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A Review of Traffic Flow Prediction Models in 5G Using Machine Learning Techniques

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Abstract: Wireless technology has advanced significantly since its origin and is now an essential aspect of our daily life. The advancement of wireless communication from the first generation (1G) to the fifth generation (5G) of technology has been revolutionary. An extensive summary of the development of wireless communication from 1G to 5G has been given in this paper. Cellular networks are heading towards becoming more diverse, broadband, integrated, and intelligent networks with the introduction of 5G networks. The goals of 5G wireless technology are to provide more users with more consistent user experiences, ultralow latency, vast network capacity, faster multi-Gbps peak data speeds and increased reliability. While the resources needed for computation and communication are also growing with the maturity of 5G technology .At the same time, cellular traffic has increased dramatically due to the widespread use of smart devices. Cellular traffic prediction is a crucial component of the resource management system for cellular networks but it confronts many difficulties due to strict standards for accuracy and dependability. Among the most important issues is how to enhance the predictive performance of Mobile data traffic.

This review describes the need of traffic forecasting in cellular network in 5G technology. A study of different models for network analysis and traffic prediction by different researchers is presented in this paper. The distinctiveness and guidelines of earlier research for traffic prediction in 5G are examined. To determine the distinctive qualities of each method used for traffic prediction in mobile network, a thorough analysis of the most popular techniques using Machine learning for predictive analysis are discussed.

Keywords: Network Traffic Prediction, Machine Learning, Spatial-temporal cellular traffic, Artificial Neural Network.

I. INTRODUCTION

An ever-expanding diversity of apps and the proliferation of connected devices have fuel the unstoppable rise in demand for mobile data services, which has accelerated the evolution of cellular networks to meet the demands of a data-intensive era. A paradigm leap in wireless communication is expected with the introduction of 5G networks, which promise not only of data speeds but also a radical new direction for network architecture.The journey from the early days of cellular networks to the current era of 5G has been marked by a continuous evolution driven by the insatiable demand for data connectivity. Beginning with the first-generation (1G) analog networks primarily focused on voice communication, subsequent generations witnessed a profound transformation. The advent of 2G brought digital communication, 3G introduced mobile data services and 4G revolutionized the landscape with high-speed broadband connectivity.

Predicting traffic either in short ranges or long range becomes a crucial aspect in this dynamic environment because of the growing demands of people's for wireless communication. Due to the increased connection of network leads to the danger associated with cyber security. Cybercriminals will have access to more digital targets and separate services will share access channel infrastructure between wireless and mobile networks [1] and it is necessary to maximise resource allocation, improve Quality of Service (QoS) [2] and guarantee the effective operation of 5G networks. However, the surge in data-intensive applications, from streaming services to augmented reality has outpaced the capabilities of existing networks, necessitating the advent of 5G.The timeline of cellular networks over a period of time are shown in

Figure 1 below.

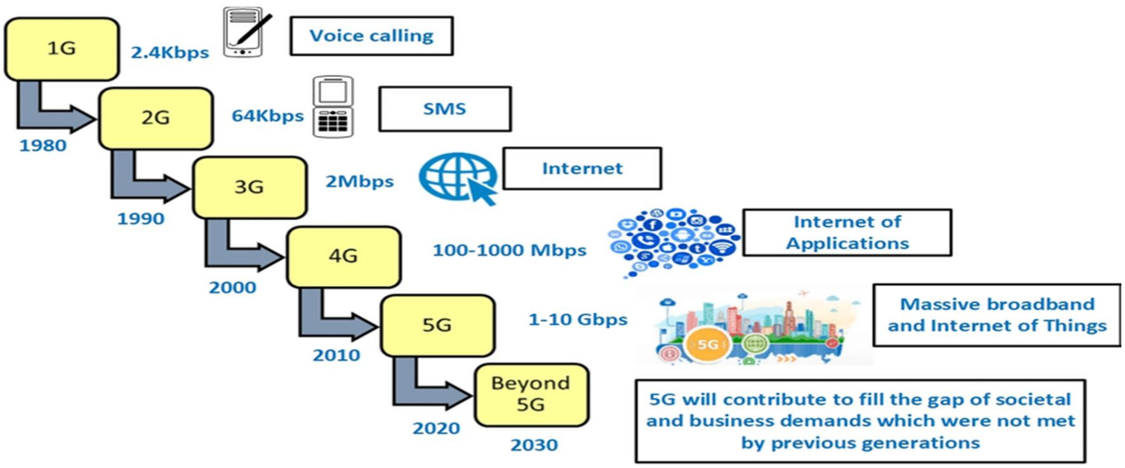

Figure 1: Timeline of cellular networks [1]

