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Beyond Traditional QoS Management: Harnessing Machine Learning for Predictive Network Service Optimization

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Abstract: Maintaining robust Quality of Service (QoS) in modern networks remains a persistent challenge, particularly given the dynamic nature of traffic patterns and increasing demand for real-time applications. Traditional rule-based QoS management approaches often fall short due to their limited adaptability and lack of predictive capabilities. This study addresses this critical gap by proposing a machine learning driven framework for proactive QoS prediction and optimization. Leveraging a large-scale dataset of historical network performance metrics, several predictive models including linear regression, random forest, and deep learning were employed to forecast key QoS indicators such as latency, throughput, jitter, and packet loss. Experimental analyses demonstrate the superior performance of the Random Forest model, achieving an R^2 score of 0.97, highlighting its efficacy in handling nonlinear, The Artificial Neural Network (ANN) also exhibited strong performance with an R^2 of 0.92, reinforcing the viability of deep learning in QoS prediction scenarios. Conversely, Support Vector Machines (SVM) were less effective due to computational constraints. These findings advocate for the integration of advanced ML algorithms into network management practices, significantly advancing proactive network optimization and service reliability. Furthermore, this research contributes a scalable and adaptable solution applicable to diverse infrastructure environments, including cloud computing, IoT, and 5G networks. Future research will focus on real-time integration and federated learning to further improve model generalizability and privacy. This study affirms the transformative potential of machine learning in redefining QoS management through intelligent, predictive analytics.

Keywords: Deep Learning, Latency, Machine Learning, Network Performance, Quality of Service (QoS)

INTRODUCTION

The rapid evolution of digital technology has significantly increased the demand for high-performance network infrastructures that provide seamless connectivity, low latency, and reliable data transmission. As organizations increasingly rely on cloud computing, real-time applications, and the Internet of Things (IoT), ensuring consistent Quality of Service (QoS) has become both critical and complex. QoS refers to a collection of performance metrics including latency, throughput, jitter, and packet loss—that collectively determine the efficiency and overall experience of network services (Michel et al., 2023; Palaios et al., 2023).

Traditionally, QoS management has depended on rule-based and heuristic-driven approaches that often involve extensive manual configuration and are typically inflexible in adapting to real-time network fluctuations (Aouedi et al., 2022; He et al., 2024). While these conventional methods provide a foundational framework for resource management, they fall short in addressing the complexities of modern digital infrastructures, particularly those powered by cloud computing, Software-Defined Networking (SDN), and 5G technologies (Kala et al., 2024; Talpur et al., 2024). Their inability to forecast service degradation or autonomously adapt to network variability highlights a crucial shortfall that limits their effectiveness in dynamic environments.

In response to these limitations, recent research has shifted toward leveraging Machine Learning (ML) and Deep Learning (DL) as advanced, data-driven alternatives for intelligent QoS management. By analyzing historical network performance data, ML models can detect latent patterns, forecast service degradation, and enable

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proactive resource allocation (Uzunidis et al., 2021). This transition from reactive to predictive QoS management marks a significant step forward in achieving greater efficiency and reliability in modern networks.

A variety of ML methods have demonstrated promise in this area. Classic models such as decision trees, support vector machines (SVM), and ensemble learning techniques like Random Forest have been successfully applied to forecast network behavior and detect performance bottlenecks (Behera et al., 2021; Li et al., 2021). Furthermore, DL approaches particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have shown strong capability in handling complex time-series data and identifying anomalies in real-time traffic (Lutz et al., 2021; Uzunidis et al., 2021). These intelligent systems not only improve prediction accuracy but also enhance adaptability in rapidly changing network environments, thus improving service quality and end-user satisfaction. Nonetheless, challenges remain. Issues such as imbalanced datasets, high computational overhead, and privacy risks associated with centralized data processing must be addressed to fully realize the benefits of ML-based QoS management (He et al., 2024; Li et al., 2021). To mitigate these concerns, Federated Learning (FL) has emerged as a promising approach that enables decentralized model training while maintaining user privacy and data security (Behera et al., 2021).

This study aims to overcome the shortcomings of traditional QoS strategies by investigating the application of ML techniques for predictive network service optimization based on historical performance data. It evaluates the effectiveness of various predictive models including linear regression, random forest, and deep learning in forecasting key QoS indicators such as latency, throughput, jitter, and packet loss. The goal is to demonstrate how ML can significantly improve predictive accuracy, enabling real-time optimization and smarter decision-making in complex network environments.

Moreover, this research proposes a scalable and adaptive ML framework designed to be integrated into modern infrastructure settings such as cloud platforms, IoT ecosystems, and 5G networks. By incorporating real-time data processing and predictive analytics, the framework aims to enhance service reliability, reduce performance variability, and lower operational costs. Beyond technical innovation, the study also addresses practical concerns like model interpretability and the ethical implications of data-driven network management, ensuring its feasibility and relevance for real-world deployment. This research contributes to the ongoing development of next-generation intelligent network management systems. By transitioning from reactive to proactive QoS management, it lays the groundwork for more resilient, efficient, and user-centric digital infrastructures.

