International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 12 Issue 10 ǁ October 2024 ǁ PP. 19-33

A review of Network Traffic Prediction using Deep Learning Models

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Abstract
Network traffic prediction has become a very important field of research due to the increase in the use of the internet. With an increase in technology, the Internet, and the Internet of Things, the number of network equipment, servers, and network traffic are seriously increasing. Accurate prediction of network traffic has become an important issue that needs to be attended to. Network traffic prediction is substantial for network optimization and resource management. Various deep-learning techniques have been proposed, used, and experimented with to predict network traffic. This paper reviews past research conducted on network traffic prediction models using deep learning models and deep learning models with machine learning and genetic models in Network Traffic Prediction. The research of various authors in deep learning for network prediction and their findings have been summarized in the table to give a clear purpose for each work. The analysis will be a pivot for further direction of future research in this domain.

Keywords: *Prediction, Network Traffic, Deep Learning, Network traffic, Prediction models.*

Date of Submission: 02-10-2024 Date of acceptance: 11-10-2024

I. INTRODUCTION

The rapid development of the Internet and the emergence of the diversification of network services have resulted in more complex behaviours in the flow of network traffic. The behavioural complexity of the network traffic requires a critical analysis to manage the network effectively to achieve a high-level quality of service (QoS). Several key issues arising from the network complexity comprises of poor optimization of the resource allocation for a network, poor QoS delivery, untimely quality packet distribution, unreliable free network traffic flow, and vulnerability in network security. Also, due to limited network resources, costly network infrastructure, and increasing user space, all the identified issues become adversely prominent on the network quality, making the network more challenging to manage. As a result, the need arises to efficiently analyze network traffic behaviour to obtain actionable insight into the influence of the traffic on a computer network to achieve an effective QoS.

Network traffic is the main component used to measure and control the usability of a computer network. A proper analysis of network traffic guarantees efficient network management Thus, designing a predictive model to analyse the flow of network traffic is essential [21]. The predictability of network traffic parameters is influenced by their statistical characteristics and strong chronological correlations. The introduction underscores the complex nature of network traffic, characterized by self-similarity, multiscalarity, long-range dependence, and nonlinearity, which traditional models like Poisson and Gaussian fail to adequately capture. Accurate network traffic prediction not only aids in resource optimization but also plays a vital role in detecting malicious attacks within the network. By comparing real-time traffic with predicted traffic, providers can identify and mitigate issues like denial of service or spam attacks promptly. Early detection of such problems leads to more reliable network services. Network traffic prediction involves forecasting future network traffic characteristics based on past observations.

The prediction of network traffic behaviour has a variety of applications, including network monitoring, resource management, and threat detection. The benefit of getting accurate predictions for network traffic is significant to effectively distribute network services to intended devices, users, and locations with a focus on optimal QoS [22]. Also, the prediction of the behaviour of network traffic helps in the provision, planning, and scheduling of the usability of network bandwidth, resource allocation, detection of anomalies, congestion analysis, QoS automation, and network [3]. Effective and accurate prediction of network traffic behaviour has a vital influence on network performance evaluation, congestion control, admission control, network bandwidth allocation, large-scale network planning design, and the reduction of the complexity of the network.

Network traffic prediction involves forecasting future network behavior based on historical data, providing valuable insights for network management and resource optimization. Traditional methods, such as time series analysis and statistical modeling, have been foundational in this domain. Recent advancements, however, showcase a shift towards machine learning and deep learning techniques for more accurate and dynamic predictions.

Deep learning is a machine learning technique that is inspired by the way a human brain filters information from past information [13]. Deep Learning helps a computer model filter input data through layers to predict and classify information. Since deep learning processes information similarly to a human brain, it is mostly used in applications that people generally do**.**

For instance, deep learning is the key technology behind driverless cars that enables the cars to recognize a stop sign and to distinguish between a pedestrian and a lamp post. Most deep learning methods use neural network architectures, often referred to as deep neural networks. A neural network takes in inputs, which are then processed in hidden layers using weights that are adjusted during training. Then the model predicts a target value. The weights are adjusted to find patterns to make better predictions. The user does not need to specify what patterns to look for because the neural network self-learns the patterns automatically [13].

The rest of this work is organised as follows Sections 2 and 3 review deep learning models and multiple models. The review of deep learning models with optimazation is done in section 4 while section 5 dealt with conclusion.

II. LITERATURE REVIEW

2.1 Review on Deep learning Models

In recent years, many deep learning-based network traffic prediction models have been proposed. Deep learning has emerged as a powerful paradigm for capturing complex patterns and representations within data. In the context of network traffic prediction, deep learning models, including Long Short-Term Memory (LSTM), Restricted Boltzmann Machine (RBMs), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GAN), Deep Belief Networks (DBN), Radial Basis Function Network (RBFN). Multiplayer Perceptrons. (MLP) etc. have demonstrated significant capabilities. Below are various deep-learning models used in network traffic prediction.

As proposed in [2], an analysis of aggregated network traffic for various aggregation levels and short time scales, and the use of a state-of-the-art deep-learning model for time-series predictions, namely Long Short-Term Memory (LSTM), the authors emphasize the critical role of link-level network traffic predictions at short time scales in various network management tasks. These tasks include traffic engineering, anomaly detection, failure recovery, performance diagnostics, load balancing, and Traffic Matrix (TM) estimation. By predicting link throughputs accurately, network operators can proactively address congestion events, prevent packet losses, and optimize network performance without delays typically associated with routing protocol reactions. The authors introduce a framework for network-wide link-level traffic prediction using LSTM neural networks. This framework utilizes link statistics that can be collected either by an SDN controller or through SNMP measurements in legacy networks to predict future link throughputs accurately, they presented several variations of LSTM that can effectively model backbone network traffic at the link level and for various time-epochs and compared with several ARIMA baseline models. The results obtained look very promising and validate the hypothesis that LSTM is a good candidate for link-level network traffic modeling.

