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Spatio-Temporal vehicle traffic flow prediction using multivariate CNN and LSTM model

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ABSTRACT

Traffic congestion is a major problem in developing and developed countries vehicle traffic management systems. Traffic control system works based on the idea of removing instabilities and avoid accidents in order to minimize the traffic and maximize the vehicle flow. To control the congestion need to predict the upcoming traffic flow and it will be useful for Advanced Traffic Information Systems (ATIS), Advanced Traffic Management Systems (ATMS) and traffic analytics. Non–linear historical data and uncertain factors influence the vehicle congestion at peak hours which cannot be considered in existing algorithms. This study proposes hybrid neural network algorithms such as Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) network for short term traffic flow prediction based on multivariate analysis. Widely referred datasets Performance Measurement Systems (PEMS) and Mesowest have been used to evaluate this model. Experiment results shows that CNN-LSTM Hybrid prediction model achieves high accuracy compared with other models.

Selection and peer-review under responsibility of the scientific committee of the International Virtual Conference on Sustainable Materials (IVCSM-2k20).

1. Introduction

Nowadays road safety, traffic control and emission have received lot of attention to the researchers. Rapid development of urbanization and increasing number of vehicle usage rise the chances of traffic flow congestion in the major cities of the world [4]. Accurate and efficient traffic congestion prediction at real time helps to assist commuters, government agencies and public. Uninterrupted vehicle flows and road structure may determines the country's economic growth [13]. As urban has limited space constraints, cannot extend the road structure or build a new lane at every time to meet the demand. Real time prediction can provide essential information to administrators about forthcoming situation of road which is used to divert into alternative roads to prevent the congestion [4].

To determine the traffic flow at the next interval usually in the range of 5 min to 30 min interval is termed as short term traffic flow prediction which is most efficient than mid-term and long-term prediction [6]. Short term traffic flow prediction supposed to detect the vehicle crowd earlier and reduce the negative impact of congestion [24]. But traffic flow not only depends on historical data, some disruptions also affect the estimation of flow. This disruptions may divided into two categories such as predictable and unpredictable. Traffic signs, stop signals, scheduled events, road constructions are predictable disruptions. Emergency road closures, accidents, breakdowns are unexpected and also unpredictable. Traffic congestion, energy consumption, pollution issues are the most bottlenecks for city development [29]. Early identification of traffic congestion helps to regulate traffic bottlenecks and it supports to intelligent transportation system (ITS). Future research aims to improve the full usage of road resources and improve the efficiency [29].

Plenty of short term prediction algorithms were developed which may divided into two categories such as parametric and non-parametric. Time series and nonlinear algorithms are parametric and machine learning algorithms are non-parametric. Autoregressive integrated moving average (ARIMA) [5,6,8], Support Vector Regression (SVR) [10], Kalman filtering [20] are some of the traditional parametric methods which have been successfully applied in transport related applications [24]. Many efforts have been made over the last decade to control and alleviate the congestion [19]. Most of the existing studies were used mathematical equations and simulation techniques to represent flow of road

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structure. Weather, accidents and rainfall or the other factors which influence the transportation network. But these factors are very difficult to represent using mathematical models [19]. With the help of technological development, Internet of things and also wide variety of sensors can collect vast amount of data which is termed as big data. For big data processing and handling nonlinear data, data driven methods were proposed. Neural network algorithms is one of the data driven non– parametric method which have been successfully applied in many applications including prediction, classification, object detection, object tracking and natural language processing [24].

The rest of the paper is organized as follows: section II reviews the related works of short term traffic flow prediction. Section III presents methodology. Section IV explores the results & discussion and conclusion is described in section V.

2. Literature review

Autoregressive integrated moving average (ARIMA) and the variations time oriented ARIMA [8], Seasonal ARIMA [2] are widely used traditional algorithms for both prediction and forecasting. ARIMA is a time serious algorithm and it is combined with other algorithms to integrate with spatial feature. C Xu et al. [5] integrated ARIMA with genetic algorithm to estimate the upcoming flow in the road. Generally ARIMA model have been used to capture the linear time serious data. Genetic algorithm was proposed to abstract feature from nonlinear historical data.

Kalman filter is a parametric approach which have been effectively applied to predict congestion based on volume or speed. ARIMA and SARIMA models does not work well when required data is unavailable. S V Kumar et al. [20] proposed congestion prediction model with kalman filter technique to overcome the problem of huge data requirement. Y Xie et al. [27] had used Kalman filter with discrete wavelet analysis for short term traffic volume prediction. Traffic volume data are frequently corrupted by noise which may affect the prediction result. Wavelet decomposition method was used to divide the data into several parts, then kalman filter was used to denoise the data and predict the congestion with high accuracy. Thus wavelet kalman filter performs better than normal kalman filter.

Deep learning algorithms have been emerging for all applications including transportation. In transportation field, particularly in traffic congestion many deep learning algorithms such as Deep belief network [1] (DBN), Convolutional Neural Network (CNN) [15,17], Long Short Term Memory network (LSTM) [3,11], Stacked Auto Encoder (SAE) [7,24] are using to predict congestion with high precision. From that CNN [19] SAE [7] are significantly used to express spatial features and Gated recurrent unit (GRU), Long short term memory network (LSTM) [7,25,26] are used to abstract time serious data.

A Koesdwiady et al. [1] used deep belief network to assess the upcoming flow based on total flow and weather data. For road safety, weather is a prevalent issue and it is crucial to consider for vehicle traffic congestion prediction. 24 unique values of weather were represented in the range of [1-10] in real numbers. All items were normalized into 0 and 1. Weather and traffic data were fused with using deep belief network which greatly improves the prediction performance and in future it is recommended that rich information from social media should consider for accurate prediction.