This evolution is underpinned by technologies such as Massive MIMO (Multiple-Input, Multiple-Output), beam forming and network slicing enabling a diverse range of applications from autonomous vehicles to the Internet of Things (IoT). However, the sheer complexity and dynamism of 5G networks demand innovative solutions to address the challenges posed by unpredictable mobile data flows. The evolution of cellular networks from 1G to 5G is remarkable with the analysts forecasting 2.7 billion 5G connections by 2025 with enhanced mobile broadband and wireless connectivity as shown in

Figure 2. In this context, the prediction of mobile data flows takes centre stage, so in order to forecast future events, predictive analysis involves analysing data using artificial intelligence [3], machine learning, statistical algorithms, and other data analysis approaches.

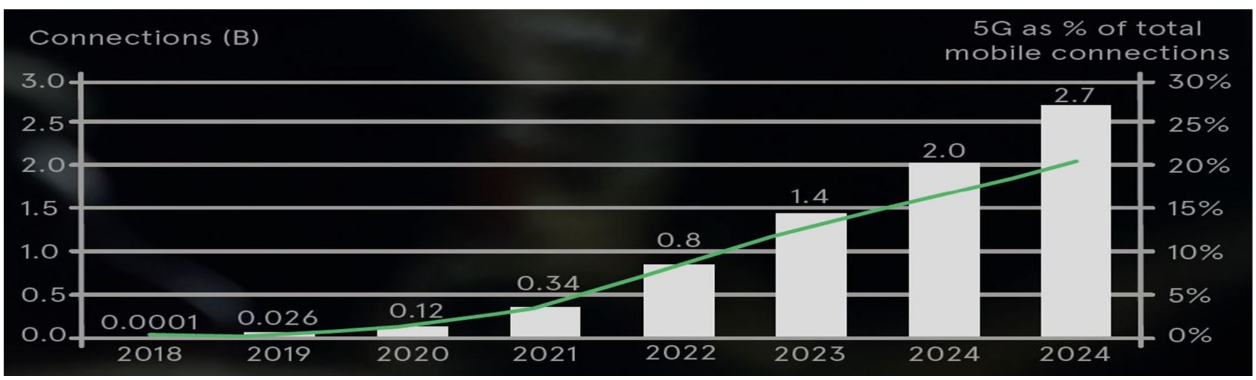

Figure 2: Evolution of 5G over time**Error! Reference source not found.**

Using historical or raw data as input, we can use many Predictive Analysis algorithms to produce clean data. In 5G networks, predictive analytics may self-diagnose and self-optimize with little to no human intervention. Additionally, it can assist telecom firms in streamlining customer experiences, enhancing performance, and optimising 5G networks. **Error! Reference source not found.**proposes for the emerging deep learning techniques for spatiotemporal modelling and prediction in cellular networks, based on big system data.[5] Presented traffic prediction based on convolutional Neural Networks (CNN).So prior to delving into predictive analytic techniques, let's examine the need of traffic forecasting in 5G.

II. NEED OF TRAFFIC FORECASTING IN 5G

The fifth generation of mobile network technology 5G is expected to outperform its predecessors in terms of speed, latency, and capacity. Global demand for mobile data traffic is being driven up by several factors including the continuous development of increasingly intelligent mobile phones and the advent of machine-to-machine connections and the availability of data-intensive and attractive applications. With 5G networks anticipated to generate far more traffic than previous generations of mobile networks so the accurate and exact mobile traffic forecasting is very critical. Predicting traffic has become one of the key enabling technologies.

Furthermore, a number of transportation services, such as route planning, traffic control, and navigation, depend heavily on traffic predictions.

Precise short-term prediction of future traffic load information enhances network energy efficiency by dynamically allocating resources according to actual traffic demand, while long-term forecasting is essential for network planning and base station localization.

