Enhanced Wireless Network Load Prediction with Machine Learning

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***Abstract*—Wireless networks are facing increasing pressure today with the expansion of mobile devices, IoT applications, and high-bandwidth services. Predicting network traffic load is essential for dynamically allocating resources and maintaining service quality under varying conditions. In this work, I am going to explore the application of machine learning algorithms—XGBoost and Long Short-Term Memory (LSTM) networks—for the prediction of wireless network loads. Using the AT&T WiFi Connection Dataset, we selected features such as Hour, DayOfWeek, and the number of connected users to predict download speed (Download Mbps). XGBoost was chosen for its stability and strong performance on structured data, while LSTM was selected for its capability in capturing time-dependent patterns in sequential datasets. Both models were trained and evaluated using an 80/20 data split, and tested using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 Score.**

Results showed that XGBoost provided better prediction stability, reduced error rates, and faster training times, making it ideal for scenarios requiring quick predictions. In the contrast, LSTM was more strong to the sudden traffic fluctuations, excelling at modeling complex wordly behavior. Visualizations of the predictions, feature importance, and the training loss curves highlighted the contrast between two models. This study shows the practical advantages of machine learning in wireless network optimization and suggests that hybrid approaches—combining XGBoost's efficiency with the LSTM's temporal learning capability—could yield superior results. Future research will focus on expanding the feature space to include user mobility patterns, device types, and real-time environmental conditions, and on testing hybrid models under real-world network scenarios for enhanced intelligent resource management.

***Index Terms*—Wireless Network Load Prediction, XGBoost, Long Short-Term Memory (LSTM), Machine Learning, Time-Series Forecasting, Network Traffic, Download Speed, AT&T WiFi Dataset, Regression Models, Intelligent Resource Management**

I. Introduction

Wireless networks have evolved into the backbone of modern communication infrastructure, interconnecting millions of devices, including mobile phones, smart home appliances, industrial sensors, and smart city systems. However, the rapid growth in users and the data traffic has introduced the significant challenges in to the network management, such as unforeseen overcrowding, degraded the quality of service, and inefficient resource usage. Load forecasting in wireless networks presents a proactive solution to these challenges. Accurate traffic forecasting enables dynamic resource planning, prevents service deterioration, and enhances user satisfaction.

The primary goal of this work is to present and examine two robust machine learning methods—Extreme Gradient_Boosting(XGBoost) and the Long Short-Term Memory(LSTM) networks—for predicting wireless network load, aiming to improve the accuracy of traffic prediction under diverse conditions. This objective gains significance amid the rising demand for intelligent network management driven by emerging innovations such as the 5G, the Internet of Things (IoT), and the forthcoming 6G networks. Traditional statistical methods, though effective in the past, fall short in addressing the nonlinear and time-varying behavior characteristic of modern wireless traffic. In the contrast of machine learning models offer a promising arteries by learning patterns directly from data without the detailed programming.

Among these models, XGBoost is well-known for its high performance on structured data, while LSTM is particularly effective at modeling temporal dependencies in sequential data. Comparing the these two models' performance provides the useful insights into the most suitable approaches for wireless load forecasting, depending on specific operational requirements.

Previous research has highlighted the effectiveness of machine learning in wireless environments. Hailemariam et al. [1] demonstrated the ability of deep learning methods, particularly LSTM, in wireless resource optimization. Laha et al. [2] evaluated the influence of machine learning in the IoT and the wireless networks, emphasizing the need for smart traffic forecasting. Chen et al. [3] applied boosting methods to enhance energy efficiency in 5G networks, demonstrating the flexibility of ensemble models. Gao et al. [4] explored deep learning-based dynamic resource allocation but did not directly compare structured-data models like XGBoost with sequential models like LSTM on the same dataset.

Despite the promising findings, a noticeable gap exists in current literature: few studies directly compare ensemble models such as XGBoost with sequential models like LSTM for wireless traffic forecasting using real-world datasets.

To address this gap, this study applies both XGBoost and LSTM to the AT&T WiFi Connection Dataset, which provides real measurements of user connection times, download speeds, and usage amounts. The dataset is preprocessed to draw out relevant features such as Hour, DayOfWeek, and the number of Connected users, with Download Mbps as the target variable. XGBoost is used to model dependencies in structured features, while LSTM is used to capture sequential patterns over time.