Q Liu et al. [17] have used convolutional neural network for traffic flow prediction using flow, speed, occupancy through three dimensional data metrics. Spatial and temporal features of road network were extracted by using ordinary convolution unit and gated convolutional unit respectively. At last regression layer was used to predict the flow for multiple detectors. Single station data only was used to predict in the existing model and in future it is recommended to use entire road network.

Z Zou et al. [30] developed the prediction model using Long Short Term Memory network. Flow data was used as a source and different learning rates were used to assess the performance of prediction model. 24 h of past historical information were used to predict the next 1 h data using machine learning algorithms. More influenced factor such as weather, rainfall are recommended to integrate with flow data for future. Y tian et al. [25] proposed LSTM based prediction model with missing data for short term prediction. But this LSTM based prediction supports only temporal correlation for traffic state identification.

Nowadays hybrid algorithms have been proposed for urban traffic flow prediction. Z Lv et al. [28] proposed LC-RNN model for traffic speed prediction. It take the advantage of both convolutional neural network (CNN) and recurrent neural network (RNN) to learn significant pattern of time serious models and adapt the traffic dynamics of nearby areas. Topology of road network were accessed by CNN. Periodicity and other context factors such as weather, holidays, peak hour were accessed by RNN to improve the accuracy with CNN. Compared with other models LC-RNN performs well in prediction and improved the accuracy.

Like vehicle flow prediction, passenger flow prediction also important for public safety and transportation management [29]. Z Zou et al. [29] proposed deep learning based traffic passenger flow prediction model. It has three layers such as residual CNN, mesh RNN and also fusion layer. CNN was used to learn traffic characteristics and RNN was used to consider the time data from multiple dimensions. Interaction among different dimensions were taken into account to improve the prediction accuracy. Convolutional neural network has multiple layers which was used to extract the spatial features. Results shows that model effectively improves the accuracy.

S Du et al. [19] suggested hybrid multimodal deep learning framework (HMDLF) for traffic flow forecasting. CNN and Gated recurrent unit (GRU) together integrated as a hybrid model to improve the prediction accuracy. In multimodal deep architecture, CNN was used to abstract the local features and GRU was used to extract long temporal dependencies. Results shows that model effectively capture the correlations between nonlinear data such as flow, speed and journey time. Interdependence are learned and explored well for a single station data. In future, adjacent road traffic network should be included to extract the interdependence. Other factors such as weather and accidents did not consider due to difficulty in data collection. Hence hybrid model need to further studied for including all factors to improve the prediction accuracy.

F Lin et al. [7] integrated sparse autoencoder with LSTM network to create a hybrid model SpAE-LSTM for considering spatio temporal features. Fully connected layers of autoencoder network mines the spatio temporal matrix with the benefit of LSTM. Results are compared with basic models such as Stacked Auto Encoder (SAE) and Long Short Term Memory Network (LSTM). The model achieved better result and also cannot improved or enhanced by extending the number of hidden units. SpAE-LSTM prediction model predicts well during rush hours than non-rush hours.

L Li et al. [14] proposed a hybrid model using both parametric and nonparametric approaches. This hybrid strategy extracts both linear and non-linear data. Autoregressive integrated moving average (ARIMA) and support vector machine (SVM) models were combined to predict the traffic congestion with abstraction of both spatial and temporal features. Results designate that model greatly improve the performance with stability and also accuracy. Work zone, incidents and bad weather conditions should be considered into future to increase the performance.

B Yao et al. [4] introduced a hybrid model with K nearest neighbour (K-NN) and Kalman filter (KF) to predict the traffic flow dynamically. Historical data were analysed to estimate the speed of target road. Relationship between historical data and current data was mapped by K-NN method. KF was applied to mine dynamic position of current road. Outcomes shows that this hybrid model outperforms than simple K-NN based prediction. But this model is only a single step prediction, in future suggests that multistep prediction is needed to provide enough guidance to transport management.

In summary most of the existing deep models were single and taken either spatial features or temporal features. Some of the hybrid models were developed and they integrated only limited factors with fusion analysis. LSTM network has the capability for multivariate analysis based traffic prediction which is explored in [21]. It integrates traffic data, weather and precipitation for single station and results illustrates that multivariate LSTM model greatly improve the performance. But upstream and downstream stations is very crucial to decide the flow of current station. In this paper Multivariate analysis is performed with integration of CNN and LSTM to capture spatial and temporal features of road network for single station.

3. Proposed methodology

3.1. Problem formulation

Traffic flow in one station should depends on the neighbouring stations of a specified road network. The main aim of traffic prediction is to estimating the future traffic condition based on historical data of an identified region. Number of vehicles travelled in a particular region not only depends on road condition, which may affect by external factors such as weather, rainfall and accidents. In this proposed method considering few weather factors such as Temperature, Dew, Relative humidity, Wind speed, Wind direction, Visibility and Precipitation with Total Flow are taken to predict the congestion. Historical data from N neighbouring stations in T previous time steps can be represented in the form of matrix for each feature and it is represented by using two-dimensional matrix M = $\begin{bmatrix} x^1_{(t-n)} & \cdots & x^1_{(t-1)} \\ \vdots & \ddots & \vdots \\ x^k_{(t-n)} & \cdots & x^k_{(t-1)} \end{bmatrix}$, where × and y axis represents time and space respectively. k is the number neighbouring stations taken to predict current station flow.

