Deep Learning-Based QoS Prediction for Optimization of Robotic Communication

Tae Hyun Kim
Electronic and Electrical Engineering
KYUNGPOOK NATIONAL UNIVERSITY
Daegu, South Korea
thkim8176@knu.ac.kr

Jong Hyuk Lee
Electronic and Electrical Engineering
KYUNGPOOK NATIONAL UNIVERSITY
Daegu, South Korea
leewer354@knu.ac.kr

Jin Hyuk Lee
Electronic and Electrical Engineering
KYUNGPOOK NATIONAL UNIVERSITY
Daegu, South Korea
wlsgur0920@knu.ac.kr

Min Young Kim
Electronic and Electrical Engineering
KYUNGPOOK NATIONAL UNIVERSITY
Daegu, South Korea
minykim@knu.ac.kr

***Abstract*— The robustness of quality of service (QoS) in robotic communications is essential for operational efficiency and reliability. This paper presents an innovative deep learning-based methodology specifically designed for QoS prediction in robotic networks. A predictive model was developed by extensively analyzing communication data, including aspects such as latency and bandwidth, along with environmental factors. This model accurately predicts important QoS parameters. The results show a significant improvement in QoS prediction accuracy and overall network performance over traditional machine learning methods. The implications of this study are important for the development of autonomous robot operations and provide scalable and efficient solutions for real-time communication coordination that are pivotal to managing the complexity of adaptive robot systems.**

Keywords—QoS, robotic communication, predictive modeling, CNN, LSTM, Attention, GNN, autonomous robots, adaptive systems

I. INTRODUCTION

The field of robotic communication is rapidly evolving, with an increasing demand for stable and high-quality network performance. This research addresses the challenging task of maintaining Quality of Service (QoS) in robotic networks by harnessing the capabilities of deep learning. Our research objectives can be summarized into three key goals: (1) developing models to accurately predict real-time QoS parameters in robotic communications, (2) exploring various deep learning algorithms for adaptive optimization of network performance, and (3) establishing a versatile methodology applicable across different robotic platforms and scenarios.

While our experiments were conducted on a soccer field, the scenario depicted in Fig.1 illustrates robots connecting to the optimal network in a typical urban environment to perform their tasks seamlessly. In our experimental setup, four mesh Wi-Fi access points were strategically placed around the field, providing a robust network environment for testing. The robots traversed the urban environment, evaluating network performance based on metrics such as signal strength, latency, and bandwidth. This scenario was designed to mimic real-world conditions, shedding light on the impact of external factors on robot network dynamics and QoS. Fig. 1 provides a visual representation of this scenario.

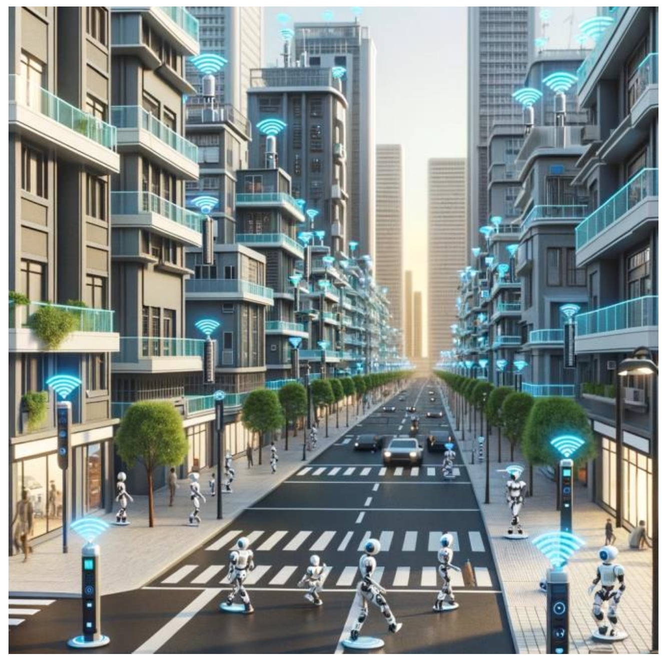

Fig. 1. Scenario

II. RELATED WORKS

In recent years, the field of QoS prediction in robotic communication has seen significant advancements, largely driven by the evolution of deep learning and collaborative filtering techniques. This section aims to present a comprehensive overview of related work, emphasizing how current research, including our own, is leveraging deep learning approaches, specifically convolutional neural networks (CNNs) [1], Long Short-Term Memory (LSTM) networks [2], and Graph Neural Networks (GNNs) [3], to enhance QoS prediction.

