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Cellular Traffic Prediction Using Deep Learning-Based Novel Fusion Neural Network And Traffic Variation Handling Algorithm

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ABSTRACT

Big data constitutes a huge amount of data that can be in form of structured or unstructured, these data are stored on daily basis. Such large volume data requires an efficient processing mechanism as it is considered as challenging as well as a complex task. However, these data are often helpful in prediction, one of the applications remains in traffic prediction in cellular networks. Traffic load prediction on network links helps in designing the resource allocation strategies, hence several types of research have been carried out in past for traffic prediction including the deep learning-based model and deep learning-based architecture are found to be more efficient than any traditional mechanism. Hence this research adopts the two different neural networks and designed Fusion Neural Network to enhance the prediction. FNN is an integration of CNN and RNN and its layer; this novel FNN architecture not only enables the exploitation of the topological properties and aims to predict the load link on the network-based but also captures and exploits custom features that establish the link relationships in the network After designing an architecture, a novel Traffic variation handling algorithm is designed to optimal error prediction. FNN is evaluated considering the Telecom Italia Big Data Challenge dataset over the different the metrics like RMSE and MAE considering the SMS, call and internet service; further evaluation is carried out through comparing with an existing model and comparative analysis proves it.

1 INTRODUCTION

The growing advancements in technology have resulted in the evolution of smartphones over the decade. Which has led to a rapid explosion and generation of data, pacing up the big data era [1]. Considering all the sources of data, the mobile traffic, by 2021 among the entire Internet traffic it will represent 20 percent and specifically, the smartphones that produce data traffic constitute 86 percent among the entire mobile traffic due to exposure towards different mobile applications which include Internet vehicles, virtual reality and live streaming [1]. To fulfil the changing needs of the consumers, a growing consensus considering artificial intelligence (AI) and deep learning (DL) in 5G mobile networks are thoroughly investigated [2]. Specifically, an International Union related to telecommunication called ITU has newly launched a focus group that contributes to the effectiveness of growing 5G networks for the assistance of AI and DL. The introduction in the field of AI enables the networks in improving efficiency, self-optimization as well as delivery ideal experiences to the user. Consequently, leading to network connections that are stable users either businesses or individuals [3] [5].

Considering the management of the automated network that is used to enhance AI, one among the most vital problems is the prediction accuracy of traffic since the requirement of various tasks in wireless communications is non-real or real-time analysis of traffic and capabilities of prediction. For example, the resource allocation about the demand aware efficiency has a huge benefit from the accuracy of future prediction wireless traffic. Although, the base station mechanism depends on the traffic prediction knowledge of a particular base station or location to attain the motive in green communications as well as the ultimate requirements of the user [6].

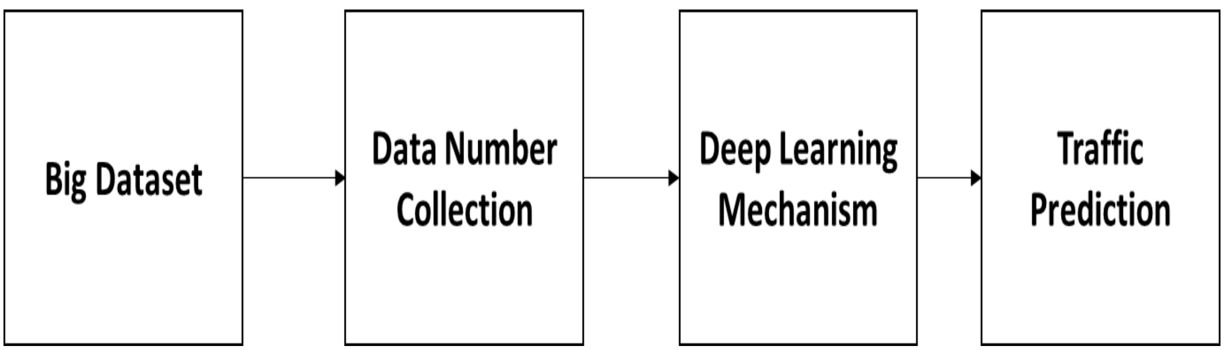

Figure 1 Typical traffic prediction through deep learning

Amid the methodologies in deep learning, recurrent neural networks (RNN) and convolutional neural networks (CNN) are fundamental structures in temporal information modelling [7]. Figure 1 shows the typical traffic prediction through a deep learning approach, any deep learning mechanism constitutes four distinctive blocks; at first Big Dataset is identified for the traffic prediction, second block shows the data number collection where number of data are collected. Third block deals with the implementation of deep learning mechanism and trained through given dataset and traffic prediction is carried out in fifth block. . Along with the time periodicity, cellular traffic distribution data has few characteristics. Therefore, most of the models in DL apprehend characteristics of spatial as well as temporal from the past data. Graph neural networks (CNN) and CNNs are used to model spatial characteristics. Two types of characteristics are extracted by a few researchers simultaneously by using layers of 3D convolutional or Conv LSTM. Along with meta-learning and reinforcement learning is implied for improving the accuracy of prediction. External information is used in many extra works that include cellular traffic data supplement, regional information for obtaining higher accuracy in results. The designed model uses the clustering concept to divide the city into different zones. Though the model reduces the mean square error, the performance of traffic prediction accuracy was not calculated. A Graph Neural Network with Decomposed Cellular Traffic model (GNN-D) was developed to improve the cellular traffic prediction by learning the spatial and temporal dependencies. The designed model failed to minimize the prediction time of continuously evolving traffic patterns. Although, the simultaneous prediction in the network of cellular traffic is a demanding task due to various reasons as stated. Firstly, mobile users require different needs at various times and places which makes it difficult to predict traffic. Secondly, the mobility of the user initiates spatial dependencies within the cellular traffic of the cells that are geographically distributed. Finally, various external factors influence the cellular traffic which may include the number of base stations. The spatiotemporal dependencies are complicated due to these factors within the cellular traffic of various base stations [8]-[10].

