CELLULAR NETWORK DATA ANALYSIS USING MACHINE LEARNING: A REVIEW

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Abstract:

The 5G network technology is a revolution and involves the goodness of communication, processing power, storage management and Machine Learning (ML). Such technology is useful in various next generation applications by scaling the computational and communication ability. Therefore, it is very useful in smart city infrastructure, automated and precise farming. In this paper, we provide an insight on 5G networks and their applications. Afterwards, a review on recent development and contributions based on ML technology and communication networks has been carried out. The review categorizes contributions based on the research trend and algorithms utilized in application development. Additionally, objectives have been formulated to provide roadmap of future research work. Finally, the conclusion of the entire work involves in this paper and our findings are reported.

Keywords: Machine Learning, Big Data, Data Analytics, Cellular Networks, Traffic Analysis, Network Traffic Prediction.

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1. INTRODUCTION

The ML (Machine Learning) is the helping hand of new generation computation and communication technology. The ML techniques are able to analyze data and can group, classify and forecast the upcoming trends of information. The involvement of big data technology with the ML enables us to deal with the huge amount of data. Additionally opens new door of opportunity to develop various different domains of applications [1]. The mix of ML and big data is called big data analytics. In order to work with large data we also requires the high speed network content delivery services. In this context recently 5G technology has been introduced.

The 5G communication technology is new generation communication revolution which enables us to send and receive bulk data in real time. Thus it provides the ease in development of interactive and efficient network based applications which can be used for smart farming, intelligent transportation system, sustainable computing, etc. therefore it is a great example of a combination of big data, ML and communication technology. The combination of these technologies is initiating new dimensions of application development [2], which offers remote automation in various industrial as well as domestic applications. Thus, the proposed work is motivated to study all the three technologies and the following key objectives are proposed for investigation:

1. ML techniques [3] becomes popular due to its capability to learn with the data samples, and can recognize and predict the trends in data. Therefore, we involve the study of ML models, which can efficiently and accurately predict future trends (i.e. supervised as well as unsupervised).

2. The predictive data analysis is essential for various applications, such as in resource management, event detection, and power preservation. Therefore, the proposed work involve a cellular network traffic data analysis using ML models for predicting the upcoming work load on BSs [4].

3. The cellular traffic trend prediction can also be useful for understanding the city road traffic conditions for smart city traffic management system. Thus, using an interactive simulation we demonstrate how predictive algorithms are beneficial for new application development [5].

The proposed work is motivated to study 5G technology in association with the application development. In this paper we start our study with a review article for providing understanding of 5G technology and their applications. Thus, next section involves a brief introduction of 5G technology. Further the literature on recent trends on mobile network workload-based work are explored, which also involve the ML techniques, in order to design and develop advance applications. Finally, a summary of studied literature by categorizing the works on the basis of research trends and utilized algorithms categories is presented. Based on studied contributions, we offer the proposal of future plan of work.

5G Network Architecture

In 2018, the 3GPP (1) defines a system that uses "5G NR" software as "5G". That is fifth generation of cellular network technology. It has three aspects:

1. Higher speed
2. Lower latency
3. Multiple connections of devices as sensors and IoT.

It is a non-stand-alone network because it needs active 4G support for initial connection [29].

5G architectures are based on software-defined platforms, where network’s functional aspects are managed through software. This offers improvement in the areas of virtualization, cloud, IT, and business intelligence. 5G architecture can also enable us to work with agile with flexibility and higher availability. This network can create software-defined sub-network also, these sub-networks called network slices. The network-slices enable managers and administrators to monitor and regulate network functionalities according to requirements [33]. Figure 2.1 introduces some essential applications and concepts of 5G Networks. [1] https://techthoroughfare.com/technology/5g-network/

Because of ML, the digital experience has been enhanced in 5G. For applications like self-driving cars, demand for a response within a fraction of a second requires enlisting automation with ML also Deep Learning (DL), and Artificial Intelligence (AI). Infrastructure cost will be reduced and connectivity will be enhanced because of automated provisioning and proactive management of traffic and service [33].

