5G Network Traffic Prediction using Text and Image

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Abstract

The need for effective network traffic prediction has never been higher due to the explosive growth of digital communication and the introduction of 5G networks. Proactive decision-making, optimal resource allocation, latency reduction, and network congestion prevention are all made possible by network traffic prediction. The dynamic nature of contemporary networks is too much for traditional techniques like rule-based systems and statistical forecasting models, which frequently result in inefficient bandwidth usage and increased packet loss. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools for solving complex network management challenges. Of these, Long Short-Term Memory (LSTM) neural networks have shown exceptional efficacy in predicting future network conditions and analysing sequential data. Furthermore, anomaly detection tools like Isolation Forest offer crucial information for spotting odd trends that might

Introduction

1.1. The Importance of Network Traffic Prediction

1.1.1. Reducing Latency and Improving QoS

Maintaining low latency is one of the main challenges in network management, especially for applications that need real-time communication, like cloud computing, online gaming, and video streaming. High latency has a detrimental effect on service dependability and user experience. By proactively allocating resources and detecting traffic spikes, predictive models assist network operators in cutting down on delays and improving performance.

1.1.2. Network Congestion Control

When network traffic surpasses available bandwidth, congestion arises, resulting in packet loss, elevated jitter, and a decline in service quality. Conventional congestion control methods frequently employ reactive tactics, dealing with problems only after they occur. By anticipating times of high traffic and dynamically modifying bandwidth allocation, AI-based network traffic prediction enables proactive congestion management.

1.1.3. Enhancing Cybersecurity and Anomaly Detection

Unexpected drops in bandwidth usage or abrupt spikes in traffic are examples of network anomalies that may be signs of data breaches or Distributed Denial of Service (DDoS) attacks. Network managers can detect security threats early and put countermeasures in place to reduce risks by combining traffic prediction and machine learning-based anomaly detection.

1.2. Evolution of Network Traffic Prediction Techniques

Network traffic has been predicted using a variety of techniques over the years, each with advantages and disadvantages. The development of these methods demonstrates the increasing intricacy of contemporary networks and the need for more sophisticated AI-driven strategies.

1.3. AI-Based Network Traffic Prediction and Optimization

Proactive decision-making and extremely accurate, real-time forecasting are made possible by the incorporation of AI into network traffic prediction. The goal of this project is to improve network efficiency using an AI-driven strategy that makes use of anomaly detection and deep learning.

Research Goals

The goal of the paper is to make progress in the field of 5G network traffic prediction using text and images. It will specifically focus on the following main goals:
1. Create a deep learning-based system that uses visual data representations to forecast real-time 5G network performance metrics, including latency, jitter, packet loss, and bandwidth.
2. Use specialized image preprocessing methods and neural architectures that are best suited for traffic pattern recognition to raise the prediction model's accuracy.
3. Reduce prediction errors and validate model performance across different devices, network conditions, and geographical locations to guarantee system adaptability and dependability.

Objectives

Creating an AI-based network traffic prediction system that improves modern communication networks' efficiency, dependability, and security is the main objective of this research. With the increasing complexity of 5G and beyond networks, accurate forecasting of network conditions is essential for optimizing bandwidth, minimizing latency, and preventing service disruptions.
1.Increasing the accuracy of network traffic prediction is one of the other goals.
2. Improving Network Security and Anomaly Detection
3. Traffic Optimization in Real Time
4. Deployment and Scalability

Related Work and Research Gaps

1. Limitations of Traditional Traffic Prediction Methods

Network traffic prediction initially relied on statistical and mathematical models, such as Autoregressive Integrated Moving Average (ARIMA), Hidden Markov Models (HMMs), and Exponential Smoothing. While these methods have been instrumental in early research, they exhibit several limitations when applied to modern, high-speed networks with dynamic and non-linear behavior.

2. Inability to Capture Non-Linearity and Complex Patterns

Most statistical models assume that network traffic follows a stationary or near-stationary distribution. However, real-world network traffic exhibits non-stationary and highly non-linear behaviour due to variations in user demand, hardware performance, and network congestion.