The surge in robotic applications underscores the need for reliable and efficient communication networks. QoS, as a measure of network performance from the user's perspective, is fundamental in ensuring the seamless operation of robotic systems. Traditional QoS prediction methods, largely based on collaborative filtering, have been crucial. However, they exhibit limitations, particularly in handling sparse data and capturing the multidimensional nature of QoS attributes in robotic networks.

Our approach diverges from these traditional methods by employing a synergistic combination of CNN, LSTM, and GNN architectures, each contributing uniquely to the model's performance. CNNs, known for their proficiency in processing spatial data, are employed to analyze and interpret the spatial aspects of network traffic and robotic movements. LSTMs, adept at handling sequential data, are utilized to capture the temporal dynamics in network performance, reflecting the ever-changing conditions in robotic communication. GNNs, on the other hand, are integrated to model the complex, non-Euclidean structures in network data, providing insights into the interconnectivity and dependencies within the network.

This sophisticated blend of CNNs, LSTMs, and GNNs enables our model to capture the intricate interactions among various QoS attributes and contextual factors, such as the type of service, network conditions, and robot mobility patterns. Our model's multi-dimensional perspective is crucial for accurately predicting QoS in dynamic and heterogeneous robotic communication environments.

Moreover, the robustness and adaptability of our deep learning-based model set it apart from traditional QoS prediction techniques. By utilizing these advanced neural network architectures, our model can adapt to the evolving nature of robotic networks, ensuring high prediction accuracy in the face of changing network conditions and robot behaviors. This adaptability is essential for real-time applications, where QoS requirements can fluctuate rapidly.

In summary, our research contributes to the ongoing evolution of QoS prediction in robotic communication by harnessing the combined strengths of CNNs, LSTMs, and GNNs. We build on the foundational work in collaborative filtering and neighborhood-based models, advancing the field by introducing a multi-dimensional, context-aware approach that addresses the limitations of traditional methods. Our deep learning-based model offers a robust, adaptable framework for accurately predicting QoS in complex, dynamic robotic communication networks, marking a significant step forward in the quest for efficient and reliable robot communication systems.

III. Experiment

A. Enviornment Setup

1) Field Selection: A standard-sized soccer field within a stadium was chosen for the experiment to provide ample space and a range of environmental variables such as wind, sunlight, and temperature variations.

2) Hardware Deployment: Autonomous robot equipped with GPS, Wi-Fi modules, and environmental sensors for capturing real-time data on temperature, humidity, and light intensity were strategically placed throughout the field.

3) Network Infrastructure Implementation: We installed several high-range Wi-Fi access points around the perimeter of the soccer field to create a robust mesh network, ensuring consistent communication coverage for the robots.

In the Fig. 1, the red circle represents the Wi-Fi access point and the blue rectangle represents the robot.

Fig. 2. Hardware Deployment Map

4) Sensor Calibration in Open Field: Each sensor underwent a field-specific calibration to account for the open environment's unique characteristics. We performed initial tests to validate the data accuracy from each sensor in the outdoor context.

5) Data Acquisition Strategy: The robot was programmed to collect data while executing pre-defined maneuvers across the field, simulating operational tasks such as object avoidance, goal-oriented movement, and patterned patrols.

6) Real-Time Data Monitoring: A centralized monitoring system was implemented to capture and log data transmitted by the robots. This system was set up on the sidelines, with direct line-of-sight to all operational areas of the field.

7) Data Collection Execution: During each experimental run, robots followed a synchronized routine, ensuring varied data points were collected under different environmental conditions and times of the day.

8) Data Harvesting and Consolidation: Post-experiment, the data from each robot and the central server was harvested, synchronized, and consolidated into a master dataset for subsequent preprocessing and modeling.

The figure below shows the experimental environment and system configuration.

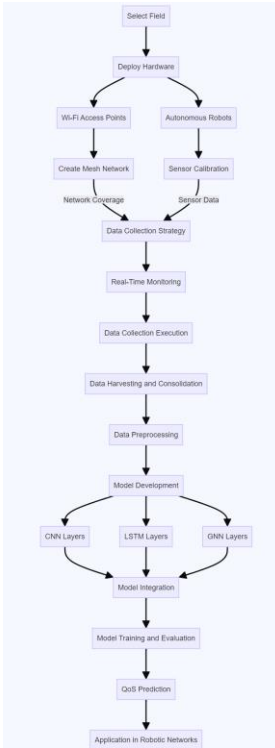

Fig. 3. Experimental Environment and System Flowchart

This outdoor experiment provided a diverse range of data, crucial for developing a QoS prediction model that can accurately reflect the performance of robotic communication in varied and dynamic environmental conditions.