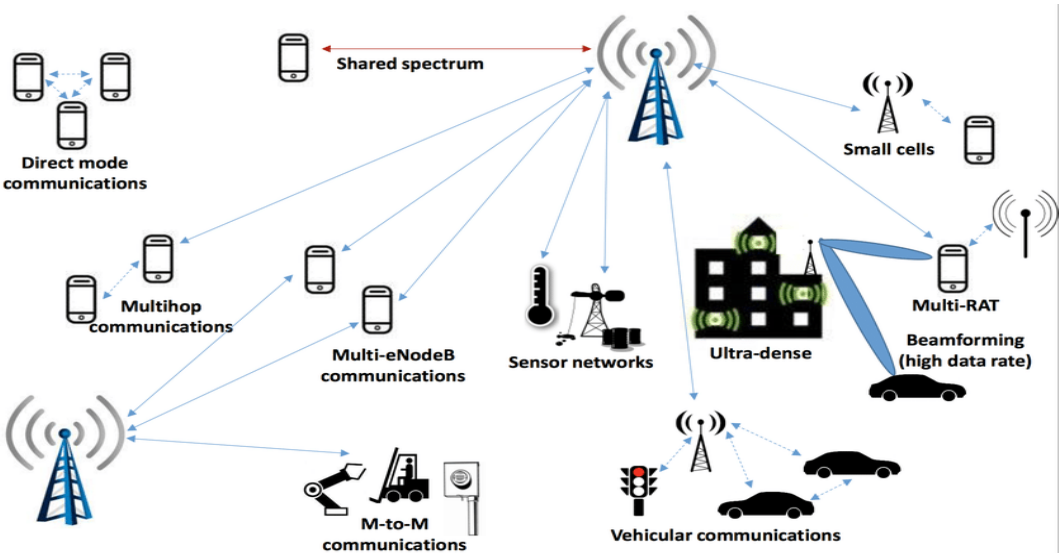

Figure 1 5G Network Architure

A. Applications

In this section we provide some applications which are providing ease in various application areas of society.

Autonomous Vehicles:

It is one of the most awaited 5G application is autonomous vehicles. To support the application, advancements are rapidly carried out in vehicle technology. 5G networks will reduce latency, so the vehicles will be able to respond 10-100 times faster than current networks. The goal is vehicle-to-everything (V2X) communication. Vehicles will be enabled to respond automatically to objects. To break or shift directions in road signs, people crossing streets, and hazards, vehicles must be able to send and receive messages during all situations [34].

Smart City Infrastructure and Traffic Management:

In many cities, Intelligent Transportation Systems (ITS) have been deploying and planning to support connected vehicle technology. The current communication systems, these systems are easy to install and automatically support smart traffic management to handle congestion and routes for emergency vehicles. Connected vehicle technology will enable vehicles to do communication to promote safety. Sensors in cities are being installed to detect movement in every intersection and keep connected with vehicles [35].

Industrial Automation:

The 5G in the industrial automation is wireless flexibility, reduces the cost of infrastructure and enhance mobility in application devices. This technology support industrial automation in the way of cut the cord and go fully independently to design new smart factories [36].

Augmented Reality (AR) and Virtual Reality (VR):

The 5G make AR and VR applications immersive and interactive. In applications, a machine that would identify parts, provide repair instructions, or show parts which not safe to touch can be seen by a technician wearing 5G

AR goggles. The opportunities will be extended for highly responsive applications that support complex tasks. AR meetings are more interactive in 3D rather than 2D [37].

IoT for Drones:
Drones have a growing set of use cases beyond the use of video and photography. Using it we put goggles to “see” beyond limits in high resolution. It will also extend the reach of controllers. These advances will have implementations in search and rescue, border security, surveillance, delivery services and more [38].

