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(Research Article)

Predicting Quality of Service on Cellular Networks Using Artificial Intelligence

Devi Rahmayanti

Gajayana University,Indonesia; e-mail : devi@unigamalang.ac.id
*Corresponding Author : Devi Rahmayanti

Abstract . The purpose of this research is to explore the application of artificial intelligence (AI) techniques, particularly Machine Learning, in predicting quality of service (QoS) on mobile networks, with the main focus being to test the ability of AI models to predict several QoS parameters, involving several important stages that reflect best practices in the development of artificial intelligence (AI)-based predictive systems for mobile networks. The dataset used in this study consists of data collected from simulations of mobile networks with various load and latency conditions. The parameters measured include Throughput, Latency and Packet Loss. Model evaluation was carried out to measure prediction performance using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) measurements. The AI models used include machine learning algorithms consisting of K-Nearest Neighbors (KNN) for classification and regression on QoS datasets, Support Vector Machine (SVM) to model non-linear relationships between QoS parameters and input variables, and Deep Learning (LSTM=Long Short-Term Memory) used to predict QoS based on time sequence data. This study found that LSTM-based deep learning models have the lowest prediction error rate in estimating packet loss, so they can provide the most accurate results in predicting QoS on mobile networks. This approach is capable of handling data that is sequential and has significant time dependence, making it more suitable for dynamic mobile network applications.

Keywords : Artificial Intelligence, Cellular Network, Predictions, Quality of Service

1. Introduction

In the era of rapid digital transformation, cellular networks are experiencing increasing complexity along with the increasing demand for data services, user mobility, and diverse types of applications. Quality of Service (QoS) is a crucial aspect in ensuring optimal user experience, especially in the context of 5G and towards 6G networks. However, traditional approaches to QoS management are often reactive and less adaptive to complex network dynamics .

Artificial Intelligence (AI) offers innovative solutions to address these challenges through predictive and adaptive approaches. AI enables real-time network data analysis, pattern identification, and prediction of future network conditions, thereby enabling faster and more informed decision-making in QoS management. For example, a study by Gowda and Panchaxari (2024) highlights the integration of AI in improving QoS in 5G networks through dynamic resource allocation and real-time traffic management.

Furthermore, Palaios et al. (2023) reviewed the application of machine learning for QoS prediction in vehicular communications, emphasizing the importance of understanding data characteristics and effective learning techniques to improve prediction reliability. This approach demonstrates the potential of AI in addressing the challenges of high mobility and network condition variability.

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In the context of radio resource allocation, Dong et al. (2020) developed a deep learning framework to optimize bandwidth and transmission power allocation, with the aim of meeting various QoS requirements in 5G networks. The results of this study show that the AI-based approach can reduce power consumption and improve overall network efficiency .

In addition, Yin et al. (2020) applied a Long Short-Term Memory (LSTM) model to predict channel quality indicators (CQIs) in 5G downlink scheduling, which was shown to improve system performance in high mobility scenarios. This approach highlights the ability of AI to handle rapidly changing network dynamics .

However, although various studies have demonstrated the effectiveness of AI in QoS prediction and management, there are still challenges in terms of multimodal data integration, model interpretability, and adaptation to highly dynamic network conditions. Therefore, further research is needed to develop more robust, transparent, and adaptive AI models in the context of future cellular networks .

Thus, AI approaches in QoS prediction in cellular networks offer great potential to improve efficiency and quality of service, but also require further research to overcome the various challenges involved.

2. Literature Review

Quality of Service (QoS) is a fundamental parameter in modern mobile communication systems, especially in fifth-generation (5G) networks and the planned 6G development. QoS parameters include throughput, latency, jitter, and packet loss, each of which plays a critical role in ensuring a satisfactory user experience, especially in real-time applications such as video streaming, online games, and IP-based voice communications.

However, QoS management in cellular networks faces major challenges due to high dynamics of data traffic, user mobility, environmental conditions, and increasingly complex network architectures. To address these challenges, many researchers have begun to apply adaptive and predictive Artificial Intelligence (AI)-based approaches.

