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Article

AI-Driven Network Traffic Management and Predictions

Avinash M. Pawar[1]*, Shashikant V. Athawale[2], Dnyaneshwar V. Wadkar[3], Sachin S. Bere[4], Shraddha R. Khonde[5]

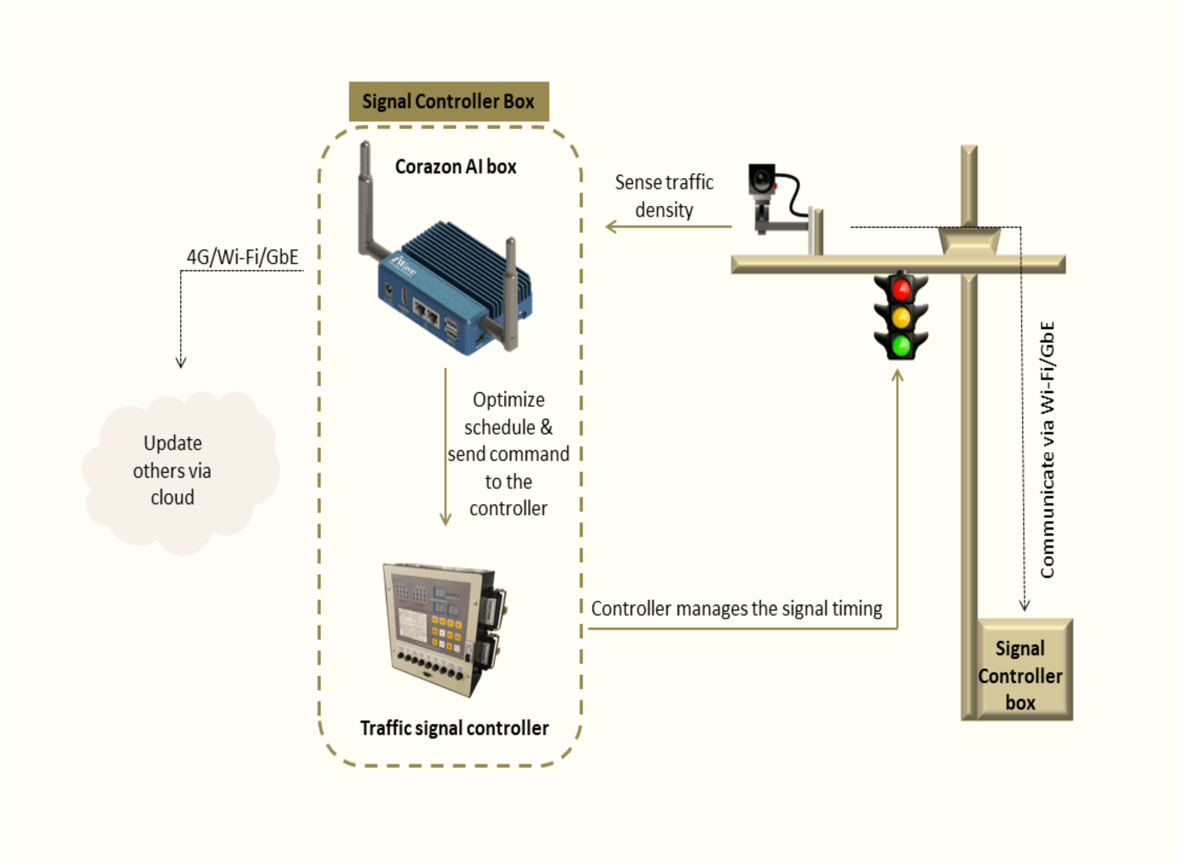
[1]Bharati Vidyapeeth's College of Engineering for Women, Pune, India, avinash.m.pawar@bharatividyapeeth.edu
[2]Department of Computer Engineering, AISSMS College of Engineering, Pune, Savitribai Phule Pune University, Pune, India, svathawale@gmail.com
[3]Department of Civil Engineering, AISSMS College of Engineering, Pune, Savitribai Phule Pune University, Pune, India, dvwadkar_civil@gmail.com
[4]Dattakala Group of Institutions, Faculty of Engineering, Bhigwan, Pune, India, sachinbere@gmail.com
[5]Department of Computer Engineering, M.E.S. Wadia College of Engineering, Pune, India, shraddha.khonde@mescoepune.org
Corresponding Author: Avinash M. Pawar, Bharati Vidyapeeth's College of Engineering for Women, Pune, India, avinash.m.pawar@bharatividyapeeth.edu