There are several other reasons for traffic forecasting:-

1) Traffic forecasting helps optimize network resources, minimizing congestion, reducing latency, and enhancing overall network efficiency.
2) Traffic forecasting helps in identifying and addressing potential latency bottlenecks by optimizing network resources in anticipation of high-demand periods.
3) Traffic forecasting aids in intelligent energy management by allowing operators to activate or deactivate network components based on anticipated demand, contributing to overall energy efficiency.
4) Traffic forecasting enables operators to anticipate and address potential congestion points, reducing the likelihood of service degradation and ensuring a positive user experience.
5) Traffic forecasting is essential for managing the communication patterns of these devices, ensuring efficient use of resources, and supporting the scalability of the network.
6) Traffic forecasting aids in identifying abnormal patterns that may indicate security threats, allowing operators to implement preventive measures and enhance overall network security.

III. RELATED WORK

Various existing prediction models can optimize the network parameters using different machine learning algorithms. Also, these machine leaning algorithms are trained using efficient optimizers in order to get better performance. This section discusses the recently developed mobile data traffic prediction models.

V. Perifanis et al.[7]proposed a federated learning technique to address a number of issues that have been discovered as a result of the non-iid data type. The suggested techniques in contrast to centralised ones reduce concerns about business secrecy and legal compliance and federated learning opens the door to widespread involvement that may result in the development of intelligent predictors. The study that was presented examined three distinct learning strategies and carried out in-depth experiments with five deep learning architectures. The findings demonstrate that federated learning offers a dynamic execution environment, has the ability to generalise and does not necessitate the transfer of private information to a third party. Furthermore local fine-tuning improves prediction accuracy as a result of which federated learning may produce models with greater intelligence than centralised and individual methods. Lastly, federated learning can expand to a large number of base stations leading tolower computational and communication costs than traditional machine learning.

V. Perifanis et al.[8] examined the prediction ability and sustainability of the most recent deep learning models for federated cellular traffic forecasting. In order to assess energy usage in terms of accuracy, designed a brand-new sustainability indicator that makes it easy to compare different machine learning models in diverse experimental settings. It has been demonstrated that larger and more intricate models yield negligible improvements in accuracy but result in a significant rise in energy usage when compared to simpler models. This paper investigate the rate at which various models converge in the future and expand the sustainability indicator that was first introduced to include robustness and assess a large and varied set of clients and datasets in order to show the federated learning's generalisation and scalability. Finally the conclusion is proposing the compromise between selection of model and accuracy for improving the robustness of model after applying regularization techniques.

Z. Wang et al.[9] suggests a time-series similarity-based graph attention network or TSGAN for the prediction of spatial-temporal cellular traffic based on this. After performing experiments, results demonstrate that in short, mid, and long-term prediction situations how TSGAN outperforms three traditional prediction models based on GNNs or GRU on a real-world cellular network dataset. GNN-powered spatial-temporal prediction models have a lot of potential and can enhance prediction performance in present 5G environments in the future. Furthermore emerging facilities like unmanned aerial vehicles (UAVs) and communication satellites will be deployed and turn into crucial types of service platforms in the vision of Industry 5.0 and sixth generation networks (6G) to provide quick and seamless networking and communication services. In this context, there may be research possibilities to solve the problem of GNNs-enabled spatial-temporal cellular traffic prediction in this promising scenario prior to the effective deployment of dynamic non-terrestrial platforms in Industry 5.0 and 6G future scenarios.

Alsaadeet al. [10] demonstrated that important traffic features like long-range dependence (LRD), short-range dependence (SRD), and so on should be captured by a solid network traffic prediction model. A hybrid SES-LSTM model was presented in this study to forecast network traffic using actual 4G LTE cellular network data.

Owing to the complexity and variety of forms of network traffic, a single exponential smoothing method was used to modify the quantities of traffic. An LSTM model was used to process the output from a single-exponential model in order to forecast the network load. An intelligent system was assessed by the use of actual mobile network traffic that was gathered and stored in a Kaggle dataset. The experiment's findings demonstrated the improved accuracy which produced R-square metric values of 88.21%, 92.20%, and 89.81% for three one-month time periods respectively. It was noted that there was little difference between the prediction values and the data. The outcome of comparison of the prediction results between our suggested system and the current LSTM model proved that suggested system performed better than expected.