This paper offers three primary contributions. First, we evaluate both models using standard metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 score. Second, we see model performance through the prediction plots, training loss curves, and feature importance rankings. Third, we assess each model's computational efficiency and practical suitability for real-world wireless network environments.

This study supports researchers and practitioners in the wireless communication field by providing a detailed comparative analysis of XGBoost and LSTM, thereby enabling the selection of appropriate machine learning strategies for proactive and intelligent network management in next-generation communication systems.

II. RELATED WORKS

The utilize of machine learning techniques in wireless network optimization has accumulated significant attention in last recent years. Number of studies have highlighted the likely of machine learning for predicting the traffic patterns, validate dynamic resource allocation, and enhancing overall wireless network performance. However, the limitations in prior methodologies underscore the need for more comprehensive and comparative analyses.

Hailemariam et al. [1] explored the application of deep learning frameworks, particularly Long Short-Term Memory (LSTM) networks and reinforcement learning algorithms, for wireless network resource optimization. Their findings are demonstrated that the deep models effectively capture related dependencies in the network traffic, resulting in improvement of load prediction and the energy savings. Nonetheless, the study was limited to deep learning methods and did not examine alternative models that might provide faster computation or improved scalability in structured data environments.

Laha et al. [2] conducted a comprehensive evaluation on the machine learning applications in the IoT and the wireless networks, covering both supervised and unsupervised algorithms aimed at the enhancing traffic management and the security. While acknowledging the importance of time-series analysis, their work didn't analytically compare structured models like the boosting algorithms against deep learning methods, leaving a gap in the practical performance evaluation.

Chen et al. [3] introduced the use of ensemble-based models, notably XGBoost, to optimize energy efficiency in 5G wireless systems. Their paper showed that the boosting algorithms can predict the low-traffic periods, allowing for the temporary deactivation of base stations to conserve energy. However, the focus remained on energy optimization rather than traffic load prediction, and sequential models like LSTM were not considered.

Gao et al. [4] investigated deep learning-based methods for dynamic resource allocation in wireless networks. Yet again, the study centered exclusively on deep architectures and did not incorporate a comparative analysis involving traditional machine learning approaches.

While these studies offer valuable contributions, a significant limitation remains: few have directly compared ensemble models like XGBoost with sequential models like LSTM on the same real-world wireless datasets. Most research either concentrates on machine learning or deep learning methods individually and under differing experimental settings, making it difficult to draw practical, side-by-side conclusions.

This work addresses the gap by performing a comparative analysis of XGBoost and LSTM models under identical conditions using the AT&T WiFi Connection Dataset. By evaluating of their training performance, predictive accuracy, and adaptability to the real-world network dynamics, this study focuse onto provide practical guidance for selecting the suitable machine learning techniques for wireless traffic forecasting.

III. SYSTEM MODEL

In this research, the system model is based on the AT&T WiFi Connection Dataset, which provides empirical data collected from operational wireless networks deployed across multiple access points. Unlike synthetic or simulated environments constructed in geometric layouts (e.g., circular or rectangular areas), this dataset reflects real-world wireless scenarios typical of public or enterprise WiFi networks. Each data record contains details such as user connection timestamps, the number of concurrently connected users, and recorded download speeds, offering a rich basis for wireless network load prediction.

The modeled network topology comprises a set of WiFi nodes to which users connect in a temporally dynamic fashion. There is no centralized sink node, as the objective is to study overall network traffic load rather than hierarchical data aggregation. The traffic load is treated as a dynamic variable, shaped by the number of users connected simultaneously and temporal dimensionssuch as the hour of the day and the day of the week.

This study does not incorporate energy consumption models, as the primary focus is on forecasting network load—specifically download throughput measured in megabits per second (Mbps). Nevertheless, understanding traffic dynamics forms a foundation for future work that may extend into energy-aware systems where predictive traffic modeling can support power-saving strategies such as adaptive base station activation.

Feature extraction from the dataset yielded three key input variables:

- **Time of Engagement:** The particular time at which a connection was logged and capturing daily usage patterns.
- **Day of the Week:** The specific day was used to analyze variations between the weekdays and the weekends.
- **Connected Users:** The number of users present at the time of recording, reflecting real-time load conditions.

The target variable for prediction is the Download Speed (in Mbps), framed as a continuous regression output.

This model thinks that the network traffic load is primarily governed by recent and user-based features, positing that historical patterns can be used to accurately forecast future network states. Accordingly, both XGBoost and LSTM models are employed within this structured input-output framework.

