Cellular Traffic Prediction through Multi-Layer Hybrid Network Domain

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Abstract

Cellular traffic prediction is one of the key research areas for telecom companies to achieve resource allocation and scheduling; also big data plays an important part in cellular prediction, as traffic prediction requires traffic involving thousands of cells. Furthermore, recent research shows the great potential of adopting the deep learning domain to predict traffic. However, training deep learning models for various prediction tasks is considered a critical task due to various reasons. This research work develops Multi-Layer Hybrid Network (MLHN) for network traffic prediction and analysis; MLHN comprises the three distinctive networks for handling the different inputs for custom feature extraction. Furthermore, an optimized and efficient parameter-tuning algorithm is introduced to enhance parameter learning. MLHN is evaluated considering the "Big Data Challenge" dataset considering the Mean Absolute Error, Root Mean Square Error and R^2 as metrics; furthermore, MLHN efficiency is proved through comparison with the state-of-art approach.

Keywords: MLHN, Network Traffic Prediction

1 INTRODUCTION

The advanced cellular network is capable of enhancing the data and functioning of the system and its interoperability, which is one of the key enabling technologies in Industry 5.0, constructed on these substantial and dependable communication services as well as the ultra-low-latency services that are in their support [1]. Data traffic has caused significant issues because of mobile carriers' rising popularity and internet access because the network is under constant strain. As this network control and management along with provisioning service for network traffic analysis and prediction, this assumes to be a crucial [2]part of cellular networks that reduces the load. Numerous studies have been done on cellular network traffic prediction, however, there are significant difficulties concerning the temporal volume and geographical dynamics that various Internet users' behavior is accommodated [3].

Cellular traffic is generated by a variety of devices used each day and businesses associated with them, particularly cellphones in these circumstances. Numerous innovative and cutting-edge studies make use of such technologies. Recently, new types of mobile traffic, such as mobile traffic classification [4], mobile traffic prediction and characterization [5], etc., have appeared. An accurate cellular network traffic prediction advances which makes it crucial each day and assists the network management system to deal with unexpected problems by proactively accommodating resources that are delivered to consumers along with industrial devices and high-end services.

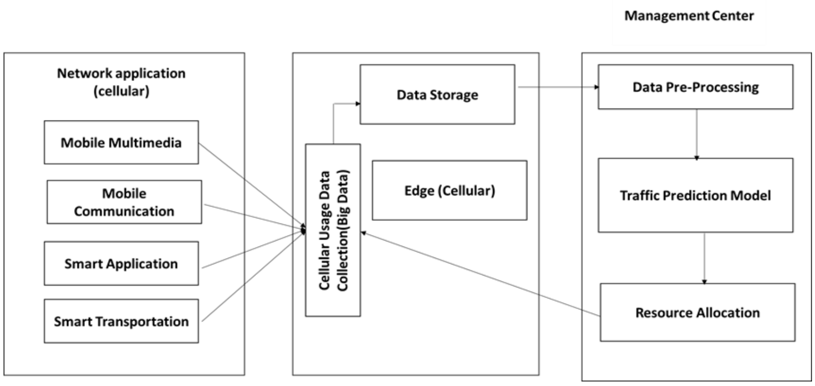

Figure 1 Intelligent Traffic Prediction

In [7] a spatiotemporal deep learning mechanism for cellular traffic prediction mechanism incorporates the attention mechanism for architecture design purposes. By consideration, in [8] a network traffic prediction model, known as STGCN-HO, the approach is proposed by utilizing the handover graph along this residual network structure to enhance the prediction performance. A novel approach is proposed in [9] for network traffic prediction known as FedDA, which employs a federated learning mechanism which collectively trains the wireless prediction model. The dual mechanism is known as the intra-cluster and the inter-cluster is known as the global model.