3.1.1. Spatial convolutional neural network

Obtaining the spatial dependencies is a challenging problem in traffic flow prediction [15]. Predicting the congestion based on external influences with spatial and temporal extractions is a critical issue. Deep learning algorithms helps to develop the model with external factors called as multivariate analysis. Vehicle traffic congestion in one link not only depends by their neighbouring stations, it also affects its utmost adjacent links [8]. CNN have been effective in many applications in order to extract features. Here construct CNN for extracting spatial features of a particular road network. Spatial dependencies of neighbouring links can be extracted by deep convolutional layers. CNN contains input layer, convolution layer, pooling and fully connected layer. Finally output layer receives features and produce output.

Convolution layer is a major part of convolutional neural network [12]. Input matrix is connected with convolution layer C and several filters and each filter carrying i*i weight matrix. Filter scan the input matrix and find convolution matrix. Convolution neuron matrix generated by the filter f is calculated by

$$C_f^{r,s} = \sigma(b_f + \sum_{x=0}^{i}\sum_{y=0}^{i} w_f^{x,y} m^{r+x,s+y} \quad (1)$$

Where b_f is the bias of the filter f, $w_f^{x,y}$is the (x,y) element of $W_f^C, m^{r+x,s+y}$ is the (r + x, s + y) element of spatio- temporal input matrix. σ is an activation function.

Pooling layer is an essential component in CNN and it is used to reduce the dimension of convolution matrix through max down sampling technique which is shown in Fig. 1 [12]. Pooling operation fetches the largest or maximum value in the feature map. The dimension of spatio-temporal convolutional matrix is reduced to j*j matrix with highest feature. Feature vector is the output of max sampling method and it is represented as p. Hidden representation and latent future are abstracted by pooling and filtering features of CNN algorithm.

3.1.2. Temporal Long short term memory networks (LSTM)

RNN (recurrent neural network) is a feed forward neural network used to extort temporal dependency from a time sequence data [11]. RNN has a "memory" to capture previous inputs to the current state for influence the output [23]. However, RNN is not able to work with long time sequence data [23]. Literature shows that long term dependencies data are inadequate in training with gradient descent error [25]. LSTM is designed for model long short term dependencies and to solve sequential problems shown in Fig. 2 [16].

A simple LSTM network (Fig. 3) contains input layer, recurrent hidden layer and output layer. Hidden layer contains memory block which is connected to layers than neurons [16,18]. It includes gates such as 'input gate' is used to receive the new information and 'forget gate' is used to decide the discarded information. Finally 'output gate' has to store the output which is going to next high level [3,18]. LSTM can keep required information through the input, forget and output gates [18]. Long short term memory network is mainly used for prediction with time serious data [3]. Time serious prediction works by combining the hidden states of previous time step data with the current time step.

Let us denote Input $Y_t = \{y_1, y_2, y_3, \ldots, y_t\}$ where t = length of input; h is a hidden state of LSTM network, $H = \{h_1, h_2, h_3, \ldots, h_n\}$. Output $Z_t = \{z_1, z_2, z_3, \ldots, z_n\}$.

Computation of LSTM network is as follows [16],

$$ht = H(W_{hy}y_t + W_{hh}h_{t-1} + b_h) \quad (2)$$

$$P_t = W_{hz}Z_{t-1} + b_z \quad (3)$$

'W' is the weight matrix. 'b' is a bias value.

$$i_t = \sigma(W_{iy}x_t + W_{hl}h_{t-1} + W_{ic}C_{t-1} + b_i) \quad (4)$$

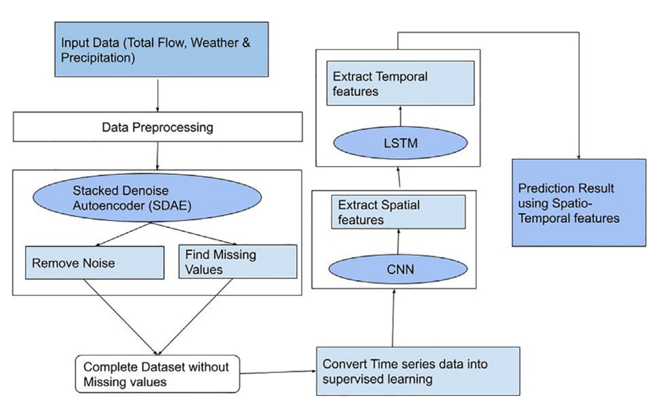

Fig. 1. Proposed framework for multivariate traffic prediction.

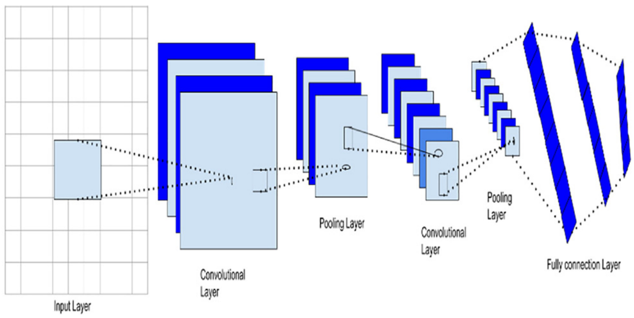

Fig. 2. Structure of CNN.