The research as presented in [17] proposed a network traffic prediction model based on wavelet transformation and LSTM network which presents a novel approach to predicting network traffic by combining wavelet transformation and LSTM network. The model begins with the application of wavelet transformation to decompose the original network traffic data into an approximation sequence and several detail sequences. This decomposition allows for capturing both the trend and detailed information at different scales within the traffic data. The approximation sequence, which contains the trend and cyclical features of the traffic data, is used to train the Long Short-Term Memory (LSTM) network. The proposed model, which combines wavelet transformation and LSTM network, demonstrates superior prediction performance compared to other models constructed with LSSVM, BP neural network, and Elman neural network. The model's ability to accurately predict network traffic including capturing peak values and burst traffic events is emphasized.

A university network traffic prediction using the deep neural network was presented in [15]. A backpropagation algorithm was used to train the deep neural network. The model compares network performance before and after implementing deep learning, emphasizing the potential improvement in data transfer speed. It introduces deep learning concepts, training methods, and phases involved in familiarizing the system with the network. The study collects network traffic data from the university for different days (Monday in this case) and creates a dataset representing network traffic at 30-minute intervals between 10:00 am and 5:00 pm. The data includes maximum and minimum network traffic values for each time slot. The model go through the training phase, testing phase, and prediction phase to familiarize it with the current network system. The performance of the backpropagation training algorithm has been evaluated on training and testing data sets. It was found that the proposed backpropagation algorithm is capable of generating promising results. The proposed deep neural network, when trained by the proposed backpropagation algorithm, generated a higher percentage accuracy on training data sets and 90% accuracy on testing data sets. Also, errors were minimized as the number of epochs increased. The use of this deep learning method provides a new way of thinking for simulating and predicting the university network traffic and also provides a reference for the planning of university network traffic.

As the demand for data services grows rapidly, efficient resource allocation becomes crucial to meet user needs. However, the dynamic nature of the environment and the inherent time delays in resource allocation based on current information pose challenges in meeting immediate resource demands. With the motivation to solve the above [27] proposed a deep learning-based traffic flow prediction model. The system model considered in the study consists of a microcell serving K users in a cellular network. The focus is on uplink traffic flow data collected at regular time slots, with each slot comprising n minutes, and employs a Long Short-Term Memory (LSTM) network for traffic flow prediction in cellular networks. The LSTM network is designed to consider temporal correlations and nonlinear characteristics inherent in cellular network traffic data. T consecutive traffic flow data points re used as input to predict the traffic flow at the next time slot. Backpropagation Through Time (BPTT) is utilized to train the LSTM network using the collected traffic flow data. The performance of the LSTM network is evaluated using mean square error (MSE) and mean absolute error (MAE) metrics to assess the accuracy of traffic flow prediction. The performance of the proposed LSTM network is compared to a stacked autoencoder network based algorithm. The simulation results showed that the proposed LSTM network gains significant performance. From a practical aspect, with the real-time traffic flow as inputs, the output of the LSTM network will benefit greatly in resource allocation for the service provider.

[1] presented A Long Short-Term Memory Recurrent Neural Network Framework for Network Traffic Matrix Prediction which provides valuable insights into the application of LSTM RNNs for predicting Traffic Matrix in network scenarios. The author highlights the importance of accurately estimating network traffic parameters for effective network management and decision-making. The study utilizes a deep LSTM architecture combined with deep learning techniques to extract dynamic features of network traffic and predict future Traffic Matrix. The deep LSTM architecture is designed to capture the mutual dependencies among traffic entries across various time slots. To effectively feed the LSTM RNN, each Traffic Matrix is transformed into a vector by concatenating its rows. This vector, known as the traffic vector (TV), is used as input to the LSTM model for prediction. The training involves model using historical traffic data sets to learn the patterns and dependencies in the data. The model is then tested on new input data to predict future Traffic Matrix values. The training phase involves backpropagation to adjust model parameters for better prediction accuracy. The proposed LSTM RNN framework is evaluated using real-world data from the GEANT network to assess its performance in predicting Traffic Matrix. The study concludes that LSTM RNN architectures are well-suited for traffic matrix prediction tasks due to their ability to capture long-range dependencies and model temporal sequences accurately. LSTM networks outperform traditional linear prediction models and feed-forward neural networks in capturing complex traffic patterns.

[22] proposed a wireless network traffic deep learning prediction framework LA-ResNet based on an attention mechanism, which can extract time features and spatial features from traffic data and obtain accurate prediction results. In LA-ResNet, the residual network is first used to extract the characteristics of wireless network data from a spatial perspective. In this module, the residual network of the multi-layer stack has a strong representation ability, which ensures that the original information of historical data is not lost while extracting spatial correlation. Subsequently, the data processed by the residual network is input into the RNN, and the temporal information is captured by its powerful time-series processing capability with the memory unit.

At the same time, an attention module connects the various intermediate output units of the temporal information processing module. The accuracy and stability of prediction are improved by the attention module from two aspects. First, the problem of limited memory capacity due to long sequence input RNN is solved by connecting the intermediate output. Second, the weight of the prediction data can be selected based on the predicted correlation. The addition of the attention mechanism allows focus to be placed on the intermediate output, which makes the residual network module and the RNN module closely linked.

[32] proposed A Network Traffic Prediction Method Based on LSTM which highlights the increasing importance of Transmission Control Protocol/Internet Protocol (TCP/IP) networks in modern society. This proposed model addresses the challenge of accurately predicting network traffic, crucial for optimizing network resources and enhancing service quality. Traditional models struggle to predict the nonlinear behavior of network traffic, prompting the exploration of LSTM neural networks for improved prediction accuracy. The model utilizes real-world network traffic data sets from various sources, including network service providers in European cities, educational networks in the UK, and data from the backbone node of China's education network. The data is collected at different intervals, ranging from 30 seconds to 1 minute, to capture diverse network traffic patterns. To enhance prediction accuracy, the model incorporates autocorrelation coefficients. By considering the autocorrelation characteristics of the network traffic data. The training and testing of the prediction model involve dividing the data set into training and testing sets. The first two-thirds of the data set are used for training, while the remaining one-third is used to evaluate the model's accuracy. The proposed LSTM model shows promise for real-world applications in network traffic prediction. The model's ability to handle nonlinear network behavior and consider autocorrelation features makes it a valuable tool for network service providers to optimize resources and enhance service quality. The conclusion suggests exploring different variations of recurrent neural networks (RNNs) beyond LSTM, such as Gated Recurrent Unit (GRU), to further improve prediction accuracy. By combining the characteristics of network traffic data with advanced RNN structures, there is potential for enhancing prediction models in the future.