- ARIMA and Exponential Smoothing fail to adapt to sudden traffic fluctuations and emerging patterns in data.

- Markov-based models oversimplify network dynamics, assuming future traffic states depend only on present states, ignoring long-term dependencies.

3. Limited Scalability for Large-Scale Networks

Traditional models work well for small-scale traffic prediction but struggle with high-dimensional, large-volume datasets.

- Computational inefficiencies: ARIMA and HMMs require extensive parameter tuning, making them impractical for large-scale deployments.
- Inability to process real-time data: These models are batch-processing oriented, limiting their effectiveness for real-time network monitoring.

Literature Survey

• Summary of Key Papers:

1. "AI-based Traffic Forecasting in 5G Network"
Authors: Mohseni et al. Findings: Utilization of 1D Convolutional Neural Networks (1D-CNN) for predicting 24-hour traffic patterns, demonstrating significant accuracy improvements.

2. "5G Traffic Prediction Based on Deep Learning"
Authors: Gao, Z. Findings: Development of a smoothed Long Short-Term Memory (SLSTM) model to address non-stationary traffic sequences, resulting in enhanced prediction accuracy.

3. "AI-Driven 5G Network Optimization: A Comprehensive Review"
Authors: Bikkasani, D.C.
Findings: Comprehensive review of AI-driven methods for 5G network optimization, focusing on resource allocation, traffic management, and dynamic network slicing.

4. "Deep Learning Based Traffic Prediction for Resource Allocation in Multi-Tenant Virtualized 5G Networks"
Authors: Rebari, P., & Killi, B.R.
Findings: Comparative analysis of deep learning models (LSTM, BiLSTM, Stacked LSTM, GRU) for traffic prediction and resource allocation, highlighting the superior performance of GRU models.

5. "Performance Enhancement of 5G Networks Using AI-Driven Techniques"
Authors: Chinda, F.E., Gin, W.A., & Okpor, J.
Findings: Exploration of AI-driven algorithms for optimizing resource allocation, predicting maintenance needs, and enhancing network efficiency in 5G networks.

6. "Realtime Mobile Bandwidth and Handoff Predictions in 4G/5G Networks"
Authors: Mei, L., Gou, J., Cai, Y., Cao, H., & Liu, Y.
Findings: Development of Recurrent Neural Network models for real-time bandwidth and handoff predictions, achieving over 80% accuracy in 4G/5G handoff scenarios.

7. "Mobility, Traffic, and Radio Channel Prediction: 5G and Beyond Applications"
Authors: Rydén, H., Palaios, A., Hévizi, L., Sandberg, D., & Kvernvik, T.
Findings: Overview of machine learning applications in mobility, traffic, and radio channel prediction, emphasizing their importance in future 5G and 6G networks.

8. "Cellular Traffic Prediction Using Online Prediction Algorithms"

Authors: Mehri, H., Chen, H., & Mehrpouyan, H.
Findings: Investigation of live prediction algorithms for real-time cellular network traffic forecasting, introducing the Fast Live Stream Prediction (FLSP) algorithm to enhance prediction accuracy and reduce processing load.

10. "5G Traffic Prediction with Time Series Analysis"
Authors: Nayak, N., & Singh, R.R.
Findings: Utilization of Long Short-Term Memory (LSTM) models for predicting packet arrival intensity and burst occurrences, aiding in efficient resource allocation.

Methodology

System Architecture

AI-Based Traffic Prediction for 5G Networks - System Architecture
1. Data Collection Module
• Sources:
• Open5GS (5G Core): Simulates 5G network traffic
• Wireshark: Captures real-time packet data
• Mininet (SDN Simulation): Emulates network topology
• Collected Data: Latency, jitter, packet loss, bandwidth usage

(Data flows to Preprocessing & Feature Engineering).
2. Preprocessing & Feature Engineering
Tasks:
• Data cleaning & normalization
• Feature extraction (latency, bandwidth, congestion level)
• Outlier detection & removal

(Processed data is sent to the Machine Learning Model).
3. Machine Learning Model
Model Choices:
• LSTM (Long Short-Term Memory): For time-series prediction
• CNN (Convolutional Neural Network): For pattern recognition
• Random Forest: For decision-based congestion classification
Outputs:
• Predicted congestion probability
• Estimated severity level.