Liu et al.[11] Proposed that this work models the traffic data as a three-dimensional traffic tensor in order to fully exploit the intrinsic temporal-spatial correlations of each traffic data. This paper suggest a novel tensor completion (TC)-based "two-step" strategy that is "data processing & decomposition + prediction," for individual traffic prediction which can recover and decompose the traffic data simultaneously in contrast to the "three-step" strategies (i.e., "data processing + decomposition + prediction") in the existing methods. To solve the resulting model an effective algorithm based on the alternating direction method of multipliers (ADMM) framework is also suggested. To the best of our knowledge, this is the first study to use the "two-step" TC-based approach for cellular network individual traffic forecast. Research carried out on an actual cellular traffic dataset provides factual support for the superiority of proposed method.

Yadav et al[12] investigated the problem of network traffic prediction classification by utilising predictive learning time series prediction techniques such as auto regressive integrated moving average (ARIMA) and long-term short-term memory (LSTM) variations. The analysis is split into two sections. First, we use a basic ARIMA model to partition the mobile traffic data into four basic components: Seasonality, Trend, Residual, and Noise. Second we use the available data to train an LSTM recurrent neural network, which allows us to anticipate the number of mobile data users for the upcoming ten years. This suggested approach will support a comprehensive understanding of large-scale mobile traffic use in metropolitan contexts and aid in decision making based on potential traffic estimates.

Zhao et al.[13] suggested a new prediction model called STGCN-HO that makes use of the handover graph's transition probability matrix. Using gated linear units and graph convolutions, STGCN-HO constructs a stacked residual neural network structure that captures the traffic's temporal and spatial features. In contrast to RNN, STGCN-HO trains quickly and concurrently forecasts base station traffic demand using data acquired from the entire graph. In contrast to CNN-grid, STGCNHO has the ability to anticipate not just base stations but also individual cells within base stations. Experiments with data from a major cellular network operator show that our approach performs better in terms of prediction accuracy than current solutions. In order to improve resource allocation and RAN management for LTE data, we intend to use its key concepts in future work to develop traffic prediction models for 5G networks and include the model into a RAN controller.

Zeng et al.[14] proposed a model the spatial-temporal cross-domain neural network model (STC-N) to consider more cross-domain data and a cross-service and regional fusion transfer learning method (Fusion-transfer) to increase the accuracy of 5G/B5G cellular network traffic forecast. A proposed approach is the fusion-transfer strategy, which combines the inter-cluster transfer learning technique with various traffic transfer learning strategies. The outcomes of the experiments demonstrate that the Fusion-transfer strategy outperforms both the model with no transfer strategy and the model with part transfer strategy proving beyond a doubt that the new Fusion-transfer strategy is superior to other transfer methods.

Zhang et al.[15] present a deep learning technique called hybrid spatiotemporal network (HSTNet), which leverages convolutional neural networks to capture the spatiotemporal properties of communication traffic. According to experimental results, HSTNet considerably increased the prediction accuracy based on MAE and RMSE when compared to the machine learning and statistics techniques currently in use. This work still has to be improved in a number of areas where model's is incapability to adapt to changes brought on by emergencies and the large-scale traffic volume forecast performance (total traffic volume of the entire city) requires improvement.

Chen et al.[16] Developed a long short-term memory (LSTM) based traffic-flow prediction algorithm with a mechanism to train mobile traffic data in a single-site mode. The traffic flow's peak value can be accurately predicted by the algorithm. We offer an intelligent IoT-based mobile traffic prediction-and-control architecture that can dynamically allocate computation and communication resources for a multi-site case. Through this study, we show how the suggested system can effectively reduce communication latency and how that can minimise the packet-loss ratio.

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He et al.[17] Presented a novel deep learning framework in this research called graph attention spatial-temporal network (GASTN) for precise citywide mobile traffic forecasting which can capture both distant inter-region relationships and local geographical dependencies when taking spatial factors into account.
In particular, GASTN models the global near-far spatial relationships and the temporal dependencies by taking spatial correlation into account through our created spatial relation graph and structural recurrent neural networks.
Shawel et al.[18] Suggested a hybrid approach consisting of the multi-seasonal process model Double Seasonal ARIMA (D-SARIMA), which focuses on the data traffic and utilise the D-SARIMA residual through an LSTM-based network. The non-linear components of the data are contained in the residues. They used K-means clustering and took the correlations between them into account. The proposed hybrid model outperforms D-SARIMA and LSTM methods according to experiment conducted with real-time datasets collected from 739 Base stations over a period of around 4 months.