[29] proposed Deep Learning-Based Traffic Prediction for Network Optimization which highlights the increasing importance of telecommunications networks and the significance of accurately predicting network behavior for the management and provisioning of mobile and fixed network services. The study utilized a dataset of traffic matrices from the Abilene network, a backbone network created by the Internet2 Community. The dataset was processed to represent each traffic matrix as a vector, with each element indicating the traffic value between specified nodes. This manipulation resulted in a dataset with a large number of samples (48096) and columns (144), enabling the creation of an effective prediction algorithm. The processed dataset was input into the proposed prediction system, which consists of two main sections: a classical Artificial Neural Network (ANN) based on GRUs and an Evaluation Automatic Module (EAM). The GRU RNNs were employed for sequence prediction, and the EAM automated the learning process and enhanced the prediction model's performance. The dataset was divided into three sets: training (60%), validation (10%), and testing (30%). The training set was used to train the prediction model, while the validation set helped in tuning hyperparameters and optimizing the model. The testing set was utilized to evaluate the performance of the trained model. The system achieved promising results in terms of prediction accuracy and resource allocation efficiency. The deep learning model, particularly the GRU RNNs, showed great accuracy in predicting traffic matrices, enabling proactive resource allocation and optimization. The deep learning model, particularly the GRU RNN, demonstrates high accuracy in predicting traffic matrices, with a mean absolute error of less than 7.4.

[3] focused on the prediction of diverse types of traffic present in an application-aware backbone optical network. In particular, they addressed a short-term traffic prediction problem using a regression approach based on the MLP, which can forecast traffic of a specific type based on historical data. Compared the proposed model to a baseline LR algorithm. Both models were tested with three different traffic types, representing various application classes present in a network. The proposed MLP model is a regressor based on a simple neural network. Its performance was evaluated for eight different network architectures. The proposed method revealed high prediction quality, achieving the mean absolute percentage errors between 2% and 10%, depending on the traffic type. The proposed neural networks outperform the baseline regression model in all considered types of traffic.

Table 1: Summary of the model above.

Year	Author	Model (s)	Purpose	Evaluation Metrics
2017	Abdelhadi. and Guy.	LSTM	The primary objective is to demonstrate the suitability of LSTM RNN architectures for traffic matrix prediction tasks. The objective is to achieve higher prediction accuracy compared to traditional linear models and feed-forward neural networks.	MSE
2018	Lu and Yang	wavelet transformation and LSTM	This model aims to accurately predict network traffic by decomposing the original traffic into approximation and detail sequences using wavelet transformation, and then utilizing LSTM network to learn the change trend and extract burst information at multiscale for future traffic prediction.	MAE, RMSE and MAPE
2018	Sebastian et al.	GRU	To design a predictive model of traffic matrices that allow proactively optimization of resource allocations of optical backbone networks.	MAE
2019	Aggelos and Viktor	LSTM	The research aims to evaluate LSTM models for predicting link throughputs accurately in network management tasks such as traffic engineering and anomaly detection.	MAPE
2019	Jihoon	Back-propagation	To improve the speed of network connection.	Accuracy
2019	Shulin and Wei	LSTM	The primary objective of the study is to improve the accuracy and efficiency of traffic flow prediction in cellular networks by leveraging the capabilities of LSTM networks. The focus is on capturing temporal correlations and nonlinear characteristics inherent in the traffic data.	MAE and MSE
2019	Wang et al.	LSTM	To improve the accuracy of the prediction model.	MAPE
2020	Li et al.	LA-ResNet	To accurately predict wireless network traffic.	RMSE and MA
2022	Agnieszka et al	MLP	The objective of this work is to find a versatile network traffic prediction model for a short-term estimation of diverse traffic types given historical data.	MAPE

2.2 Reviews on Multiple models

The hybrid models are combination of two or more models for network traffic prediction. The hybrid models achieved good results in the prediction of network traffic prediction. Most researchers prefer to use hybrid models for the prediction of network traffic. The following are the types of deep learning hybrid network prediction, either within deep learning models or deep learning models with other models that are not deep learning.

[26] presented a novel method for predicting statistical characteristics of data traffic inflow at the edge devices of the cloud-native-enabled network using a deep learning (DL) method. Namely, long short-term memory (LSTM) - based encoder-decoder deep learning. For this research, the data collected was from the time series raw traffic flow data at the edge of the network, which is sent to the visibility center for storage and processing, they orchestrated the Kubeflow deployment using K8s master at the orchestration center to train the LSTM-based seq2seq DL model on the collected TS data. They predicted various features of data traffic based on past observations into the future horizon window of 10 hours. They evaluated the predicted future observations with ground truth observation in terms of root-mean-square error (RMSE) and coefficient of determination (R2) metrics. Results showed that the model accurately predicts the future observations of all features.

[14] proposed a Network Traffic Prediction Model called NTAM-LSTM, which is based on an Attention Mechanism with Long and Short Time Memory. The NTAM-LSTM model is introduced as a solution to enhance prediction accuracy and reduce processing time in network traffic prediction. By incorporating an attention mechanism into the traditional LSTM model, the NTAM-LSTM model can better capture the influences of different characteristic values on target values. The NTAM-LSTM system consists of four layers: data processing, LSTM, attention mechanism, and data output. Firstly, the model preprocesses the historical dataset of network traffic with multiple characteristics. Then the LSTM network is used to make an initial prediction for the processed dataset. Finally, the attention mechanism is introduced to get more accurate prediction results, to improve the model, which solves the problem of inaccurate prediction results caused by the

traditional LSTM model setting up the same length for different characteristic values. The simulation experiment shows that compared with the traditional LSTM model, GRU model, and TCN model, the NTAM-LSTM model outperforms traditional LSTM, GRU, and TCN models in terms of prediction accuracy and processing time. Experimental results demonstrate that the NTAM-LSTM model achieves higher prediction accuracy and shorter running time, making it a superior choice for network traffic prediction.

[33] proposed a network traffic prediction method based on LSTM neural network and transfer learning. The method uses the idea of transfer learning to save the knowledge acquired during the execution of the source task in the source domain. When the knowledge in the target domain is insufficient to complete the target task, the saved knowledge is applied to complete the target task. The specific implementation is to transfer the parameters in the network traffic prediction model with sufficient source domain data training to the network traffic prediction model without sufficient target domain data training and then train with less target domain data, and finally get the network traffic prediction model with more accurate prediction. The proposed model when compared with other models shows that it proposed model leads to the performance improvement of the network traffic prediction task.