In [10] five various types of deep learning models are used for wireless traffic usage forecasting known as the single AP for significant spatial correlations exist. The researchers collaborate the statistical tools along with the deep learning models for predicting the accuracy. In [11] a single-cell level cellular traffic prediction mechanism by the LSTM approach with Gaussian Process Regression (GPR) enhances the performance. In this approach, periodic components are extracted based on the utilization analysis carried out. Here LSTM is used for this learning process as well as a long-term dependency for random values and GPR is applicable here to estimate the residual random components for the network traffic prediction mechanism as proposed in [12]. This aims at enhancing the accuracy of fluctuation-based pattern clustering. A novel model-based approach to LSTM known as TPBLN, this mechanism is proposed for the prediction of baseline components, wherein a probability model predicts the residual component, this parameter is calculated by adopting maximum likelihood estimation.

1.1 Motivation and contribution of research work

With the rapid development of mobile cellular technologies and the increasing popularity of mobile and Internet of Things (IoT) devices, timely mobile traffic forecasting with high accuracy becomes more and more critical for proactive network service provisioning and efficient network resource allocation in smart cities. Traditional traffic forecasting methods mostly rely on time series prediction techniques, which fail to capture the complicated dynamic nature and spatial relations of mobile traffic demand.

Furthermore, motivated by the aforementioned phenomena, this research develops a novel deep learning architecture for traffic prediction and analysis, further contribution of research work is given as follows:

- This research work develops a Multi-Layer Hybrid Neural Network (MLHN) architecture for traffic prediction and analysis; MLHN comprises multiple layers for the different types of input in the network for efficient feature extraction.
- An optimized parameter-tuning algorithm is introduced that aims to automate the parameter for better prediction.
- MLHN is evaluated considering the “Big Data Challenge “ dataset; evaluation is carried out on various services such as SMS, Call and Internet; efficient analysis is carried out considering the sub-services like Incoming calls and outgoing calls, Received SMS and sent SMS.

- MLHN is compared with different state-of-art techniques considering the various metrics.

This particular research is organized as follows: The first section starts with the network traffic prediction model, furthermore, several existing models are discussed along with its shortcoming, and the section ends with the motivation and contribution of MLHN. The second section presents the MLHN model along with its mathematical modelling. MLHN model is evaluated in the third section considering various metrics.

2 Proposed Methodology

The intelligent Cellular traffic prediction model helps mobile operators with efficient and optimal allocation of resources. Furthermore, the prediction model involves thousands of cells; hence, it is important to exploit the features in optimal way. This research work presents the MLHN(MultiLayer Hybrid Network) which aims to extract the various feature at a different layer.

2.1 System modelling and preliminary analysis

The communication network is decentralized across geographically distributed areas. Across every region, the client holds the wireless network traffic data by considering the local model update. In each region, a local client records the traffic that pairs the local model update $F = \{1, \dots \dots, t \dots., T\}$ depicts this client set, then$t$ is the index and T the total count of adjacent clients. This adjacent traffic information is segmented into g time slots, T_m is the parameter depicting the network traffic volume and the close dependence shown by $K_m = \{T_{m-n}, T_{m-n+1,}, \dots, T_{m-1}\}$ given as the input feature, wherein n is shown as the set of data points. However, T_m is given as the estimated target which is labelled as given as the output j_m , by considering the prediction ahead of one step. The input-output pair is summed as $\{ K_m, j_m)$ determined by the sliding –window mechanism. The randomly created types of samplesN_k differs apart each client to client and zero sample approximation aimed at each client, the sample is responsible for each client to another. The training dataset of the $m-th$client,β_g is partitioned along the support setβ_g^u, the collection of queries given asβ_g^r. The knowledge is secured by internally transferring it by $\beta_g^u$to β_g^r. By aggregation of the local models communicate with the central server and accommodate the features of the global model to the central server for each model of the local client. The main aim here is to determine the network traffic prediction to generate a model via a constraint α that reduces the loss function for the dataset depicted as, j_m and the comparison value as j_m.