IV. COMPARATIVE ANALYSIS OF THE REVIEWED APPROACHES

Publication Year	Authors	Aim	Techniques used	Inferences	Dataset used	Performance Parameters
2023	VasileiosPerifanis,Nikolaos Pavlidis[7]	Federated learning for 5G base station traffic forecasting	deep learning	Tackled several identified challenges owing to the non-iid data nature. Minimize business confidentiality and regulatory issues.	(PDCCH) dataset in Barcelona, Spain	Computational Cost
2023	V. Perifanis et al.[8]	Towards Energy-Aware Federated Traffic Prediction for Cellular Networks	federated learning technique	trade-off between accuracy and energy consumption	Dataset from Barcelona, Spain	Performance in terms of carbon footprint
2022	Z. Wang, J. Hu, G. Min [9]	Spatial-Temporal Cellular Traffic Prediction for 5G	graph neural networks (GNNs) technique	Spatial-temporal analysis of real-world cellular network traffic.	multi-source dataset of urban city of Milan	Energy efficiency, Accuracy
2021	Alsaade and Hmoud Al-Adhaileh[10]	To propose an intelligent model for cellular traffic prediction	SES-LSTM technique	Predicted values are highly closer to the actual ones	Kaggle	Accuracy
2021	Liu et al. [11]	Individual traffic prediction in cellular networks based on tensor completion	Prophet+GPR+ ADMM	Enhanced performance on real time data	Real world data	MAE, RMSE, MAPE
2021	Yadav et al. [12]	To predict	ARIMA+LSTM	Predict for	Real world	Correlation

		mobile data traffic in urban environment		succeeding ten years	data set	coefficient
2020	Zhao et al. [13]	To design a cellular traffic prediction model using handover graph in the DL model	STGCN-HO model	Reduced prediction error on real world dataset	Real world data	RRMSE, RMSE, MAE, Training time
2020	Zeng et al. [14]	To develop a cross-service and regional fusion transfer approach for cellular traffic prediction	deep transfer learning and cross-domain data	Improved performance on cross-domain dataset	Sms, call, Internet	RMSE, MAE, R2, Variance
2020	Zhang et al. [15]	To develop a prediction model to capture spatio temporal features of the network	HSTNet technique+ DenseNet	Highly robust	Telecom Italia dataset	MAE and RMSE
2020	Chen et al.[16]	To achieve effective traffic flow prediction in 5G networks	DBLS	Low complexity	ZTE Corporation data	Accuracy, Running time
2020	He et al. [17]	To develop a predictive model for city wide mobile traffic	GASTN	Enhanced prediction results	Real world data set	NRMSE, MAPE, MAE
2020	Shawel et al. [18]	To design a hybrid predict ion model	D-SARIMA	Properly utilize linear and non-linearity data	Real world data set	RMSE, MAE

V. DATA FLOW PREDICTION ALGORITHM IN 5G INDUSTRY USING MACHINE LEARNING

Algorithms for machine learning are those that can identify hidden patterns in data, forecast results, and enhance performance via independent experience. In machine learning, different algorithms can be applied to different tasks [19].For example, the KNN algorithm can be used to classification problems, whereas basic linear regression can be applied to prediction problems like stock market prediction.