LITERATURE REVIEW

In recent years, the management of Quality of Service (QoS) in modern networks has become increasingly complex due to the dynamic nature of network traffic, the rapid growth of real-time applications, and the diverse range of connected devices and infrastructures. Traditional QoS mechanisms, which typically rely on static, rule-based configurations, are proving inadequate in meeting the stringent and evolving performance requirements of contemporary networks. This has led to a paradigm shift toward more intelligent, adaptive, and data driven approaches particularly those grounded in machine learning (ML) and deep learning (DL). Numerous studies have explored AI-based frameworks for enhancing network performance through techniques such as resource allocation, service provisioning, and automated model management. While these contributions offer valuable insights into specific facets of QoS, those study often fall short in addressing predictive QoS modelling, especially in terms of utilizing historical network data to anticipate performance degradation before it impacts service delivery. This predictive capability is increasingly crucial for enabling proactive network optimization.

Table 1. Previous research in comparative analysis of related studies

Author(s)	Research Title	Description	Gap
(Dong et al., 2021)	Deep Learning for Radio Resource Allocation with Diverse Quality-of-Service Requirements in 5G	This study applies deep learning to optimize radio resource allocation in 5G networks, aiming to minimize power consumption while maintaining QoS requirements. It uses neural networks to predict the best allocation strategies dynamically.	Unlike this study, which predicts QoS parameters based on historical network performance, this paper focuses on resource allocation in 5G systems. It does not address broader QoS management across different network infrastructures.

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(Nouruzi et al., 2022)	Online Service Provisioning in NFV-enabled Networks Using Deep Reinforcement Learning	This research applies Deep Q-Networks (DQN) for optimizing service provisioning in NFV-enabled networks. The goal is to minimize resource utilization costs while maintaining QoS standards dynamically.	This study focuses on NFV (Network Function Virtualization) and resource allocation using reinforcement learning, whereas this research applies supervised learning methods (Random Forest, XGBoost, Deep Learning) to predict QoS values. This study approach is more focused on historical trend analysis and proactive QoS management, rather than real-time dynamic resource adjustments.
(Mazhar et al., 2023)	*Quality of Service (QoS) Performance Analysis in a Traffic Engineering Model for Next-Generation Wireless Sensor Networks*	Proposes a traffic engineering model with a dynamic queuing mechanism for real-time communication in next-gen wireless sensor networks. Highlights vulnerabilities in traditional QoS models and proposes improvements via adaptive queuing based on service priority.	Focuses on queue-based optimization rather than predictive modeling using machine learning. Unlike this study, it does not utilize historical network data for forecasting QoS metrics.
(Osman et al., 2024)	*A Novel Network Optimization Framework Based on Software-Defined Networking (SDN) and Deep Learning (DL) Approach*	Introduces a dynamic QoS framework combining SDN and deep learning to manage sensitive traffic and prioritize bandwidth allocation in enterprise networks.	While it leverages DL for decision-making, the approach is reactive. It does not employ supervised learning to predict QoS metrics from historical trends, as emphasized in this research.
(Aboughaly & Hannan, 2024)	*Enhancing Quality-of-Service in Software-Defined Networks Through Firefly-Fruit Fly Optimization and Deep Reinforcement Learning*	Combines bio-inspired optimization and DRL to dynamically enhance QoS in SDN. The system adapts to changing network conditions using learned experiences.	Focuses on adaptive QoS through reinforcement learning and optimization, not on proactive QoS prediction based on past network performance data as in this study.
(Cristobo et al., 2024)	*Global Quality of Service (QoX) Management for Wireless Networks*	Proposes a comprehensive QoXphere model integrating QoS, QoE, and QoBiz dimensions. Emphasizes machine learning for global QoS optimization and user satisfaction in wireless environments.	Provides a broad, integrative management approach but lacks focus on specific ML-based predictive modeling of QoS metrics, which is central to this study.

Recent advancements in intelligent Quality of Service (QoS) management have yielded significant progress, a closer examination of existing studies summarized in Table 1**,** reveals that many focus on narrow or domain-specific aspects of the broader QoS challenge. (Dong et al., 2021) employ deep learning to enhance radio resource allocation in 5G networks, targeting energy efficiency while maintaining QoS. Although effective within its scope, the study lacks general applicability across heterogeneous network environments and does not incorporate predictive modeling based on historical performance data. Similarly, (Nouruzi et al., 2022) utilize deep

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reinforcement learning (DQN) to optimize service provisioning in NFV-enabled networks, yet their work is centered on real-time adaptability rather than proactive forecasting, which limits its capacity for anticipating future performance degradation. (Mazhar et al., 2023) propose a dynamic queuing mechanism for next-generation wireless sensor networks, addressing real-time traffic management through adaptive prioritization. While their contribution is valuable, the absence of machine learning techniques or historical trend analysis reduces its predictive strength. (Osman et al., 2024) present a novel framework that combines Software-Defined Networking (SDN) with deep learning to manage bandwidth allocation dynamically. Despite its innovative integration, the framework remains reactive, responding to present conditions rather than anticipating future QoS demands. In a similar vein, (Aboughaly & Hannan, 2024) introduce a bio-inspired optimization approach using Deep Q-Learning for SDNs. Although the model adapts to changing network states effectively, it does not leverage historical data for predictive insight. (Cristobo et al., 2024) take a more comprehensive approach by integrating QoS, Quality of Experience (QoE), and Quality of Business (QoBiz) into a unified QoX management model. Their framework provides a valuable strategic perspective but lacks the granularity required for machine learning–based predictive modeling of core QoS metrics.