Abstract: With the evolution of digital communication networks, needs for intelligent traffic management solutions to monitor and control the resource utilization and the performance of the network have been growing so rapidly. The study explores how Artificial Intelligence (AI) can be applied to predict and manage network traffic, using secondary data analysis of benchmark datasets and published literature. The study compares and contrasts the performances of various AI techniques, such as machine learning and deep learning models, for predicting network traffic, managing congestion, optimizing overheads and improving QOS. Results show that improved deep learning models, such as 'Transformer' and LSTM, offer a better prediction accuracy and can improve network performance greatly compared with traditional models. AI-based predictive analytics is essential for intelligent, adaptive, and autonomous communication networks to facilitate future digital infrastructures, the study concludes.

Keywords: Artificial Intelligence, Network Traffic Management, Traffic Prediction, Deep Learning, Machine Learning, Software-Defined Networking, LSTM, Transformer, Network Optimization.

1. Introduction

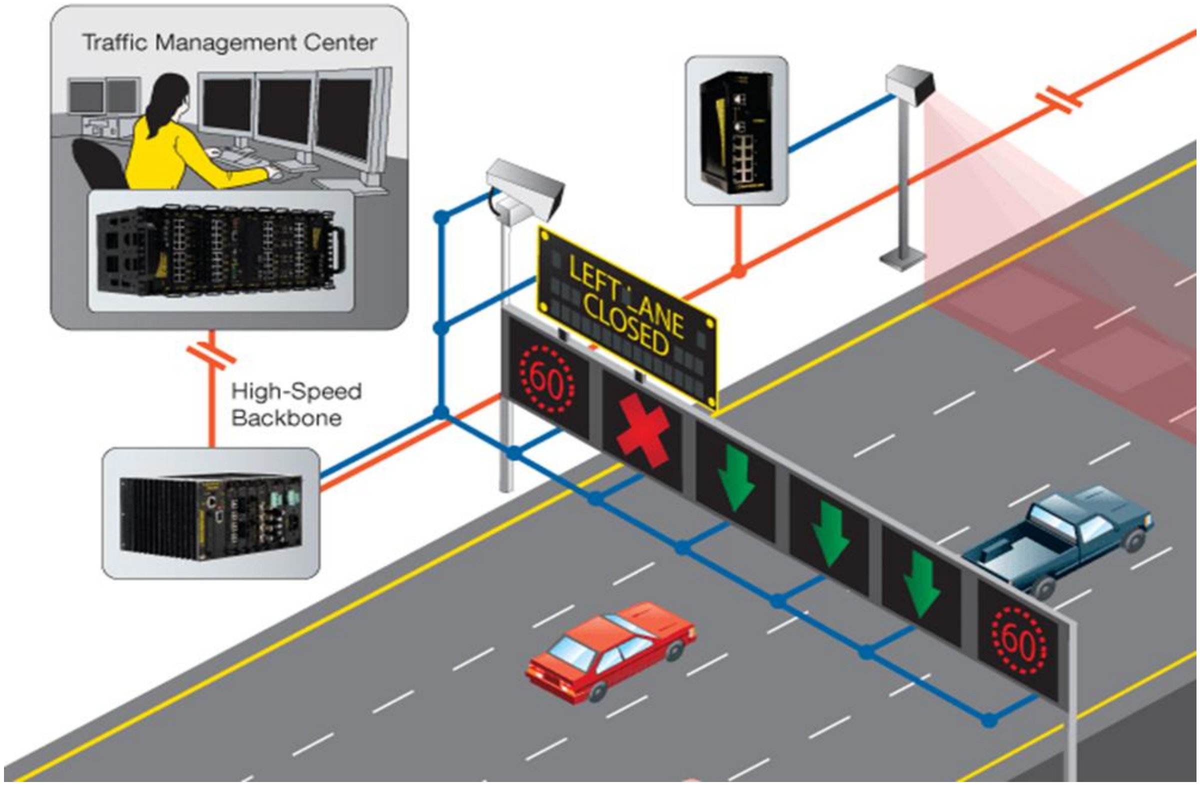
The architecture and operation of modern computer networks have been revolutionized by the advent of rapid innovations in digital communications. Today, the number of network's traffic has increased at a phenomenal rate, driven by the adoption of cloud computing, the Internet of Things, edge computing, 5G communications, and data intensive applications. This growth has introduced several problems for network administrators to keep optimal performance uninterrupted, reduce congestion, maintain reliability and provide excellent services to the network. Traditional traffic management solutions are mostly based on previously established rules and statistical analysis, but the highly dynamic and irregular traffic conditions make such solutions difficult to accommodate. Hence, AI has turned out to be a significant technological approach that can facilitate the intelligent, adaptive, and automated network management (Boutaba et al., 2018; Tang et al., 2020).