$$\underset{\tau}{\overset{Red}{}}\frac{1}{G}\sum_{g=1}^{G} T(\alpha;\beta_g), \quad (1)$$

Here $T(\alpha;\beta_g)$ shows the loss function determining the network traffic volume j_m . By considering the mean squared error (MSE) as the metric, the loss function is determined by:

$$T(\alpha;\beta_g) = \frac{1}{M_g}\sum_{\{a_m,b_m\}\in\beta_g} (j_m - j_m)^2 \quad (2)$$

The traditional network traffic prediction targets and train the model by accommodating all clients, the main aim here is to determine a model which adapts to a rapid heterogeneous distribution circumstance. Managing and minimizing the loss occurrence amid the two values of each client's network traffic value is predicted based on this proposed model. This technique is built by preceding one among the few steps responsible for fine-tuning the dataset. This is stated by below equation:

$$\underset{\tau}{\overset{Red}{}}\frac{1}{g}\sum_{g=1}^{G} T(\alpha-\partial), \sum_{k=0}^{K-1} \rho_\alpha T(\alpha_{g,s};\beta_g^u);\beta_g^r), \quad (3)$$

Here $\rho_\alpha T(\alpha_{g,s};\beta_g^u)$ depicts the adjacent gradient of the $s-th$ steps for the update. $s \in [0, S). \alpha - \partial\sum_{k=0}^{K-1}\rho_\alpha T(\alpha_{g,k};\beta_g^u)$ Is the fine-tuned model obtained preceding the query-set β_g^u. The equation (9) is used for minimizing the average loss for the fine-tuned model on the query-set β_g^r, by adapting new tasks for the model to adapt in.

2.2 Prediction Model

Our proposed model is fed by three inputs. the first input is the ($T_{v-1}, \ldots, T_{v-o}, o \in Ƥ$) this sequence of the network traffic matrix before the specified period. The second input sequence here (j) references along the data for date-time corresponding to the time-duration on a particular hour on a day of a week. The last input provided here depicts the cross-domain datasets by incorporating T_{Bst}, and POI distribution as T_{POI} as well as the T_{soc} as sociality. To handle various inputs relevant to the data and their features, three types of neural networks are formulated as below:

2.2.1 First Layer Modelling:

The first input fed here is video data that consists of o number of frames where each frame consists of a one-channel image. This is a CNN model that consists of strong capabilities to model this spatial interdependence, which efficiently fuses the localized information area that necessarily features extraction for particular tasks. This time sequence of the data is specifically not caught via the CNN model. These LSTM networks model the sequence of information for the cellular traffic. A dual layer ConvLSTM network is formulated via a parallelly developed model for Spatio-temporal interdependencies for the particular sequence.

Each cell here consists of a memory cell µ that gathers the relevant state information. This cell is accessed and altered via three controlling gates the input gate IG, forget gate FG, and the OG. However here a new input is fed to the ConvLSTM unit, and the data gathered here is stored in the µ if the IG is activated here. Parallelly the past cell status is adapted here and is forgotten via the process if the FG is switched on. ß is controlled via the output gate which is the final input state. This states whether the output of the cell µ is proliferated via a final state or not. The main functionality here states that for a particular frameT_{v-m}, here $m \in$ {1, 2,….., o} where ∂(.) shows the activation function. , whereas * denotes the convolutional operation and ∘ is the Hadamard product

$$IG^{C} = \partial(WT_{tI} * T_{Y} + WT_{xI} * ß_{Y-1} + T_{cI} \circ \mu_{Y-1} + q_{I}),$$
$$FG^{C} = \partial(WT_{tF} * T_{Y} + WT_{xF} * ß_{Y-1} + T_{cF} \circ \tanh(WT_{t\mu} * T_{Y} + q_{F}),$$
$$\mu_{Y} = \partial(FG^{C} \circ \mu_{Y-1} + IG^{C} \circ\circ \tanh(WT_{t\mu} * T_{Y} + T_{xc} * \mu_{Y-1} + q_{c}),$$
$$OG^{C} = \partial(WT_{tO} * T_{Y} + WT_{xO} * ß_{Y-1} + T_{cO} \circ T_{Y} + q_{O}),$$
$$ß^{C} = \partial \circ \tanh(T_{Y}). \quad (4)$$