1.1 MOTIVATION AND CONTRIBUTION OF RESEARCH WORK

The above-mentioned works focus wholly on the dataset of cellular data and different external factors that include base station information and distribution of POIs that are hardly considered. Although, it has been understood that these factors influence the correlation directly to the cellular traffic generation [5] [6]. However, the present works on the prediction of traffic network-wide have failed in capturing the diversity of patterns of various city traffic similarities of different services and functional zones. Motivated by the problems mentioned above, the proposed work mainly focuses on the accuracy of traffic prediction based on deep learning in the cellular networks considering the big data cross-domain scenario. Hence this research work adopts a fusion approach for accurate prediction. The further research contribution is given as follow:

1. This research work adopts the fusion approach in deep learning and proposes FNN architecture for traffic prediction.
2. Fusion Neural network fuses the two distinctive neural networks and develops an architecture for traffic prediction.
3. Novel FNN predicts the next load link of the network through past observation of links; the novelty of the model lies in exploiting the custom features which relates to relations among links and later training the network; further error is minimized to observe high prediction.
4. After designing an architecture, a novel Traffic variation handling algorithm is designed to optimal error prediction
5. Fusion Neural Network is evaluated considering the publicly available dataset that comprises different services. Further, a model is evaluated considering the metrics like RMSE and MAE.

This particular research work is organized as follows; the first section starts with a background of telecommunication traffic concerning big data and further need for traffic prediction and review of a few related work. This section ends with research motivation, second section designs and develops Fusion Neural Network with architecture diagram and mathematical formulation. The third section evaluates the FNN to prove the model efficiency concerning different metrics.

2 RELATED WORK

Recently, researchers have made great attempts to resolve the challenges that are mentioned above. Whereas, the prediction of cellular traffic is looked at as a forecasting problem of time series. Considering the method of solving, the existing works can be split into two, namely, methods based on machine learning and statistics. In the first method, cellular traffic is predicted and modeled based on probability distribution or statistics.

In [11], Conv LSTM and a deep connection of CNN are adopted for simultaneously capturing the spatial as well temporal dependencies along with the data considered for cross-domain, this is used to achieve the experiment results on the dataset of Milan cellular traffic. Although, methods based on RNN have not been able to deal with the mutations in traffic considering temporal dimensions. The methods based on CNN only concern the dependencies that are spatial along adjacent regions while the impacts from cells that are cellular distant are neglected. Recently, the methods of graph learning have been applied in the prediction of road traffic [12] [13] and forecasting of passenger demand [14], the main idea is capturing the temporal-spatial dependencies by utilization of both RNN and GNN advantages. However, the cellular traffic pattern generally is of higher complexity as compared to road traffic because of the connections that are indeterminate among various cells. Hence, the methods of learning based on a fixed graphical structure are hard to adapt to the prediction of cellular traffic. Addressing the problem mentioned above, various efforts are applied. In [15], a learning method of the graph along with a convolutional graph network (GNC) is proposed and GRU with help of additional information relating to traffic handovers to attain accurate prediction of cellular traffic. In [16], a learning approach of a graph was proposed with traffic inter tower or intra tower data which is parameterized, directed at capturing spatial correlations of long-distance cellular traffic.

In [17], attention based on structural RNN is applied to the graph of cellular traffic by model pre-clustering simultaneously, the spatial correlations, and temporal dependencies. Although the methods based on graphs that are mentioned above rely on constructed connections that are pre-determined based on outcomes on pre-clustering or external information. Therefore, the global spatial correlations that are hidden are not captured efficiently. Considering the inspiration towards recent advances in mechanisms of attention and graph attention network (GAT) [18].

For more accurate capturing of the temporal dependency that is long term and reduction of the time consumed in the prediction of traffic data, [19] propose attention that is time0wise with the help of a convolutional neural network structure (TWAC Net) for the prediction of cellular traffic. The proposed TWAC Net has an attention mechanism that is time-wise by adopting to long-range capturing of temporal dependencies of the data on cellular traffic and a convolutional neural network (CNN) has been adopted for capturing spatial correlation. The TWAC Net performance in the prediction of traffic has real-world testing using datasets of cellular traffic.

To improve the traffic prediction accuracy with minimum time, Expected Conditional Maximization Clustering and Ruzicka Regression-based Multilayer Perceptron Deep Neural Learning (ECMCRR-MPDNL) technique is introduced. The ECMCRR-MPDNL technique initially collects a large volume of data over the spatial and temporal aspects of cellular networks. Then the collected data are trained with multiple layers such as one input layer, two hidden layers, and one output layer. The activation function is used at the output layer to predict the network traffic based on the similarity value with higher accuracy. These predictors are evaluated using real network traces.