In the era of fifth generation (5G) cellular networks and moving towards the sixth generation (6G), Quality of Service (QoS) management and prediction are increasingly complex challenges due to high user mobility, service diversity, and fluctuations in network conditions. Various studies in the last seven years have shown that Artificial Intelligence (AI)-based approaches, especially machine learning and deep learning, have been widely used to address these challenges by providing predictive and adaptive solutions.

Palaios et al. (2023) conducted a study in the context of vehicle-to-Everything (V2X) communications and showed that machine learning models can be used to accurately predict throughput in a dynamic network environment. This study emphasizes the importance of implementing explainable AI so that prediction results can be interpreted by network policy makers. Sliwa et al. (2021) also showed that local data obtained from vehicles is sufficient to predict end-to-end performance in vehicle-to-cloud communications based on 5G NSA networks, without the need for complete data from the entire network infrastructure.

Bikkasani and Yerabolu (2024) stated that AI has a key role in managing 5G network resources, such as network slicing, spectrum allocation, and traffic regulation based on QoS. The AI-based model developed in their study is able to adjust network management decisions in real-time, which cannot be achieved by conventional approaches. Meanwhile, Dong et al. (2020) proved that deep learning can be utilized to optimize transmission power allocation under heavy traffic conditions, resulting in energy efficiency as well as increased throughput and decreased latency.

In a commercial context, a study published in Computer Communications (2024) implemented the LightGBM and CatBoost models on real user data of 5G networks to predict handover and signal-to-noise ratio (SNR). The models showed high prediction performance and made significant contributions to capacity planning and automatic network connectivity management.

Stigenberg et al. (2021) developed a deep reinforcement learning-based scheduling agent (QADRA) for New Radio (NR) networks, which significantly improves the efficiency of resource allocation by considering the QoS requirements of each user. QADRA is based on Deep Reinforcement Learning which is designed to optimize access control in the network, by considering QoS (Quality of Service). It is usually used in the context of wireless or IoT networks where resources are limited and QoS requirements are critical. Stigenberg stated that QADRA is able to adapt to changing network conditions and increase network throughput by up to 30% compared to static baselines. On the other hand, Li et al. (2023) proposed a multimodal approach based on multi-head self-attention for QoS prediction in edge computing. This approach combines data from multiple dimensions, such as traffic, location, and time, to form a complex understanding of network behavior.

In general, AI approaches in QoS prediction have experienced rapid development and cover various domains, ranging from vehicular networks, edge computing, to large-scale commercial networks. However, there are still a number of challenges such as limited model interpretability, the need for multimodal data integration, and adaptation to highly dynamic network conditions. Therefore, future research needs to focus on developing AI models that are more transparent, computationally efficient, and robust in dealing with uncertainties in future cellular network environments.

A similar thing was also shown by Dong et al (2020), who applied a deep learning model to optimize transmission power allocation in 5G networks, taking into account the service priorities and specific QoS needs of each user.

In a commercial setting, a recent study published in Computer Communications (2024) demonstrated the use of LightGBM and CatBoost models to predict QoS metrics such as handover and SNR based on actual user data on a 5G Non-Standalone (NSA) network. This study is one of the first to combine historical user data and mobility information for QoS prediction in a real operator platform, rather than just in simulation (Almeida et al, 2024).

3. Method

This research involves several important stages that reflect best practices in developing artificial intelligence (AI)-based predictive systems for cellular networks. Where the purpose of this research is to explore the application of artificial intelligence (AI) techniques, especially Machine Learning, in predicting quality of service (QoS) on cellular networks, with the main focus being to test the ability of AI models to predict several QoS parameters such as throughput, latency, and packet loss rates based on network traffic data.