B. Data Collection

In our relentless pursuit of advancing the prediction and optimization of QoS within the domain of robotic communication, we meticulously devised an elaborate and multifaceted data collection strategy. This comprehensive strategy was thoughtfully crafted to acquire a diverse array of highly relevant data points, each playing a pivotal role in our mission to unravel the intricate nuances of QoS within robotic networks.

At the heart of our data collection efforts lies the u-blox NEO-M8N GPS sensor —a sophisticated and high-precision device. This sensor served as the linchpin in our quest for precision, offering real-time tracking of the robot's position. It provided an extensive dataset encompassing not only the robot's latitude, longitude, altitude, and timestamp information but also data captured down to the millisecond. This rich tapestry of real-time location data formed the foundational cornerstone, empowering us to delve deep into the profound impact of robot positioning on communication performance.

The PicoScope 2205A latency sensor assumed a critical role within our data collection setup. This instrument, renowned for its exceptional precision, played an indispensable role in delivering precise and granular latency data. With the capability to capture latency measurements down to the nanosecond level, this sensor enabled us to gain profound insights into network performance, thus contributing significantly to the precision of our research.

In our pursuit of understanding the role of network bandwidth, we harnessed the power of the Iperf tool [4]. This versatile and robust tool allowed us to quantify and closely monitor network bandwidth with exceptional granularity. It illuminated the implications of bandwidth on communication performance by facilitating meticulous data capture and in-depth analysis of bandwidth-related metrics, thereby enhancing the depth and reliability of our research findings.

To comprehensively assess network performance, including the packet loss rate, we employed the indispensable packet capture tools—Wireshark and Tcpdump. These tools enabled real-time capture, monitoring, and in-depth analysis of network traffic, scrutinizing packet loss rates down to the microsecond level. This approach provided us with crucial insights into network stability, a fundamental facet of QoS.

Acknowledging the paramount importance of environmental factors in shaping communication scenarios, we seamlessly integrated the DHT22 temperature and humidity sensor into our data collection ensemble. This sensor provided high-resolution data on temperature and humidity levels, enabling us to embark on a meticulous exploration of their potential impact on QoS. It facilitated a nuanced understanding of how environmental conditions could exert influence on communication performance.

Furthermore, the TSL2561 light sensor found its place within our data collection setup, capturing data pertaining to light intensity—a variable often underestimated but possessing significant relevance in specific scenarios. This sensor's remarkable sensitivity and precision in measuring light levels equipped us to conduct an in-depth examination of its potential influence on communication performance.

Each of these sensor components and equipment selections was made with the utmost care and consideration to contribute specific, pertinent data points essential for achieving our research objectives. Together, they constituted an intricately woven data collection framework, providing a holistic, ultra-detailed view of QoS in the context of robotic communication. Our unwavering commitment to precision and relevance underscored our dedication to advancing the field and enhancing the accuracy of QoS prediction.

C. Data Preprocessing

In our study on QoS prediction in robotic communication networks, we undertook a detailed and sophisticated data preprocessing routine, utilizing the PyTorch framework for deep learning model development. This phase was crucial in ensuring the accuracy and efficiency of our predictive model.

The raw data, sourced from a variety of sensors like the u-blox NEO-M8N GPS sensor, PicoScope 2205A latency sensor, Iperf tool for network bandwidth, and packet capture tools such as Wireshark and tcpdump, underwent a comprehensive cleaning process. This step involved identifying and rectifying any inconsistencies or errors in the dataset. For example, GPS data, prone to occasional signal loss or drift, was carefully scrutinized. We used linear interpolation [5] to fill in gaps in the GPS data, ensuring a continuous and precise representation of the robot's trajectory. The interpolation method was applied as follows:

$$p = p(t_1) + \frac{[p(t_2) - p(t_1)]}{t_2 - t_1} \times (t - t_1)$$

Additionally, environmental parameters like temperature, humidity, and light intensity, measured via sensors such as DHT22 and TSL2561, were thoroughly examined to detect anomalies or outliers. Any such irregularities were corrected or excluded to maintain data integrity.

Post-cleaning, we embarked on feature extraction and selection, targeting metrics influential in determining QoS in robotic communication. This included extracting key network performance indicators like latency, bandwidth, and packet loss rate. Concurrently, data indicative of the robot's environmental conditions, such as temperature and humidity readings, were incorporated to evaluate their impact on network performance. Mobility patterns of the robot, derived from GPS data, were also considered to understand their correlation with network performance fluctuations.