In the above-stated equation $WT(.)$ and $q(.)$ are the biased weights that are learned. Besides, $tanh(.)$ here indicates the hyperbolic tangent function that works as a non-linear transformation input. The gates IG^{C},FG^{C},μ_{Y}, OG^{C}, $ß^{C}$ here in this ConvLSTM unit along the tensors that are dimensioned. The output stated here of the ConvLSTM is shown as the $\delta_{zv} \in H^{FM*X*Y}$, where FM shows the Feature Maps.

2.2.2 Second Layer Modelling

When the mobile users ask for services, the date and time of this network cellular traffic information are recorded, the data is extracted and shown as the features, four types of data are extracted as i.e., which day of the week, which hour of the day, whether it is a weekend or a feature vector e . This feature vector here is fed to a dual-layer network where the dimensionality of e is upgraded from 4 to$FM * X * Y$. This equation for feature vector is mathematically stated as δ_{data}

$\delta_{data} = \partial\left(WT^{2}_{Data}\,\partial(WT^{1}_{Data}\,e + q^{1}_{Data}) + q^{2}_{Data}\right),$	(5)

WT^{p}_{Data}andq^{p}_{Data} are the learning parameters at the $p - th$ layer where $p \in \{1, 2\}$. After this operation is reframed the output is given by δ_{data} .

$\delta_{data} = RF_{\delta_{data}},$	(6)

2.2.3 Third Layer modelling

The model is affected via external factors by traffic generated and learns these representations with the cross-domain datasets, a dual-layer CNN architecture is built here. In the dual-layer CNN architecture the parameters $T_{POI}, T_{soc} T_{cross}$ fed into a tensor through this concatenation function. Once the non-linear transformation is carried out on T_{cross}, The features are represented initially given by cross-domain datasets as δ_{cross} written as:

$\delta_{cros\,s\_dataset} = comp\_func(WT_{cross\_dataset} * T_{cross\_dataset})$ $T_{cross\_dataset} = T_{Bst} \oplus T_{POI} \oplus T_{Soc}$	(7)

Here $\oplus$ indicates the concatenation operator parallelly, $WT_{cross\_dataset}$ are the weights associated with the learning parameters along optimization $comp\_func(.)$ is the composite function which implements this batch normalization (Batch_norm) function, rectified linear units (ReLU) and the convolution operation (Conv) consecutively.

3 PERFORMANCE EVALUATION

Big data plays an important role in network traffic management, as it comprises a huge number of data along with various factors. Moreover, considering the network traffic management concerning big data, MLHN is designed. This section evaluates MLHN considering the metrics like MAE, RMSE and R^2. Furthermore, MLHN is designed considering python as a programming language with several deep learning libraries. MLHN evaluation is proved by comparing with a model like STCNET [13] and the existing model CNNLSTM-2D [14].

3.1 Dataset Details

A wide range of experiments are taken into consideration here to consider the Telecom Italia Big Data challenge dataset [15], the call detail records from Milan city are taken into consideration by considering 100*1000 grids of the size of 235*235 square meters. There exist 5 types of call detail records in the dataset, these consist of incoming calls, outgoing calls, SMS received sent SMS and the internet. One call detail record is generated at each particular time for the internet connection given as one the user issue or receives a call or SMS. For internet calls, details records are generated each time the internet connection begins or ends for a duration of the period for data that exceeds 5 MB. The interval is given between the duration of call detail records for ten minutes. Here the length of the period for utilizing multiple resource allocation is said to be one hour and not 10 minutes. Here because the period is set for 1 hour basis and not the original CDRs are used for training and testing the proposed model. The original data shape for wireless network traffic data for each type of wireless traffic is. To utilize the spatial-temporal aggregation mechanism, the original wireless traffic data is combined into an equivalent of two parts. The input data as well as the target output data.