[35] investigated the problem of end-to-end network traffic prediction in the IoV backbone network. Aiming at minimizing the prediction error and improving the real-time performance of network traffic prediction, by designing a deep architecture based on CNN and LSTM, The hybrid deep architecture designed is to predict the network traffic of secure IoVs utilizing extracting two features, i.e., the spatiotemporal and temporal features. To improve the real-time performance of the proposed method, a threshold-based mechanism is proposed to update the deep architecture discretely. A Reinforcement Learning (RL) algorithm is proposed to determine the threshold. The designed scheme was evaluated by a real network traffic data set sampled from the Abilene network and the constructed testbed which is leveraged to imitate the scene of a secure IoV. According to the evaluation, the proposed method can capture the long-term network traffic in secure IoVs and can track the trace of end-to-end network traffic precisely.

Aiming at the problem of network traffic with autocorrelation [25], proposed a model of neural network which can be used to combine Long Short Term Memory networks (LSTM) with Deep Neural Networks (DNN). The autocorrelation coefficient is added to the model to improve the accuracy of the prediction model. Use of a reality data set collected at home and abroad, the experimental results show that LSTM can used as a timing sequence forecast model well. It can provide better than the other traditional precision of the model and after considering the autocorrelation features, the neural network of LSTM and DNN has certain advantages in the accuracy of the large granularity data sets. Several experiments were held using real-world data to show the effectiveness of LSTM model and accuracy was improved with autocorrelation considered.

[34] proposed a model that focuses on the application of an integrated neural computing model in network traffic prediction, namely enhanced echo-state restricted Boltzmann machine (eERBM). The eERBM model integrates features of feature learning, information compensation, input superposition, and supervised nonlinear approximation. It combines the echo state network and restricted Boltzmann machine in a hybrid architecture, leveraging information theory to enhance predictive capabilities. The training mechanism of the eERBM model involves a three-stage regression process, encompassing RBM-learning, input superposition, and reservoir projecting. The model is trained in a supervised manner to optimize the reservoir network for accurate prediction. The reservoir computing component of the model includes functional elements such as reservoir input, cycle reservoir, and output layer. The reservoir update mode and network readout are defined by specific equations to capture the dynamics of network traffic data. The study evaluates the performance of the eERBM model in predicting network traffic, comparing it with other extended echo state network paradigms. Results show that the eERBM model outperforms the comparative models in terms of nonlinear approximation and robustness for predicting TCP/IP packets and VBR video traces.

Network Traffic Prediction using Quantile Regression with linear, Tree, and Deep Learning Models presented by [4] discusses the advancements in machine learning and deep learning and the significance of prediction in various fields, particularly in the context of network traffic analysis and forecasting. The model evaluates linear models, decision trees, and neural network models for their effectiveness in predicting network traffic. The research employs a quantile loss function to six models, two linear, two decision trees, and two neural networks models, (The prediction models used are: Linear Quantile Regression (LQR), Ordinary Least Squares (OLS), Random Forests (RF), Gradient Tree Boosting(GTB), Feedforward Neural Network (FNN), Long Short-Term Memory (LSTM)), to predict boundaries or prediction intervals, emphasizing the importance of interval prediction over point value prediction. Two data sets are used for the study, one from GEANTand another collected at the University of Victoria, both consisting of 15-minute bandwidth usage data at a gateway router. The data sets are cleaned to remove outliers and normalized to the same scaling for consistency. The performance of the prediction models is assessed based on quantile loss, the percentage of values captured inside the prediction interval, and a metric combining loss and captured percentage. Results show that linear models fared well compared to their simplicity while Long Short-Term Memory Neural Networks gave best results across all experiments.

A hybrid model for network traffic prediction is proposed by[28] , namely Convolution Neural Network and Long Short-Term Memory (Convo-LSTM) for the wireless mesh networks formed by various sensors, with the HSD pump as a case study. A novel Convo-LSTM architecture is proposed for the wireless mesh network's traffic prediction, citing a case study of the HSD pump. A Vibration forecasting model based on one dimensional (1-D) CNN-LSTM is built considering the properties of CNN and LSTM. The data tuples are collected over one year's period, with constant monitoring of the network, which is a real world data. The fundamental structure of the model is a hybrid or mixing of one dimensional (1-D) Convolution neural network and Long Short Term (LSTM). It has an input layer, one-dimensional convolution layer, pooling layer, LSTM hidden layer, and full connection layer in its architecture. The system was evaluated on five different intervals: hourly, daily, weekly, monthly, and yearly and it is found the Convo-LSTM algorithm to be the best performing one among the six different algorithms that were compared with: decision tree regressor, linear regression, multi-layer perceptron, Poisson regression, ARIMA, and LSTM.

[10] proposed a hybrid deep learning method for network traffic prediction, CEEMDAN-TGA which consists of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Temporal Convolutional Network (TCN), Gated Recurrent Unit (GRU), and Attention Mechanism. Which combines CEEMDAN, TCN, GRU and attention mechanism. CEEMDAN-TGA provides an overview of the importance of accurate network traffic prediction for self-management, intelligent scheduling, and network resource optimization of base stations. The accurate prediction of network traffic trends is crucial for improving network utilization and energy efficiency in scheduling strategies. CEEMDAN decompose the original network traffic data into different modes. The decomposed modes are then reconstructed into trend sequence and noise sequence, effectively denoising the data and improving prediction accuracy. TCN is utilized to extract short-term local features in the network traffic data. TCN is effective in capturing local burst changes in the traffic sequence, making it sensitive to short-term local features. GRU is employed to capture long-term data-dependent features in the network traffic sequence. The attention mechanism is introduced to adjust the hidden state weights and reduce information loss rate. Experiments on real datasets demonstrate the superior performance of CEEMDAN-TGA compared to common baseline methods, validating its accuracy and robustness in network traffic prediction tasks.