3 PROPOSED METHODOLOGY

Network traffic prediction has been for a long; however, increase in a large amount of data led the research to be a focus on developing the data-driven approach. In general, the data-driven approach is divided into two distinctive categories i.e. statistical and machine learning. Recent development in deep learning puts a huge advantage over the statistical approach; In general, prediction is designed as the statistical mechanism is utilized extraction of precise and relevant information and feature from a large amount of data. These data are utilized through gathering and analyzing the recent past events in the network. Accurate traffic prediction at BS (Base Station) assures the optimal QoS (Quality of Service), this has given an edge for research motivation to employ the ongoing technologies such as deep learning. However, considering the deep learning architecture like CNN or RNN, each possesses limitations. Hence, this research work adopts the fusion and proposes an FNN architecture.

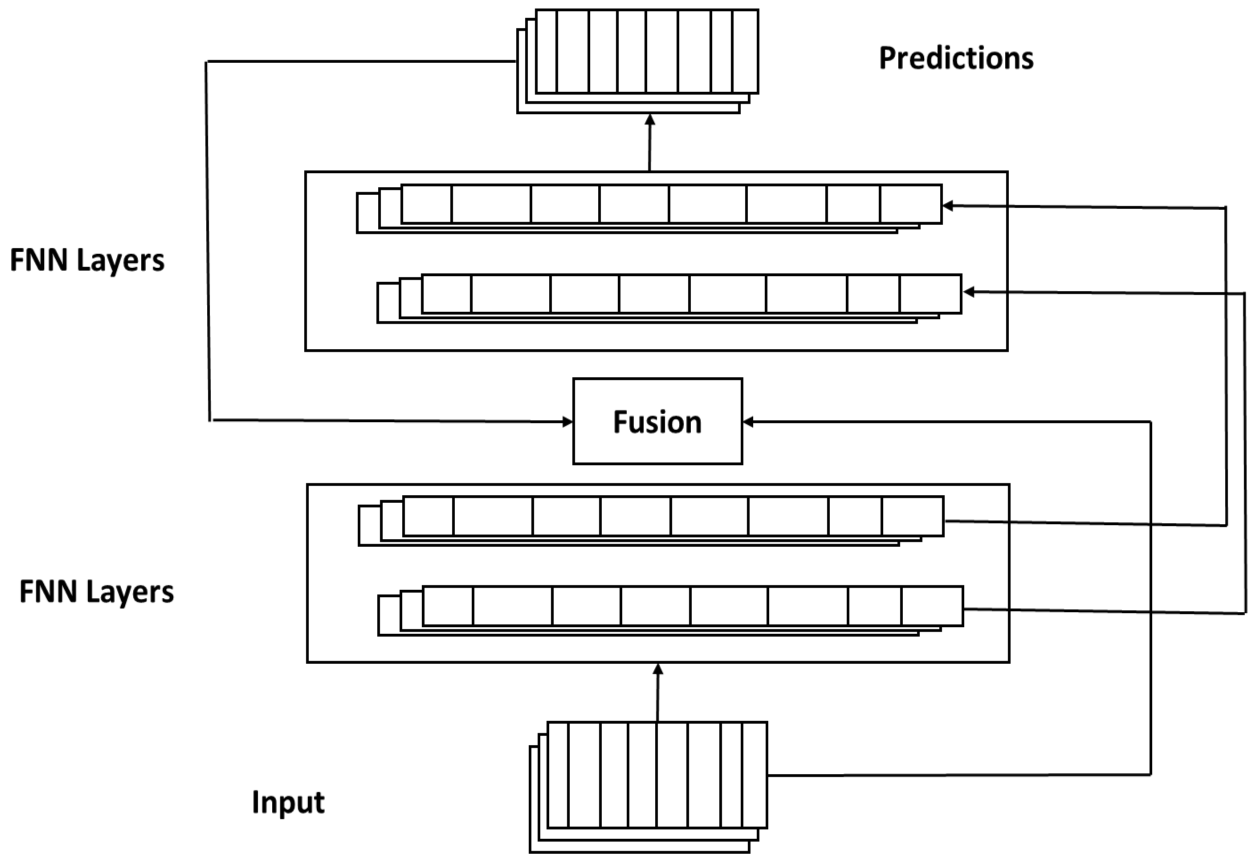

Figure 2 Fusion Neural Network for traffic prediction

FNN is a novel architecture developed by integrating the layers and process of CNN and RNN as presented in figure 2. It comprises an Input block and prediction block as an output; further, these are two layers that perform the encoding and decoding process, and later they are interconnected. At first input data from a dataset is fed into the first FNN layer1; the final states of this layer are connected to the upper FNN layer for initialization. Further, upper FNN layers are used for predictions based on given GT (Ground Truth). The novelty of FNN lies in creating the target through backpropagation, which solves issues of capturing dependencies. Further, the traffic variation handler algorithm is designed to predict the error optimally.

3.1 Preliminary

Fusion Neural Network is an integration of two different neural network layers, thus this section discusses the background of different neural networks and its layer adopted for designing the neural network. Moreover, the convolutional layer is adopted from the Convolutional Neural network. In general convolution among the given two signals is given as:

$$(z * y)(v) = \sum_{t=0}^{V} z(v).y(v - V) \tag{1}$$

Where y indicates the kernel and V indicates respective support. Although, Convolutional Neural Network is adopted for a 2D specific domain, however, it also possesses a great advantage in a 1D domain. In the case of cellular traffic prediction, a kernel is used for tuning the temporal dynamic level such that filters can capture.