These studies collectively presented in table 1, highlight the growing emphasis on intelligent and automated network management but also expose a crucial research gap, the need for predictive QoS modeling grounded in historical network data. Addressing this gap, this research introduces a novel methodology by integrating historical network performance data into predictive models, enabling proactive QoS adjustments before service degradation occurs. approach directly tackles the challenge of real-time QoS prediction using supervised learning techniques. The experimental results demonstrate that machine learning models significantly outperform traditional rule-based QoS management strategies in accuracy and efficiency, providing a more robust and scalable solution. coupled with the authors emphasis on predictive analytics rather than reactive resource allocation, positions the authors work as a more comprehensive and impactful contribution to the field of intelligent network management.

METHOD

Data Overview

In his study, we adopt the proposed research flow illustrated in Figure 1, which outlines the systematic stages of data preparation, model development, evaluation, and visualization to ensure a structured and replicable analysis process.

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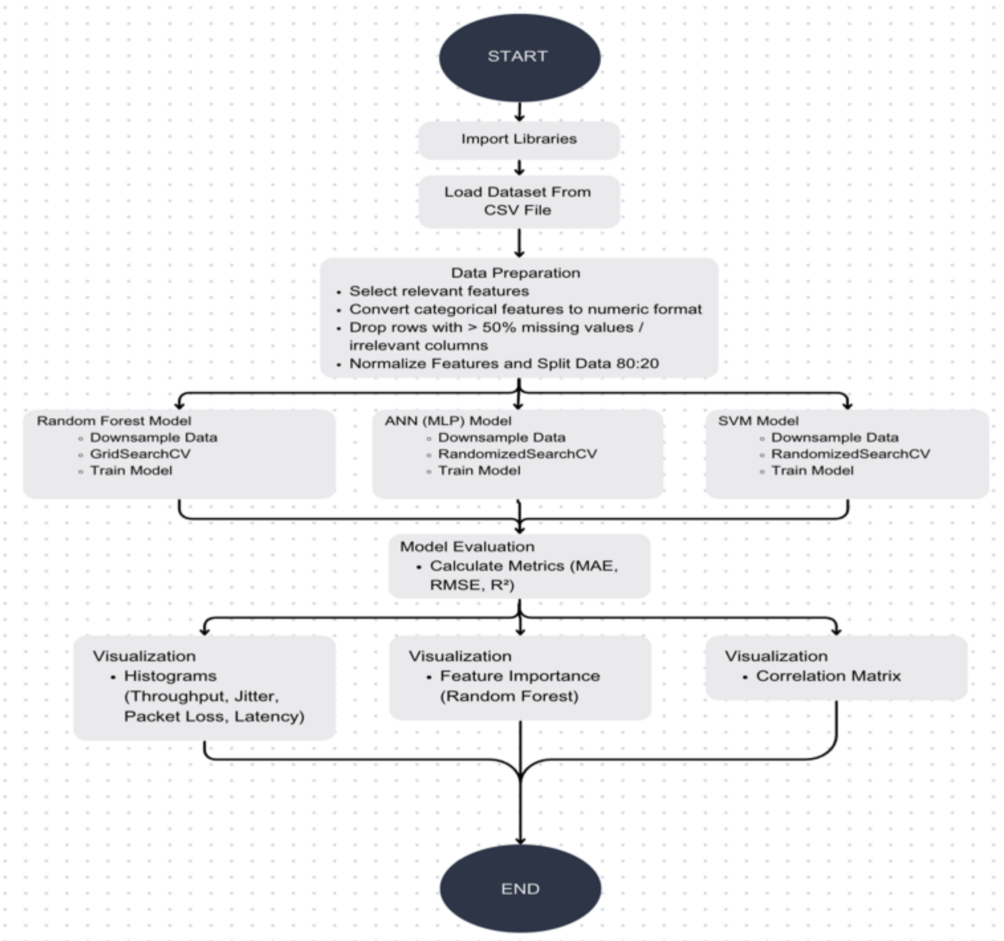

Fig. 1 Proposed Flow of QOS Management research
Sources: Researcher Property

This study employs a comprehensive, real-time dataset consisting of 564,000 records and 26 attributes representing various Key Performance Indicators (KPIs) essential for evaluating Quality of Service (QoS). The dataset includes primary metrics: latency, throughput, packet loss, and session success rate, all of which serve as core input variables for training predictive machine learning models (Alghofaily, 2023; Alzoman & Alenazi, 2021). Widely recognized in both academic and operational contexts, these KPIs enable high-precision modeling and forecasting of network behavior, supporting the development of intelligent and proactive QoS management strategies. (Hameed et al., 2022; Preciado-Velasco et al., 2021).

Table 2. Key Feature

Field	Description
kpi_latency_int_msec	Represents the internal network latency measured in milliseconds
kpi_latency_ext_msec	This metric represents the external latency of the network, measured in milliseconds
kpi_mean_flow_total_throughput_bps	Measures the average total data throughput across all flows
kpi_data_packet_loss_rate	Percentage of data packets lost during transmission
kpi_service_access_succ_rate	The ratio of successful connections in a session.
kpi_rating	Target label, which indicates the service quality on a certain scale.