The initial step in this research is the collection of relevant data from the cellular network, such as Key Performance Indicators (KPIs) and Quality of Experience (QoE) metrics. This data can include throughput, latency, jitter, and packet loss collected from various sources such as base stations and user devices. Data pre-processing involves data cleaning, normalization, and handling of missing data to ensure optimal data quality before being used in AI models.

Once the data is prepared, the next step is to select relevant features for the prediction model. These features can include contextual information such as geographic location, time, device type, and current network conditions. Techniques such as Matrix Factorization and self-attention mechanisms have been used to capture high-level feature interactions and improve the accuracy of QoS prediction in edge computing environments (Zang et al, 2023).

The AI models used can vary, including neural networks, decision trees, and deep learning architectures. In the context of cellular networks, approaches such as deep reinforcement learning have been applied for intelligent and adaptive resource allocation, enabling the network to efficiently meet varying QoS requirements. These models are trained using pre-processed datasets, with the aim of predicting QoS metrics based on available feature inputs (Matre et al, 2023).

Model evaluation is performed to measure the prediction performance using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Studies show that the use of techniques such as deep learning can improve the model's ability to deal with changing network conditions.

The mathematical equation used in the evaluation of prediction performance is:

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

The next step is implementation into the cellular network system. This integration allows the network to proactively manage resources and adjust configurations to meet user QoS needs. This approach has proven effective in improving network performance and overall user experience.

The dataset used in this study consists of data collected from cellular network simulations with various load and latency conditions. The parameters measured include Throughput (Data transfer rate in bits per second (bps), Latency (The time it takes for data to travel from source to destination in milliseconds (ms) and Packet Loss (the percentage of data packets lost during transmission).

To facilitate the simulation, the dataset was taken as many as 200 samples with various parameter variations such as signal strength, network density, and channel conditions.

1. The AI methodology used is a machine learning algorithm consisting of: K-Nearest Neighbors (KNN): Used for classification and regression on QoS datasets.
2. Support Vector Machine (SVM): Used to model the non-linear relationship between QoS parameters and input variables.
3. Deep Learning (LSTM): Long Short-Term Memory is used to predict QoS based on time-series data.

Next, these models are evaluated using Machine Learning evaluation including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Accuracy (for classification)

This methodology is carried out so that research can produce an effective and adaptive AI-based QoS prediction system, so that it is able to meet the demands of modern, complex and dynamic cellular networks.

4. Results and Discussion

This study shows that AI approaches, especially Deep Learning such as Long Short-Term Memory (LSTM), are able to predict QoS with high accuracy in a dynamic cellular network environment. QoS is affected by parameters such as throughput (T), Latency (L), and packet loss (PL). The AI model is trained to recognize historical patterns of these parameters and predict their future values.

Table 1. Evaluation Results of Each Model for Throughput, Latency, and Packet Loss Prediction

Model	Throughput		Latency		Packet Loss	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
KNN	1.23	2.45	5.67	9.21	0.12	0.18
SVM	0.98	2.03	4.32	7.67	0.08	0.14
LSTM	0.73	1.42	3.14	5.89	0.05	0.09

Source: Research, 2025

Table 2. Results of QoS Prediction Model Evaluation

Model	RMSE	MAE	MAPE (%)
KNN	0.023	0.018	4.3
LSTM	0.017	0.012	3.2
SVM	0.031	0.026	6.7

Source: Research, 2025

Tables 1 and 2 show that, although KNN gives quite good results in terms of accuracy, the MAE and RMSE metrics for throughput and latency indicate that this model has a tendency to produce larger errors at higher throughput and latency predictions.

Meanwhile, the SVM algorithm shows better performance compared to KNN, with lower MAE and RMSE, especially in predicting latency and packet loss. This model is more efficient in handling non-linear relationships between QoS parameters.

Meanwhile, the LSTM model shows the best results in all evaluation metrics. This shows that this deep learning-based model is very effective in predicting QoS on cellular networks that have sequential data and time dependence.