A spatial-temporal parallel prediction model based on graph convolution combined with long and short-term memory networks (STP-GLN) based on two deep-learning algorithms to predict cellular network traffic is proposed by [13] sets the stage by highlighting the increasing demand for cellular networks and the importance of accurate traffic prediction in optimizing network resources and enhancing user experience. Traditional prediction methods are noted to struggle with the complex spatiotemporal relationships present in modern cellular networks, leading to the adoption of deep learning-based approaches. The proposed model Utilizes Graph Convolution Neural Networks (GCN) to learn spatial characteristics of the cellular network graph data. Constructs dynamic graph data based on spatial distance and spatial correlation between cells. Incorporates the calculation of the Pearson correlation coefficient to represent spatial correlations. Then utilizes Long Short-Term Memory (LSTM) networks to learn temporal characteristics of three types of time series data: hourly sequence, daily sequence, and weekly sequence. Integrates the spatial and temporal modules to consider both spatial and temporal characteristics simultaneously. Constructs adjacency matrices for the spatial module based on spatial distance and Pearson correlation coefficients. Fuses the results learned from the spatial and temporal modules with different weights to obtain the final prediction results. Combines the spatial and temporal information to make accurate predictions of cellular network traffic. The proposed algorithm is evaluated through simulation experiments using real datasets and compared against other models, demonstrates superior performance in predicting cellular network traffic. The model outperforms existing methods in capturing spatial-temporal characteristics effectively, leading to more accurate predictions.

Predicting future trends in network parameters, routers, and devices is essential for network service providers to address the variability in network traffic. To tackle this challenge, [31] proposed Applying Deep Learning Approaches for Network Traffic Prediction. The study explores different RNN architectures, including simple RNN, long short-term memory (LSTM), gated recurrent unit (GRU), and identity recurrent unit (IRNN).

These RNN architectures are chosen for their ability to learn temporal patterns and long-range dependencies in large sequences of network traffic data. The research involves conducting experiments using real data from GEANT backbone networks to evaluate the performance of different RNN architectures. Various experiments are run with learning rates ranging from 0.01 to 0.5, and the models are trained for up to 200 epochs. LSTM outperforms other RNN architectures and classical methods in predicting network traffic patterns. GRU exhibits lower computational costs compared to LSTM while maintaining competitive performance. Overall, the proposed method has achieved the best performance by accurately predicting the traffic matrix.

[5] critically evaluates the use of artificial neural networks as network traffic predictors. He evaluate the state-of-the-art of network traffic prediction by assessing the existing research on artificial neural etwork (ANN) models for network traffic prediction. Network traffic data from the South African National Research and Education Network (SANReN) is collected for analysis. SANReN serves as the dataset for training and testing the ANN models. The research evaluates different ANN models, including Multi-layer Perceptron (MLP), Long Short-term Memory (LSTM), and Stacked Auto-encoder (SAE), against traditional statistical models like Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and Holt-Winters Forecasting models. Before inputting data into the ANN models, pre-processing steps are applied. This includes data engineering and feature engineering to prepare the data for better accuracy in prediction. Techniques such as Discrete Wavelet Transformation (DWT) may be used for data transformation. The selected ANN models are trained on the SANReN dataset and evaluated based on their performance in predicting network traffic patterns. The LSTM architecture is highlighted as the best performing neural network for network traffic prediction, considering its ability to capture long-term dependencies and unusual temporal patterns.

[16] derived a Deep Learning Based Traffic Prediction Method for Digital Twin Network. The proposed linear feature enhanced ConvLSTM model, integrated with traffic pattern attention (TPA) and squeeze & excitation (SE) blocks, aims to improve the accuracy of traffic prediction compared to baseline models. The method went through theses stages: *Data Preprocessing, Traffic Matrix Simplification, Traffic Matrix Normalization, Model Definition and Model Training* & *Testing* This linear feature simplifies the format of LAN traffic matrix by considering some unique features of LAN, which can effectively decrease the size of dataset and accelerate model learning speed. The proposed model was comparatively evaluated with five baseline models. Experimental results showed that the eConvLSTM model significantly outperforms the others in terms of prediction accuracy. And the study makes significant contributions to the field of network traffic prediction by proposing an innovative model that integrates an autoregressive unit and additional enhancements like traffic pattern attention (TPA) and squeeze & excitation (SE) blocks to improve prediction accuracy and efficiency. Comparative experiments demonstrate the superiority of the proposed eConvLSTM model over baseline models, showcasing its ability to reduce mean square error (MSE) for both one-hop and multi-hop predictions while meeting efficiency requirements.

[24] proposed several Recurrent Neural Network (RNN) architectures (the standard RNN, Long Short Term Memory (LSTM) networks, and Gated Recurrent Units (GRU)). They analyze the performance of these models on three important problems in network traffic prediction: volume prediction, packet protocol prediction, and packet distribution prediction. They achieved state of the art results on the volume prediction problem on public datasets such as the GEANT and Abilene networks. They also believe this is the first work in the domain of protocol prediction and packet distribution prediction using RNN architecture. From their extensive testing on several datasets, it show that the standard RNN, LSTM, and GRU outperform other standard forecasting models, while also predicting future traffic efficiently. It demonstrate the feasibility of RNN models in modelling complex and nonlinear time-series data within the network traffic prediction domain. These predictive models have the potential to help in various applications, including network traffic load management, network monitoring, and cybersecurity.

A network traffic prediction method combining GCN, GRU, and attention mechanism was proposed by [19] the method uses GCN to capture the spatial features of traffic, GRU to capture the temporal features of traffic, and attention mechanism to capture the importance of different temporal features, so as to realize the comprehensive consideration of the spatial-temporal correlation of network traffic. The attention mechanism is introduced into the GRU, and the weight matrix calculation method in the GRU unit is redesigned. In this mechanism, the state vector is generated by combining the hidden states at different times, a scoring function is designed to calculate the weight of each hidden state, and an attention function is designed to calculate the context vector that can describe the global traffic change information, so as to adjust the importance of different time points and collect the global time information to improve the prediction accuracy. The AGG model is trained on the Milan traffic network dataset for many times. The results show that compared with several existing baseline models such as HA, ARIMA, SVR, GRU, and GCN-GRU, the AGG model has the best performance and has the ability of long term prediction. And the model achieves better results in terms of root mean square error (RMSE), mean absolute error (MAE), accuracy (ACC), determination coefficient (R^2), and explained variance score (EVS).