Further, RNN (Recurrent Neural Network) is another network layer adopted in designing the Fusion Neural Network; RNN architecture holds the ability to keep track of previous computation which helps in modeling the input data. In Fusion Neural Network, custom RNN is designed adapted to make effective modelinging temporal dependencies on the input data. For a given input vector $z(v)$ of past step and current input step be$(v+1)$, RNN performs below operations in a recursive manner.

$k(v) = \tau(Y_k[Z(v), j(v-1) + d_k])$	(2)

In the above equations, Y_k indicates the learnable kernels for input and d_k indicates the input bias.

$\hat{e}(v) = \tau(Y_e[Z(v), j(v-1) + d_e])$	(3)

Y_e Indicates learnable kernels for input modulation and d_k indicates input modulation bias.

$h(v) = \tau(Y_h[j(v-1), z(v)] + d_h)$	(4)

Y_h Indicates the forget learnable kernels and d_h indicates the forget bias.

$e(v) = g(v) \odot e(v-1) \odot \hat{e}(v)$	(5)

In the above equations, $\odot$ indicates the matrix multiplication

$q(v) = \sigma(Y_q[j(v-1), z(v)] + d_q)$	(6)

W_o Indicates the learnable output gates and b_o indicates the output bias.

$j(v) = q(t) \odot av(E(v))$	(7)

Moreover, these gates in the network are combined to perform the operation which aims at remembering the information and forgetting input data. Later hidden state h is used to encode with the last information.

3.2 Problem definition

Let's consider a backbone network that are connected with node set and links set; further it is presumed that nodes are placed at the shortest path. Then resulting traffic load can be measured through the designed matrix. Proposed FNN aims to exploit the additional information in terms of custom features. Custom feature exploitation is carried out through the designing the directed graph In a given time t can be further represented in form of matrix$Z(v) \in T^{OX1} \geq 0$, here M indicates the total number of links in a given network. Given the traffic loads sequence computed over the given time slots V, the traffic loads can be forecasted over the time $v+1$ concerning $n \in \{1, \dots, N\}$, further represented as$Z^{(v+1)}$.To extract the deep information, directed graph H is represented with traffic crossing and given as $Z(v) \in T^{oX1} \geq 0$ with matrix Y and the problem is designed as

$Z^{(v+1)} = H(Y, Z^{(v+1)}, \ldots . Z(v))$	(4)

Where H indicates the estimator with Y matrix.

3.3 Modeling of spatial dependency

The fusion approach is designed through random walk on the designed graph with probability of $\propto$ belongs to $[0,1]$ along with matrix denoted as $F_q^{-1}Y$ where F_q is the diagonal matrix along with a unit that belongs to T^P which also indicates the unit vector. Moreover, after the iterative process , it leads to the stationary distribution i.e. $R \in T^{PXP}$, ith row of these matrix indicates fusion through the node $x_k$belongs to X. Further, closed form solution is developed for designing the optimal stationary distribution.

$R = \sum_{m=0}^{inf} \alpha(1-\alpha)^k (F_o^{-1}Y)^m$	(5)

In the above equation, m indicates the fusion process, in general, proposed model uses finite steps for fusion, and weights are trained at each step.

3.4 Fusion Neural Network (FNN)

Let's consider a graph of pair $I = (X, G)$ which indicates the node-set and edge set respectively. Further, there is another alternative approach to describe I with $(Z \in T^{PXr}, Y \in T^{PXr})$ where T indicates attributes and Pindicate the number of nodes; Y indicates the weighted matrix which aims to encode the relations among the nodes and Z indicates feature matrix.

$Z(I, h(\eta)) = \sum_{m \text{ is } 0}^{m-1} \left(\eta_{l,1}(F_0^{-1}Y)^{\ m} + \ \eta_{m,1}(F_0^{-1}\ Y^{trans})^{\ m}\right). Z$	(6)

In the above equation, $\eta \in T^{mX2}$ is kernel parameter,$F_0^{-1}Y$ indicates the transition matrix of fusion of neural network and$F_0^{-1}\ Y^{trans}$ indicates the respective transpose. Fusion parameter is introduced for designing the fusion of convolutional layer along with θ is introduced as the common fusion parameter. Moreover, this fusion convolutional layer is trained for mapping the feature matrix $Z \in T^{PXR}$ to output as $J \in S^{PXR}$; this process is computed using the below equation.

$J_s = \tau\left(\sum_{r \text{ is unit}}^{R} Z_r * H\left(g_{\omega_{s,r}}\right)\right)$ for all s belongs to $\{1, \ldots \ldots, S\}$	(7)

In the above equation$\omega \in T^{SXrXmX2}$ indicates the trainable tensor parameters. Moreover considering the layers of CNN and RNN; FNN is designed and can be formulated through the below equations i.e. equations 4 to equations 7/

$t(v) = \tau(\delta_t * I\,[Z\,(v), J(\,v-1)] + d_t)$	(8)

$E(v) = av\,(\delta_E * H[Z(v), (t(v) \odot J(v) - 1)] + d_e)$	(9)

In the above equations, i.e. $\odot$ indicates tensor operation (usual multiplication is performed) and t indicates the resetting the cells in-network, v indicates the updation and E indicates the cells in the network.