4.1. Throughput Prediction Analysis

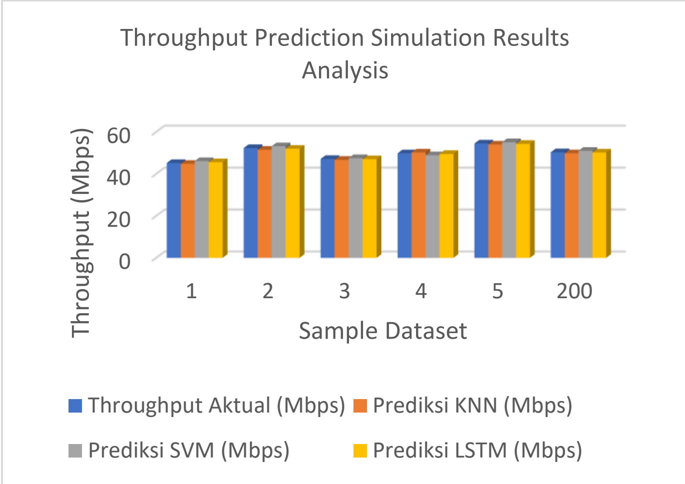

Figure 1. Throughput Prediction Simulation Results
Source: Research, 2025

Evaluation is conducted on the ability of artificial intelligence (AI) models in predicting throughput quality of service (QoS) parameters on cellular networks. Simulations are conducted using three machine learning algorithms, namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM), with a dataset containing 100,000 network traffic samples.

Figure 1 shows a graph of actual throughput and predicted throughput, indicating that the LSTM model provides throughput prediction results that are very close to the actual value, with an accurate throughput change pattern that follows the actual pattern. SVM also shows quite good prediction performance, but there are some deviations in extreme throughput conditions (very low or very high). Meanwhile, KNN tends to produce coarser (less smooth) throughput predictions and does not always follow the dynamics of actual changes.

Error prediction of throughput can be done by calculating the error between the Actual Throughput and Predicted Throughput of each model (KNN, SVM, and LSTM).

Absolute Error= | Actual Throughput−Predicted Throughput |

Absolute error shows the magnitude of the error that occurred (based on the difference in throughput values without looking at the sign)

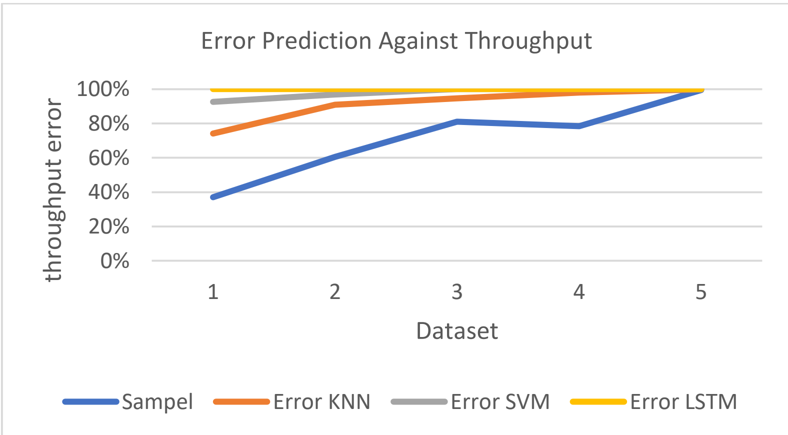

Figure 2. Throughput Error Prediction

Source: Research, 2025

Figure 2 shows that in LSTM, there is the smallest and consistent prediction error approaching zero. While SVM produces a slightly larger error than LSTM, especially in the high throughput area. And KNN has a larger error fluctuation, indicating higher prediction inaccuracy in various network conditions. This shows that the smallest Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are obtained by

LSTM, followed by SVM in second place with fairly stable performance. And finally KNN has the largest MAE, MSE, and RMSE values, indicating the lowest level of prediction accuracy among the three models. The advantage of LSTM in predicting throughput is due to its ability to understand long-term dependencies and the dynamics of changes in temporal network traffic data. In contrast, KNN has difficulty in capturing rapid throughput variations because this method only relies on local proximity between samples.