These fields in table 2, kpi_latency_int_msec, kpi_latency_ext_msec, kpi_mean_flow_total_throughput_bps**,** kpi_data_packet_loss_rate, and kpi_service_access_succ_rate are particularly emphasized due to their direct influence on network reliability. The target variable, kpi_rating, classifies overall service quality on a structured

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scale, ensuring a systematic evaluation framework (Preciado-Velasco et al., 2021). Given the increasing demand for low-latency, high-throughput communication and the rapid proliferation of smart devices, these KPIs have become critical in maintaining robust and efficient network operations (Tomar et al., 2022).

Data Preprocessing

To uphold data integrity and optimize predictive performance, a rigorous data preprocessing pipeline was implemented. Features deemed irrelevant or containing excessive missing values were systematically excluded, including those with 100**%** missing data (kpi_tls_handshake_latency_msec) and others exceeding a 50% missing threshold. Missing values within retained numerical attributes were addressed through median imputation, preserving the underlying statistical distribution of the dataset (Astrakhantsev et al., 2023).

Furthermore, numerical variables were normalized using Min-Max Scaling, ensuring a standardized range between 0 and 1, This step was essential to improve algorithmic stability and prevent scale-based bias during model training (Alzoman & Alenazi, 2021). To facilitate a reliable evaluation process, the dataset was partitioned into 80% training data and 20% testing data, following best practices in machine learning experimentation (Hameed et al., 2022).

Machine Learning Models

The application of machine learning techniques for predicting Quality of Service (QoS) metrics represents a transformative advancement in modern network management. By enabling early detection of performance degradation and supporting proactive optimization strategies, machine learning offers a data-driven foundation for intelligent, adaptive, and efficient network service delivery. Furthermore, a Feature Importance Analysis was conducted to identify and rank the most influential KPIs contributing to service quality predictions, offering actionable insights for proactive network management (Alzoman & Alenazi, 2021).

To construct the predictive model, three prominent machine learning algorithms were selected. Random Forest (RF) is an ensemble-based method that mitigates overfitting by aggregating the outputs of multiple decision trees trained on random subsets of the data. This majority-voting mechanism enhances model robustness, particularly in high-dimensional environments characterized by noisy or heterogeneous inputs conditions frequently encountered in real-world network traffic (Aureli et al., 2022; Khan et al., 2021). RF's ability to handle diverse data types and interactions among variables makes it a reliable choice for QoS classification tasks. Support Vector Machine (SVM**)** excels in scenarios where clear class boundaries exist. It constructs an optimal hyperplane that maximizes the margin between classes, offering high classification performance, especially in structured feature spaces. Furthermore, its flexibility through kernel functions allows SVM to model non-linear relationships, making it suitable for capturing the complex dependencies among QoS parameters often observed in dynamic network environments (Hao Xu et al., 2023; Xie et al., 2022). And Artificial Neural Networks (ANN) offer a deeper, more flexible architecture capable of modeling intricate, non-linear relationships across multiple input features. Composed of interconnected layers of computational nodes, ANNs excel at learning hierarchical feature representations and adapting to underlying patterns in historical QoS data. Their strength lies in their ability to generalize across complex datasets, yielding high prediction accuracy even in the face of subtle or hidden dependencies (Al Moteri et al., 2023a; Ghuge et al., 2023). This makes ANNs particularly effective in environments where service quality fluctuates rapidly, such as in 5G and IoT ecosystems. Each algorithm was chosen for its theoretical strengths and proven effectiveness in addressing complex classification tasks within QoS-related domains.

Implementation and Evaluation

This study investigates the practical implementation of machine learning models, namely Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN), for the classification of Quality of Service (QoS) in contemporary network environments. This endeavor is particularly timely and significant, as it advances the shift from reactive to proactive network management by embedding predictive analytics into complex and evolving infrastructure contexts, including 5G, the Internet of Things (IoT), and edge computing systems (A Ilemobayo et al., 2024).

To ensure the effectiveness of the predictive models, a rigorous data preprocessing pipeline was established. This included cleaning the raw dataset, applying Min-Max normalization to scale numerical values, and handling missing entries through median imputation. These steps were essential for preparing the dataset for model training and evaluation. Following standard practice, the dataset was partitioned into an 80:20 ratio for training and testing, supporting both robust model development and reliable performance validation (Hoque & Aljamaan, 2021). In this study, a classification-based approach is employed to categorize network service quality into two discrete classes "Good" and "Bad" based on key performance indicators such as latency, throughput, packet loss, and jitter. This binary classification scheme provides a clear operational framework for distinguishing between optimal and degraded network conditions, thereby facilitating more responsive and informed network management.

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A key component of the implementation phase involved hyperparameter tuning, which was conducted using both Grid Search and Random Search strategies. These optimization techniques were applied to refine the learning parameters of each model: adjusting the number and depth of trees for Random Forest, selecting kernel types and regularization parameters for SVM, and determining the layer configuration, learning rate, and batch size for ANN. This process proved vital in enhancing each model's accuracy, generalization, and adaptability to complex network traffic conditions and variable data distributions (A Ilemobayo et al., 2024). Additionally, a Feature Importance Analysis was conducted particularly for the Random Forest model to identify which QoS parameters had the greatest influence on the classification decisions. Metrics such as latency and packet loss emerged as dominant predictors, offering actionable insights for network engineers and administrators seeking to prioritize service optimization based on data-driven evidence (Hutter et al., 2019).