B. Working
5G will introduce improved network architecture, refer figure 1. In 4G, the global standard for a capable wireless interface cover spectrum is not used. MIMO is incorporated in new antennas which enable to transfer more data at the same time. But 5G technology is not limited to the radio spectrum. It is designed for supporting the heterogeneous network combining wireless technologies either licensed or unlicensed [32]. The 5G mobile network offers key features beyond 4G [30].

- Low latency.
- Higher data speeds.
- Higher wireless capacity, for device connectivity.
- Reduced energy consumption.
- Resource virtualization.
- Service-oriented resource allocation On-demand.
- Automated management.
- Multi-tenancy.

The functions and architecture of 5G networks are expected to be agile to accommodate the heterogeneous requirements of applications. The devices are able to download a full-length HD movie in seconds; it is connecting things everywhere – reliably, without lag. We can measure, understand and manage things in real time. That improves the performance of applications and other digital experiences i.e. gaming, video conferencing, and self-driving cars. In the earlier cellular technologies was suffers from connectivity issues. But with 5G connectivity has reached the next level where the connection is delivered from the cloud. This network is virtualized and software-driven, and they exploit cloud technologies. The network will simplify mobility, with seamless roaming capabilities between cellular and Wi-Fi. Mobile users can stay connected as they move between outdoor connections and inside buildings without user intervention [31].

C. Advantages
The 5G network offers the following advantages with different applications.

1. Increased speed and bandwidth.
2. Greater device density aids mobile e-commerce.
3. Improved WAN connections.
4. Better battery life for remote IoT devices.
5. Enhanced security with hardened endpoints.

2. LITERATURE SURVEY

This section reports some essential contributions (i.e. research articles and technical development), which are developed in recent years.
X. Wang et al [6] describe the main drivers of cellular traffic through a large dataset. Creators uncover concentrated Spatiotemporal Dependency (SD) among ignored cell towers. To portray the SD model of metropolitan cellular traffic and disintegration of in-cell and inter-cell information traffic is proposed, and graph-based Deep Learning (DL) for exact traffic forecast is applied. Results exhibit that strategy reliably performs and show how the deterioration of traffic can be utilized for event derivation. Traffic learning and expectation are utilized to assess the exhibition of networks. Big data makes it conceivable to investigate at the application level. ***R. Li et al [7]*** gather application-level traffic and study the modeling and forecast. The outcomes show some traffic displaying qualities at an assistance granularity, including α-stable property and the sparsity. They propose traffic forecast framework to investigate and foster a dictionary learning technique. The outcomes demonstrate that could offer a brought solution. Cutting edge DL models are studied by ***C. W. Huang et al [8],*** including RNN, 3D-CNN, and a blend of CNN and RNN (CNN-RNN). The investigations uncover that CNN and RNN can extract topographical and temporal traffic highlights. Contrasting with DL and non-DL

methodologies, CNN-RNN is a reliable with 70 to 80% forecasting exactness.

A Spatio-Temporal Neural Network (STN) is introduced by ***C. Zhang et al [9]*** for exact network-wide traffic determining and feature extraction capacities of DL. A system for tuning STN is introduced and empowers with restricted ground truth. At that point present a Double STN (D-STN), which joins the forecasts with insights, for long term projections. They show that D-STN performs as long as 10-hour long forecasts with wonderful precision. ***B. Yang et al [10]*** show that organized social media can work as an indicator for wireless data interest. A contextual analysis is performed on the data utilized over labeled Twitter data. The investigation shows that social media movement can precisely anticipate long-term traffic load. The connection between social media activity and traffic load complies with a law and clarifies more than 71%–79% of the fluctuation in genuine traffic. ***K. Ruler et al [11]*** contribute to use the call detail information to distinguish anomalies. The K-mean utilized for validation and check, locating anomalies, to plan resource allocation and fault recognition and evasion. Second, prepare anomaly-free data and train a NN. They notice the impact of anomalous exercises and MSE. Finally, utilize an ARIMA model to anticipate future traffic. This anomaly-free information better sums up the learning models.

