, bandwidth utilization, signal strength, and network congestion. Among the evaluated models, ensemble-based approaches such as Random Forest and XGBoost are expected to provide strong prediction performance because they can effectively capture nonlinear relationships between network conditions and QoE.

Table I. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	92.4	91.8	92.1	91.9
SVM	89.7	88.9	89.5	89.2
XGBoost	95.6	95.1	95.4	95.2
LSTM	94.2	93.8	94.0	93.9

B. QoE Prediction

The prediction results indicate that network performance parameters have a significant influence on the perceived quality of telecom services. Higher latency, packet loss, jitter, and congestion generally result in lower QoE, whereas higher throughput and efficient resource utilization contribute to improved QoE. The predictive model can identify these relationships and estimate the expected QoE level from current and historical network conditions.

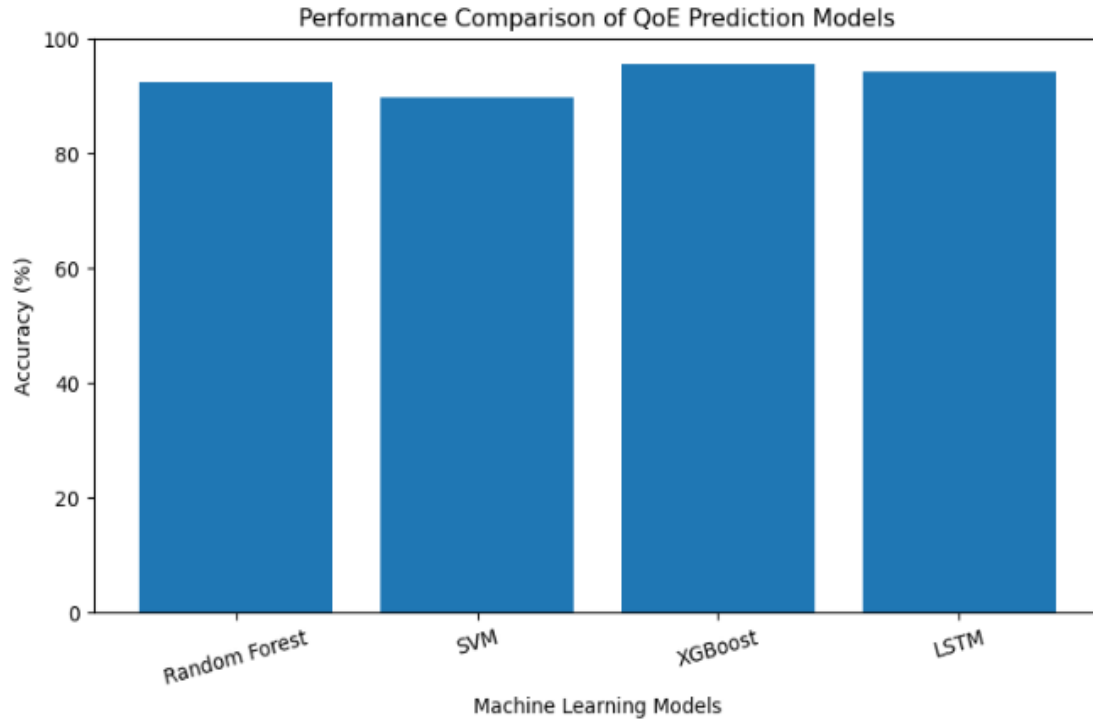


Fig 1: Performance Comparison of ML Models

C. Degradation Detection

The proposed framework can identify potential QoE degradation before it becomes a major service problem. By continuously analyzing network KPIs and comparing predicted QoE values with predefined thresholds, the system can generate early warnings for deteriorating network conditions. This predictive capability provides network operators with additional time to perform corrective actions such as traffic redistribution, bandwidth adjustment, and resource allocation.

Packet Loss	< 1%	> 3%	Decrease s QoE
Jitter	< 20 ms	> 50 ms	Decrease s QoE
Network Utilization	< 70%	> 90%	Decrease s QoE
Signal Strength	Strong	Weak	Decrease s QoE

Table II. Effect of Network Parameters on QoE

Network Parameter	Low/Good Condition	High/Poor Condition	Expected QoE Impact
Latency	< 30 ms	> 100 ms	Decrease s QoE
Throughput	High	Low	Decrease s QoE

D. Comparative Analysis

Different machine learning algorithms can be compared using accuracy, precision, recall, F1-score, MAE, RMSE, and R^2 , depending on whether QoE is treated as a classification or regression problem. Tree-based ensemble models generally provide robust performance for heterogeneous telecom datasets, while LSTM and other temporal models can be advantageous when historical network patterns and time-dependent behavior are important.