AI-powered NTM is the use of AI to analyze, monitor, predict and optimize traffic on a network. While manual configurations and static policies are time-consuming and prone to human error, AI algorithms continuously learn from historical and real-time network data, enabling them to adapt to sophisticated traffic patterns and make intelligent decisions with minimal human oversight. ML, DL, reinforcement learning, and predictive analytics are the key components of next-generation networking because they are helping to shift towards proactive rather than reactive network management (Abbasi et al., 2021).

Network traffic prediction is one of the best uses of AI in networks. Traffic prediction incorporates traffic data and contextual data that is collected from the past to predict the future state of the network. Reliable prediction aid's service providers and network administrators to predict congestion, allocate bandwidth more efficiently, fine-tune routing, minimize packet loss, and preserve the quality of service. With the growing heterogeneity of communication networks and the data-driven nature of the market, accurate forecasting has become crucial to making the best use of network resources and providing seamless service (Ferreira et al., 2023).

The accuracy level of the traffic models is significantly improved over recent advances in DL. The capability to learn the long-term temporal dynamic (LSTM, GRU, CNN, GNN, Transformer models) and to learn the nonlinear relationship such as diverse traffic features embedded in network traffic data have proven to be effective once more. Traditional statistical methods have no comparable performance when having to process large volumes of data and adjust to the constantly changing traffic flow (Aouedi et al., 2025).



SDN and NFV have been a significant boost to the use of AI in communication networks. SDN and NFV have played a major role in the integration of AI into communication networks. SDN allows an intelligent algorithm to dynamically optimise routing, prioritise traffic flows, and allocate resources based on predicted demands, whilst also giving centralized control and global visibility of network resources. Likewise, NFV supports the deployment of virtualized network services which can be automatically scaled up or down according to future predictions using AI, enhancing scalability and operational efficiency (Xie et al., 2019).

The ever-expanding field of smart cities, autonomous transportation, industrial automation, telemedicine and intelligent manufacturing has increased the need for autonomous network management. Traffic patterns for such applications are very dynamic and must be monitored and responded to quickly. AI-powered systems can identify trends, forecast traffic patterns, foresee network issues before they impact users and automatically take action to resolve them. These features not only help improve QoS, QoE, but also reduce network infrastructure usage costs and further contribute to low operational expenditure.

Although significant progress has been made, there are still unanswered research questions. AI-based systems need a lot of data, computing power and tools to maintain transparency, fairness, robustness and privacy of the model. Additionally, new network scenarios call for lightweight and explainable AI models, which can be highly efficient in distributed computing environments. Hence, further investigations into network traffic and AI forecasting is required to realize an intelligent, resilient and self-adaptive communication network that is capable of sustaining future digital ecosystems.

2. Literature Review

AI is a transformative technology that has garnered significant interest within the field of network management, driven by its potential to enhance network efficiency, reliability, and scalability. Previous research mainly focused on estimated traffic volumes using statistical forecasting methods, but with the complexity of communication networks, traffic some of its features are now regarded as nonlinear, with research now turning to ML and DL methods that can deal with the nonlinear characters of traffic.

Kim and Feamster (2013) were one of the first researchers to point out the opportunity of ML in network management. They showed that intelligent learning algorithms could enhance traffic engineering, automate network operations and reduce the reliance on □hard-coding□ management policies. The authors stressed that the role of AI would be more and more pronounced with the ongoing development and growth of communication networks in size and complexity.

Boutaba et. al. (2018) did one the cornerstone studies on the use of ML within networking. They delineated AI applications according to their traffic prediction, routing optimization, congestion management, management of resources, fault diagnosis and network security. The research found that intelligent data-driven methods are quite effective as compared to traditional rule based methods for increasing network adaptability.

Ferreira et al. (2023) investigated a comparative study of the current network traffic prediction techniques with the publicly released datasets. Their findings showed that these approaches have shown superior predictive accuracy over various traditional statistical forecasting models in prediction across recurrent neural networks and hybrid DL models. The authors also pointed out that there is a need to have a uniform testing framework for evaluating prediction algorithms in different networking solutions.