S. Dawoud et al [12] present a Power Management System that applies a provisioning strategy to BSs. This framework is a Hybrid Traffic Prediction Model that predicts the workload of BS. A test is executed to assess the framework using real data. The outcomes show the chance of turning off 49% of the BS at certain times. ***J. Feng et al [13]*** propose Deep Traffic Predictor (DeepTP), a DL-based model, which predicts traffic requests from spatial-reliant and long-term cellular traffic. It comprises of a feature extractor for dependencies and encoding, and a successive module for displaying convoluted varieties. In the feature extractor, a correlation determination for spatial and embedding system to encode data is presented. They apply a seq2seq model with attention mechanism for the consecutive model. Tests exhibit that model outflanks by more than 12.31%. ***H. He et al [14]*** centers around foreseeing client mobility patterns dependent on various qualities. For that, gather real-world data from LTE network followed by clustering the client into fixed or mobile with a location-entropy-based technique, and afterward present the Intelligent Time Division (ITD) and Time-Based Markov (TBM) model for the location forecast. Analyses show the adequacy and better performance of the strategies.

For recognizing network irregularities using mobile traffic a system is proposed by ***H. D. Trinh et al [15]***. Using the LTE Downlink Control Channel it gathers the data and to recognize traffic anomalies a DL technique is used. They can get fine-grained and high-resolution information for the clients associated with LTE, through a semi-supervised methodology. Two algorithms dependent on stacked-LSTM Neural Networks: 1) LSTM Auto-encoder, to recreate the examples 2) LSTM traffic indicator, to anticipate the traffic. ***L. Nie et al [16]*** proposes a network traffic expectation strategy dependent on DL and Spatiotemporal Compressive Sensing. The strategy receives DWT to extract low-pass segment that depicts the long-range reliance. A model dependent on the Deep Belief Network (DBN) is worked by gaining from the separated low-pass components. The Spatiotemporal Compressive Sensing technique is utilized to anticipate the excess high-pass components that communicates the gusty and inconsistency of traffic. The ML empowers us to anticipate traffic in urban communities and assist with improving the plan and the management of transport services. ***A. M. Nagy et al [17]*** give a traffic forecast techniques, additionally giving an outline of the current data sources and prediction models.

Y. Hua et al [18] propose a DL model dependent on LSTM, called Random Connectivity LSTM. In the development of NN, a prominent advancement is made by RCLSTM, wherein stochastic way neurons are associated. Numerous neural associations missing with certain sparsity and this prompt the reduction in boundaries to be trained. To anticipate traffic RCLSTM is applied and with 35% availability. The performance of RCLSTM turns out to be progressive nearer to the classical LSTM. A techno- economic examination and mathematic were considered by ***G. Smail et al [19].***

Likewise, a pricing model is proposed. The two components, Capital and Operative Expenditure were contrasted with anticipated revenue. The outcomes show that 5G is helpful for lower cost, average data consumptions, and clients. The investigation of Price Elasticity of Volume gives a significant advantage. They affirm the reuse of existing sites can diminish the effect on costs. ***C. Zhang et al [20]*** propose a DL architecture, named as Spatial-Temporal Cross-area neural Network (STCNet). By including a convolutional LSTM network, STCNet has the capacity to demonstrate spatial-temporal conditions. Three sorts of cross-space datasets are gathered to capture the components. A clustering is utilized to segment city-regions as various functional zones and coincides among cellular traffic, and a progressive inter-cluster transfer learning is used. The information transfer among traffic is also investigated. The STCNet is approved through real world datasets. The outcomes show the transfer learning dependent on STCNet achieves 4%~13% additional performance. ***S. Zhang et al [21]*** exploit an ML technique to gauge the BS traffic and propose a BS sleeping methodology dependent on forecasted traffic. They break down multi-views: temporal influence, spatial influence, and event influence. And propose a multi-view ensemble learning model to learn the traffic. The assessment shows that forecasting improves about 40%. Assess the BS sleeping technique yields about 10% more energy saving. ***Y. Zhang et al [22]*** gather a dataset called WeChat Net. They work with three applications, i.e., the data scattering in cellular network, the traffic forecast in network, and the mobile populace projection and at last talks about the new applications. ***X. Fan et al [23]*** concentrate on how to reuse building sensing information to predict traffic volume using BuildSenSys, a framework for close traffic forecast. It comprises two sections, i.e., Correlation Analysis and Cross-domain Learning. A multi-source dataset is utilized to uncover how and why building sensing information is connected with traffic. An RNN for traffic volume forecast dependent on cross-domain learning with two techniques is used. Cross-domain attention technique catches the traffic connections and extracts the relevant information. A technique is utilized to show the temporal conditions. The analysis exhibits that BuildSenSys beats most benchmark strategies with 65.3% precision. ***M. F. Iqbal et al [24]*** investigate various predictors which have high precision and low intricacy and power utilization. Three classes, including time series, ANN, and wavelet transform-based predictors, are analyzed using real traces. Introduced the exactness and cost examination in intricacy and force utilization. ***A. Azari et al [25]*** planning traffic forecast method that utilize factual, rule-based, or DL strategies.