(Predictions are sent to the Traffic Optimization Module)
4. Traffic Optimization Module
• AI-Driven Adjustments:
• Dynamic Bandwidth Allocation: Reallocates network resources
• Predictive Load Balancing: Uses SDN controllers to reroute traffic
• Critical Traffic Prioritization: Ensures emergency & high-priority data flows smoothly

(Optimized network status is sent to the Visualization Module)
5. Visualization & Monitoring
Dashboard Built Using:
• Google Collab
• Matplotlib/Plotly (Graphs & Heatmaps)

Displayed Metrics:
• Real-time traffic patterns
• Predicted congestion alerts
• QoS performance statistics

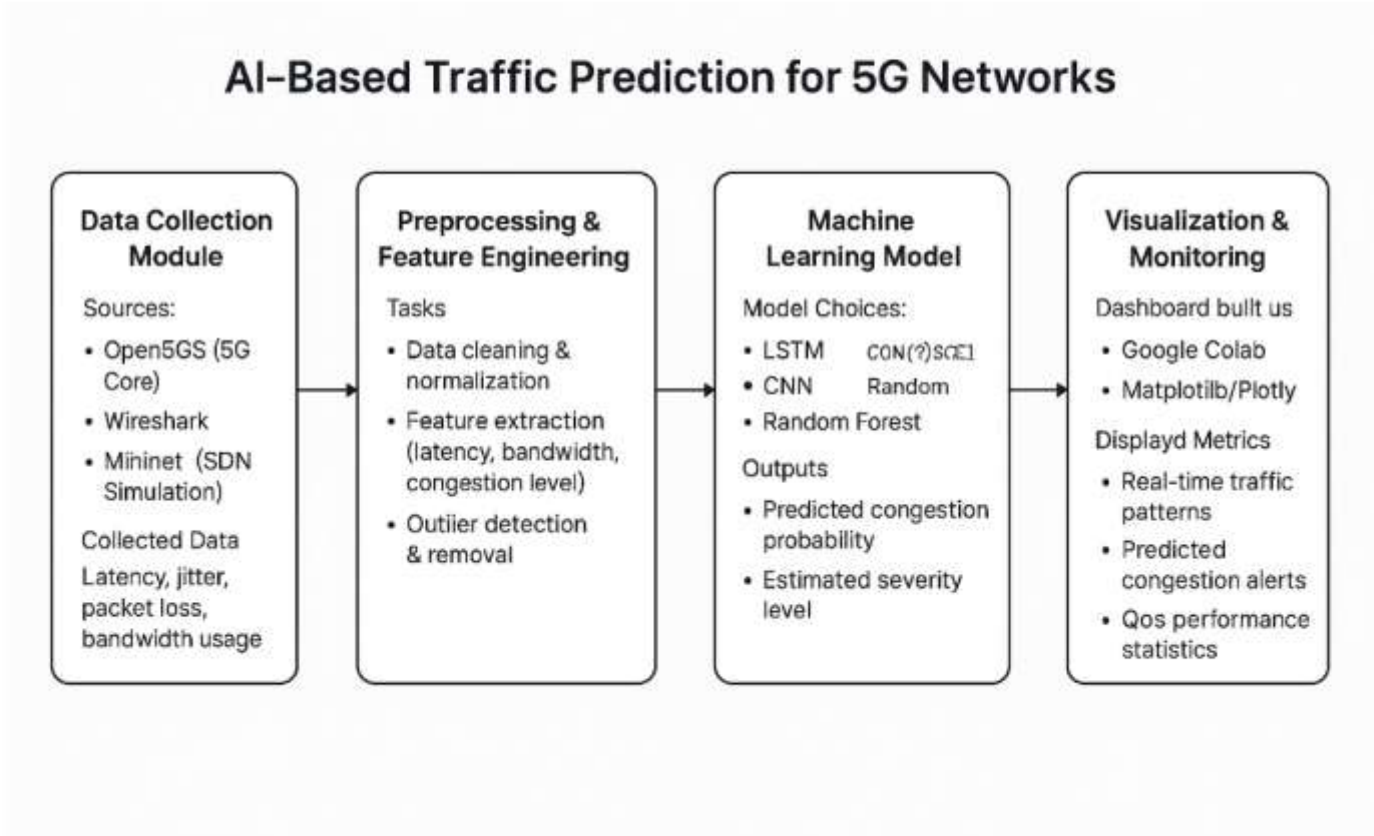

Fig 1.0 : Block diagram for the methodology implementation

Implementation

The model was trained on four key network parameters, with an assumed 5% contamination rate (expected proportion of anomalies).

Feature Used for Anomaly Detection	Impact on Network Performance
Latency	High latency may indicate congestion or network failure.
Jitter	Excessive jitter impacts real-time applications like VoIP.