$w(v) = \tau(\delta_w * I\,[Z\,(v), J(\,v-1)] + d_w)$	(10)

$J(v) = w(v) \odot J(v-1) + (1 - w(v)) \odot E(v)$	(11)

Further, in the above equations, δ_t, δ_E and δ_w indicates kernels parameter learnt while training. Further d_t , d_e and d_w indicates the observed bias with respect to model time given v. Hence, the custom features which relates to topological relations are exploited to predict and through considering the problem as regression error is minimized. Further, FNN is evaluated in the next section of research.

3.5 Traffic Variation handling

Traffic Variation handling allows the optimal prediction in traffic cellular prediction, using the Fusion Neural Network traffic variation handling is computed for analyzing the prediction error. Algorithm shows the traffic variation handler

Traffic Variation handler algorithm	
Step1:	Start
Step2:	Compute moving average
Step3:	$\varrho(p) = \varsigma(p) * M(p)$
Step4:	$opt\_param = \chi(p) - \varrho(p)$
Step5:	Denote C as residual Highlight variation observed

Step6:	if($\varsigma(\mathrm{p}) - \varrho(\mathrm{p})$) is less than C Then Highlight sample at given time n as variation observed
Step7;	Add p to variation set C
Step8:	Return C

Moreover, output of the algorithm learning, decision function is designed which aims to evaluate the traffic. Mean Square error is computed between the predicted sequences through below equation.

$$\mathrm{N}_{\xi}(\mathrm{p}) = \frac{1}{\mathrm{Y}}\frac{1}{\mathrm{F}}\sum_{\mathrm{Y}}\sum_{\mathrm{F}}\left[\vartheta_{\delta}\left(\mathrm{z}(\mathrm{p})\right) - \mathrm{z}(\mathrm{p})\right]^2 \quad (12)$$

$$\mathrm{N}_{\xi}(\mathrm{p}) = \frac{1}{\mathrm{F}}\sum_{\mathrm{F}}\left[\vartheta_{\delta}\left(\mathrm{z}(\mathrm{p})\right) - \mathrm{z}(\mathrm{p}+\mathrm{Y})\right]^2 \quad (13)$$

4 PERFORMANCE EVALUATION

There has lack of research on the analysis of per user traffic in cellular networks, for deriving and following traffic-aware network management. In fact, the legacy design approach, in which resource provisioning and operation control are performed based on the cell-aggregated traffic scenarios, are not and efficient and need to be substituted with user-centric predictive analysis of mobile network traffic. Here, we shed light on this problem by designing traffic prediction tools that utilize standard machine learning (ML) tools, including long short term memory (LSTM) and autoregressive integrated moving average (ARIMA) on top of per-user data. FNN integrates the two different neural network architectures this section evaluates the proposed FNN considering the dataset. Moreover, FNN is modelled through python as a programming language considering the model configuration with 8GB RAM and 1TB hard disk on windows 10. To evaluate the two distinctive SE (Root Mean Square Error) and MAE (Mean Absolute Error) are considered. The differences of the average square root are calculated using RMSE between the results that are predicted and individual differences having equal weights. The absolute differences average is calculated using MAE and individual differences having equal weights. To prove the model efficiency, FNN is compared with other baseline model including the existing model [21]

4.1 Dataset Details

The real-world dataset termed as “Telecom Italia Big Data Challenge” [22] has been released in the city of Milan, Italia. Huge research teams have access to this same dataset; therefore, different methods of traffic predictions are advanced in this field. However, there is no recent update on the statistics, the standardized, open richest dataset “Telecom Italia Big Data Challenge” provides opportunities in carrying out extensive comparisons and research. The dataset contains three categories of traffic records, namely, Internet service, SMS service and Call service data that are dated from 11-01-2013 to 01-01-2014 having intervals of 10 minutes. The city of Milan was split into cells of dimension 100×100, where $235\text{m} \times 235\text{m}$ was the size of every cell. At an interval of 10 minutes, the data of every category of cellular traffic was recorded as well as aggregated in every cell. The values that are missing from every cell are filled before the commencement of the experiment by interpolation of the values of traffic volumes of the neighboring cells.

4.2 Comparison Method

On performance verification of the proposed method considering the cellular traffic prediction, MVSTGN is compared with the below-mentioned baseline methodologies:

A. **ARIMA [23]:** ARIMA is a time series linear model used in various predictions of traffic.
B. **SVR [24]:** SVR is a methodology of machine learning and is used widely in addressing traffic nonlinearities.
C. **Spatial-Temporal Dense Connected CNN (ST- Dense Net) [25]:** It has been designed for simultaneously capturing the temporal and spatial correlations by a CNN architecture that is temporal-spatial.
D. **Spatial-temporal cross-domain neural network (STC Net) [11]:** It is an advanced temporal-spatial cellular model of traffic prediction, on further consideration of information relating to cross-domain.
E. **LSTM [26]:** LSTM is a model that has a strong sequence that is largely used in capturing temporal dependencies of prediction tasks related to cellular traffic.
F. **MVSTGN:** MVSTGN integrates the convolutional approach in traffic analysis which enables the optimal exploitation of spatio-temporal relationship.