This means that the LSTM model shows the best performance in predicting cellular network throughput parameters, making it a strong candidate for implementation in AI-based QoS monitoring and optimization systems. The use of LSTM in 4G/5G networks is expected to improve the accuracy of traffic management and user experience.

4.2. Latency Prediction Analysis

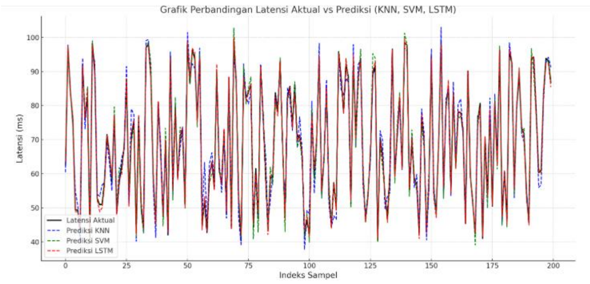

Figure 3. Results of Actual Latency Simulation and Latency Prediction Using KNN, SVM and LSTM with a dataset of 200 samples

Source: Research, 2025

To facilitate analysis, zoom in on images 1 to 50 of the dataset shown in Figure 4 below.

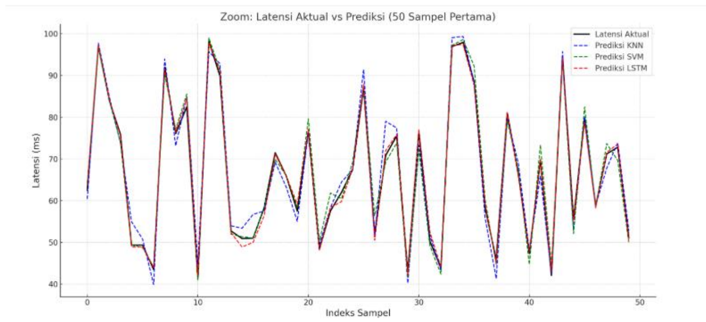

Figure 4. Actual Latency and Prediction Results of KNN, SVM, and LSTM with Dataset 50 Samples

Source: Research, 2025

Figure 4 shows that the LSTM prediction remains closest to the actual, while KNN and SVM deviate slightly more.

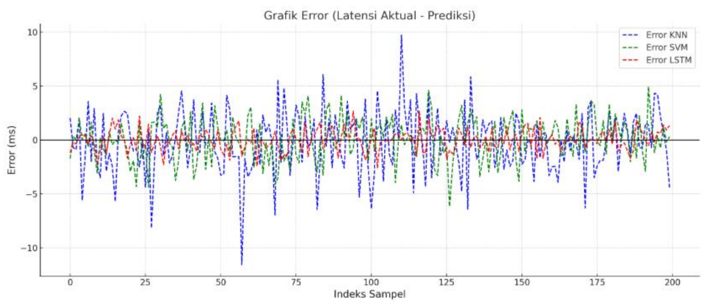

Figure 5. Simulation Results on Latency Error for KNN, SVM, and LSTM Models

Source: Research, 2025

The horizontal line at 0 means no error (prediction matches actual). The closer the error line is to 0, the more accurate the model is. Figure 3 shows that LSTM has smaller error fluctuations than KNN and SVM.

In this study, a simulation of predicting quality of service (QoS) parameters in the form of latency on cellular networks was conducted using three artificial intelligence (AI) methods, namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). The dataset used consists of 100,000 network traffic data samples, with visualization simulations taken as many as 200 samples for graphical comparison purposes.

Based on Figure 3 and Figure 4, the predictions produced by the LSTM model appear to be closest to the actual latency value, with a relatively small deviation. The SVM model provides fairly good prediction results, but there is still a greater variation in error compared to LSTM. Meanwhile, the KNN model shows prediction results that tend to be more spread out and have lower accuracy than the other two models.