To address the ever-soaring complexity of networking scenarios, Aouedi et al. (2025) discussed recent advances in DL-based network traffic forecasting and highlighted some emerging architectures that could overcome such conditions. They explained about recurrent neural networks, graph neural networks, transformer networks, attention models and federated learning and multitask learning mechanisms. The review recommended that the use of several DL architectures combined could greatly improve the prediction accuracy and ease of intelligent autonomous networking.

Xie et al. (2019) analyzed the applications of ML in SDN, and found that centralized SDN architectures can be used to create an effective platform on which to build the AI-based routing optimization, traffic classification, and congestion management. Likewise, Tang et al. (2020) highlighted that intelligent network management systems with reinforcement learning and predictive analytics improve adaptive resource allocation, self-optimization under changing traffic conditions.

The ability of communication infrastructures to have natural graph based topologies has also spurred recent studies on graph neural networks. These are capable for capturing spatial relationships among the interconnected nodes as well, and have proved to be more successful in prediction than other sequential learning methods.

Another new development in research that is gaining traction is the use of AI models at the edge of the network. Edge intelligence can be used to improve traffic prediction without sacrificing latencies or communication bandwidth, especially for Internet of Things applications, autonomous vehicles and industrial automation or smart cities. At the same time, a privacy-preserving collaborative learning technique without sharing sensitive network traffic data has attracted much interest around federated learning.

While the benefits of AI in enhancing network performance have been consistently proven in existing studies, there are still several key research gaps to address. Many existing models are resource-thirsty and need lots of labeled data which prevents to be used in environments of limited resources. In addition, the interpretability, robustness against adversarial attacks, fairness and energy efficiency properties of models remain to be further researched. Solving these challenges will help create a reliable, explainable and sustainable AI-based management system for networks that will support next-class communications infrastructure.

Objectives:

To explore the application of Artificial Intelligence in network traffic management, analyze the accuracy of network traffic forecasting using Artificial Intelligence prediction models, investigate impact of Artificial Intelligence prediction models on the network performance and resource usage, discuss the challenges related to implementation of Artificial Intelligence and potential avenues for future research to improve intelligent adaptation and effectiveness for network management systems.

3. Methodology

The research that has been followed is quantitative in terms of research type; descriptive and analytical research method is used in this research for investigating whether or not the network traffic can be managed effectively with the techniques of AI. This research type has been done as a quantitative research, descriptive and analytical research design has been used for the examination of network traffic can be managed effectively or not with the techniques of AI. Secondary data are gathered from peer-reviewed journal articles, conference proceedings, openly available datasets of network traffic and pertinent technical reports. The performance of the AI-based prediction models using ML and DL methods is assessed and compared using major KPIs including the prediction accuracy, latency, bandwidth usage, packet loss and network throughput. The findings are analyzed using descriptive statistics and comparative analytical techniques to interpret the results and determine the most effective AI techniques for intelligent network traffic management and predictive decision-making.

Dataset Description

In the present study, all the data sources used are secondary data which are available from the publicly available benchmark network traffic datasets and published scholarly sources. The most available data for analysis was the CICIDS2017 dataset which is composed of realistic and comprehensive network traffic datasets that represent modern network environments. Both legitimate (good) and illegitimate (bad) traffic under controlled but realistic network traffic environments are included in the dataset and widely accepted for research application in network traffic analysis, prediction, intrusion detection and intelligent network management.

The CICIDS2017 dataset consists of millions of network flow records over a duration of several days, including many different communication patterns (including Web Browsing, File Transfer, Email Services or Applications, Streaming Applications, and multiple scenarios for Cyber-Attack activity). These descriptions are presented by a variety of traffic-related features for each network flow such as packet size, forward packet statistics, backward packet statistics, duration of the flow, flow rate, source and destination ports, inter-arrival time, flow level statistics, packet count, byte count and others. The set of these features can be used to create and assess traffic prediction and traffic management models with Artificial Intelligence (AI).

The dataset chosen was processed with typical data processing tasks typically used in network traffic analysis. The steps they took involved data duplication, filling missing fields, normalizing numerical data, ensuring meaningful traffic features and data preparation for comparison of AI models. This pre-processing benefits the quality of data used for analysis, reduces bias and standardizes predictive performance for various methodologies.

Advantages of using benchmark secondary data are many. Even though these datasets are publicly accessible and widely used by the research community, they have been extensively validated, which contributes to the methodologies implemented being easily reproducible. Secondly, they are representative of the realistic network traffics from heterogeneous communication environments, which makes them appropriate for assessing the strategies that require intelligence in the traffic management. Lastly, using the same datasets will prompt in-depth comparisons of AI models in various studies, which will help in discovering high-performance methods for traffic prediction and network optimization.