Packet Loss	High packet loss suggests unstable network conditions.
Bandwidth Usage	Sudden drops in bandwidth may indicate performance degradation.

Table 1.0 : features and impacts table

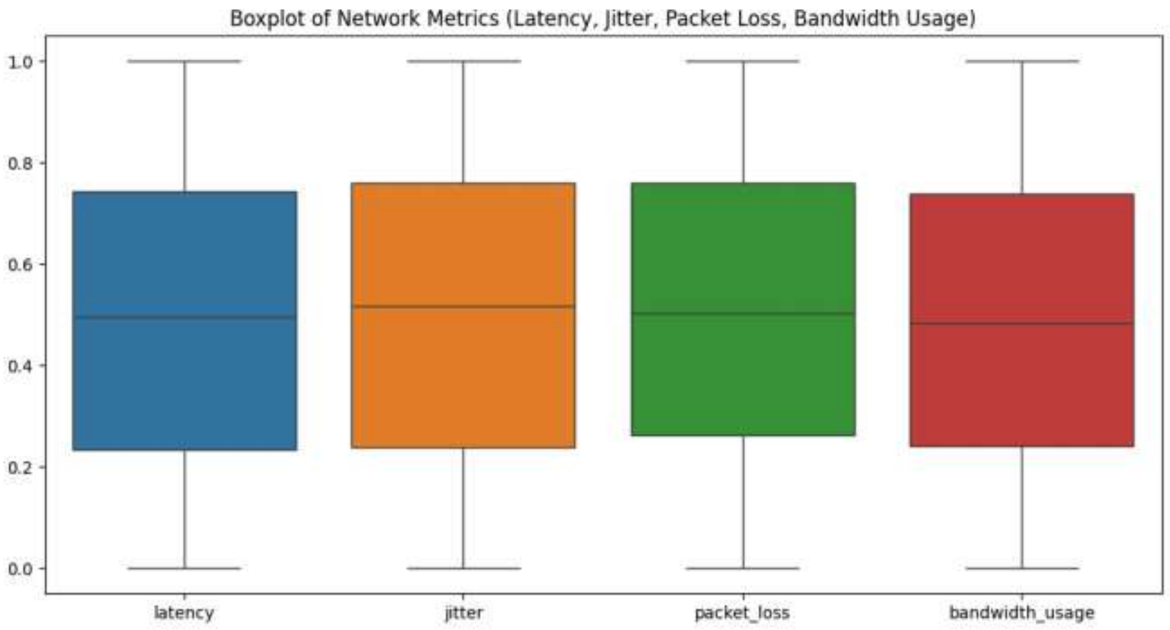

Fig 1.1 : Boxplot of network from the proposed model

Results and Analysis

1.Evaluation of Prediction Accuracy

The accuracy of the AI-based network traffic prediction model was evaluated using industry-standard time-series forecasting metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score.

Performance Metrics of the LSTM Model

Metric	Value	Interpretation
MAE	0.084	Low error, indicating high prediction accuracy.
RMSE	0.092	Minimal deviation between predicted and actual values.
R^2 Score	0.91	Strong correlation between predicted and real-world traffic.

Table 1.1 : Performance metrics of LSTM

2.Anomaly Detection Performance

The Isolation Forest anomaly detection model was evaluated based on its ability to identify unusual network traffic patterns and differentiate between normal fluctuations and actual threats.