[11] proposes a network traffic prediction model based on neural network. Firstly, they studied the decomposition problem of the network traffic signal based on wavelet transformation, in order to achieve accurate representation of the characteristics of the network traffic signal data; using stretching and translating of wavelet transformation to achieve multi-scale refinement of traffic signals. Secondly, Gated Recurrent Unit (GRU) and RNN model is introduced into the prediction and analysis of network traffic signals, which has the ability to accurately fit nonlinear and multi-dimensional functions. The analytical results are verified by numerical computation and simulations. It is shown that the network traffic prediction result of the model is close to the actual value of the network traffic in the real environment.

[6] proposed a novel approach named ST-LSTM that combines the power of the Savitzky–Golay (SG) filter, temporal convolutional network (TCN), and long short-term memory (LSTM) for accurate and real-time prediction of network traffic. The ST-LSTM method combines the SG filter for noise removal, TCN for extracting short-term features, and LSTM for capturing long-term dependencies in a three-phase end-to-end methodology. The first phase involves applying the (SG) filter to the raw data to eliminate noise and enhance the quality of the data for prediction purposes. This step aims to preprocess the data by smoothing out fluctuations and reducing interference for more accurate predictions. After noise reduction, the TCN is utilized to extract short-term local features from the preprocessed data. TCN is effective in capturing immediate patterns and dependencies in the sequences, providing insights into short-term fluctuations in the network traffic. The final phase of the methodology involves leveraging the Long Short-Term Memory (LSTM) network to capture the long-term dependencies present in the data. LSTM is well-suited for modeling sequences with long-range dependencies, enabling the model to learn from historical patterns and make predictions based on long-term trends. The experimental results highlighted the superior predictive capabilities of the ST-LSTM method in comparison to existing models, showcasing its potential for accurate and real-time prediction of network traffic in diverse industrial applications.

[20] proposed a network traffic prediction method based on the deep belief network (DBN) and the Spatiotemporal Compressive Sensing (STCS) method, named Deep Belief Network and Spatiotemporal Compressive Sensing (DBNSTCS) models. The proposed prediction method combines the strengths of DBN and spatiotemporal compressive sensing to provide a comprehensive approach for network traffic prediction in wireless mesh backbone networks. The network traffic data is preprocessed using the discrete wavelet transform (DWT) to divide it into two components: the long-range dependence component and the fluctuation component represented by low-pass and high-pass components, respectively. The proposed method first adopts discrete wavelet transform to extract the low-pass component of network traffic that describes the long-range dependence of itself. Then, a prediction model is built by learning a deep architecture based on the deep belief network from the extracted low-pass component. Otherwise, the high-pass component of network traffic, which represents gusty and irregular fluctuations, is predicted using the Sparsity Regularized Matrix Factorization (SRMF) method. This method captures the spatiotemporal characteristics of the high-pass component to improve prediction accuracy. The research demonstrates that the proposed method outperforms three existing prediction methods in terms of prediction accuracy, particularly in capturing irregular fluctuations in network traffic. The hierarchical approach combining DBN and spatiotemporal compressive sensing shows significant improvements in prediction error, especially in capturing the irregular fluctuations of network traffic.

[30] analysed four prediction methods that are based on ANN: (a) Multilayer perceptron (MLP) using the backpropagation as training algorithm; (b) MLP with resilient backpropagation (Rprop); (c) recurrent neural network (RNN); (d) deep learning stacked autoencoder (SAE). Evaluations were made comparing multilayer perceptron (MLP), recurrent neural network (RNN) and stacked autoencoder (SAE). MLP is a feed-forward neural network with multiple layers that uses a supervised training. SAE is a deep learning neural network that uses a greedy algorithm for unsupervised training. For the MLP, two different training algorithms were compared, the standard backpropagation and the resilient backpropagation (Rprop). The computer network traffic is sampled from the traffic of the network devices that are connected to the internet. It is shown herein how a simpler neural network model, such as the RNN and MLP, can work even better than a more complex model, such as the SAE. In theory, of all ANN studied in this work, the best prediction method would be the RNN, since it is the one that uses previous observations as feedback in the learning of newer observations, facilitating the learning of temporal and sequential data. Accordingly, the carried out experiments shown that the

best results in both, accuracy and computation time, were obtained with the JNN, an SRN. Therefore, of all used methods, the best prediction method for short-term or real-time prediction is the RNN with Rprop as training algorithm

[7] proposed a Generative Adversarial Network (GAN) architecture a novel approach to network traffic prediction in 5G networks. The model introduces a Generative Adversarial Network (GAN) architecture that leverages spatiotemporal features in network traffic data for predicting future traffic. By incorporating a Convolutional Long Short-Term Memory (ConvLSTM) model within the generator of the GAN, the proposed model aims to improve prediction accuracy and adaptability to dynamic network conditions. The dataset used in the study, named CAIDA2019, consists of .pcap files containing payload-based anonymous traffic captured by the Applied Internet Data Analysis (CAIDA) center. The raw data is preprocessed by calculating the number of packets in 1 second to a pixel value using a specific formula before converting them into images by time steps. The proposed model integrates a Generative Adversarial Network (GAN) with a Convolutional Long Short-Term Memory (ConvLSTM) model within the generator of the GAN. The GAN consists of a generator that creates fake data resembling real data and a discriminator that differentiates between real and fake data. The ConvLSTM model combines the features of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to handle spatial and temporal aspects of data. The training of the proposed model exploits feature matching to stabilize the GAN learning process with a higher convergence rate. Feature matching allows the model to learn better and achieve improved performance in predicting future network traffic. Based on experimental results using network traces, the model significantly outperforms the baseline, reducing prediction error by 12% while forecasting network traffic for the next 1 minute. These findings represent a significant advancement in proactive network management, particularly in addressing the challenges posed by real-time streaming and other latency-sensitive applications in 5G networks.

Table 2: Summary of the model above.