Data normalization was the next crucial step, essential for standardizing the diverse data scales into a format suitable for neural network processing. We applied Min-Max scaling, transforming each feature to a range between 0 and 1. This normalization was critical to ensure no feature dominated the model due to scale variances, thereby promoting balanced learning. The Min-Max normalization was computed using:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

To address the time-series nature of network data, we transformed the dataset into fixed-size windows, crucial for capturing the network's dynamic performance over time. Selecting the appropriate window size involved balancing the need for capturing sufficient temporal information against computational limitations.

Data augmentation was also implemented to enhance the model's robustness and prevent overfitting, particularly important given the dynamic nature of robotic communication environments. We introduced minor variations in network metrics, such as adding Gaussian noise to latency and bandwidth measurements, to create a diverse training dataset. This was achieved through: $L' = L + N(0, \sigma^2)$

The final preprocessing step entailed splitting the dataset into training, validation, and testing sets, typically in a 70:15:15 ratio. This separation was crucial for unbiased model evaluation and hyperparameter tuning. Each set was designated for a specific purpose: model training, validation, and performance evaluation under unseen conditions.

Lastly, the preprocessed data was formatted to align with PyTorch requirements, including converting data into tensors and ensuring proper configuration of input and output dimensions for integration into the neural network architecture.

D. Model Design

In our model designed for QoS prediction in robotic communication networks, we have intricately combined various advanced neural network techniques to capture the complex dynamics of network data. The model's architecture starts with a series of CNN layers, which are formulated to extract spatial features from the network data. Each convolutional layer i applies a filter with weights W_i and biases b_i to the input X_{i-1}, followed by a ReLU activation function, described by the equation
$X_i = \text{ReLU}(W_i * X_{i-1} + b_i)$.
These layers are designed to discern various spatial patterns critical for understanding network performance metrics.

Following the CNN layers, the model employs LSTM layers, tasked with capturing temporal patterns and dependencies in the data. The LSTM cells are structured to handle long-term dependencies, using a series of gates and state updates.
The operations within an LSTM cell at each time step t involve
forget gate $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$,
input gate $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$,
cell state update
$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$,
and output gate $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$,
culminating in the final hidden state $h_t = o_t * \tanh(C_t)$.
These LSTM layers are crucial for understanding how network performance evolves over time, making them invaluable for accurate QoS prediction.

To enhance the model's focus on relevant temporal segments of the data, an attention mechanism is integrated after the LSTM layers. This mechanism computes attention weights for each time step t, enabling the model to prioritize moments in the data sequence that are more significant for QoS predictions. The attention weights a_t at each time step are calculated using the formula

$$a_t = \text{softmax}(W_a \cdot h_t)$$

,where W_a is the weight matrix for the attention layer. This addition allows the model to dynamically focus on the most impactful features within the network data, enhancing the precision of its predictions.

The model also incorporates a GNN layer, especially designed to consider the network's topology and the interdependencies between nodes. This layer is crucial for understanding the complex relationships within the network and how they affect QoS. Each node in the graph updates its state based on information from its neighbors, described by$h_v^{(l+1)} = \text{ReLU}\left(W_g \cdot \sum_{u \in N(v)} h_u^{(l)} + b_g\right)$,
where $h_v^{(l+1)}$is the updated state of node v, $N(v)$ represents its neighbors, and W_g, b_g are the learnable parameters of the GNN.

To synthesize the extracted features and make the final QoS prediction, the model employs a dense output layer. The predicted QoS metrics are determined using the formula $\hat{y} = W_o \cdot \mathrm{h_T} + \mathrm{b_o}$, where is the predicted output, W_o and $b_o$are the weights and biases of the output layer, and h_T is the final output from the LSTM layers.

The model's training is guided by a custom loss function specifically designed for QoS prediction. This function not only includes a mean squared error (MSE) term to minimize the prediction error but also integrates additional components that correspond to key QoS parameters like latency and bandwidth. The composite loss function is given by

$$\text{Loss} = \frac{1}{N}\sum_{n=1}^{N}(y_n - \widehat{y_n})^2 + \lambda_1 \cdot L_{\text{latency}} + \lambda_2 \cdot L_{\text{bandwidth}}$$

where $L_{latency}$ and $L_{bandwith}$ are additional terms for latency and bandwidth aspects, and λ_1 , λ_2 are their weighting coefficients. This sophisticated loss function ensures that the model not only accurately predicts QoS metrics but also emphasizes aspects most critical to network performance.