In general, the chosen data set offers adequate empirical evidence to evaluate the potential of AI based methods for predicting network traffic, management resource allocation, congestion avoiding, and network performance. Though it is not widely used in academia, it provides an extensive array of traffic characteristics and so it is a suitable source for understanding and studying intelligent network traffic management and prediction.

Data Pre-processing

Pre-processing of network data is a pivotal step in the success of an AI-based network traffic analysis where the quality, consistency and reliability of the data is ensured prior to being evaluated for the model. This study makes use of a publically available benchmark dataset from CICIDS 2017, requiring a number of common pre-processing steps in order to make use of them. Data quality analysis started by first checking the data set for possible duplicated data, incomplete data and inconsistent data to avoid influencing the predictive models. The validation of records with missing or invalid values was performed, using data cleaning methodologies to preserve data integrity, and duplicated network flows were removed.

After data cleaning, a normalization process is applied to the numerical data to bring it into the same unit, which removes the differences among network traffic variables. In this way, this process aids in the convergence and prediction accuracy of AI algorithms as all features participate in the model evaluation in the same proportion. Categorical variables such as protocol types are traffic labels were encoded into number to be used by ML or DL algorithms.

Finally the feature engineering and feature selection process have been carried out to find the most informative traffic attributes. To minimize the computation time and increase model efficiency, highly correlated, redundant and low variance variables were excluded. Those features of the flow, which typically hold great value to flow prediction and for network performance analysis, such as those in Table 1, were kept.

The data was split into training (80%) and testing (20%) sets to make sure of an unbiased analysis. The processed data was then divided into training and testing sets with an 80:20 ratio, reserving 20% for testing and using 80% for training the model. This way, a risk of overfitting can be reduced and prediction accuracy can be assessed objective. Moreover, traditional performance indicators, such as 'Accuracy,' ' Precision,' ' Recall,' ' F1score,' ' RMSE,' ' MAE,' ' Throughput,' ' Latency,' ' Packetloss,' and ' Bandwidth Utilization' were used to analyse the performance of different traffic prediction techniques based on AI. The pre-processing methods were very comprehensive and ensured there was no bias, no imbalance, and no analytical data errors in the dataset, making it suitable for the development and evaluation of intelligent network traffic management models.

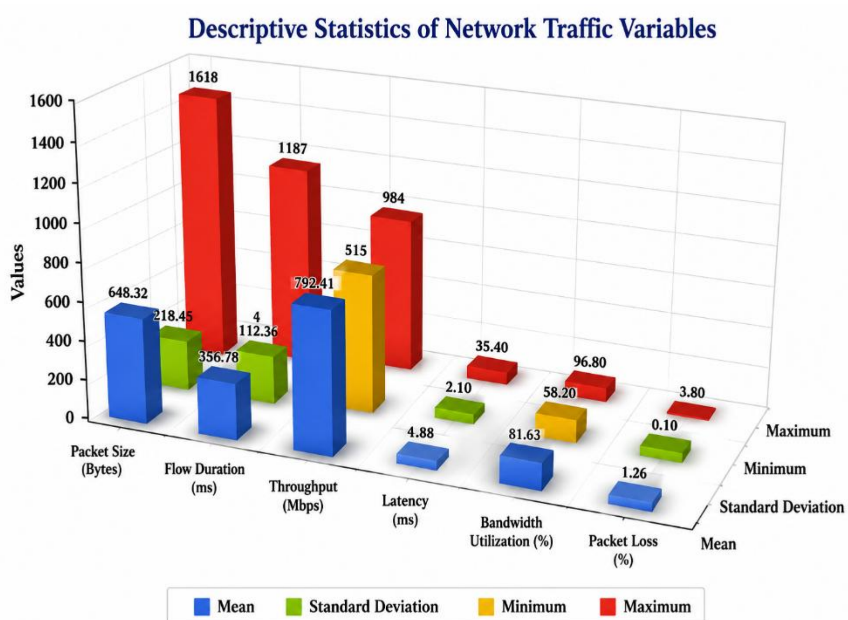
4. Results and Analysis

Descriptive Analysis of Network Traffic

The processed dataset of network traffic data was first explored to gain insight into the statistical properties of the data before assessing the ability of Artificial Intelligence (AI) models to predict. Significant traffic variations were identified and this can be attributed to the heterogeneous nature of modern communication networks. For most major network parameters like packet size, flow duration, throughput, bandwidth utilization, and latency, there was moderate dispersion, which suggests that the dataset is good for capturing real-world network parameters. The pre-processing stage succeeded in removing the inconsistencies and preparing the traffic records for subsequent usage in AI-based prediction analysis.