The evaluation of machine learning models for Quality of Service (QoS) prediction relies on several well-established performance metrics. Indicators such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) offer a structured and quantifiable approach for comparing predictive accuracy across models. Recent studies have demonstrated that Artificial Neural Networks (ANNs) consistently exhibit superior performance in capturing the nonlinear and complex interdependencies among Quality of Service (QoS) parameters. This capability makes ANNs particularly well-suited for dynamic, high-variability, and data-intensive network environments, where traditional models often struggle to maintain predictive accuracy(Al Moteri et al., 2023b; Patel et al., 2024).

Overall, these evaluation practices support the development of more accurate, explainable, and adaptive models for QoS prediction. As machine learning continues to evolve, such approaches will be essential for designing next-generation, self-optimizing communication systems that are both resilient and user-centered.

RESULT

This study provides critical insights into the predictive capabilities of machine learning models in assessing Quality of Service (QoS) within network environments. Through extensive analysis, key relationships among latency, throughput, packet loss, and jitter were identified, offering a deeper understanding of how these parameters influence network performance.

Correlation Between QoS Parameters

A detailed correlation analysis revealed strong interdependencies among QoS parameters. Correlation analysis between quality of service (QoS) parameters is performed to understand the relationship between external latency, internal latency, packet loss, and throughput.

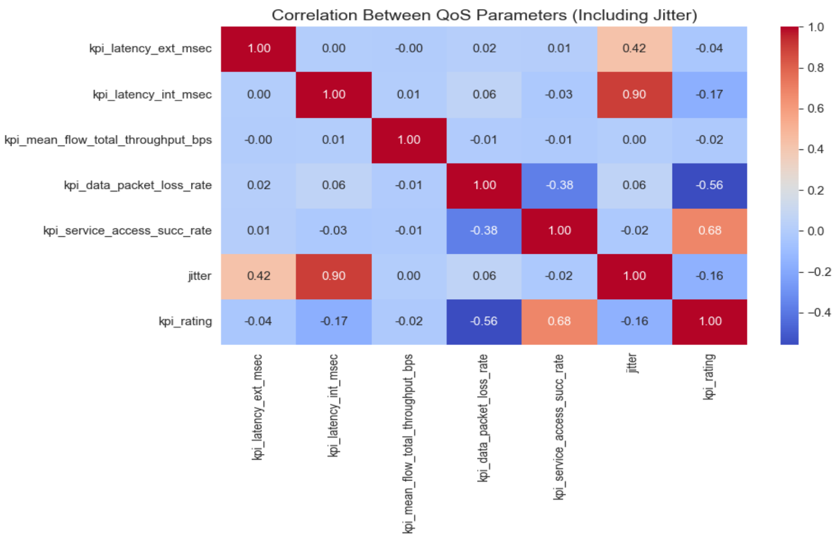

Fig. 2 Correlation Analysis
Sources: Researcher Property

The Figure 2 shows the correlation heatmap between parameters, this illustration's offers a comprehensive view of the interrelationships among core Quality of Service (QoS) indicators, now including jitter as an additional performance metric. This extended analysis provides deeper insights into how latency, throughput, packet loss, session success rate, and jitter collectively influence perceived network quality. One of the most prominent findings is the strong positive correlation (0.90) between jitter and internal latency **(**kpi_latency_int_msec**)**, suggesting that jitter is not only driven by fluctuations in network delay but is fundamentally linked to the latency

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behavior within the network infrastructure. This high degree of association underscores jitter's value as a proxy for network instability, especially in real-time services such as VoIP or video conferencing. Furthermore, jitter also exhibits a moderate correlation with external latency **(**kpi_latency_ext_msec**)** at 0.42, reinforcing its role in capturing temporal variations in packet delivery across both internal and external network paths.

As observed previously, packet loss **(**kpi_data_packet_loss_rate**)** and session success rate **(**kpi_service_access_succ_rate**)** maintain strong inverse and direct correlations with the QoS rating, at -0.56 and 0.68, respectively. These findings are consistent with prior research indicating that packet loss and successful session establishment are vital determinants of end-user experience (Debnath et al., 2021). These metrics continue to emerge as key determinants of end-user experience, where low packet loss and high success rates are directly aligned with favorable service quality assessments.

Meanwhile, throughput (kpi_mean_flow_total_throughput_bps) remains weakly correlated with all parameters, confirming its limited standalone explanatory power within this dataset. Additionally, a very strong positive correlation (0.90) between int_latency and jitter suggests that as latency increases, network instability also rises, adversely affecting real-time applications such as Voice over Internet Protocol (VoIP) calls and video streaming. These findings emphasize the necessity of proactive monitoring and optimization of latency and jitter to ensure stable and reliable network performance (Shi et al., 2022; Woźnicki et al., 2020).

Distribution of QoS Parameters

A statistical analysis of QoS metrics revealed distinct distributional characteristics.