Table 1RMSE comparison

Methodology	SMS	CALL	Inter Net
ARIMA	40.1875	24.6042	150.029
SVR	33.0081	22.38	127.7005
LSTM	39.6033	22.3111	141.3343
ST-Dense Net	31.3021	19.6701	125.0611
STC Net w/o (cross+	32.6001	17.7448	94.1415
meta) STC Net w/ (cross+ meta)	30.3221	17.9901	93.8873
MVSTGN-ES	24.9796	14.6816	88.6983

Fusion Neural Network -PS	18.25	9.5	12.13

Table 2 MAE comparison

Methodology	SMS	CALL	Inter Net
ARIMA	71.823	47.7327	240.3088
SVR	75.2546	46.2231	215.7935
LSTM	72.8344	44.11	231.7825
ST-Dense Net	60.3758	43.9073	196.3721
STC Net w/o (cross+	57.7105	40.1073	172.7059
meta) STC Net w/ (cross+ meta)	54.1664	34.3346	167.3321
MVSTGN-ES	49.0515	30.9443	165.0445
Fusion Neural Network -PS	32.52	14.318	17.263

4.3 SMS Service

In this subsection, evaluation is carried out on sms service, figure 3 and figure 4 shows the comparative analysis of different methodologies based on RMSE and MAE metrics. Less error value of RMSE and MAE suggest efficient cellular traffic prediction. In fgure3, ARRIMA observes RMSE value of 71.823, SVR observes 75.2546, RNN based LSTM observes RMSE of 72.8344. Similarly, ST-Dense net, STCNET(with cross and meta) and STCNET (without cross and meta) observes RMSE value of 60.3758, 57.7105 and 54.1664 respectively. Further, existing model MVSTGN observes RMSE of 49.05 whereas proposed FNN achieves RMSE of 32.52.

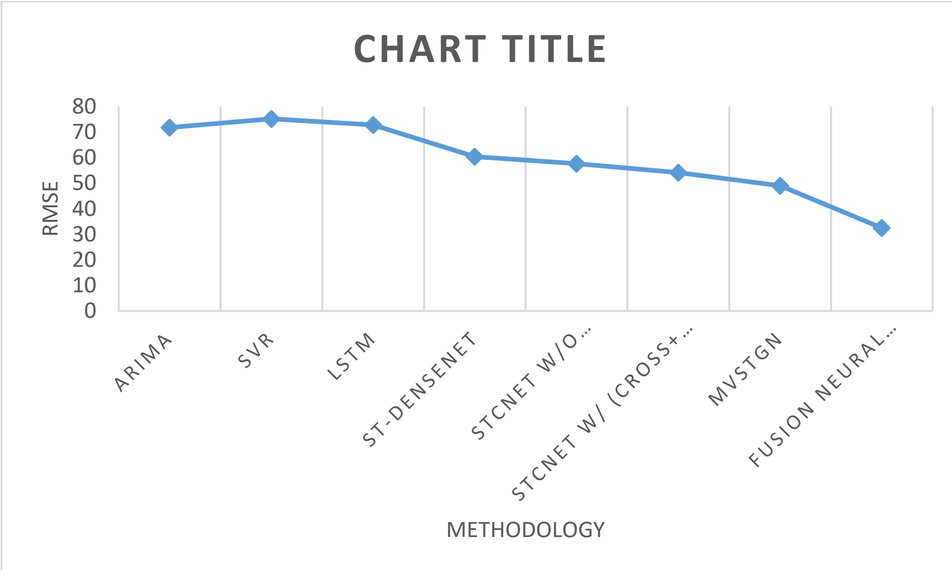

Figure 3 RMSE comparison on SMS service

Figure 4 shows the Mean Absolute Error comparison of different methodologies; few state of the art technique like ARIMA and SVR observes MAE of 40.1875 and 33.018 respectively. RNN architecture LSTM observes Mae value of 39.6033. Further ST with dense net, STCNET(with cross and meta) and STCNET(without cross and meta) observes MAE of 31.3021, 32.6001 and 30.3221 respectively. Existing methodologies MVSTGN observes MAE of 24.9796 whereas proposed FNN observes 18.25.

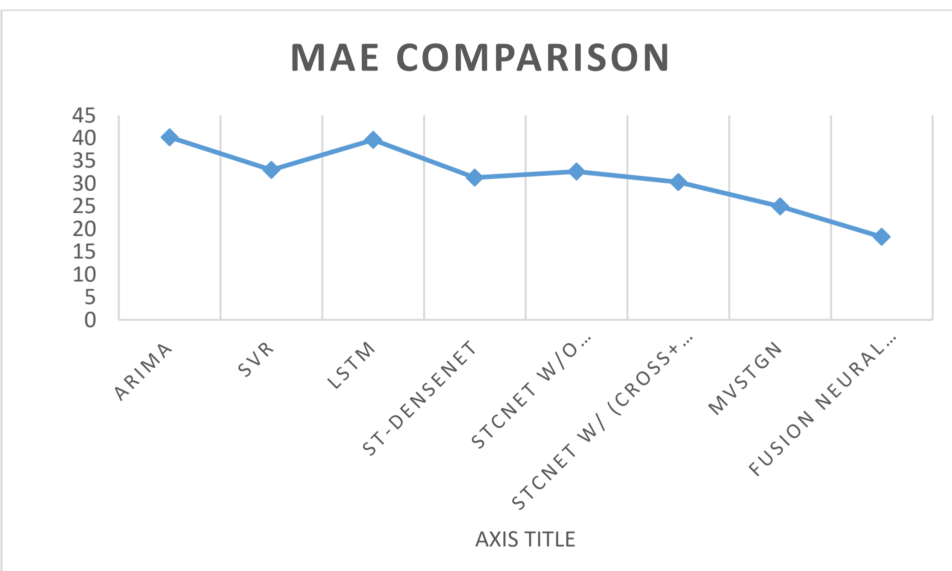

Figure 4 MAE comparison on SMS service

4.4 Inter Net Service

Internet service is considered as one of the major service in cellular telecommunication, hence this service requires the major priority for prediction; moreover traditional mechanism like ARIMA and SVR observes RMSE of 240.3088 and 215.7935 respectively. LSTM observes RMSE of 231.7825; ST with Dense Net, STCNET (with cross and meta) and STCNET(without cross and meta) observes 196.3721, 172.7059 and 167.332. Existing model MVSTGN observes 165.044 whereas Fusion Neural Network observes 17.263