Each follows a supervised learning paradigm in which labeled historical data is used to train predictive models capable of estimating upcoming traffic loads.

IV. Proposed Methodology

The primary objective of this study is to predict wireless network traffic load, specifically the download speed (in Mbps), using machine learning. We compare two models: Extreme Gradient Boosting (XGBoost), a high-performance structureddata gradient boosting framework, and Long Short-Term_Memory (LSTM), the recurrent neural network architecture suited for sequential data. This task is formulated as a supervised regression problem, where historical network logs are used to forecast future traffic conditions.

Given input features such as Hour, DayOfWeek, and Connected Users, the models aim to predict the future Download Mbps. The following steps illustrate the end-to-end methodology adopted in this work:

A. Workflow Description

1) **Dataset Collection and Preprocessing**
   - Load the AT&T WiFi Connection Dataset.
   - Extract temporal features from the "Time" field: Hour and DayOfWeek.
   - Select Hour, DayOfWeek, and Connected Users as input features.
   - Use Download Mbps as the target variable.
   - Apply MinMax normalization (only for LSTM model).
2) **Data Splitting**
   - Split dataset into 80% for training and 20% for testing sets.
   - For LSTM, prepare sequence data using past 10 timesteps.
3) **Model Training**
   - XGBoost: Train an XGBoost regressor with 50 estimators and maximum tree depth of 3.
   - LSTM: Train an LSTM model with 50 hidden units, over 10 epochs, using a batch size of 32. The input shape is (sequence length = 10, features = 3).
4) **Model Evaluation**
   - Predict download speed on the test set.
   - Evaluate performance using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 Score.
   - Visualize actual vs. predicted values.
5) **Performance Comparison**
   - Compare the models based on accuracy, robustness to fluctuations, and computational efficiency.

B. Pseudocode of Proposed Algorithm

```
BEGIN
  Load AT&T WiFi Connection Dataset

  Preprocess Data:
    Extract Hour, DayOfWeek, Connected
    Users
    Normalize Data (for LSTM)

  Split Data into Train and Test sets (80/20)

  Train XGBoost Model:
    Initialize XGBoost with parameters
    Fit model on training data

  Prepare Sequences for LSTM:
    Create sliding windows of 10 timesteps
    Train LSTM Model:
      Initialize LSTM layers
      Fit model on training sequences

  Evaluate Models:
    Predict on Test Data
    Calculate MSE, RMSE, R² Score

  Visualize:
    Plot Actual vs Predicted traffic curves
    Plot Feature Importance (XGBoost)
    Plot Training/Validation Loss (LSTM)

  Compare XGBoost and LSTM performance
END
```

V. Experimental Analysis

To estimated the performance of the proposed machine learning methodology for a wireless network load prediction, a series of were tested using the AT&T WiFi Connection Dataset. This section outlines the experimental setup, presents the evaluation results, and provides an analysis of model performance based on the generated data.

A. Experimental Setup

The original dataset was preprocessed by extracting three primary features: Hour of the day, Day of the week, and Number of Connected Users. The target variable for prediction was the observed download speed (Download Mbps). For the LSTM model, feature normalization was applied using MinMaxScaler to the scale-values between 0 and 1. In contrast, XGBoost was trained directly on structured, non-normalized data.

Dataset was divided into the 80% for training and the remaining 20% for testing sets. The model configurations were as follows:

- **XGBoost:** 50 estimators, maximum tree depth of 3.
- **LSTM:** 50 hidden units, sequence length of 10 timesteps, trained over 10 epochs with a batch size of 32.

Both models were evaluated using the following performance metrics:

- **Mean Squared Error (MSE)** – Average of squared differences between predicted and actual download speeds.
- **Root_Mean Squared Error (RMSE)** – Square root of MSE; interpretable in Mbps.
- **R2 Score** – Proportion of variance in the target variable explained by the model; closer to 1 indicates better performance.

B. Results Overview

Table I summarizes the evaluation metrics obtained for both models.