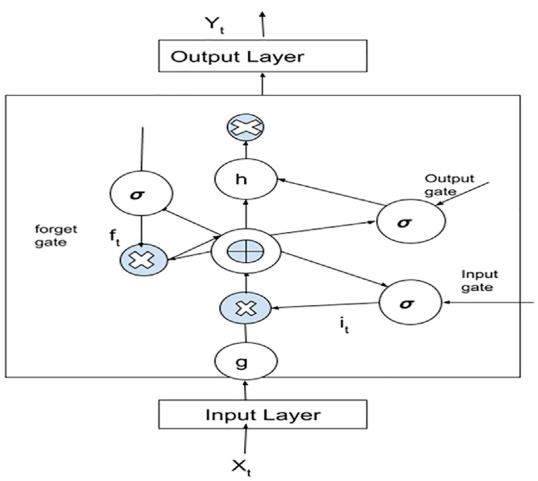

Fig. 3. Structure of LSTM block [11].

$$f_t = \sigma(W_{fy}x_t + W_{hl}h_{t-1} + W_{fc}C_{t-1} + b_f) \quad (5)$$

$$C_t = f_t * C_{t-1} + i_t * g(W_{cy}y_t + W_{hh}h_{t-1} + W_{cc}C_{t-1} + b_c) \quad (6)$$

$$O_t = \sigma(W_{oy}x_t + W_{hh}h_{t-1} + W_{oc}C_{t-1} + b_o) \quad (7)$$

$$h_t = ot * h(Ct) \quad (8)$$

σ is the sigmoid activation function [26] which is defined in Eq. (9).

$$\sigma = \frac{1}{1 + e^x} \quad (9)$$

g(.) and f(.) is an Exponential Linear Unit (ELU) activation function with range [-1, 1] and it is showed in Eq. (10) [22].

$$\left\{ f(p) = \left\{ \begin{array}{ll} r & r > 0 \\ \alpha.(e^2 - 1, r \le 0 \end{array} \right\} \right. \quad (10)$$

Where r = input, α = constant and e = exponent.

LSTM has the ability to store long term information and can determine the information which is not needed (to be forgotten) by the current state and historical information [11]. Multiple variables of time serious problem is converted into supervised learning problem for multivariate traffic prediction. Prediction helps to commuters and road users to make better travel decisions and alleviate traffic congestion and collision [25].

Algorithm: Multivariate spatio temporal vehicle traffic prediction
Multivariate Input: I={Total flow (X1), Temperature (X2), dew point (X3), humidity (X4), wind speed (X5), wind direction (X6), visibility(X7),Precipitation (X8)
1: Step 1: Remove noise and Impute missing values
2: Initialization: Weights (w) and bias, epoch σ, no of hidden layers h;
3: Add noise (σ) to each feature and pass into stacked autoencoder (SDAE) separately;
4: Train and test the model;
5: Output: Complete data T1={X1,X2.....Xn}
6: Step 2: (Conversion for multivariate Prediction)
7: while (T1 > Xn)
8 Convert time serious data into supervised learning
9: T2= {X1,X2.....Xn}
10: Step 3: Prediction
11: Extract Spatial and temporal features by CNN
12: Initialization : Weights (w) and bias (b), epoch σ, no of hidden layers h;
13: Input: Imputed data T2 = {X1,X2.....Xn}
14:
15: for i = 0 to epoch do
16: Pass into convolution layer LSTM layer
17: Perform operations from equations (1) to (10).
Train the model;
18: Calculate error;
19: Update parameters;
20: end;
21: for i = 0 to epoch do
22: Test the model to generate the result;
23: end;
24: Output: Prediction result Z = {Z1}

4. Experimental results & discussion

4.1. Datasets

Sensors, loop detectors are used to collect both traffic, weather and precipitation data. Traffic data is collected from Performance Measurement System (PeMS) [31] which is a database collected the traffic related information from 44,734 detectors that are placed all over the California county of USA. Data have been collecting at every 30 s at accumulated into 5-minute interval. Weather features such as Temperature, Dew point, Relative humidity, Wind speed, wind direction, visibility and precipitationare collected at 5-minute interval from Mesowest [32] database which also depends the origin of California County Table 2.

Both data are selected based on the criteria of Longitude and Latitude which is shown in Table 1. District 5 Central Coast in the California county has selected to evaluate the result. Three stations (501014052, 501014062, 501014082) data are chosen from US101-N highway (freeway road)-santa maria city to implement the model. Weather station KSMX from the same santa maria city is chosen to integrate with total flow to analyse the result.

These external factors slow down the vehicle speed and also make traffic live in crowd areas. Four months of data from January 1st to April 31st 2017 are utilized for training and test the model. Three months of data is used to train the model and one month of data is used to test the model. Augmentation of upstream and downstream stations data enlarge the data set size. Generalization technique dropout is used in the hidden layers of the model to

Table 1
Longitude and latitude of traffic and weather data.

Type of Data	Station Name	Latitude	Longitude
Total flow	501014052, 501014062, 501014082	34.9273334.9392234.94722	−120.417703−120.417619−120.417389
Weather	KSMX	34.89408	−120.45212
Precipitation	KSMX	34.89408	−120.45212

Table 2
Variables and units.

Variable	Unit
Temperature, Dew Point	Fahrenheit
Humidity	Percentage
Wind speed	Knots
Wind direction	Degrees
Precipitation	Inches
Visibility	Statute miles

avoid overfitting. Dropout is supposed to use large networks with different architectures simultaneously (Table 3).

4.2. Experimental settings

4.2.1. Experimental setup

Keras library is used to implement CNN-LSTM based multivariate prediction model shown in Fig. 4. 12 GB Tesla GPU hardware machine is used for all experiments. Both CNN and LSTM network has the capability to integrate multiple factors through the conversion of time series data to supervised learning. 1D CNN and Max Pooling method are using in CNN model. Kernel size is fixed as 3. Exponential Linear unit (ELU) activation function is used in both CNN and LSTM network.

