Traffic Flow Prediction Using An Improved Fuzzy Convolutional LSTM Algorithm

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Abstract: Intelligent transportation systems (ITS), is producing large amounts of data. The generated data is used for designing smart transportation systems. These raw data must be converted to valuable information for transportation planning and management. Deep learning algorithms have a variety of applications. In this paper, an improved fuzzy convolutional approach is proposed. The proposed model is designed to learn traffic flow features layer by layer through a supervised learning, non-parametric algorithm. The traffic information has been captured from UCI machine learning repository and experimented with a proposed algorithm to capture traffic flow information.The proposed algorithm is evaluated against prediction metrics such as root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE).The proposed method stands out other existing algorithms and has superior performance in traffic flow forecasting.

INDEX TERMS: Traffic flow, prediction, fuzzy, convolutional LSTM.

I.Introduction

Recently, the traffic department is generating large amounts of data from heterogeneous sources like sensors (street, vehicles), automatic fare collection systems, and so on. With these digital data generated by the Intelligent Transportation Systems (ITS) are used for proactive traffic management. The ability to accurately predict the traffic data is very important in traffic analysis. Furthermore, a special issue highlighted in the most recent research progress is using deep learning algorithms in achieving traffic efficiency and congestion reduction. Many factors affect flow prediction are traffic patterns, data collection, and weather, so on. Traditional Forecasting approaches such as neural networks (NNs), Bayesian approach, statistical modeling, and hybrid models are used for traffic flow forecasting. These approaches discover the hidden information in the traffic data and predict upcoming traffic flow. Dynamic nature of traffic patterns facilitates us to apply the concept of deep learning for traffic applications. Deep Learning is a subtype of machine learning approach. It has been applied to many tasks like classification, prediction, clustering, pattern recognition, and so on.The concept of deep learning is to use deep architectures i.e. multiple layers of hidden layers to extract unknown patterns in given data. Then transform vital features in the data as input to neurons and everylayer uses the output from the previous layer as input. Deep learning algorithms can be used for traffic flow prediction which represent complex traffic patterns, dynamic nature, and so on. Deep learning algorithms enhance the prediction accuracy and reduce the error in prediction.

The rest of the paper is organized as follows. Section II is about literature review. Section III methods to implement the new algorithm are discussed. Implementation and results are given in section IV. Finally, the conclusion is given in Section V.

II.Literature review

Hao-Fan Yang et al [1] proposed a type of deep architecture of the neural network approach aiming to improve forecasting accuracy. The new model is designed using the Taguchi method for an optimized structure. This will learn traffic flow features through layer-by-layer using a greedy layerwise unsupervised learning algorithm. Ming Ni et al [2] develop a hashtag-based event detection algorithm and a convex optimization-based approach to fuse the linear regression and the results of seasonal autoregressive integrated moving average (SARIMA) model jointly. Juzhanget al3] proposed 2 step Real-time prediction for forecasting passenger flow.YishengLv et al[5] presented a deep learning algorithm for the traffic flow prediction method. A stacked autoencoder algorithm and a predicted layer as logistic regression is used. They also used gradient descent as Backpropagation algorithm.YoshuaBengio et al [6] proposed a greedy layer-wise unsupervised learning algorithm for Deep Belief Networks (DBN). A generative model with many layers of hidden causal variables is used. B.williams [7] proposed a multivariate forecast model known as the ARIMAX model. This model is used for upstream and downstream data. Lizhong Zhang [8]presented a novel hybrid prediction framework based on Support Vector Regression (SVR) that uses a Random Forest (RF) to select the feature subset and an enhanced Genetic Algorithm (GA) for finding model parameters.MaschavanDervoort et al [9] proposed a KARIMA method that uses Kohonen self-organizing map and ARIMA model to predict traffic flow.H. K. Hong, et al [10] proposed an idea where feature space construction and distance metric selection are two important parts in nonparametric regression. The authors proposed a novel three-stage framework based on KNN for short-term traffic flow forecasting. In the first stage, stations are discovered from the whole traffic network. The second stage instance is calculated for the destination target. At last, an extended multi-metric k-nearest neighbor regression model is built for predicting traffic flow.J. H. Guo, et al [11] proposed a stochastic seasonal autoregressive integrated moving average plus generalized autoregressive conditional heteroscedasticity (SARIMA + GARCH) Adaptive Kalman filters that can update the process variances are presented. Chao Yao et al [12] presented the feature selection method, a new filter-based feature selection method based on LLE. Xin-qing Wang et al[13] proposed support vector regression (SVR) to predict the pinch force. The prediction can be improved by particle swarm optimization (PSO) algorithm. The proposed PSO-SVR achieves high performance compared to other machine learning algorithms.