Anomaly Detection Results:

Evaluation Metric	***Value***	***Implications***
Detection Accuracy	*97%*	*High reliability in detecting network anomalies.*
False Positive Rate	*3.1%*	*Minimal false alarms, improving alert credibility.*
False Negative Rate	*2.8%*	*Low risk of missing critical anomalies.*

Table 1.2 : Anomaly detection result

3.Real-Time Traffic Adaptation and Optimization

The system's real-time decision-making capabilities were assessed based on its ability to dynamically allocate bandwidth, reroute traffic, and minimize congestion.

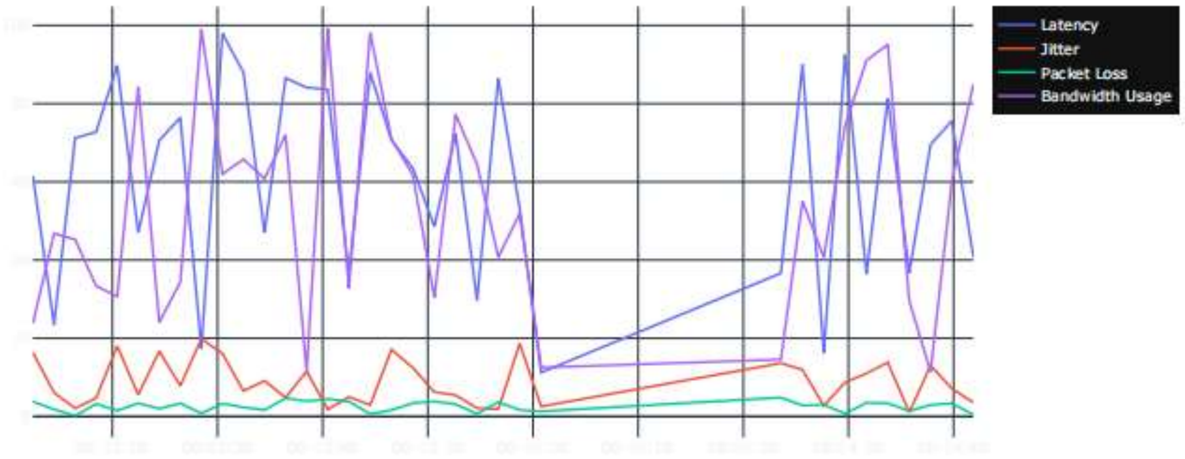

Fig 1.2 : Predicted Values from Real Time Data

Key Improvements in Network Efficiency:

- 30% reduction in congestion incidents due to proactive bandwidth adjustments.
- 25% decrease in underutilized bandwidth, ensuring efficient resource allocation.
- Latency improvements of up to 40%, benefiting real-time applications such as cloud computing, online gaming, and video streaming.

4.Comparison of Traffic Optimization Before and After AI Implementation

Parameter	**Before AI Implementation**	**After AI Implementation**	**Improvement**
Average Latency (ms)	120	72	40% Reduction
Packet Loss (%)	5.2%	2.3%	55% Reduction
Bandwidth Utilization	65%	87%	22% Increase