4.2.2. Performance metrics

Relative Error (MRE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Accuracy (Acc) measures are used to determine the performance of prediction model [25].

Mean Absolute Error (MAE = $\frac{1}{n}\sum_{i=1}^{n}|a-p|$

Mean Relative Error (MRE) $=\frac{1}{n}\sum_{i=1}^{n}\frac{|a-p|}{a}$

Root Mean Square Error

(RMSE) $=\sqrt{\frac{1}{n}\sum_{i=1}^{n}|a-p|^2}$

Accuracy (Acc) = $(1-\frac{1}{N}\sum_{i=1}^{N}\left|\frac{\widehat{x-y_i}}{x_i}\right|)*100$

4.2.3. Comparison of results

The results are compared with other models such as ARIMA, KNN, LSTM (Univariate & Multivariate) and CNN algorithms. All algorithms have experimented for 50 epochs. Results shown in Table 4.

Table 3
Summary of CNN-LSTM Model shown in Table 3.

Model: "sequential_3"		
Layer (type)	Output Shape	Param #
conv1d_6 (Conv1D)	(None, 1, 128)	3200
max_pooling1d_6 (MaxPooling1 (None, 1, 128)	0	
dropout_6 (Dropout)	(None, 1, 128)	0
conv1d_7 (Conv1D)	(None, 1, 64)	24,640
max_pooling1d_7 (MaxPooling1 (None, 1, 64)	0	
dropout_7 (Dropout)	(None, 1, 64)	0
lstm_3 (LSTM)	(None, 50)	23,000
dense_6 (Dense)	(None, 50)	2550
dense_7 (Dense)	(None, 1)	51

Total params: 53,441.
Trainable params: 53,441.
Non-trainable params: 0.

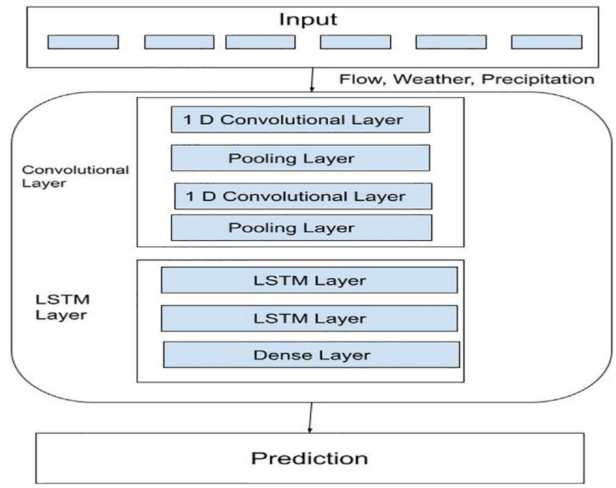

Fig. 4. Structure of Multivariate CNN-LSTM.

Table 4
Comparison of various prediction algorithms based on error rate and accuracy.

Prediction Model	RMSE	MAE	MRE	ACC (%)
ARIMA	25.01	18.64	0.28	53.25
KNN	24.83	17.19	0.24	62.85
LSTM (Univariate)	23.72	16.66	0.22	72.85
CNN (Multivariate)	19.733	14.63	0.18	78.95
LSTM (Multivariate)	19.376	14.27	0.17	80.95
CNN–LSTM (Multivariate)	**16.788**	**11.57**	**0.14**	**85.75**

Convolutional neural network is performed well in extracting spatial features than temporal. Long short term memory network is a well-known time series machine learning algorithm and it was mainly used to extract temporal features. Both algorithms are supporting multivariate time series analysis. When integrate both CNN LSTM with multivariate analysis error rate is gradually reduced which is increasing the prediction accuracy.

Single station 501,014,062 is selected as current station and 501,014,052 and 501,014,082 are upstream and downstream stations respectively. Current station (single) data are evaluated with weather and precipitation features using LSTM network [21]. When other factors such as weather and rainfall are integrated with flow data, it greatly improves the performance from univariate prediction (LSTM) and it reduces the RMSE error rate from 23.72 to 19.37 and accuracy is improved from 72.85 to 80.95.

Downstream and upstream stations are taken into account with current station in CNN LSTM hybrid model. Hybrid model greatly helps to extract both spatial and temporal features and also have the ability to consider other factors which influence the vehicle congestion. When consider neighbouring stations RMSE error rate

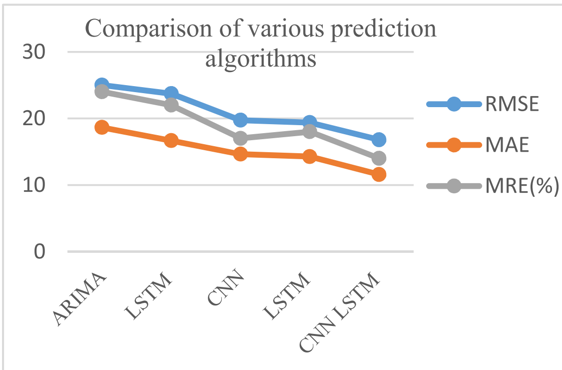

Fig. 5. Comparison of univariate and multivariate prediction algorithms.

is reduced from 19.37 to 16.78 and accuracy is improved from 80.95 to 85.75.

Various univariate and multivariate prediction algorithms are compared using RMSE, MAE, MRE and Accuracy. Table 4 and Fig. 5 shows CNN-LSTM model performs better than all other algorithms in terms of reducing error rate and improves accuracy.