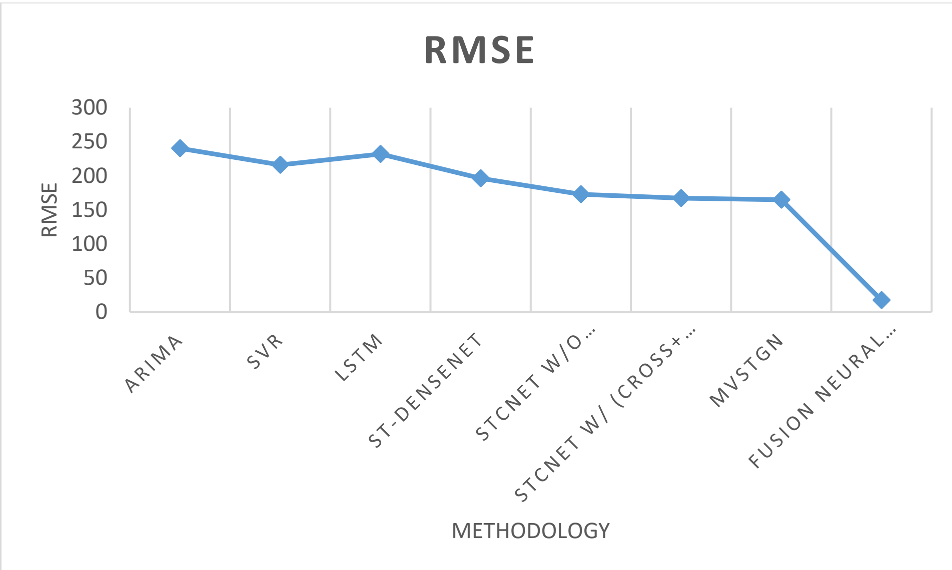

Figure 5 RMSE comparison on Internet service

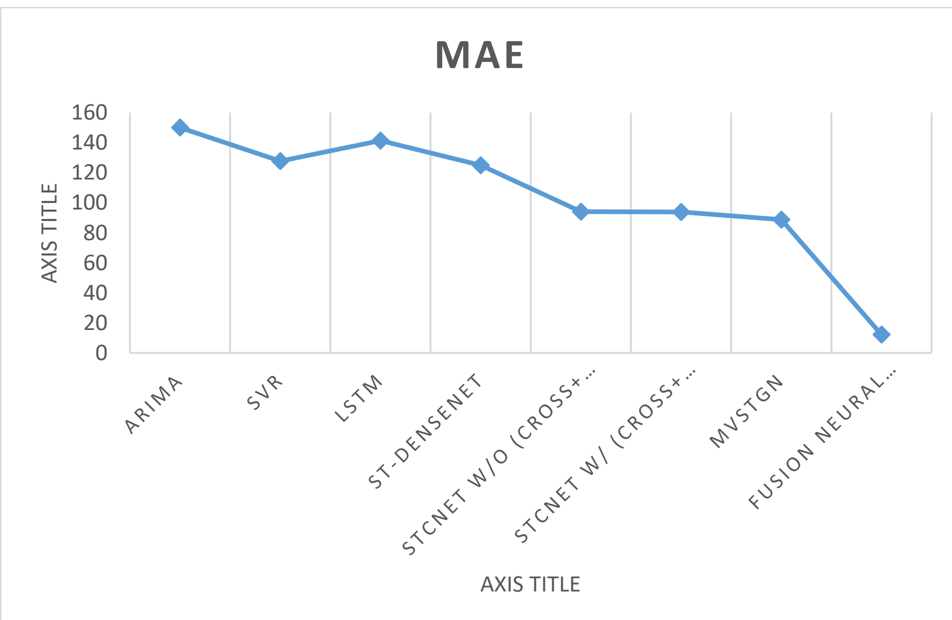

Figure 6MAE comparison on Internet service

4.5 Call Service

In cellular network, call facility is another service that are used widely, figure 7 and figure 8 shows the RMSE and MAE comparison with other existing model respectively. Moreover traditional mechanism like ARIMA and SVR observes RMSE of 47.7327and 46.2133 respectively. LSTM observes RMSE of 44.11 ; ST with Dense Net, STCNET (without cross and meta) and STCNET(with cross and meta) observes 43.90, 40.10 and 34.33. Existing model MVSTGN observes 30.94 whereas Fusion Neural Network observes 14.318