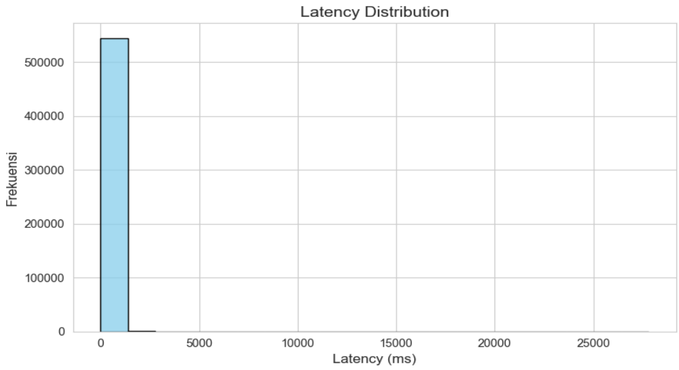

Fig. 3 Histogram of Latency Distribution
Sources: Researcher Property

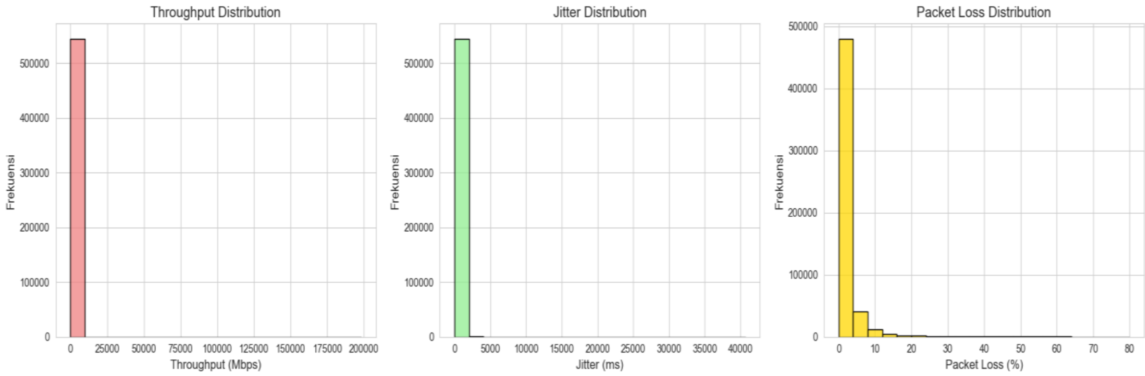

Fig. 4 Histogram of Throughput, Jitter and Packet Loss Distribution
Sources: Researcher Property

The distribution plots presented in Figures 3 and 4 provide essential insights into the statistical behavior and variability of core Quality of Service (QoS) indicators, including latency, throughput, jitter, and packet loss. These visualizations are critical for understanding the dynamic nature of network performance and for informing the selection of predictive modeling techniques. As illustrated in the latency distribution plot, the vast majority of network latency measurements are concentrated near the lower end of the scale, particularly below 1,000 milliseconds. The histogram exhibits a strong right skew, indicating that while most network sessions experience low latency, a small number of extreme outliers can reach values exceeding 25,000 milliseconds. These outliers,

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although rare, represent critical moments of network delay that may severely affect time-sensitive applications such as video conferencing or online gaming.

The throughput distribution similarly reveals a high concentration of values in the lower spectrum, with most data points falling below 25,000 Mbps. Although the x-axis extends to significantly higher values, the actual frequency of such high-throughput instances is negligible. The distribution appears sharply left-skewed, which may be indicative of bandwidth bottlenecks or limitations in capacity provisioning across large portions of the network. Jitter, which reflects the variability in packet delivery times, also follows a right-skewed distribution. The majority of jitter values are well below 1,000 milliseconds, but some extreme cases approach or exceed 40,000 milliseconds. The distribution of packet loss reveals a steep drop-off pattern, where most observations cluster near 0%, but with a long tail extending beyond 70%. These insights highlight the dynamic nature of network performance and underscore the importance of real-time monitoring and adaptive QoS management strategies *(Wainer & Fonseca, 2020).*

Performance Evaluation of Machine Learning Models

The predictive performance of various machine learning models was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2)**.** A comparative analysis between Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) revealed significant differences in accuracy and generalization capabilities

Table 3. Evaluation Results

Model	MAE	RMSE	R^2
Random Forest	0.019574	0.120826	0.971002
SVM	0.249716	0.337560	0.773664
ANN	0.105836	0.203027	0.918123

Among the evaluated models, the Random Forest algorithm exhibited the highest predictive accuracy, achieving an R^2 score of 0.97 alongside the lowest MAE and RMSE values. This exceptional performance underscores the model's capacity to capture complex, nonlinear patterns inherent in diverse network traffic conditions, making it particularly well-suited for dynamic Quality of Service (QoS) environments. The Artificial Neural Network (ANN) model also demonstrated strong performance, with an R^2 value of 0.92, reflecting its robust generalization capabilities across varying data distributions. In contrast, the Support Vector Machine (SVM) model showed comparatively lower predictive power. This underperformance may be attributed to challenges in hyperparameter optimization and the model's computational intensity, which can hinder scalability in large-scale network datasets. These results confirm that deep learning techniques offer substantial improvements over traditional machine learning models in QoS prediction and network performance optimization (Wainer & Fonseca, 2020; Woźnicki et al., 2020).