Predictive analytics and predictive modeling are other terms frequently used to refer to machine learning. There are four types of machine learning algorithm on the basis of learning: supervised, semi-supervised, and unsupervised and reinforcement. Algorithms may be grouped on the basis of their function like tree based and neural network methods. Many factors such as the nature of the problem and type of data influence the best machine learning technique for prediction. The testing and assessment of the particular problem and dataset at hand should be the foundation for algorithm selection. There are many algorithms grouped according to the timeline based on regression, instance based, Decision trees, Clustering, association rule learning, artificial neural network and deep learning in the Figure 3:

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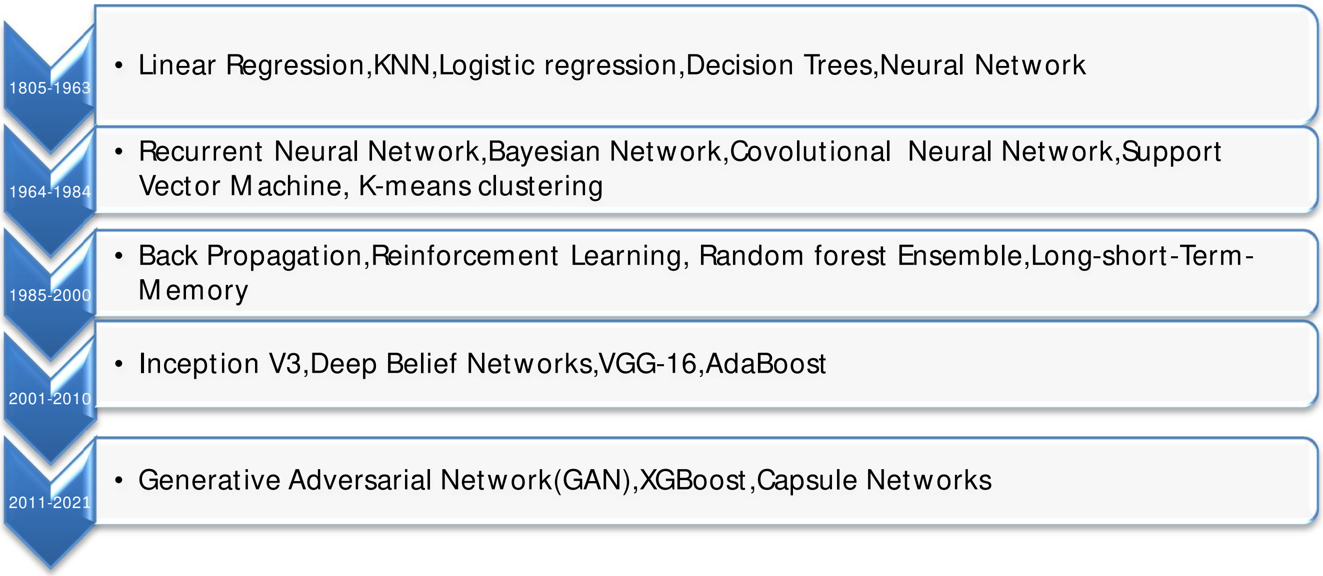

Figure 3: Timeline of Machine Learning algorithms [21]

The traffic prediction broadly may be classified on the basis of statistical learning models, Machine learning models and Deep learning models. Traffic patterns at various scales such as during the day or on different days of the week or seasonal etc. can be identified using statistical approaches. Compared to machine learning ones, they are typically simpler, quicker, and less expensive to execute. But because they are unable to handle as much multivariate data, they are less accurate. With machine learning (ML), you may develop prediction models that take into account vast amounts of heterogeneous data from many sources. When compared to machine learning (ML) or statistical techniques, deep learning (DL) methods have demonstrated a continuously high level of forecasting accuracy routinely reaching up to 90% for traffic predictions. Neural networks are the foundation of deep learning algorithms.

A lot of research has been done on using ML systems and deep learning to predict traffic on the cellular networks. The scope of this research is primarily on the analysis of traffic prediction in 5G using different variants of machine learning and deep learning algorithms. The most common and popular algorithms used in predictive analysis are:

LightGBM (Light Gradient Boosting Machine) is utilised for efficient and accurate machine learning operations. Large datasets are easily handled by it, and it provides quick training and prediction times. It's favoured mostly for classification and regression. In **Error! Reference source not found.** paper demonstrates random forest (RF) and LightGBM to mobile network traffic prediction by utilising RF to filter redundant features and using LightGBM to train prediction model. Additionally, there is a fresh approach to traffic prediction by utilizing LightGBM and the ensemble framework of bagging. A traffic dataset from real life is used to assess the suggested model. The experiment's findings demonstrate that when compared to a single LightGBM with the same number of decision trees and a few other well-known algorithms such as ARIMA, multi-layer perceptrons (MLP) and linear regression (LR), the suggested model significantly enhances prediction performance.