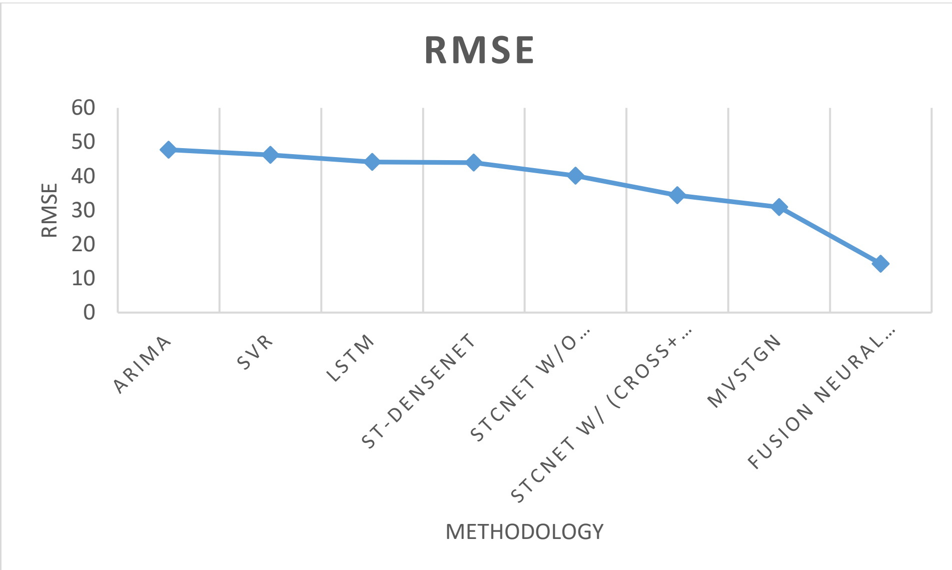

Figure 7 RMSE on call service

Figure 8 shows the MAE comparison on Call service, traditional mechanism like ARIMA and SVR observes RMSE of 24.6042 and 22.38 respectively. LSTM observes RMSE of 22.13; ST with Dense Net, STCNET (without cross and meta) and STCNET(with cross and meta) observes 19.6701, 17.7488 and 17.9901. Existing model MVSTGN observes 14.68 whereas Fusion Neural Network observes 14.318

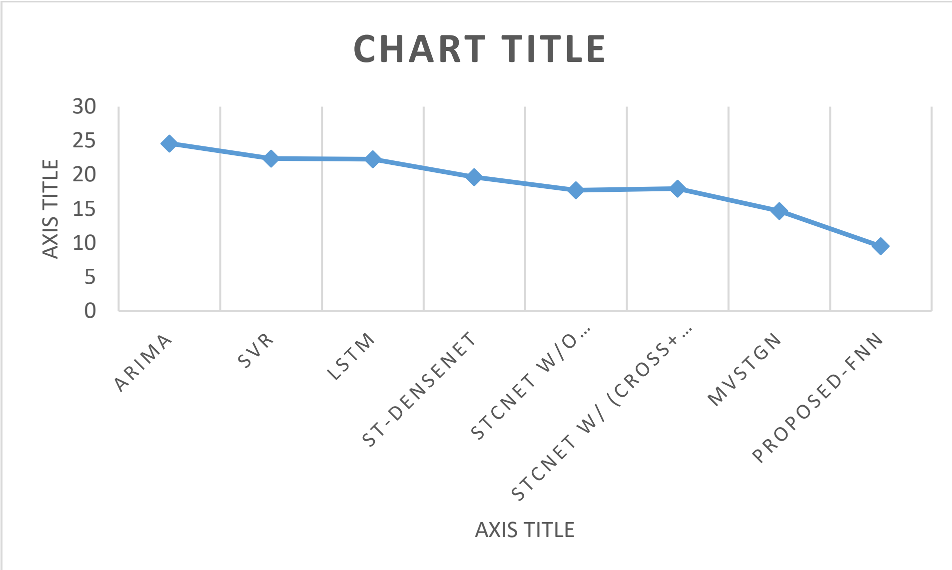

Figure 8 MAE comparison on call service

4.6 Comparative analysis and discussion

Fusion Neural Network is designed to optimize the feature and learn the feature in deep, this section highlights the improvisation observed over the existing model. Table 3 shows the improvisation over the existing model considering RMSE and MAE as the evaluation parameter. In the case of CALL service, FNN observes improvisation of 35.29% in terms of RMSE and 53.72% improvisation in MAE. Similarly, considering the SMS service, proposed methodology FNN observes improvisation of 33.70 and for internet service, 89.54% improvisation is observed.

Table 3 Improvisation over the existing model

	CALL	SMS	INTERNET
RMSE	35.2931561	26.9403834	86.3244279
MAE	53.72	33.70	89.5404

Conclusion

In past few years, cellular traffic has registered enormous growth with increase in mobile devices; large amount of data is collected at cell towers which are utilized for the daily management of the network. Moreover, with an increase in the volume of cellular big data, traffic prediction is one of the primary and challenging tasks due to the establishment of spatial and temporal dynamics through various user behavior. FNN observes marginal improvisation over the existing model considering RMSE and MAE as the evaluation parameter. In the case of CALL service, FNN observes improvisation of 35.29% in terms of RMSE and 53.72% improvisation in MAE. Similarly, considering the SMS service, proposed methodology FNN observes improvisation of 33.70 and for internet service, 89.54% improvisation is observed. Through the experimental observation, it is observed that the fusion approach observes high improvisation over the existing model. Moreover, the future scope of this research lies in the evaluation of another service with further metrics.

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