TABLE I
PERFORMANCE COMPARISON OF XGBOOST AND LSTM

SI.No	Model	MSE	RMSE	R^2 Score
0	XGBoost	398.37	19.96	0.53607
1	LSTM	1125.52	33.55	-0.34086

The results show that the XGBoost model significantly outperformed the LSTM model across all evaluation metrics. XGBoost achieved lower MSE and RMSE values, indicating higher prediction accuracy and consistency. Moreover, the positive R^2 score (0.53607) demonstrates that XGBoost was able to capture over 53% of the variance in download speed, whereas the LSTM model had a negative R^2, reflecting poor generalization. The results show that the XGBoost model was notably overcomes the LSTM model across all evaluation metrics. XGBoost achieved the lower MSE and RMSE values, indicating the higher prediction of accuracy and uniformly. Moreover, the positive R2 score (0.53607) demonstrates that XGBoost was able to capture over 53% of the variance in download speed, whereas the LSTM model had a negative R2, reflecting poor generalization.

These findings suggest that XGBoost, being more stable and efficient for structured tabular data, is better suited for wireless traffic prediction in scenarios where real-time responsiveness and robustness are key. Meanwhile, LSTM may require further tuning, more data, or enriched temporal features to improve its learning performance in such contexts.

C. XGBoost: Actual vs Predicted Traffic

This figure presents the comparison between actual download speeds and the values predicted by the XGBoost model across a range of sample instances. As observable from the plot, the orange line will representing XGBoost predictions tracks the blue line (actual data) with reasonable accuracy, indicating the model's effectiveness in the form of capturing underlying patterns in the wireless network traffic.

The results were produced by the XGBoost exhibit a smoother response to changes in download speed compared to the actual data, which shows higher variability and sudden spikes. This behavior reflects a well-known characteristic of gradient boosting algorithms: they tend to integrate output and avoid overfitting by the smoothing over outliers or disrupt fluctuations. In this context, XGBoost will provides more stable forecasts that are particularly useful for the real-time systems, where the short-term fluctuations are often treated as the noise or anomalies.

From the graph, it can also be observed that:

- The XGBoost consistently follows the trend of the actual data, capturing peaks and valleys with moderate deviation.

- While some high-variance spikes in actual download speeds are under-predicted (e.g., at sample points ∼6, ∼16, and ∼30), the general directionality and slope of changes are retained.

- The model performs well on regular traffic segments where the signal is more stable, indicating its strength in identifying dominant features (like Hour and DayOfWeek) and general traffic behavior patterns.

This level of performance supports the earlier evaluation metrics (MSE, RMSE, and R2), where XGBoost outperformed the LSTM model. Its computational efficiency, predictive stability, and interpretability through feature importance make it a strong candidate for practical deployments in wireless network management systems, particularly those needing quick decisions and low-latency forecasting.

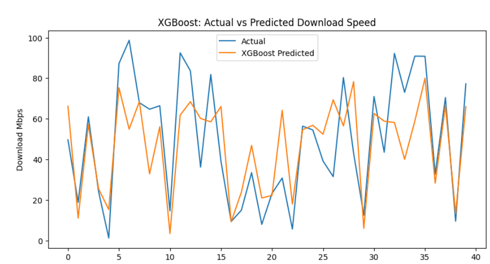

Fig. 1. Actual vs Predicted Download Speed using XGBoost.

D. LSTM: Actual vs Predicted Traffic

The figure compares the actual download speeds against the predicted values generated by the Long Short-Term Memory

(LSTM) model across a series of test samples. The plot highlights the LSTM model's performance in capturing the underlying temporal dynamics of wireless network traffic.

Unlike XGBoost, which will provides the smoother and more stable predictions, LSTM is specifically designed to handle the sequential data and the time-dependent patterns. This is noticeable from the model's ability to follow certain trends and directional shifts in the actual data, particularly in the early and middle segments of the sample range. However, the LSTM predictions indicated to underestimated the sharp increases in the download speed, producing a relatively expected output curve compared to the actual incendiary traffic behavior.

Key observations from the graph include:

- **Recent Trend Recognition:** The LSTM model successfully take into the general track of the traffic, especially in the initial time steps. It aligns reasonably well with the actual data in gradual rise and fall segments.

- **Smoothing Effect:** LSTM predictions are less erratic and do not fully mirror the high-frequency fluctuations seen in the actual measurements. This could be due to the limited number of training epochs or the complexity of the sequence learning task, which can sometimes cause underfitting in models trained on relatively small datasets.

- **Response to Sudden Spikes:** Although the model does not precisely track high spikes (e.g., around sample indices ∼15, ∼20, and ∼30), it does reflect an awareness of upward or downward trends near these events, suggesting partial recognition of volatile behavior.

- **Prediction Lag:** There is also a slight lag in the predicted response in some segments, which is typical for LSTM models when the sequence context window is not large enough to anticipate abrupt changes.