These findings highlight the superiority of ensemble learning approaches, particularly Random Forest, in delivering accurate and resilient QoS predictions. Moreover, they reaffirm the growing consensus in recent literature that deep learning models, such as ANN, consistently outperform traditional machine learning techniques in modeling the intricate interdependencies of network parameters. As demonstrated in prior studies (Wainer & Fonseca, 2020; Woźnicki et al., 2020), the integration of data-driven learning mechanisms provides a significant advantage for predictive network performance optimization, offering a practical pathway toward intelligent, self-optimizing communication systems.

Impact of QoS Parameters on Network Service Quality

Session success rate and packet loss emerged as the most impactful, exhibiting strong correlations with service quality rating positive (0.68) and negative (-0.56) respectively. These findings highlight the operational significance of ensuring successful session completions while minimizing packet degradation to uphold user satisfaction and maintain service reliability. Interestingly, while latency has traditionally been considered a key QoS indicator, the observed correlation values with service rating were relatively weak (kpi_latency_int_msec: -0.17; kpi_latency_ext_msec: -0.04).

Key Contributions and Future Directions

This study makes several substantive contributions to the evolving field of intelligent network service management. First, it demonstrates the effectiveness of ensemble and deep learning models, particularly Random Forest and Artificial Neural Networks (ANN), in accurately predicting QoS outcomes using historical performance data. The Random Forest model achieved an exceptional R^2 score of 0.97, surpassing both SVM and ANN in

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predictive accuracy, while ANN maintained **strong generalization** with an R^2 of 0.92. These results highlight the robustness of these models in capturing the nonlinear and interdependent nature of network behavior, even under conditions of skewed distributions and extreme outliers. Ultimately, this study reinforces the role of machine learning as a critical tool for adaptive and automated QoS optimization, paving the way for smarter, more resilient network infrastructures that can dynamically adjust to evolving network demands (Liang et al., 2022; Woźnicki et al., 2020; Zhang et al., 2017).

DISCUSSIONS

The integration of machine learning models into the prediction and optimization of Quality of Service (QoS) parameters in modern network environments has yielded notable advancements. Among the evaluated algorithms, Random Forest emerged as the most effective, achieving an R^2 score of 0.97. This exceptional accuracy confirms its capacity to capture nonlinear dependencies in QoS metrics (Yufei Tao & Inti Ruminahui Toalombo Chicaiz, 2024). Moreover, Random Forest's resilience in handling variable network traffic conditions underscores its robustness in adapting to the heterogeneity and unpredictability of real-world network scenarios (Giuliano & Lu, 2021). Artificial Neural Networks (ANNs) also demonstrated strong performance, with an R^2 score of 0.92, indicating solid generalization across diverse operational contexts (Padmavathy et al., 2023).

Together, both models validate the interdependent behavior of key network parameters latency, jitter, and packet loss which jointly influence service reliability and user satisfaction. Correlation analysis further supports this interdependency. For instance, packet loss exhibited a significant negative correlation with service quality ratings ($r = -0.56$), highlighting its detrimental impact on end-user experience. Conversely, service access success rate displayed a strong positive correlation with user satisfaction ($r = 0.68$), reinforcing its essential role in sustaining seamless connectivity (Ahadi Ningrum & Rifqi Mulyawan, 2024). Interestingly, throughput demonstrated near-zero correlation with these metrics, indicating that bandwidth alone is insufficient to ensure optimal service performance especially under latency-sensitive conditions (P. Yang et al., 2024). A particularly impactful contribution of this study lies in the incorporation of jitter as a derived feature, calculated from the absolute difference between internal and external latency. This approach effectively captures temporal variability in packet delivery, a key factor often overlooked in conventional QoS assessments (X. Fu et al., 2023). By integrating jitter into the predictive pipeline, the models gained enhanced sensitivity to real-time disruptions, critical for applications such as VoIP and video streaming, where microsecond-level inconsistencies can compromise perceived quality.

Crucially, the findings of this study make a compelling case for transitioning away from traditional QoS mechanisms, which typically depend on static thresholds and manually defined configurations. Such approaches, while foundational, struggle to accommodate the dynamism of modern network traffic and frequently lead to suboptimal resource allocation (Dorokhin et al., 2020). In contrast, machine learning models offer the flexibility and foresight to predict potential performance degradation, optimize routing decisions, and prioritize traffic proactively. Their real-time adaptability makes them especially suitable for complex environments such as 5G, IoT, and edge computing systems, where low latency and high availability are paramount (Liu, 2021; H. Yang et al., 2021).

These results reinforce the limitations of traditional rule-based QoS management approaches, which struggle to adjust dynamically to evolving network conditions. Instead, machine learning-driven predictive models offer a more efficient and proactive alternative, allowing for preemptive intervention before service quality declines.

Machine Learning Model Performance and Implications

The experimental results of this study affirm the strong predictive power of machine learning models in forecasting key Quality of Service (QoS) parameters under dynamic and heterogeneous network conditions. Among the algorithms evaluated, Random Forest emerged as the most accurate, achieving the highest R^2 score. This model's effectiveness lies in its capacity to capture nonlinear relationships and complex interactions across high-dimensional QoS metrics. Its robustness, interpretability, and scalability make it particularly well-suited for real-time QoS prediction in environments characterized by traffic volatility and diverse service demands.