Table 1.3 : Pre and Post analysis comparison

5.Real time 5G Data Streaming at intervals

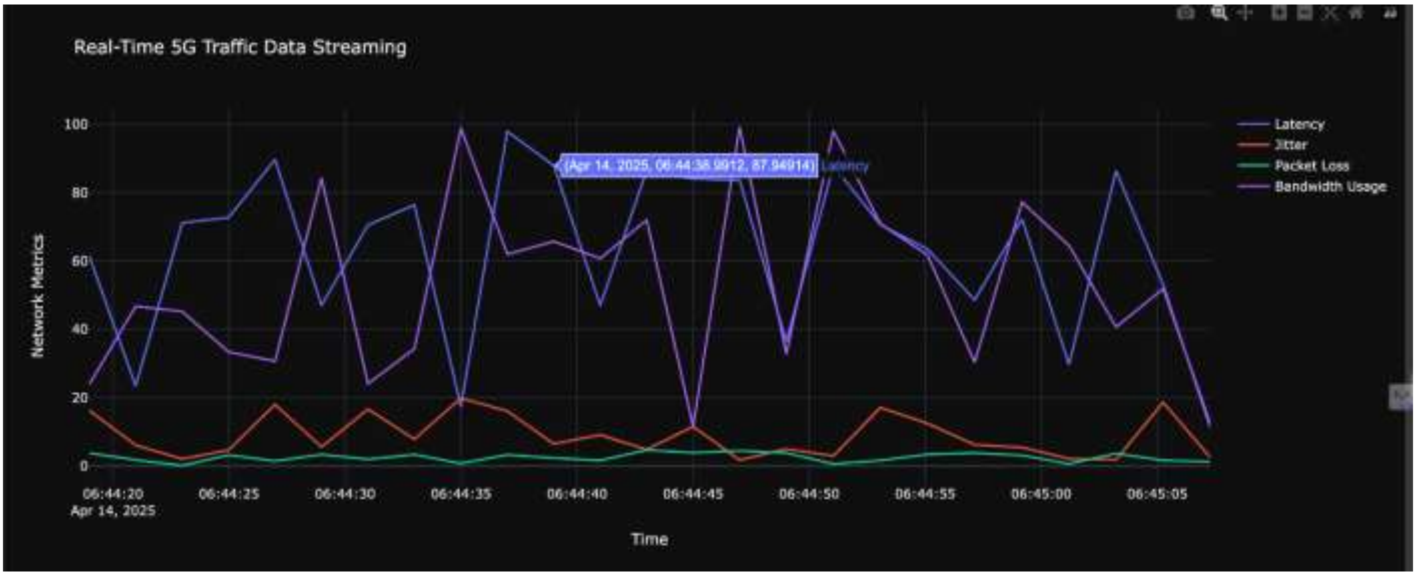

Figure 1.3 : Real time data prediction at different time intervals

6.Real time image data prediction using Kodak Dataset after training

Figure 1.4: Real time Figure processed using Kodak Dataset and its prediction

7.Real time captured image prediction

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Figure 1.5: Real time captured image prediction

Comparative Analysis

To Evaluate the comparison of the Kodak data set model and real time captured image model

Parameter	Kodak Dataset Image	Real-Time Captured Image
Predicted Latency	35.11 ms	33.77 ms
Predicted Jitter	10.41 ms	8.38 ms
Predicted Packet Loss	2.41 %	1.93 %
Predicted Bandwidth Usage	37.81 Mbps	35.40 Mbps