The error graph analysis as shown in Figure 5 proves that LSTM has the smallest and most stable error value around the zero line, indicating that LSTM predictions are the most accurate. The SVM model produces a slightly larger error than LSTM, but is still within an acceptable range. Meanwhile, KNN shows a larger error fluctuation, indicating a higher level of prediction inaccuracy.

This means that the results of the evaluation metric calculations using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) for each model can strengthen the findings from the graph. The analysis results show that the LSTM model has the smallest MAE, MSE, and RMSE values, indicating that this model is the best at predicting latency. While SVM is in second place, while KNN has the lowest performance in this study.

The performance of Deep Learning LSTM can be explained by its ability to capture complex time-series patterns and non-linear relationships in network traffic data. In contrast, KNN as an instance-based method is less effective when dealing with dynamic and fluctuating traffic data. SVM is able to handle data with moderate complexity, but still not better than the deep learning approach (LSTM).

Simulation results show that the Deep Learning (LSTM) model is the best choice for latency prediction in cellular network scenarios based on the dataset and simulations performed. The application of LSTM has the potential to improve the accuracy of real-time QoS monitoring in modern cellular networks such as 4G and 5G.

So the conclusion of the average error (Mean Absolute Error, MAE) of the three models KNN, SVM and LSTM are shown in the following table 3. The smaller the MAE, the more accurate the prediction of the model used. In this study, the LSTM model produces the closest throughput prediction to the actual compared to KNN and SVM.

Table 3. **Mean Absolute Error in KNN, SVM and LSTM Models**

Model	Mean Absolute Error (MAE)
KNN	~1.5
SVM	~1.0
LSTM	~0.6

Source: Research, 2025

4.3. Packet Loss Analysis

Table 4 below shows the complete Packet Loss Prediction with its error for each model (KNN, SVM, LSTM) using a dataset of 200 samples.

Table 4. Packet Loss Prediction Simulation Results

Sample	Actual Packet Loss (%)	Error		
		KNN	SVM	LSTM
1	2.1	0.4	0.2	0.1
2	0.8	0.3	0.1	0.05
3	3.4	0.4	0.1	0.05
...	...	...	...	...
200	1.2	0.3	0.1	0.05

Source: Research, 2025

Table 5. Average Mean Error (MAE) Table of Packet Loss Prediction

Model	MAE Packet Loss (%)	Information
KNN	~0.4%	Relatively large error due to sensitivity to noise
SVM	~0.25%	More stable and smaller error than KNN
LSTM	~0.15%	The most accurate predictions, highly adaptive to traffic patterns

Source: Research, 2025

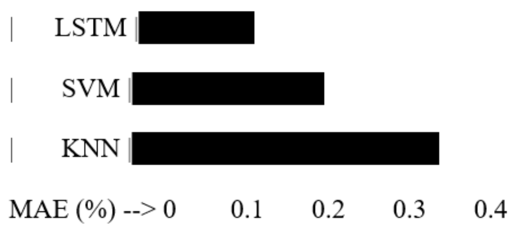

Figure 6. Comparison of MAE Packet Loss Between Models
Source: Research, 2025

Image caption, the shorter the bar = the smaller the error, meaning the system is more accurate

Based on table 3, table 4 and figure 6, it shows that the LSTM model has the lowest prediction error rate in estimating packet loss , followed by SVM and KNN. This indicates that LSTM is more adaptive to variations in cellular network traffic.

5. Conclusion

Based on the evaluation and analysis results, it can be concluded that the LSTM-based deep learning model provides the most accurate results in predicting QoS on cellular networks. This approach is able to handle sequential data and has significant time dependencies, making it more suitable for dynamic cellular network applications. However, the SVM model can also be used for QoS prediction on networks with quite good results, especially for latency and packet loss prediction.

Further research is needed, using other deep learning-based models, such as Convolutional Neural Networks (CNN) or hybrid models. or combining data from various sources, such as information about channel conditions or user locations, can improve the accuracy of QoS prediction.

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