3.2 Metrics evaluation

MLHN (Multi-Layer Hybrid-Network) is evaluated considering the three distinctive metrics MAE(Mean Absolute Error), RMSE(Root Mean Square Error) and R^2, these are computed as below:

A. Mean Absolute Error

Mean Absolute Error is defined as the summation of absolute difference among predicted and computed values.

$$MAE = \left(\sum_{j=1}^{l} \left|w_j - v_j\right|\right)(l)^{-1}$$

In the above equation, j indicates the variable, l indicates the non-missing data points, w_j as the predicted value and v_j as actual value.

B. Root Mean Square Error

Root Mean square Error or RMSE is defined as the measure of difference among values predicted through MLHN and the value observed.

$$RMSE = \sqrt{\left(\sum_{j=1}^{l} (v_j - v_j^{'})^2\right)(N)^{-1}}$$

In above j indicates the variable, l indicates the non-missing data points, $v_j^{'}$ indicates the time series (estimated) and v_j indicates the time series (actual)

C. R-squared

$\boldsymbol{R^2}$or R-squared can be defined as the ratio of unexplained variation denoted as ρ and total variation $\rho^{'}$

$$R^2 = 1 - \frac{\rho}{\rho^{'}}$$

3.3 Internet Service prediction

Figure 2 shows the model comparison considering MAE metrics for Internet service. In below figure, considering the existing model Bi-Directional model performs better with an MAE score of 55.44 whereas the proposed model observes 47.5869

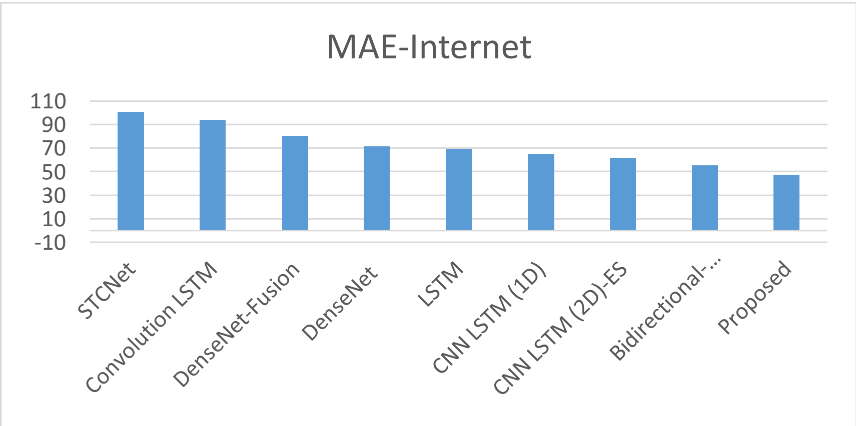

Figure 2 MAE comparison over internet services

Figure 3 shows the model comparison considering MAE metrics for Internet service. In below figure, considering the existing model Bi-Directional model performs better with an MAE score of 135.57 whereas the proposed model observes 127.65