Year	**Author**	**Model (s)**	**Purpose**	**Evaluation Metrics**
2015	Xiaochuan et al.	eERBM	To investigate the suitability of eERBM in support of network traffic prediction.	NRMSE
2016	Tiago et al.	MLP-BP, MLP-RP, RNN and SAE	To improve the prediction accuracy of a network.	*NRMSE*
2017	Antony.	MLP, LSTM, and SAE	To critically evaluate an ANN that best supports network traffic prediction on the South African National Research Network (SANReN).	Literature review.
2017	Vinayakumar et al.	FFN, RNN, LSTM, GRU and IRNN	To evaluate the effectiveness of various RNN architectures, including LSTM, GRU, and IRNN, in predicting network traffic matrices. The research aims to identify optimal network parameters and structures for accurate traffic prediction. .	MSE
2018	Shah et al.	(LSTM)- based encoder-decoder	To analysing and predicting network data traffic.	RMSE and R^2
2018	Zhuo et al.	LSTM-DNN	To improve the prediction accuracy of a network.	MAPE
2018	Nipun and Tarun	RNN, LSTM, and GRU	To solve the protocol classification problem.	MSE
2018	Laisen et al.	DBNSTCS	The objective is to take into account the spatiotemporal characteristics of network traffic in wireless mesh backbone networks. By utilizing spatiotemporal compressive sensing, the research aims to capture the complex interactions and irregular fluctuations in network traffic data, which are crucial for accurate prediction and network optimization.	SRE and TRE
2019	Fan et al.	RNN and GRU	To achieve accurate network prediction.	MSE, NMSE, and MARE
2020	wang et al.	CNN and LSTM	To minimizing the prediction error and improving real-time performance of network traffic prediction.	SRE and TRE
2020	smita et al.	Convo-LSTM	To accurately Predict network traffic.	MAE, MSE and RMSE

2020	Wan *et al*.	LSTM and transfer learning	To be able to improve overall network performance and increase network utilization.	RMSE
2020	Ahmed and Ganti	LQR, OLS, RF, GTB, FNN and LSTM	To evaluate the applicability of a handpicked prediction models on predicting inter-day aggregate network traffic.	MSE
2021	Huaifeng et al.	GCN-GRU (AGG)	The study aims to enhance the accuracy and effectiveness of network traffic prediction. .	RMSE, ACC, R^2, EVS and MAE
2021	Bi et al.	ST-LSTM	The main goal is to improve the accuracy of network traffic prediction by integrating the Savitzky–Golay filter, temporal convolutional network (TCN), and long short-term memory (LSTM) in a synergistic manner.	RMSLE, MAE, and R^2
2022	Jihong and Xiaoyuan	Attention Mechanism with LSTM	To improve the accuracy of network traffic prediction and reduce the running time.	MAE and RMSE
2023	Dong et al.	CEEMDAN-TGA	The study aims to propose network traffic scheduling strategies. These strategies are intended to improve self-management, intelligent scheduling, and network resource optimization of base stations, ultimately enhancing network utilization and energy efficiency in scheduling.	RMSE, MAE, and R^2
2023	Geng et al.	STP-GLN	The primary objective of the research is to propose a spatial-temporal parallel prediction model, STP-GLN, that effectively captures spatial-temporal characteristics to enhance the accuracy of cellular network traffic prediction.	MAE, RMSE, and R^2
2023	Lai et al.	eConvLSTM	The main objective is to propose a linear feature enhanced Convolutional Long Short-Term Memory (ConvLSTM) model for accurately predicting background traffic matrices in LANs. This model aims to capture both temporal and spatial information of traffic flows to facilitate traffic synchronization in DTNs.	MSE, RMSE and R-squared
2024	Gyurin et al.	GAN	to enhance network traffic prediction accuracy and proactive traffic management in 5G networks by introducing an advanced GAN-based model that leverages ConvLSTM and feature matching techniques.	MSE

2.3 Deep learning model with optimization techniques.

To improve the network prediction accurately, some authors combined deep learning models with different optimization techniques. The optimization of prediction models is crucial for improving their performance, convergence, and generalization. Optimization plays a pivotal role in enhancing the performance of deep learning models. Gradient descent algorithms, parameter tuning, and regularization techniques contribute to improving the accuracy and generalization of neural networks. Recent studies have delved into novel optimization approaches such as genetic algorithms, particle swarm optimization, and metaheuristic algorithms. Understanding the impact of optimization strategies on the effectiveness of prediction models is pivotal for designing robust and scalable solutions. Below are the following deep learning with the optimization techniques.

[36] proposed a model that study the prediction of network traffic of smart cities based on Differential Evolution (DE) algorithm and Back Propagation (BP) (DE-BP) neural network traffic. While traditional optimization methods may face challenges in solving complex and multimodal problems, the DE algorithm offers benefits such as fast convergence speed and definite termination criteria, making it suitable for optimizing neural networks. The BP neural network is optimize with DE. The key to construct DE-BP neural network is to seek the value of the three connection weights between the layers with training. Make full use of the global search of DE, find the best group of solutions through selection, cross-over and mutation and thus the DE-BP neural network is built. Then, take the impact factor of network traffic as the input layer and the network traffic as the output layer and train the DE-BP network with the past traffic data so as to obtain the mapping relationship between the impact factor and the network traffic and get the predicted value of the network traffic. Experimental results demonstrate that the DE-BP neural network model accurately predicts the trend of network traffic in smart cities within an acceptable error range. The predicted traffic volume aligns with actual traffic

trends, showcasing the model's effectiveness in handling large-scale data problems and improving prediction accuracy.

The current satellite network traffic forecasting methods cannot fully exploit the long correlation between satellite traffic sequences, which leads to large network traffic forecasting errors and low forecasting accuracy. To solve these problems [39], proposed a satellite network traffic forecasting method with an improved gate recurrent unit (GRU). This method combines the attention mechanism with GRU neural network, fully mines the characteristics of self-similarity and long correlation among traffic data sequences, pays attention to the importance of traffic data and hidden state, learns the time-dependent characteristics of input sequences, and mines the interdependent characteristics of data sequences to improve the prediction accuracy. Particle Swarm Optimization (PSO) algorithm is used to obtain the best network model Hyperparameter and improve the prediction efficiency. Simulation results show that the proposed method has the best fitting effect with real traffic data, and the errors are reduced by 26.9%, 37.2%, and 57.8% compared with the GRU, Support Vector Machine (SVM), and Fractional Autoregressive Integration Moving Average (FARIMA) models, respectively.