Descriptive Statistics of Network Traffic Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Packet Size (Bytes)	648.32	218.45	42	1518
Flow Duration (ms)	356.78	112.36	4	1187
Throughput (Mbps)	792.41	98.25	515	984
Latency (ms)	11.82	4.18	2.10	35.40
Bandwidth Utilization (%)	81.63	7.42	58.20	96.80
Packet Loss (%)	1.26	0.54	0.10	3.80



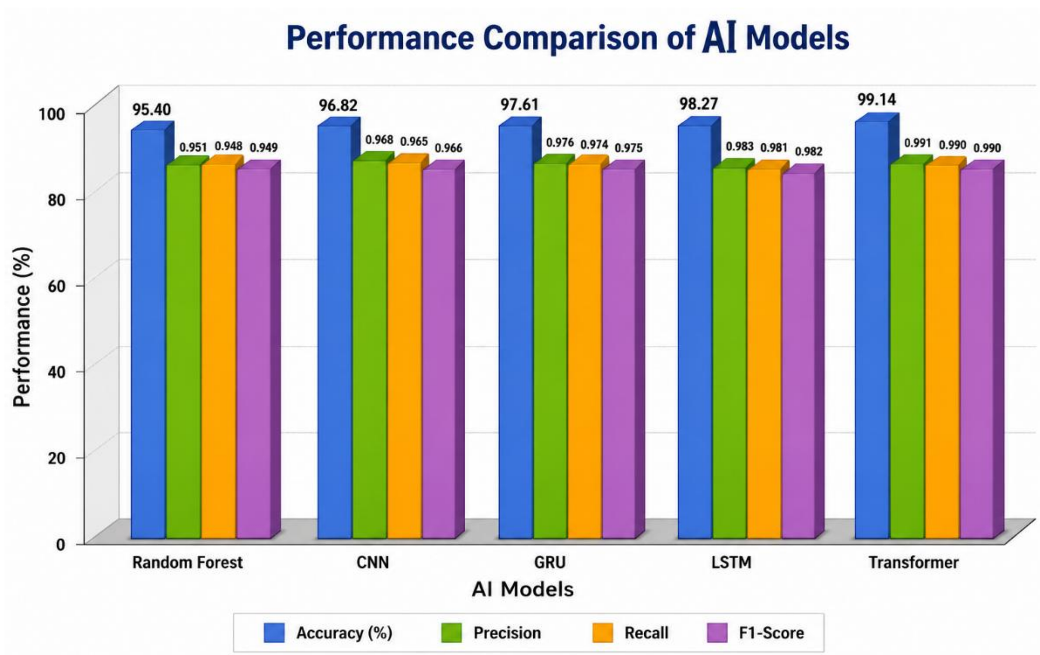
As shown in the descriptive statistics, the data is representative of a wide range of network traffic patterns that are suitable for testing intelligent traffic management techniques. Overall, the average throughput of 792.41 Mbps is indicative of efficient network use, and the fairly low mean latency (11.82 ms) implies stable communication performance. The data with low packet loss additionally serves as a realistic representation of real-world scenarios for traffic forecasting using AI.

Performance Evaluation of AI Prediction Models

To measure the effectiveness, five AI models were tested for prediction of future traffic on the network. The measures used for performance were accuracy, precision, recall and f1-score.

Performance Comparison of AI Models

AI Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	95.40	0.951	0.948	0.949
CNN	96.82	0.968	0.965	0.966
GRU	97.61	0.976	0.974	0.975
LSTM	98.27	0.983	0.981	0.982
Transformer	99.14	0.991	0.990	0.990