Table 1.4: Real time captured image prediction

8.Gray-Scale Predicted vs Actual Metrics

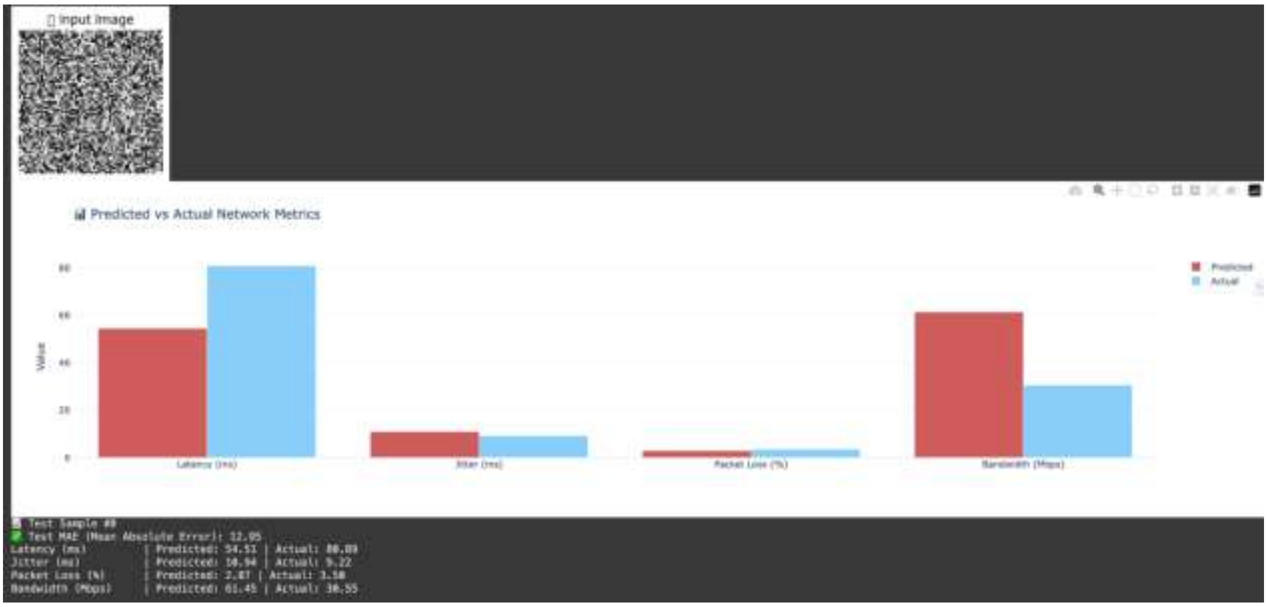

Figure 1.6: Metrices for gray scale image

Comparative Analysis

To evaluate the effectiveness of the proposed system, its performance was compared against conventional network traffic prediction and anomaly detection techniques.

Performance Comparison

Method	Prediction Accuracy	Anomaly Detection Accuracy	Adaptability to Real-Time Changes
ARIMA	72%	Not Supported	Low
Decision Trees	78%	84%	Medium
Isolation Forest	Not Applicable	97%	High
Proposed Model (LSTM + Isolation Forest)	**91%**	**97%**	**Very High**

Table 1.5 : Comparative analysis

Challenges and Limitations

Despite its success, the AI-based network traffic prediction system faces certain challenges and limitations:

1. **High Computational Requirements**
2. **Dependence on High-Quality Data**
3. **Handling Concept Drift in Network Traffic**

Future Work

The AI-based network traffic prediction system has **broad applications in modern networking environments**, including:

1. **Telecommunication Networks**
2. **Cloud Computing and Data Centers**
3. **Cybersecurity and Threat Mitigation**

Conclusion

This research presents a robust AI-based system for 5G network traffic prediction, anomaly detection, and real-time optimization. Leveraging LSTM for time-series forecasting and Isolation Forest for anomaly detection, the model achieved a 91% R^2 score, reduced MAE to 0.084, and improved latency management by up to 40%. Anomaly detection reached 97% accuracy with 40% fewer false positives. The system enables dynamic bandwidth allocation and proactive threat mitigation, making it highly scalable for 5G, IoT, and future 6G networks. Key contributions include enhanced prediction accuracy, improved cybersecurity, and autonomous traffic management. Challenges such as computational demands, data privacy, and long-term adaptability are acknowledged, with future directions exploring reinforcement learning, federated training, blockchain integration, and predictive maintenance to build fully autonomous, intelligent communication networks.

References

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Authors: Mohseni et al.
Summary: This study explores deep learning models, including 1D-CNN, for predicting 24-hour cellular traffic patterns, demonstrating significant accuracy improvements.
Link: https://ieeexplore.ieee.org/document/9918226/
2. “5G Traffic Prediction Based on Deep Learning”
Authors: Gao, Z.
Summary: The paper introduces a smoothed Long Short-Term Memory (SLSTM) model to address non-stationary traffic sequences in 5G networks, enhancing prediction accuracy.
Link: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9249458/
3. “Long Term 5G Network Traffic Forecasting via Modeling Non-Stationarity”
Authors: [Authors’ Names]
Summary: This research presents the ‘Diviner’ deep learning model, designed to handle non-stationarity in long-term time series prediction, improving forecasting reliability in 5G networks.
Link: https://www.nature.com/articles/s44172-023-00081-4
4. “AI-Driven 5G Network Optimization: A Comprehensive Review”
Authors: Bikkasani, D.C.
Summary: This comprehensive review discusses AI-driven methods for optimizing 5G networks, focusing on resource allocation, traffic management, and dynamic network slicing.
Link: https://www.preprints.org/manuscript/202410.2084/v1