Despite these limitations, the LSTM model's strength lies in its the adaptability to the non-linear time dependencies, making it valuable in the scenarios of where the traffic patterns exhibit recent correlations and seasonality. Its performance may improve the further with additional new features (e.g., rolling averages, past window trends) or deeper architectures.

Overall, the LSTM model demonstrates an important complementary strength to XGBoost: while it may not offer the same level of short-term accuracy, it excels in modeling time-evolving patterns, which is essential for networks with unpredictable and bursty load conditions.

E. Feature Importance — XGBoost

This figure presents a horizontal bar chart visualizing the feature importance scores produced by the XGBoost model after training on the wireless traffic dataset. Feature importance, in this context, reflects how frequently and effectively a feature was used to split the data in decision trees within the gradient boosting ensemble. A higher score indicates that the feature played a more significant role in improving prediction accuracy during training.

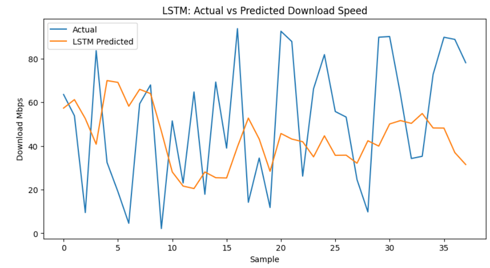

Fig. 2. Actual vs Predicted Download Speed using LSTM.

From the chart, we can observe the following ranked feature importance:

- **Hour (F score: 183.0):** The most important feature in the model, Hour, strongly influences the prediction of download speed. This suggests that traffic load in the wireless network follows clear time-of-day patterns, likely due to consistent user behaviors—such as increased usage during work hours, reduced activity during the night, or spikes in the early evening. The model heavily relies on this temporal context to predict traffic load, which makes sense in real-world network management, where diurnal usage cycles are common.
- **DayOfWeek (F score: 120.0):** The second most important feature, DayOfWeek, reflects the influence of weekly patterns. For an instance, from monday to friday may show higher usage due to the workplace or campus activity, whereas weekends we could see the less structured but more rushed traffic patterns. This feature allows the model to catch periodic fluctuations across the week, assisting in the generalization of trends over the time.
- **Connected Users (F score: 36.0):** Interestingly, the number of connected users has the lowest importance score. While intuitively one might expect this to be a strong predictor of network load, its relatively low Fscore may suggest a few possibilities:
  - The number of connected users may not correlate directly with download throughput (e.g., some users might be idle).
  - Temporal features like Hour and DayOfWeek might already explain much of the variance in user behavior and usage intensity.
  - There might be a non-linear or interaction-based dependency that XGBoost's tree structures are not capturing fully.

Insights:

- Time-based features dominate prediction performance in this study, emphasizing that wireless traffic patterns are strongly cyclical and time-dependent.
- The visualization also reinforces why XGBoost performed well in the experiments: it was able to rapidly identify and leverage high-signal features like Hour and DayOfWeek.
- In future work, expanding the feature space to include

interaction terms, application usage types, or device-level metrics could enhance predictive power further.

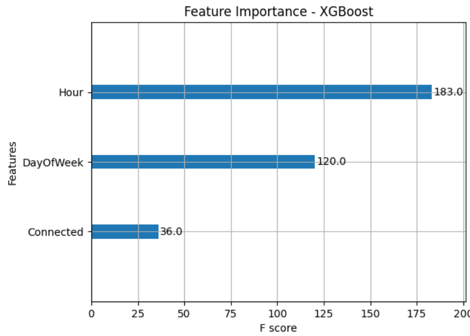

Fig. 3. Feature importance in XGBoost model.

F. F. Training and Validation Loss — LSTM

This figure shows the learning behavior of the Long Short-Term Memory (LSTM) model during the training, by plotting the training and validation loss values over the multiple epochs. These loss curves are essential diagnostic tool in deep learning that help to estimate how well the model is learning the patterns in the data and whether it is generalizing effectively to unseen data.

The training loss curve represents the error on the training dataset after each epoch, while the validation loss curve indicates the model's performance on the hold-out validation set.