Table 1 Literature Summery

Ref. No	Application	Methods	Contribution
6	Predict cellular traffic	Graph-based, Deep Learning	Decomposition of in-cell and inter-cell traffic. Results are consistent and show decomposition of traffic can be used for event inference.
7	Traffic prediction	Dictionary Learning	Examine different types of application-level traffic. The results prove it could offer a unified solution.
8	Traffic prediction	CNN-RNN	Shows CNN and RNN can extract geographical and traffic features. CNN-RNN is a reliable with 70 to 80% accuracy.
9	Traffic forecasting	Spatio-Temporal neural Network, Double Spatio-Temporal neural Network	Spatio-Temporal neural Network designed for precise Demonstrate the D-STN schemes perform up to 10-hour long predictions. And achieves 61% smaller errors.
10	Predict long-term traffic demand	Review/ case study	Case study on geo-tagged Twitter data to show social media activity can predict long-term traffic demand and traffic demand obeys power law

11	Predict future traffic	K-Means Clustering	To detect anomalies, resource distribution, fault detection and avoidance, prepare anomaly free data. The effect of anomalous activities in training.
12	Forecasts workload of BS, with real data	Hybrid Traffic Prediction Model	The results show the possibility of turning off 49% of the BS at some times of the day.
13	Forecasts long-period cellular traffic	Deep Traffic Predictor	Consists of a feature extractor, encoding, and a sequential module. Apply a seq2seq model with attention mechanism.
14	Location prediction	Location-Entropy-Based Method, Time Division and Time-Based Markov	Collected real-world data from LTE network, by data clustering into stationary or mobile, using location-entropy-based method.
15	Detecting network anomalies of connected users	LSTM-AE, LSTM-PRED	Two algorithms based on stacked-LSTM: 1) LSTM Auto encoder, 2) LSTM traffic predictor, and use prediction error to detect anomalies or not.
16	Network traffic prediction	Spatiotemporal Compressive Sensing	DWT to extract low-pass component for long-range dependence and model learning on the deep belief network.
17	Predict traffic in transport services	Traffic Prediction Methods	Provides a traffic prediction method, with existing data sources and prediction models.
18	Predict traffic	Random Connectivity LSTM	Reduces the parameters to be trained in RCLSTM. With 35% neural connectivity can speedup learning process.
19	A pricing model for two factors, Capital and Operative Expenditure	Techno-Economic Analysis and Mathematic	Results show that 5G is beneficial due to the average data consumptions and users connectivity. Confirm reuse of existing sites have a large impact on costs.
20	Traffic prediction	Clustering Algorithm, STCNet model	Modeling spatial–temporal dependencies, clustering is used to segment city areas using transfer learning strategy. That brings 4%~13% extra performance.
21	Predict load, for BS sleeping strategy	Traffic Prediction Algorithm	Analyzed traffic for temporal, spatial, and event influence. Evaluation shows prediction improves about 40% and BS sleeping strategy yields about 10% energy saving.
22	Traffic prediction, and population distribution projection.	Network Traffic Prediction	A dataset called WeChatNet of link reposting. Also discuss potential opportunities.
23	Traffic volume prediction	Designed BuildSenSys using Correlation Analysis and Cross-domain Learning	It captures the building-traffic correlations and extracts relevant sensing data. Then, model the dependencies. It demonstrates up to 65.3% accuracy.
24	Traffic prediction	Double Exponential Smoothing Predictor	Predictors with high accuracy, low complexity and power usages in time series, ANN, and wavelet. The double exponential smoothing provides reasonable results.
25	blind classification of applications	Blind Classification	Impact of parameters, i.e. prediction length, features, granularity, on accuracy. A threshold