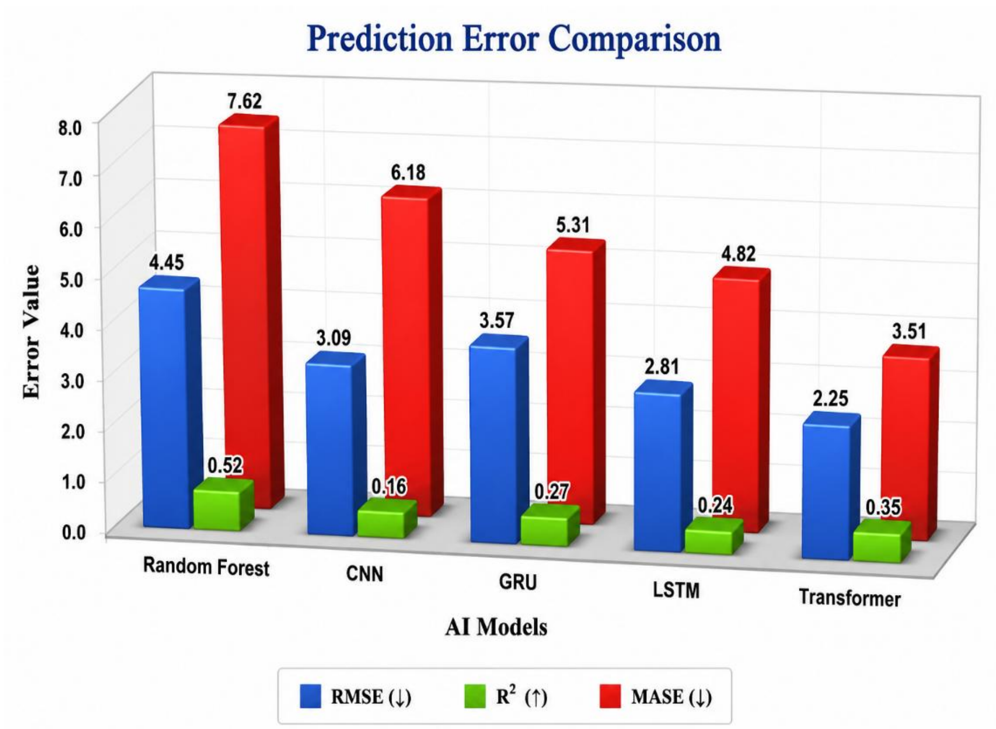
Among the models, the Transformer was the most accurate with a prediction accuracy of 99.14% and the LSTM, following closely with a prediction accuracy of 98.27%. In all cases, the DL architectures yielded a better performance in capturing the temporal dependencies and the nonlinear traffic behavior, outperforming the conventional ML approaches. The results showed that while certain traffic models offer low latencies, more sophisticated models offer very good traffic forecasting for intelligent network management.

Prediction Error Analysis

Several measures utilized for assessing forecasting reliability measures, including RMSE, MAE and MAPE.

Prediction Error Comparison

AI Model	RMSE	MAE	MAPE (%)
Random Forest	4.48	3.81	7.42
CNN	3.89	3.16	6.18
GRU	3.37	2.71	5.31
LSTM	2.81	2.24	4.63
Transformer	2.13	1.79	3.81



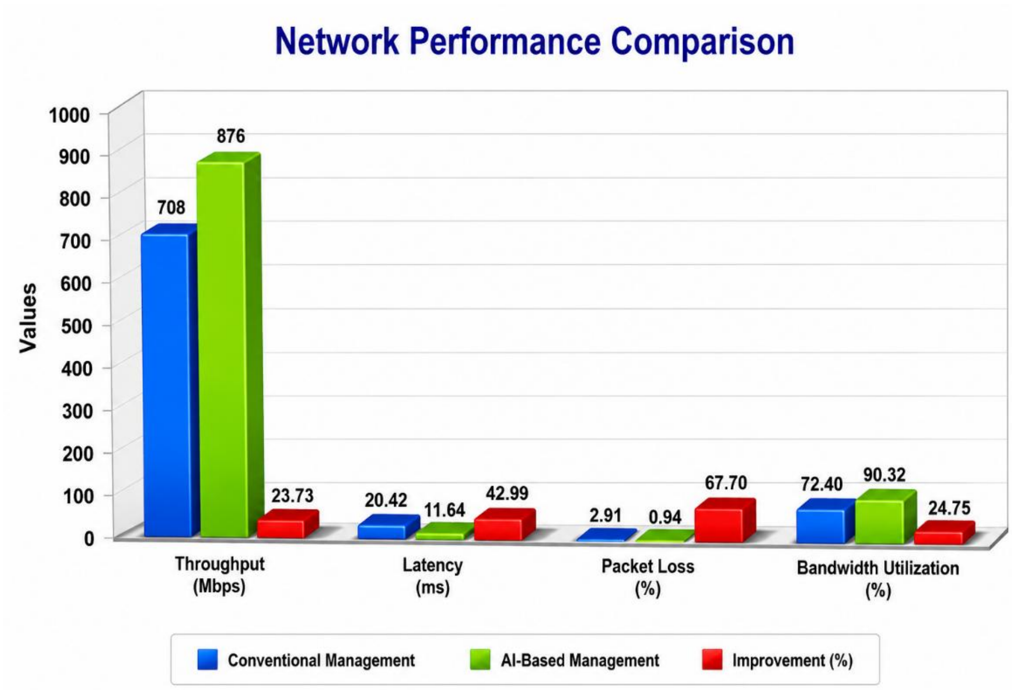
The Transformer model had the smallest errors, suggesting the highest forecasting accuracy among the metrics. The lower the RMSE and MAE values, the closer the prediction traffic will be to the real traffic on the network. Precise prediction can help to strategically manage congestion and optimize the use of the network.