Stacked denoise autoencoder is used to remove the noise and find the missing values[2,3]. Missing values in the input data affect further analysis and prediction result. Fig. 6 compare the results with LSTM and CNN LSTM multivariate models for missing and without missing values. Each precision of prediction result is important for road transportation as it prevents accidents, collisions and more congestion. Results shows that estimate the missing values increase the prediction accuracy in both of the models.

SDAE with ELU activation function greatly improve the imputation result which highly helps to reduce error rate of prediction value.

4.2.4. Impact of precipitation on vehicle flow

Three types of rainfall has occurred such as light, moderate and heavy. Light rainfall is taken as the range less than 0.10 in. per hour. Moderate rain fall has considered as 0.10 to 0.30 in.. Heavy rainfall is greater than 0.30 in.. From light to heavy rainfall has occurred on February 6th and it is considered as rainy day which is showed in Fig. 7a.

Vehicle flow is measured in both rainy day and also normal day. Heavy rainfall slow down the vehicle speed and greatly reduces the average flow of vehicles in a road. Vehicle flow has counted at every one hour which is showed in Fig. 7b. Predicting the vehicle flow of February 6th based on flow and also based on weather and precipitation are showed in Figs. 8a and 8b. 5 min interval data are taken to predict and analyse the result. Integration of weather and precipitation predict the vehicle flow high accurate.

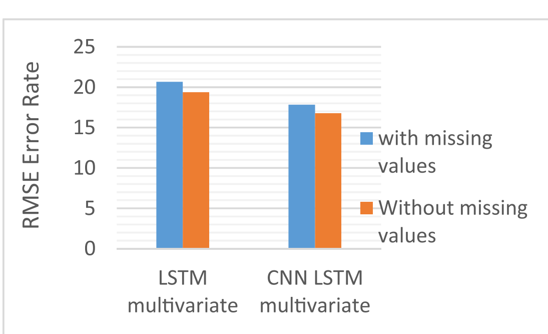

Fig. 6. Comparison of prediction model with missing and without missing values.

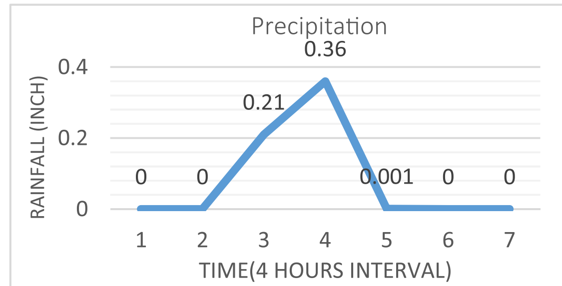

Fig. 7a. Rainfall measurement on feb 6th.

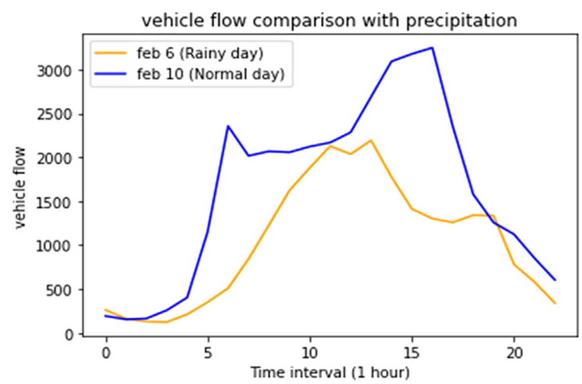

Fig. 7b. Impact of rainfall on vehicle flow.

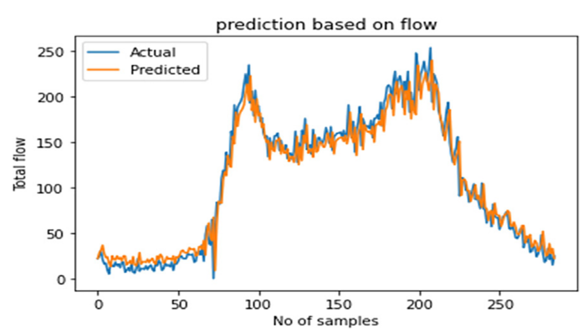

Fig. 8a. Vehicle flow prediction based on flow.

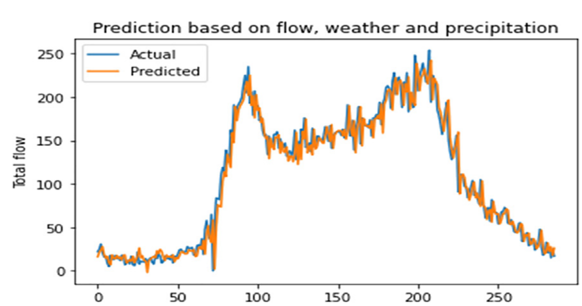

Fig. 8b. Vehicle flow prediction based on flow, weather and precipitation.

4.2.5. Impact of adverse weather conditions on vehicle flow

High temperature of weather gradually reduces the number of vehicles usage in road. Compare the temperature on both February 1st and February 15th. February 1 has time temperature than

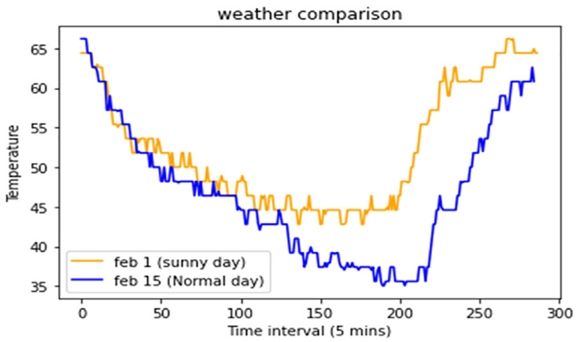

Fig. 9a. Weather on feb 1st and feb 15th.