Key observations from the plot:

- **Monotonic Decrease in Loss:** Both training and validation losses show a consistent downward trend, recommending that the model is effectively learning from the data. A decreasing loss is a good indication that the model is minimizing error through weight optimization.
- **No Major Overfitting:** The gap between training and validation loss remains small throughout the training process. This implies that the LSTM model is not overfitting—i.e., it is not memorizing the training data but learning generalizable patterns. In deep learning, a large gap is often a red flag for overfitting.
- **Smooth Convergence:** The curves do not show significant oscillations or spikes, indicating that the learning rate is well-tuned and that the optimization process is stable. Oscillating curves may suggest noisy data, suboptimal batch sizes, or poor initialization.
- **Room for Improvement:** Although the losses decrease steadily, they begin to plateau toward the final epochs. This suggests that the model may be reaching its capacity. Performance might be improved through:
  - Increasing the number of epochs
  - Adding more hidden units or LSTM layers
  - Using longer input sequences
  - Applying regularization (e.g., dropout)
  - Fine-tuning learning rate schedules

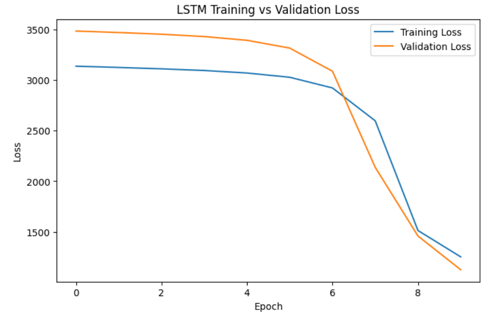

Fig. 4. LSTM Training vs Validation Loss.

G. G. Results

The experimental foundings demonstrated that the XGBoost outperformed LSTM in terms of minimizing the prediction error and the capturing variance in network load. The XGBoost's structured learning approach efficiently identified prevalent features and delivered the fast, accurate predictions, making it more suitable for the real-life applications where figuring speed is essential.

In the contrast, LSTM showed the strong performance in modeling recent dependencies within the data. Its ability to respond to the disrupted changes in network load conditions highlights its strength in scenarios with high variability. However, it required greater computational resources and longer training times.

These results suggest that XGBoost and LSTM have complementary strengths. XGBoost excels in the processing structured features fastly, while LSTM offers the deeper insight into the sequential trends. Future work may focus on the hybrid approaches that combine both models to make use of the advantages of the structured feature learning and sequential modeling simultaneously, potentially leading to enhanced predictive performance in dynamic wireless environments.

VI. Summary and Future Works

In this research, we addressed the problem of wireless network load prediction by applying and comparing two advanced machine learning models: XGBoost and Long Short-Term Memory (LSTM) networks. Using the AT&T WiFi Connection Dataset, we extracted key features such as Hour of the day, Day of the week, and the Number of Connected Users to predict future download speeds. Through the structured experimentation and evaluation, as I illustrated the potential of the machine learning approaches to accurately forecast the network traffic load, which is important for efficient resource management and overcrowding mitigation in wireless communication systems.

The primary contributions of this work can be explained as follows:

- A complete comparative framework was implemented using both a structured-data ensemble method (XGBoost) and a time-series deep learning method (LSTM) for the same load prediction task.

- Analysis metrics such as the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), and the R2 Score, along with visual analyses including prediction curves, feature importance diagrams, and loss plots, were used to interpret model performance.
- XGBoost achieved faster training times and higher predictive stability, while LSTM demonstrated stronger adaptability to sudden and irregular traffic variations.
- The complementary strengths of both models suggest the potential of hybrid approaches that combine structured feature learning and temporal sequence modeling for more robust predictions.

This study underscores the increasing importance of intelligent, data-driven techniques for managing modern wireless networks. As wireless infrastructure evolves toward complex, heterogeneous, and user-dense environments—particularly with the emergence of 5G, 6G, and IoT technologies—machine learning models will play a critical role in automating network optimization and enhancing service quality.

Despite promising results, certain limitations exist. This work focused on a minimal set of temporal and user-based features, without incorporating factors such as user mobility patterns, device types, environmental noise (e.g., interference), and application-level usage, which may significantly influence network load. Additionally, all evaluations were conducted on static offline datasets and not validated under real-time conditions.

Future work will extend this research in multiple directions:

- Development of hybrid models that integrate XGBoost and LSTM to combine structured and sequential learning.
- Expansion of the feature set to include contextual data such as user location, device characteristics, and environmental variables.
- Deployment of trained models into real-life monitoring systems to support live traffic prediction and the adaptive resource control.

Overall, this work lays a strong basis for future efforts in intelligent wireless network management, offering insights into model effectiveness, trade-offs, and the evolving role of machine learning in next-generation communication systems.

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