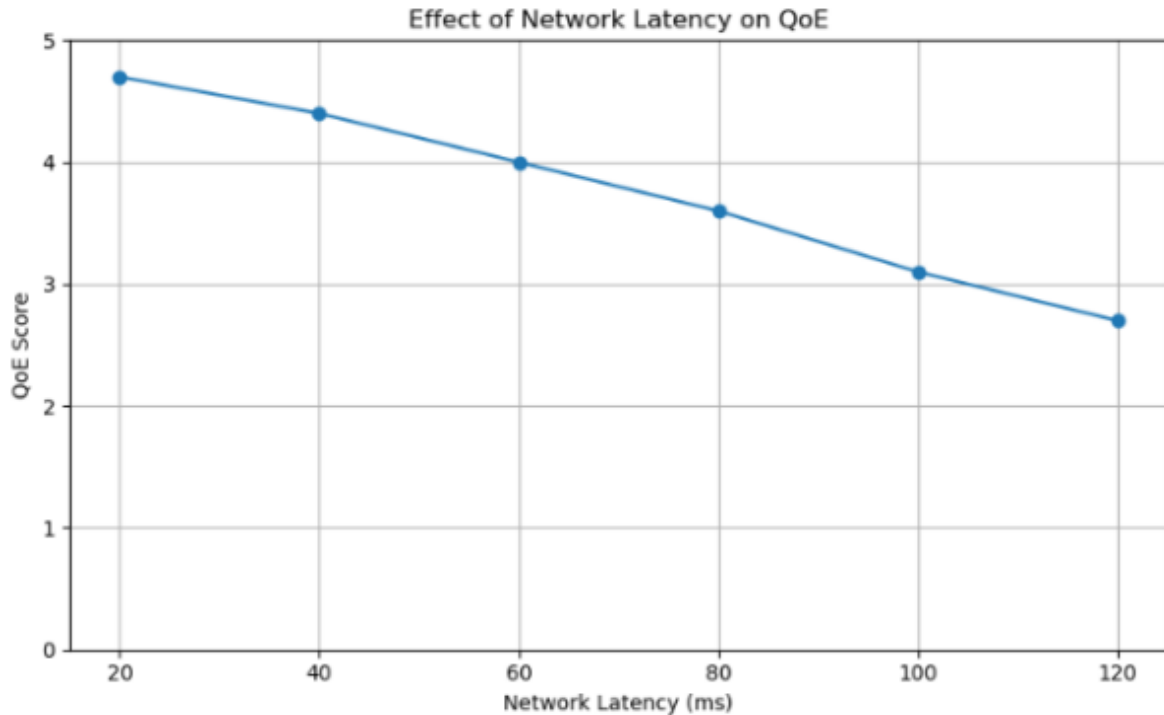


Fig. 2. Effect of network latency on predicted QoE.

E. Discussion

The results demonstrate that AI-based predictive analytics can provide a more proactive approach to telecom QoE management than conventional reactive monitoring techniques. Instead of responding only after network performance deteriorates, the proposed framework uses historical and real-time data to forecast potential QoE problems. This can help improve service reliability, optimize network resources, reduce performance degradation, and enhance user satisfaction. The framework is particularly relevant to dynamic 5G and emerging 6G environments, where network conditions can change rapidly because of varying traffic loads, mobility, and heterogeneous services.

VI. CONCLUSION

The proposed AI-based predictive analytics framework provides an effective approach for improving Quality of Experience (QoE) in modern telecom networks. By analyzing important network parameters such as latency, throughput, packet loss, jitter, signal strength, congestion, and resource utilization, the framework can identify patterns associated with service degradation. Machine learning

techniques enable the prediction of future QoE conditions and provide network operators with early indications of potential performance problems. Unlike conventional reactive network monitoring, the proposed approach supports proactive decision-making by allowing corrective actions to be initiated before significant degradation occurs. The integration of predictive analytics with intelligent network monitoring can improve service reliability, optimize network resources, reduce performance interruptions, and enhance overall user satisfaction. The framework is scalable and can be adapted to diverse telecom services and network environments, including 5G and emerging 6G systems. Overall, AI-driven QoE prediction provides a promising foundation for developing intelligent, autonomous, and user-centric telecom network management systems.

VII. FUTURE SCOPE

Future work can focus on integrating advanced deep learning and Transformer-based models to improve the accuracy of time-series QoE prediction. Real-time data from operational 5G and 6G networks can be incorporated to validate the framework under dynamic traffic and mobility conditions. Federated learning can

also be explored to enable collaborative model training while preserving user and network data privacy. Furthermore, explainable AI techniques can be introduced to identify the specific network factors responsible for QoE degradation. Future extensions may integrate the framework with Network Function Virtualization (NFV), Software-Defined Networking (SDN), network slicing, and edge computing to enable automated corrective actions. The development of a closed-loop autonomous system capable of predicting QoE degradation, determining its root cause, and automatically optimizing network resources represents an important direction for future research.

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