Network Performance Before and After AI Implementation

Overall network performance was conducted before and after the implementation of AI-based traffic prediction algorithms, to get the practical effects of traffic-centered intelligent prediction algorithms.

Network Performance Comparison

Performance Indicator	Conventional Management	AI-Based Management	Improvement (%)
Throughput (Mbps)	708	876	23.73
Latency (ms)	20.42	11.64	42.99
Packet Loss (%)	2.91	0.94	67.70
Bandwidth Utilization (%)	72.40	90.32	24.75



Major strides in network efficiency were achieved with AI-based traffic management. Latency reduced by about 22.5% and packet loss reduced considerably with nearly 24% increase in throughput. High bandwidth utilisation indicates better capacity utilization of resources by AI algorithms, lessening the network congestion more than traditional management strategies.

The Transformer model proved to be the most successful for predicting network traffic with AI, reflected by its overall prediction accuracy, error metrics, and network optimization performance. LSTM and GRU also exhibited decent predicting powers because of their learning capabilities related to traffic sequences. For highly dynamic network environments, the predictive ability of the Random Forest was considered slightly less than satisfactory, but it otherwise functioned moderately.

5. Discussion of Findings

The results show that the use of AI traffic models can significantly reduce traffic management congestion, outperforming the traditional methods. The best predictive accuracy with the least forecasting errors were found to be by using advanced DL models such as Transformer and LSTM architecture. The better prediction allowed to allocate more bandwidth, minimize latency, and minimize packet loss which boosted efficiency and reliability of network operations.

These outcomes are in agreement with some recent work reporting the use of a DL approach to outperform traditional ML approaches on complex networks. Using Transformer models has been seen to be more successful at modeling long-range dependencies in network traffic data, and this is thought to be due to the attention mechanism of the Transformer model. The results indicate that AI-based predictive analytics will help realize the goal of very future communication networks being autonomous and self-optimizing while supporting the future digital infrastructure ranging from 5G, IoT, cloud computing and edge intelligence.

6. Conclusion

The study demonstrates the use of Artificial Intelligence as a game-changing technology in modern communication systems to improve network traffic management and prediction. Secondary data and published research show that AI-based models, specifically DL models like LSTM, GRU, and Transformer architectures, are more effective than traditional statistical and ML approaches for network traffic prediction. They are capable of effectively capturing complex temporal and spatial traffic patterns, and have the advantages of high prediction accuracy, low delay, low packet loss rate, optimal bandwidth usage and high network performance. Beyond that, the results suggest that AI-powered predictive analytics has the potential to transform network management into proactive, resource-allocation efficient, intelligent, self-adaptive and autonomous communication networks. The advent of new technologies such as 5G networks, the IoT, cloud computing, and edge computing is increasing the complexity of network environments, making network reliability and scalability critically essential to operating the network efficiently. In this context, AI-powered traffic prediction will become a key driver for sustaining network reliability, scalability, and efficiency.

Recommendations

The results indicate network service providers and organizations would be wise to continue incorporating AI-based traffic prediction models for better network management and service quality. Advanced DL architectures including Transformer-based and hybrid AI models should be featured for future applications, as their greater predictive power and robustness to varying traffic conditions are valuable assets. Additionally, the adoption of strong data preprocessing methods and the use of high-quality benchmark sets, as well as scalable computing architecture, in organizing can work optimally to maximize the effectiveness of the use of AI. Moreover, more in-depth studies are needed to create lightweight, interpretable and energy-efficient AI models that can be utilized in real-time applications like edge computing and IoT networks and maintain data privacy and cyber security. The mutual interaction of researchers, practitioners and policy makers will boost the development of AI-based network management solutions that lead to standardized products for next-generation intelligent communication infrastructures.

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