Artificial Neural Networks (ANNs) also demonstrated impressive performance, closely trailing Random Forest. The model's strong generalization ability across various operational contexts reinforces its suitability for network prediction tasks. Its architecture enables it to detect subtle patterns in historical QoS data, supporting more accurate anticipation of performance degradation and service anomalies. These findings are consistent with prior studies that underscore the superiority of deep learning models—especially ANN and Long Short-Term Memory (LSTM) networks—for modeling complex and nonlinear QoS behavior (Chaturvedi & de Vries, 2021; Zhan, 2024).

In contrast, the Support Vector Machine (SVM) model exhibited considerably lower performance. Despite its theoretical strength in handling high-dimensional data, its practical application in this study was hindered by computational inefficiencies. In particular, hyperparameter tuning for SVM was prohibitively time-consuming,

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with the search process exceeding 600 minutes without yielding optimal configurations. To preserve computational feasibility and maintain consistency within the study's comparative framework, the SVM implementation was limited to a simplified setup using a radial basis function (RBF) kernel with baseline values for C and epsilon. While this compromise ensured model viability, it also highlighted SVM's limitations in large-scale or time-sensitive deployments.

Practical Applications and Future Research Directions

Beyond theoretical advancements, these findings have substantial real-world implications. Integrating machine learning-driven QoS prediction into network management systems can significantly improve reliability, efficiency, and user experience. By enabling automated predictive analytics, network administrators can detect early signs of performance degradation and adjust parameters dynamically to maintain optimal service levels. This capability is particularly valuable in 5G networks, cloud computing environments, and Internet of Things (IoT) ecosystems, where traffic patterns are highly dynamic and require intelligent resource allocation (Assegie et al., 2022; Huang, 2024). Future research should explore hybrid frameworks that combine the interpretability and speed of Random Forest with the deep contextual learning capabilities of neural networks. Such integration could push the boundaries of predictive accuracy and operational scalability in QoS management. Moreover, the adoption of federated learning and continuous real-time data integration would further enhance privacy-preserving model training while enabling consistent performance across distributed network nodes.

For Artificial Neural Networks (ANNs) in particular, additional optimization remains a fertile area for exploration. Techniques such as Grid Search and Random Search can be employed to fine-tune hyperparameters, potentially unlocking even higher predictive accuracy. Additionally, ensemble learning techniques, which combine multiple machine learning models, could further enhance model robustness and stability across varying network conditions (M. Fu et al., 2023). Future research should also explore real-time data stream integration, enabling predictive models to continuously learn and adapt to evolving network conditions. Moreover, implementing federated learning methodologies could enhance data privacy by allowing models to be trained in a distributed manner, eliminating the need to transmit sensitive network data across multiple servers (Elvin & Wibowo, 2024; Kevin et al., 2025). By pursuing these research directions, the integration of machine learning in intelligent network management can be further refined, paving the way for fully automated, adaptive, and high-efficiency QoS optimization strategies.

CONCLUSION

This study has compellingly demonstrated the transformative potential of machine learning-based predictive models in advancing Quality of Service (QoS) management within contemporary network environments. The framework proposed herein, which leverages historical network performance data, has shown remarkable efficacy in the proactive prediction of key QoS parameters including latency, jitter, packet loss, and throughput. This predictive capability not only enhances the precision of network analysis but also empowers system engineers and administrators to make intelligent, data-informed decisions that improve overall service quality and resilience.

Among the evaluated models, Random Forest emerged as the most effective, achieving an R^2 score of 0.97. This high level of accuracy affirms the model's robustness in capturing nonlinear patterns within diverse traffic conditions and validates its practical applicability for real-time QoS prediction. The Artificial Neural Network (ANN) also performed commendably, recording an R^2 score of 0.92, which reinforces the relevance of deep learning methods in modeling complex, dynamic relationships among network parameters. Conversely, the Support Vector Machine (SVM) model demonstrated substantial computational limitations and comparatively lower predictive performance. These constraints underscore the challenges SVM faces in large-scale, real-time network scenarios, and signal the need for more scalable and adaptive modeling strategies in such contexts.

The correlation analysis conducted in this study further elucidated the interdependent nature of QoS metrics and user-perceived service quality. A strong negative correlation between packet loss and user satisfaction ($r = -0.56$) highlights the detrimental impact of transmission unreliability, while a positive correlation between service access success rate and user ratings ($r = 0.68$) emphasizes the importance of service continuity and accessibility. Additionally, the analysis identified jitter, particularly when influenced by internal and external latency disparities as a critical indicator of network instability, especially in latency-sensitive applications such as Voice over IP (VoIP) and video streaming.

Importantly, this research represents a paradigm shift from traditional, static QoS management often reliant on heuristic rules and fixed thresholds towards a dynamic, adaptive, and predictive optimization framework. While conventional approaches may falter in the face of increasingly complex, high-velocity network environments characterized by 5G, IoT, and edge computing, the proposed models offer real-time monitoring, early degradation detection, and automated resource optimization. These capabilities collectively enable a more resilient, responsive, and user-centric network management paradigm. In essence, the future of QoS management resides in embracing machine learning as a cornerstone of intelligent network operations. By aligning predictive analytics with

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operational control, netw ork stakeholders can usher in an era of proactive service assurance driving performance, scalability, and user satisfaction across next-generation digital infrastructures.

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