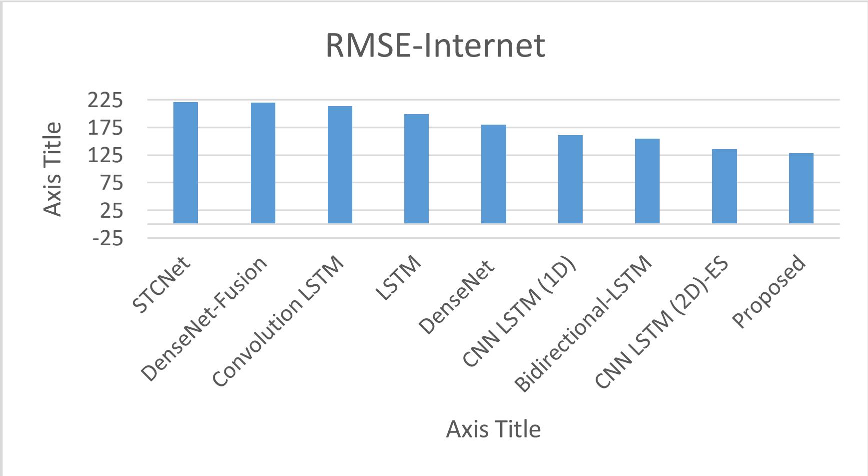

Figure 3 RMSE comparison over Internet service

Figure 4 shows the model comparison considering R-squared metrics for Internet service. In below figure, considering the existing model Bi-Directional model performs better with an MAE score of 135.57 whereas the proposed model observes 127.65

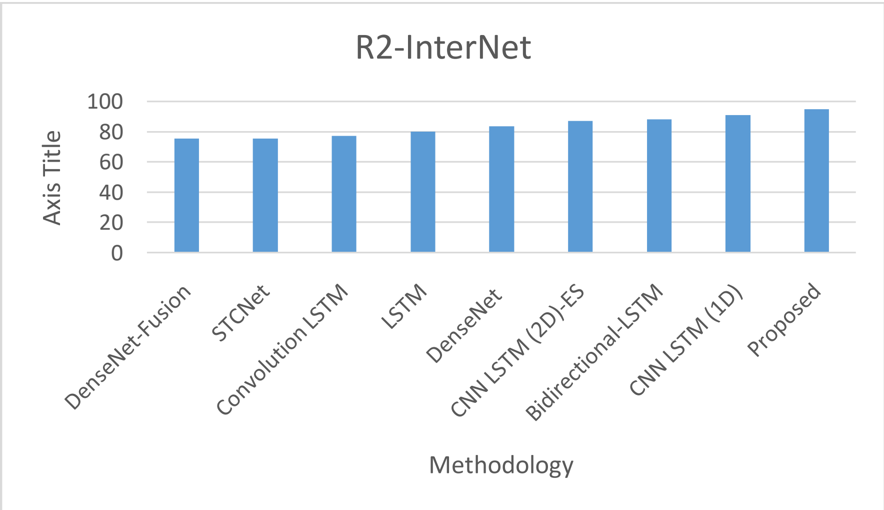

Figure 4 R-squared comparison over the Internet service

3.4 Comparative Analysis

Table 5 presents MLHN improvisation over the existing model; considering MAE, RMSE and R2 it observes improvisation of 9.80 %, 20.599% and 8.75% respectively.

Table 1 Improvisation of the existing model

Service	MAE(in percentage)	RMSE(in percentage)	R2(in percentage)
Internet	9.80	20.599	8.75

4 CONCLUSION

Cellular traffic prediction will play a key role Cellular Traffic Prediction possesses several applications such as designing future smart cities, Network Traffic Management and so on; moreover, deep learning adoption for traffic prediction has increased the higher chances of understanding the traffic models. This research work introduced MLHN architecture for traffic prediction; MLHN comprises multiple layers, which is utilized for multiple input. MLHN aims at extracting the custom feature; also an efficient parameter tuning and learning algorithm are designed that can reduce the error through an automated learning approach. MLHN has been evaluated considering the “Big Data Challenge” dataset, which comprises three services i.e. SMS, CALL and INTERNET; further analysis, is carried out on an incoming call and outgoing call, Received SMS and sent SMS considering the various state-of-art technique. MLHN performance is proved through performing the comparative analysis and it suggests that MLHN observes marginal improvisation over the other model.

Moreover, every year telecommunication domain observes a major revolution like 5G, 6G and many more to come this makes more traffic and efficient management, which makes it more complicated. Hence, future work should focus on complexity reduction.

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