GPR (Gaussian Progress Regression): A nonparametric, Bayesian method of regression that is gaining popularity in machine learning is called Gaussian process regression (GPR). GPR has a number of advantages, including its ability to evaluate prediction uncertainty and its performance on tiny datasets. In [21] paper proposes user traffic forecast approach based on Prophet and Gaussian process regression. The suggested approach divides the user traffic time series into high-frequency and low-frequency components by first using a discrete wavelet transform. The long-range reliance of user network traffic is carried by the low-frequency component, and the erratic and gusty variations are revealed by the high-frequency component. Next, using the features of the two components as a basis, the Prophet model and Gaussian process regression are used to predict the two components, respectively. The suggested model works better than the current time series prediction technique, according to experimental results.

GMM (Gaussian Mixture Model): A probabilistic model known as a Gaussian mixture model makes the assumption that every data point originates from a mixture of a limited number of Gaussian distributions with unidentified characteristics. It can be thought of as a generalisation of the k-means clustering approach which is used for both density estimation and classification. In [23]paper the density patterns are found on a daily or weekly basis using clustering-based GMM models.

The cloud platform ThingSpeak which is utilised for analysis and visualisation of traffic density patterns have produced results on real-time traffic data by using accuracy, precision, recall, and F-score as metrics.[24]demonstrate that for various 5G network scenarios like the accuracy and calculation time of the suggested deep learning estimator based on the Gaussian Mixture Model (DLEGMM) are assessed. The simulation results demonstrate thatfor a longer computation time, the DLEGMM works better than the GMM technique based on the Expectation-Maximization (EM) algorithm in terms of the accuracy of the end to end (E2E) delay estimates.

LSTM (Long short-Term Memory): LSTM is a deep learning technique which is used for both learning long-term dependencies and non-liner traffic flow data [25][24]. LSTM networks differ from typical forecasting models because they consider temporal–spatial correlation in traffic systems. Mostly linear models like ARMA and ARIMA are unable to capture the stochastic and nonlinear aspects of traffic flow [26]. So for short-term traffic flow using neural network (NN) the combination of both Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) model can outperform auto regressive integrated moving average (ARIMA) models. [27]offers a combined traffic flow prediction model based on deep learning graph convolution neural network (GCN), long-term memory network (LSTM), and residual network (RESNET) in an effort to increase the accuracy of traffic flow prediction. LSTM is used to extract time structure features from traffic data, while GCN is used to extract topology structure features. These features are then combined with ResNet to optimise the overall model, lessen the likelihood of gradient disappearance or explosion in network degradation, and ultimately achieve traffic flow prediction.

FFNN (Feed forward Neural Network): In a feed-forward neural network, each node carries out a straightforward computation and the result is sent to the layer's subsequent node. The output layer which is the last layer in the network produces the network's forecast.**Error! Reference source not found.**[28]proposed a plan for forecasting traffic flow information using four machine learning techniques—Feed Forward Neural Networks (FFNN), Radial Basis Function Neural Networks (RBFNN), Simple Linear Regression Model, and Polynomial Linear Regression Model to lessen the issue of traffic congestion. In [29]the network is trained using the time delay data. The traffic data for the first 300 days of 2008 is utilised to generate the time delay data. Using the actual 301st day observation data, the feed forward neural network model's performance is verified.

VI. CONCLUSION

This paper summarizes the timeline of cellular network from 1G to 5G. Efficient resource management is necessary for fifth-generation (5G) networks. It should dynamically adjust to the network's current load and user requirements. This effort is aided by the monitoring and forecasting of network performance requirements and measurements. Because of the traffic's non-stationary and dynamic spatial-temporal correlation, cellular traffic prediction is difficult. Cellular network traffic prediction is a crucial component of communication network design, management, and optimization modelling. Cellular traffic prediction can help a network plan its capacity and enhance its quality of service. Reliable traffic forecasting methods are necessary to enhance resource management and services. Over the past ten years, the analysis and prediction of cellular network traffic has become a subject of continuous research in various sub-fields of networks. A number of efficient network traffic algorithmshave been put into practice by countless academics for the analysis and prediction of network traffic. In this paper, we reviewed earlier network traffic analysis research and discussed various approaches of data prediction algorithms in 5G using machine learning. The tabular arrangement of all the surveyed papers shall give an overview of the research work in the analysis and prediction of network traffic. This paper opens a scope of development of new models for the task of predictive analytics. There is also an opportunity to add additional features to the existing models to improve their performance in the task.