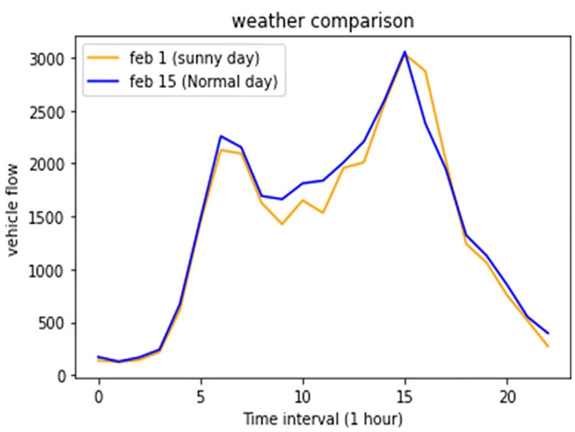

Fig. 9b. Vehicle flow comparison based on weather.

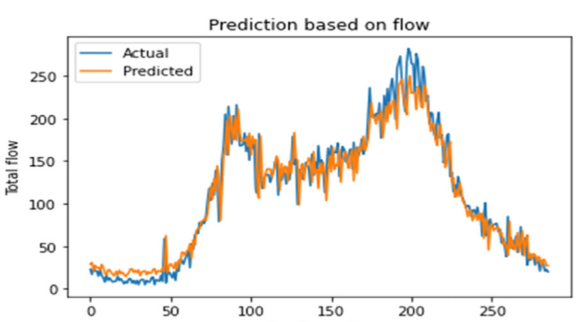

Fig. 10a. Vehicle flow prediction based on flow.

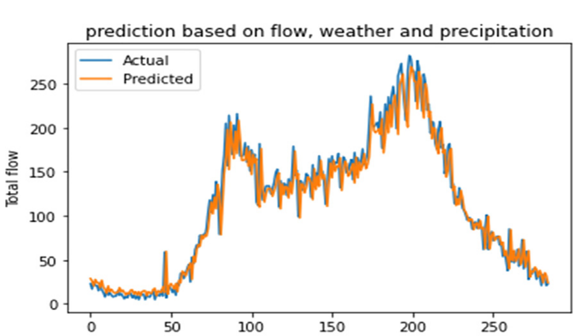

Fig. 10b. Vehicle flow prediction based on flow & weather.

February 15th and it showed in Fig. 9a. Vehicle flows are measured at ever one hour for both normal and sunny day (Fig. 9b).

Predicting the flow of vehicle on sunny day based on only flow data and based on flow with weather has showed in Figs. 10a and 10b.

5 min interval data are used for accurate prediction of traffic flow. February 1st prediction based on flow and based on flow and weather are showed in Figs. 10a and 10b. External factors greatly helps to predict the vehicle flow congestion accurately and efficiently.

5. Conclusion

Multivariate prediction with spatio-temporal consideration is a challenging issue in vehicle traffic congestion prediction. In this work Convolutional Neural Network and Long Short Term Memory Network is introduced as a hybrid model to integrate multiple factors such as total flow, weather and precipitation with extraction of spatial and temporal features of upstream and downstream stations. Both traffic and weather data contains missing values which is filled using stacked denoise autoencoder (SDAE). Both CNN and LSTM has the capability to integrate multiple factors, in which CNN is used to extract spatial features of upstream and downstream stations and LSTM is used to extract time serious data of neighbouring stations. Single time step data only taken for multivariate analysis. In future multistep and multivariate data should consider to improve the prediction accuracy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] A. Koesdwiady, R. Soua, F. Karray, Improving traffic flow prediction with weather information in connected cars: a deep learning approach, IEEE Trans. Veh. Technol. 65 (12) (2016) 9508–9517.
[2] B.M. Williams, L.A. Hoel, Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: theoretical basis and empirical results, J. Transp. Eng. 129 (6) (2003) 664–672.
[3] B. Yang, S. Sun, J. Li, X. Lin, Y. Tian, Traffic flow prediction using LSTM with feature enhancement, Neuro Comput. 332 (2018) 320–327.
[4] B Yao, Z Wang, M Zhang, P Hu, X Yan, "Hybrid model for prediction of real-time traffic flow", Proceedings of the institution of civil engineers, Transport, Volume 169, issue TR2.pp: 88-96, April 2016.
[5] C. Xu, Z. Li, W. Wang, Short term traffic flow prediction using a methodology based on autoregressive integrated moving average and genetic programming, Transport 31 (3) (2016) 343–358.
[6] D. Zeng, J. Xu, J. Gu, L. Liu, G. Xu, "Short Term Traffic Flow Prediction Using Hybrid ARIMA and ANN Models", 2008 Workshop on Power Electronics and Intelligent Transportation System, Guangzhou, pp. 621-625 IEEE, 2008.
[7] F. Lin, Y. Xu, Y. Yang, H. Ma, A spatial-temporal hybrid model for short-term traffic prediction, Math. Probl. Eng. 2019 1-12.
[8] H. Dong, L. Jia, X. Sun, C. Li, Y. Qin, Road traffic flow prediction with a Time oriented ARIMA model, in: 2009 *Fifth International Joint Conference on INC*, IMS and IDC, 2009, pp. 1649–1652.
[9] H. Tang, Y. Liang, Z. Huang, T. Wang, L. He, Y. Du, X. Yang, G. Ding, "Key technology of real-time road navigation method based on intelligent data research", Hindawi Publishing Corporation, 2016 2016 1-16 1874945.
[10] J. Ahn, E. Ko, E.Y. Kim, "Highway Traffic Flow Prediction using Support Vector Regression and Bayesian Classifier", 2016 International Conference on Big Data and Smart Computing, (BigComp), Hong Kong, pp: 239- 244, 2016.
[11] J. Li, L. Gao, L. wei, Y. Shi, "Short term traffic flow prediction based on LSTM", Ninth international conference on Intelligent control and information processing", Wanzhou, pp.251-255, 2018.