	traffic		shows relation between threshold, prediction length, and features.
26	Comparative analysis of predictors	DNN, Extreme Gradient Boosting Trees, Semi-Markov, SVM, SLAW	They evaluate the model based on ability to predict and time to train and prediction. XGBoost stands with high accuracy.
27	Traffic management based on prediction	Intelligence Technique	The technique at static agent uses data for monitoring and prediction of traffic and times, to ensure smooth traffic flow.
28	Traffic prediction for urban wireless networks	Multivariate LSTM model, Prediction Algorithm	Based on causal analysis, multivariate LSTM models are used to predict CDR. Then prediction is used to process real data.

The effect of different parameters, like the length of forecast, feature set, and granularity of information, are examined. The blind classification of producing traffic dependent on the statistics is also given. The outcomes show the presence of a threshold, after which, DL can outflank, and before, statistical learning. This threshold addresses a coupling between threshold, the length of forecast, and the list of features. ***H. Gebrie et al [26]*** perform comparative examination of four techniques: Deep Neural Network (DNN), Extreme Gradient Boosting Trees (XGBoost), Semi-Markov, and SVM. The examination on a dataset created by Self-similar Least Action Walk model, they assess the model on the capacity to predict. XGBoost stands apart as a reasonable winner among all.

S. Chavhan et al [27] propose traffic management framework dependent on the prediction to decrease the issues in a city region. The static agent is accessible at local and dispatches mobile agents to zones. The mobile agents use a procedure to gather and share traffic stream, historical information, assets, Spatio-temporal data, and others. The method at static agent utilizes verifiable and Spatio-temporal information for observing and forecast traffic density and times. The static agent advances information for picking ideal routes, to guarantee smooth traffic. The investigation is done using NS2, SUMO, OpenStreetMap (OSM), and MOVE device. ***K. Zhang et al [28]*** proposes a traffic examination and forecast framework for metropolitan wireless correspondence networks by consolidating CDR investigation and multivariate calculations. A spatial- temporal modeling is utilized for authentic traffic information and causality examination is applied to information. In light of investigation, multivariate LSTM models are utilized to anticipate future CDR. The calculation is utilized to handle real information.

3. LITERATURE SUMMARY

This section offers the recent development in improving cellular traffic prediction and management techniques. That also helps to understand different applications based on traffic prediction.

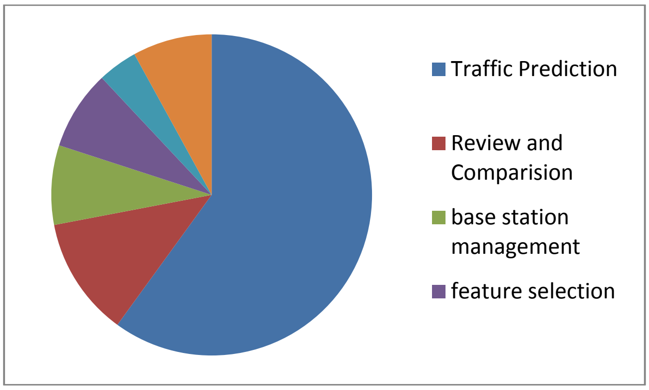

Figure 2 Research Trends

Thus, a review of 66 research article has been carried out from different sources i.e., research journals and conferences papers and then scrutinized according to the utilization of cellular traffic prediction and relevant applications. Among some more relevant and essential contributions are reported in Figure 2.