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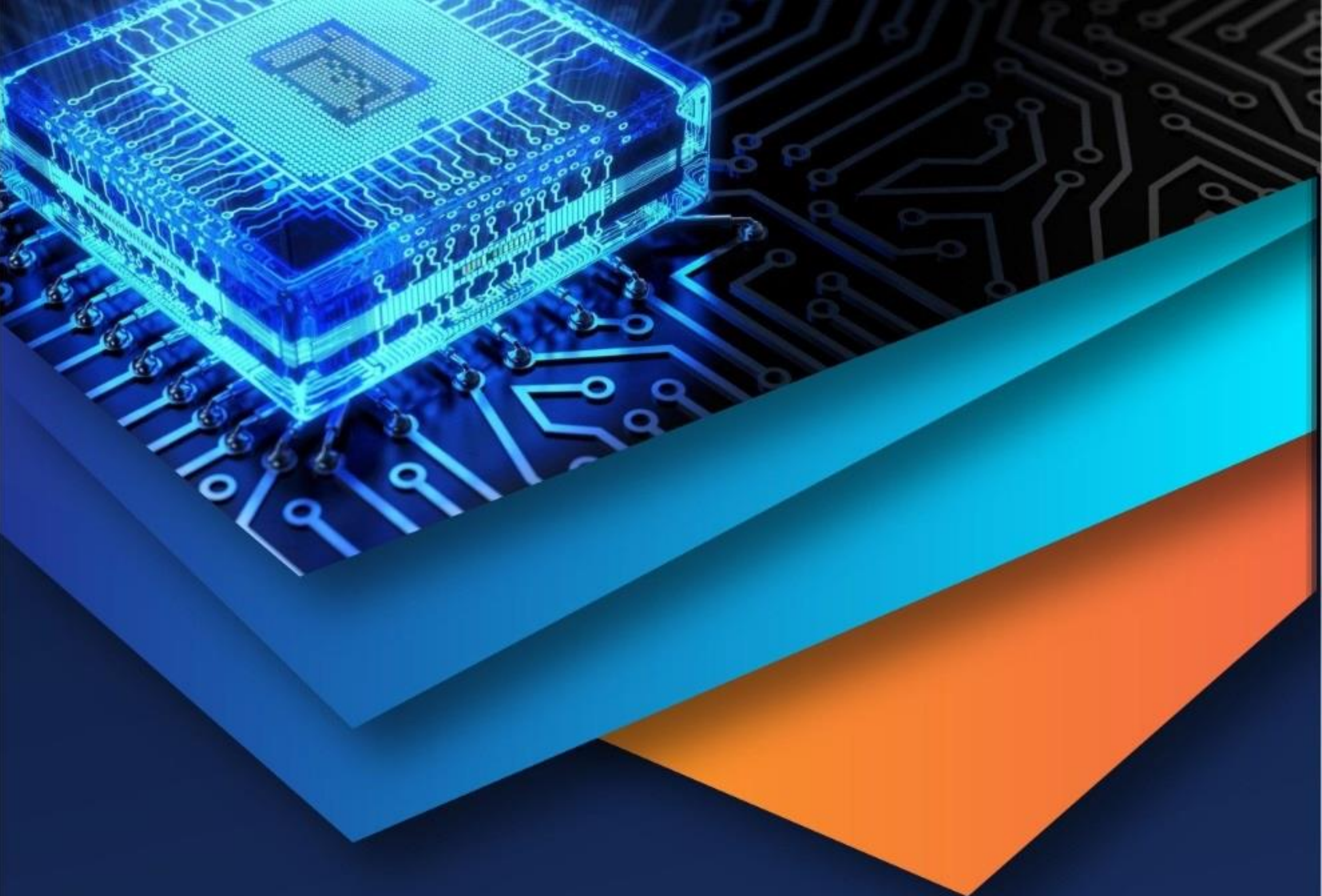

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