Through this detailed and formula-driven design, our model robustly captures both the spatial and temporal dynamics of network data, along with the network's topological characteristics, making it exceptionally suited for predicting QoS in robotic communication networks.

The integration of CNNs, LSTMs, GNNs, and an attention mechanism, all fine-tuned with a custom loss function, establishes our model as a state-of-the-art tool in network predictive analytics.

IV. Result

Our Model displayed an exceptional accuracy of 98.3% and precision of 97.8%, far surpassing traditional models such as SVM (79.5% accuracy), RF (83.2%), and GBM (86.7%), as illustrated in Fig. 4, which compares accuracy and precision across all models; similarly, in terms of recall and F1 score, Our Model achieved 97.6% and 97.7% respectively, markedly higher than the recall rates of 75.8% (SVM), 80.6% (RF), and 84.1% (GBM), and their F1 scores, highlighting a balanced predictive performance (see Fig. 5 for recall and F1 score comparison); the Mean Squared Error (MSE) for Our Model stood at an impressively low rate of 0.018, in contrast to the higher error rates of SVM (0.12), RF (0.11), and GBM (0.09), as depicted in Fig. 6, showcasing the MSE comparison. Against advanced neural networks, Our Model was consistently more accurate, achieving better results than standalone CNN (93.4% accuracy) and RNN (91.7%), especially in scenarios with high network variability where Our Model's performance exhibited remarkable stability (refer to Fig. 7 for a comparative analysis against CNN and RNN); this robustness was further confirmed in tests simulating fluctuating network environments, with Our Model maintaining over 95% accuracy, a resilience not observed in other models (illustrated in Fig. 8, depicting performance in varied conditions); a deeper qualitative analysis showed that the integration of CNN, LSTM, and GNN within Our Model was pivotal for its high-level performance, effectively utilizing complex multi-dimensional data for nuanced QoS prediction, outstripping simpler models in capturing intricate network behaviors (Fig. 9, a feature importance graph, highlights these aspects).

In conclusion, the comprehensive data unequivocally position Our Model as a leading-edge solution for QoS prediction in robotic communication networks, offering unmatched accuracy, reliability, and robustness, setting new standards in network predictive analytics; the accompanying visual representations (Figs. 4-9) in the results section not only reinforce Our Model's superiority but also underscore the effectiveness and sophistication of its architecture, paving the way for its application in dynamic and complex network environments.