According to collected recent research works are scattered in different domains. These works consume communication technologies and relevant areas of data to forecast the traffic pattern. The traffic load prediction techniques can be used for managing the city traffic, preserving energy, computational resources and other urban resources. In this context the available researches are focused on developing techniques of network traffic prediction, carry out reviews and comparative performance study, managing base station resources like computational resources as well as energy, developing feature selection techniques and preparing the costing models. The research trends in collected literature have been highlighted in figure 3.1. In this figure the different recent area of interest is described in cellular traffic modeling and prediction.

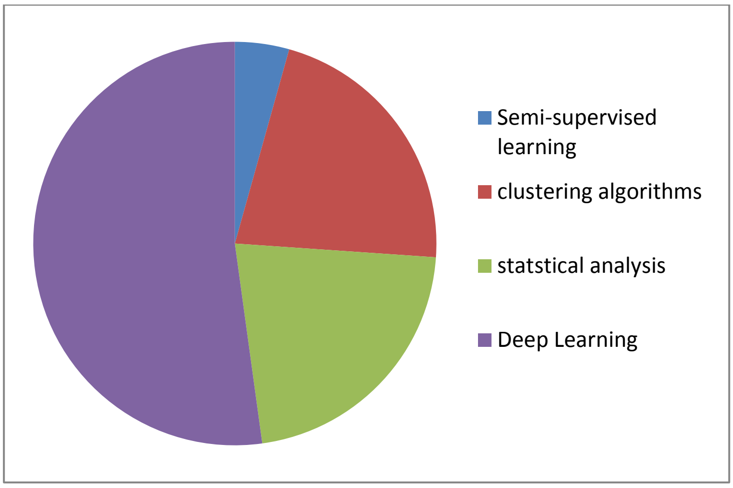

Figure 3 Algorithms used

In addition, we also investigate the different kinds of algorithms which are used for traffic prediction. The utilized algorithms are given in Figure 3. That diagram shows the type of used algorithms for developing prediction techniques which we categorized in Deep Learning, supervised learning, unsupervised learning, and semi-supervised learning algorithm. In recent years most of techniques utilizing the deep learning techniques because a significant amount of data required being process for accurately understanding the patterns of the traffic in different areas of applications.

4. FUTURE OBJECTIVES

The technology based on 5G networks involves the connectivity among each and every digital device. To maintain the connectivity and support to different applications these devices generate a significant amount of data. In order to deal with massive data, we need to involve the cloud computing, big data analytics and ML. All these technologies are helpful in various prospects to improve service quality of networks by using resource demand prediction and management, identifying the gatherings, monitoring and tacking, smart traffic management systems. Therefore, the future objectives will include the following work.

1. Investigate the performance of different unsupervised learning algorithms like Self Organizing Map (SOM), Fuzzy C Means (FCM), and k-Means clustering algorithms and also the performance of supervised learning algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN), Bays classifier, Linear Regression (LR) and Decision Tree (DT). Dataset available in Kaggle repository will be used for training & testing of models.
2. Simulate the 5G network application using a semi-structured network infrastructure

design, with random mobility to support real world applications.
3. Generate and refine the dataset to network traffic prediction, management of resource demands, and base station sleeping strategy implementation.
4. To develop a real time traffic prediction model for managing resource

5. CONCLUSION

The 5G network can use the ML techniques to manage their own resources. ML techniques can do prediction, classification, pattern recognition, filtering and many more applications. The huge data analysis generated from the 5G network usages can be helpful in development of various other domains of applications such as traffic management, smart city infrastructure and others. Hence a significant scope for analysis and development of new applications using ML techniques for benefit of society can be explored.

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