[12] J. Wang, Q. Gu, J. Wu, G. Liu, Z. Xiong, "Traffic Speed Prediction and Congestion Source Exploration: A Deep Learning Method", 2016 IEEE 16th International Conference on Data Mining, PP: 499-508, 2016.
[13] K. Kumar, M. Parida, V.K. Katiyar, "Short Term Traffic Flow Prediction In Heterogeneous Condition Using Artificial Neural Network", Transport, pages:397-405, 2013.
[14] L Li, Shanglu He, Jian Zhang, Bin Ran, Short-term highway traffic flow prediction based on a hybrid strategy considering temporal–spatial information, J. Adv. Transp. 2016 2029–2040.
[15] L. Zhao, Y. Song, C. Zhang, Y. Liu, P. Wang, T. Lin, M. Deng, H. Li, "T-GCN: a temporal graph convolutional network for traffic prediction", arXiv, dec 2018.
[16] M. Chen, G. Yu, P. Chen, Y. Wang, "Traffic Congestion Prediction Based on Long-Short Term Memory Neural Network Models",17th COTA International Conference of Transportation, CICTP 2017, pp.673-681, 2017.
[17] Q. Liu, Short-term traffic speed forecasting based on attention convolutional neural network for arterials, Comput.-Aided Civ. Infrastruct. Eng. 2018 1–18.
[18] R. Fu, Z. Zhang and L. Li , Using LSTM and GRU Network methods for Traffic flow prediction,‖ 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC), Wuhan, pp. 324-328, 2016.
[19] S. Du, T. Li, X. Gong, Z. Yu, S.-J. Horng, A Hybrid method for traffic flow forecasting using multimodal deep learning, *arxiv* (2018).
[20] S.V. Kumar, Traffic flow prediction using kalman filtering technique, Procedia Eng. 187 (2017) 582–587.
[21] S. Narmadha, V. Vijayakumar, Multivariate time series traffic prediction using Long short Term Memory network, Int. J. Sci. Technol. Res. 9(4) 2020 1026-1031.
[22] S. Narmadha, V. Vijayakumar, An improved stacked denoise autoencoder with Elu activation function for traffic data imputation, Int. J. Innov. Technol. Explor. Eng. (IJITEE) 8 (11) (2019) 3951–3954.
[23] X. Luo, D. Li, Y. Yang, S. Zhang, Spatiotemporal traffic flow prediction with KNN and LSTM, J. Adv. Transp. 2019 2019 1-10, Hindawi, 4145353.
[24] Y. Jin, W. Xu, P. Wang, J. Yan, "SAE network: a deep learning method for traffic flow prediction", 5th international conference on information, Cybernetics and computational social systems (ICCSS), pp: 241-246, IEEE, 2018.
[25] Y. Tian, K. Zhang, J. Li, X. Lin, B. Yang, LSTM-based traffic flow prediction with missing data, Neuro Comput. 318 (2018) 297–305.
[26] Y. Tian, L. Pan, Predicting short term traffic flow by long short term memory recurrent neural network, in: 2015 IEEE International Conference on Smart City/SocialCom/SustainCom together with DataCom 2015 and SC2 2015, 2015, pp. 153–158.
[27] Y. Xie, Y. Zhang, Z. Ye, Short-term traffic volume forecasting using kalman filter with discrete wavelet decomposition, Comput.-Aided Civ. Infrastruct. Eng. 2007 326–334.
[28] Z. Lv, J. Xu, K. Zheng, H. yin, P. Zhao, X. Zhou, "LC-RNN : A Deep learning model for traffic speed prediction", Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence (IJCAI-18), 3470-3476,2018.
[29] Z. Zou, H. Peng, L. Liu, G. Xiong, B. Du, M.Z.A. Bhuiyan, Y. Long, D. Li, "Deep Convolutional Mesh RNN for Urban Traffic Passenger Flows Prediction", 2018 IEEE Smart World, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovations, PP: 1305-1310,2018.
[30] Z. Zou, P. Gao, C. Yao, "City-level traffic flow prediction via LSTM networks," ICAIP '18 Proceedings of the 2nd international conference on Advances in Image Processing, pp. 149-153, june 2018.
[31] http://pems.dot.ca.gov/.
[32] http://mesowest. (The University of Utah.)

Further Reading

[1] M.M. Hamed, Hashem R. AI-Masaeid, Zahi M. Bani Said, "Short-term prediction of traffic volume in urban arterials J. Transp. Eng. 1995 49-254.
[2] S. Narmadha, V. Vijayakumar, A study on imputation methods for vehicle traffic data, Int. J. Recent Technol. Eng. (IJRTE) 7(5S) 2019 415-420.
[3] S. Narmadha, V. Vijayakumar, "An Effective Imputation Model for Vehicle Traffic Data Using Stacked Denoise Autoencoder", ICCVBIC 2019, AISC 1108, pp. 71–78, 2020.