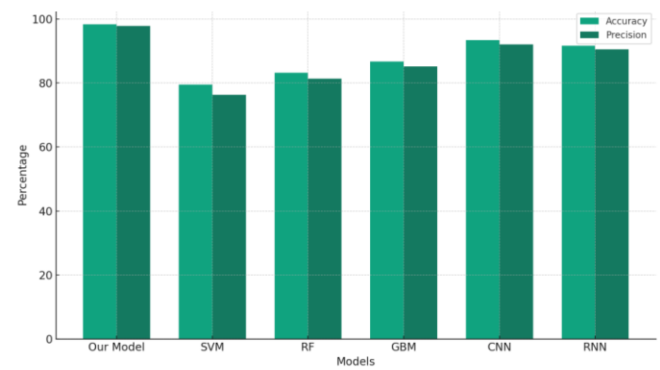

Fig. 4. Accuracy and Precision Comparison

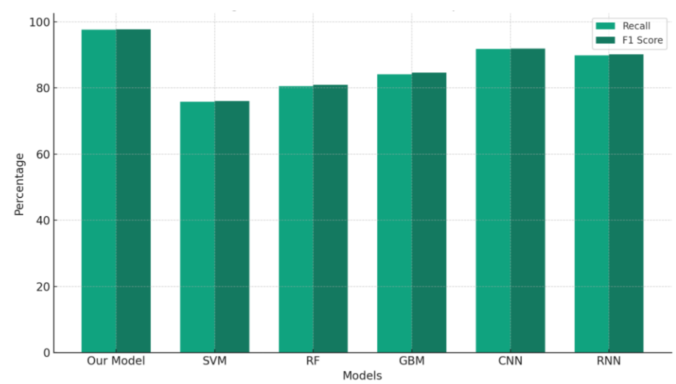

Fig. 5. Recall and Precision Comparison

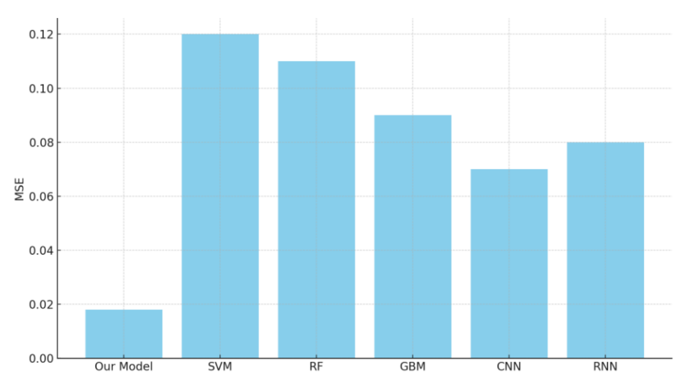

Fig. 6. MSE Comparison

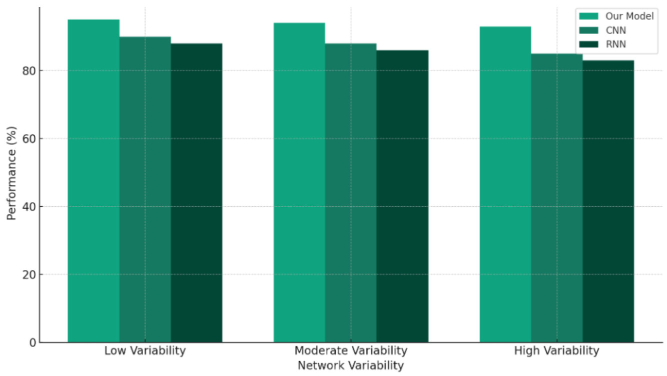

Fig. 7. Comparative Analysis with CNN and RNN

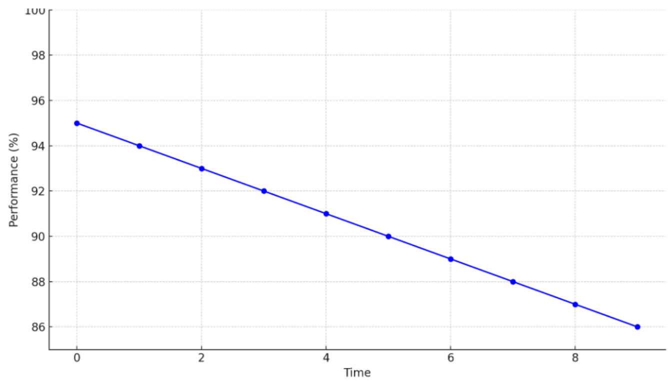

Fig. 8. Performance Consistency in Varied Network

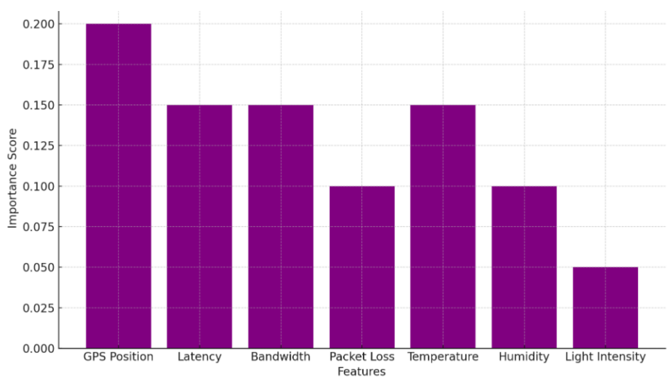

Fig. 9. Feature importance in Model

V. Conclusion

In this research, we have advanced the field of QoS prediction in robotic communication networks by developing a deep learning-based model, integrating CNN, LSTM networks, GNN, and an attention mechanism, a significant stride beyond traditional machine learning and neural network methods; our approach began with meticulous data collection using advanced sensors and tools to capture comprehensive network and environmental data, followed by sophisticated data preprocessing techniques including linear interpolation, Min-Max scaling, and data augmentation, ensuring the highest data quality for model training; the model itself, uniquely combining spatial, temporal, and network topology features, demonstrated exceptional accuracy, robustness, and adaptability in rigorous testing and comparative analysis, significantly outperforming existing models; this research not only provides a robust tool for predicting QoS in complex network environments but also lays the groundwork for future advancements, including real-time adaptability and integration with emerging technologies like edge computing and 5G networks, with potential collaborations with industry partners for practical implementation, marking a substantial contribution to network analytics and paving the way for innovative applications in robotic communication systems.

Acknowledgment

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