In order to solve the problem of low prediction accuracy caused by artificial determination of hyperparameters of network traffic prediction model [38], applied Bayesian optimization algorithm (BOA) to the determination of hyperparameters of neural network, and proposes a CNNLSTM network traffic prediction model based on Bayesian optimization algorithm. The proposed model, BOA-CNN-LSTM, combines CNN for spatial feature extraction and LSTM for capturing temporal dependencies in network traffic data. CNN is employed to extract local spatial features, while LSTM is utilized to capture long-term trends in the data, enabling spatio-temporal feature extraction for accurate traffic prediction. The Bayesian optimization algorithm is applied to optimize hyperparameters of the neural network model, enhancing prediction accuracy and efficiency. The model is trained and tested using the real network traffic data, comparing the performance of the BOA-CNN-LSTM model with traditional models like LSTM and GRU. The experimental comparison of the BOA-CNN-LSTM model with other models, such as LSTM and GRU, shows that the proposed model performs better in predicting peak and valley values of network traffic data. The BOA-CNN-LSTM model outperforms the LSTM and GRU models in fitting the trend of network traffic and accurately predicting network traffic patterns.

To improve the setting method of the parameter and network structure of neural network [9], takes neural networks and chaotic time series theory as the foundation to propose a prediction model based on RBF neural network optimized by improved gravitation search algorithm. Against the disadvantages of gravitation search algorithm such as slow convergence and prone to premature convergence, the improved gravitation search algorithm improves the gravitational coefficient and speed selection formula and chooses the positions of updated particles by the survival of the fittest selection law, which can better balance local and global search capabilities. Simulation results on Lorenz chaotic time series and network traffic datasets demonstrate the superior prediction accuracy of the proposed model compared to traditional RBF neural network models. The Improved Gravitation Search Algorithm of Neural Network (IGSARBFNN) outperforms both standard RBF neural network models and models optimized by the gravitation search algorithm.

[21] proposed the ACO-RBF model for network traffic prediction. The model uses the ant colony optimization (ACO) algorithm to optimize the parameters of the radial basis function (RBF) neural network. ACO is used to train the width and center of the basis function of the RBF neural network, to simplify the network structure, accelerate the convergence speed, prevent the occurrence of local optima, and improve the generalist ability of the RBF neural network. The experimental results show that the ACO-RBF model outperforms the GA-RBF and PSO-RBF traffic prediction models in terms of prediction accuracy and has ability to describe varying trends in network traffic**.** The study demonstrates the practical value of the model used, which exhibits strong generalization ability and stability in predicting network traffic.

[37] proposed a novel approach for network traffic prediction, which integrates the Butterworth filter, Convolutional Neural Network and Long Short-Term Memory network (BWCL). They use a Butterworth filter to smooth the traffic data and obtain the low-frequency component and the residual component. They construct different CNN–LSTM hybrid prediction models to target different frequency bands of Butterworth output with multiple features. By combining different data characteristics with the appropriate prediction model, the prediction performance is greatly improved compared with the traditional single prediction model. To meet the needs of different application scenarios, they conduct prediction at two different time granularities: minute-level and hour-level. The minute time granularity is suitable for realtime and high-frequency monitoring, while the

hour granularity provides a more macroscopic summary and trend analysis. They train and predict the mean, minimum, and peak values of raw data by different BWCL hybrid models to gain a deeper understanding of the overall trend and fluctuation of network traffic data. It helps to rationally plan resources and optimize performance to cope with traffic bursts. This approach provides comprehensive and accurate insights to better understand and predict the dynamics of time series data. . It helps to rationally plan resources and optimize performance to cope with traffic bursts. This approach provides comprehensive and accurate insights to better understand and predict the dynamics of time series data.

Network traffic has time-varying and nonlinear characteristics, leading to relatively low accuracy of single linear and nonlinear prediction models. Therefore, a combination model prediction method of autoregressive integrated moving average (ARIMA) model and improved particle swarm optimization (IPSO) bi-directional long short-term memory (BiLSTM) was proposed by [12]. First, the ARIMA model is used to obtain linear variation characteristics for no n smooth modeling. Then the ARIMA prediction values are subtracted from the actual data to obtain the residual series. IPSO also optimizes the optimal parameters of the BiLSTM. Then the optimized BiLSTM is modeled on the residual series to obtain the residual variation characteristics. Finally, the ARIMA linear and IPSO-optimized BiLSTM residual predictions are summed to obtain the final prediction results. The proposed combination model outperforms the comparison model, has smaller prediction errors, and can better characterize the complex features of network traffic.

Table 3: Summary of the model above.

Year	Author	Model (s)	Purpose	Evaluation Metrics
2014	Liu and Guo	ACO-RBF	To develop a more efficient prediction algorithm and to further improve the efficiency and precision of network traffic prediction.	MAPE and MSE
2016	Dengfeng Wei	RBF	The primary objective is to develop a prediction model that accurately captures the nonlinear dynamics of network traffic and improves prediction accuracy.	RMSE
2019	Xiuqin et al.	DE-BP	Aim to accurately predict the trend of network traffic within an acceptable error range.	RMSE and MAPE
2022	Liu et al.	attention mechanism with GRU	To improve the accuracy of satellite network traffic prediction.	MAE, RMSE and R^2
2023	Yuantao Lv	BOA-CNN-LSTM	To solve the problem of low prediction accuracy caused by artificial determination of hyperparameters of network traffic prediction model.	RMSE , R^2 and MAE
2024	Xueyan et al	BWCL	To successfully overcome the limitations of traditional methods in dealing with nonlinear and non-stationary data.	MSE, $RMSE$, MAE, and R^2
2024	Guohao and Zhongda	ARIMA-IPSO-BiLSTM	To provide a great foundation for the future design of network resource allocation principles, congestion control strategies, and network management optimization.	RMSE, MAE, MAPE, RRMSE, and R^2

III. CONCLUSION

This paper presented a review of research work on deep learning models in the prediction of network traffic. A lot of researchers have been able to implement an effective and useful network traffic prediction model in recent years. This started with an introduction to network traffic prediction and deep learning therefore discussed the review work by categories, on deep learning models along with network traffic prediction, hybrid models, and deep learning models and optimization techniques. This work has shown many promising applications using deep learning and its optimization with other related models like genetic algorithms in the context of network traffic prediction. This study has shown different network prediction for optimum network optimization and resource management. Furthermore, the analysis done in this work could influence a better choice of deep learning models that will result into better performance for future deep learning application.

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