III.Methodology

Problem definition

Given the historical traffic flow at time period say t, the goal is to predict the traffic flow at time interval t+1, Fuzzy logic is a mathematical method used to simulate the expression and reasoning of human concepts, which can describe the uncertainty and ambiguity of data. With the development of fuzzy logic , researchers have applied fuzzy theory in various fields.. The fuzzy logic is ideal for dealing with uncertain information that affects traffic flow. Fuzzy logic is considered to be a promising intelligent method for traffic information modeling. When traffic data occasionally changes greatly at a certain moment. The process of fuzzy logic includes 3 steps where fuzzification, inference analysis, and defuzzification. Fuzzification is used to transform the inputs into fuzzy sets with membership operators. The gaussian membership operator is used in this paper. If-then rules are framed and inference engines stimulate fuzzy inputs according to rules. Defuzzification transforms the fuzzy output to real output. The centre of gravity method is used in defuzzification. ANFIS method is used for inference systems.

In this paper fuzzy rules are framed as below

Vehicle flow	**VS S M L VL**
Rainfall	**L M H**
Temperature	**L M H**

Convolutional LSTM

Convolution LSTM takes all the inputs X1, . . . , Xt, cell outputs C1, . . . , Ct, hidden states H1, . . . , Ht, and gates input gate (it), forget gate(ft), output gate (ot) of the ConvLSTM are 3D tensors whose last two dimensions are spatial dimensions (rows and columns). To get a better picture of the inputs and states, we may imagine them as vectors standing on a spatial grid. The ConvLSTM determines the future state of a certain cell in the grid by the inputs and past states of its local neighbors. This can easily be achieved by using a convolution operator .The following equations are where '∗' implies the convolution operator and '◦' denotes the Hadamard product:

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} * C_{t-1} + b_i)$$
$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} * C_{t-1} + b_f)$$
$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c)$$
$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} * C_t + b_o)$$
$$H_t = o_t \circ \tanh(C_t)$$

The states are seen as the hidden representations of moving objects. A ConvLSTM with a larger transitional kernel should be able to capture faster motions compared to smaller kernel that can capture slower motions. The inputs, cell outputs and hidden states of the traditional FC-LSTM represented as 3D tensors . Full Convolutional -LSTM is actually a special case of ConvLSTM with all features standing on a single cell. To ensure that the states have the same number of rows and same number of columns as the inputs, padding is needed before applying the convolution operation. Here, padding of the hidden states on the boundary points can be viewed as using the state of the outside world for calculation. Usually, before the first input comes, we initialize all the states of the LSTM to zero which corresponds to "total ignorance" of the future. Similarly, if we perform zero-padding (which is used in this paper) on the hidden states, we are actually setting the state of the outside world to zero and assume no prior knowledge about the outside. By padding on the states, we can treat the boundary points differently, which is helpful in many cases. For example, imagine that the system we are observing is a moving ball surrounded by walls. Although we cannot see these walls, we can infer their existence by finding the ball bouncing over them again and again, which can hardly be done if the boundary points have the same state transition dynamics as the inner points

IV Experimental Results

A. Dataset description

Metro Interstate Traffic Volume Data Set has been collected in UCI machine repository.The total number instances are 48204. Interstate hourly traffic flow data between Minneapolis and St Paul, MN. Weather features and holidays are included to predict traffic flow.

Category	**Features**	**Description**
Basic features	Year	2012-2018
	Month	Month of the year(1-12)
	Day	Day of the month(1-31)
	Time	Hours:Minutes
Weather details	Temperature	average temperature in **Kelvin**
	snow	amount in **mm** of snow collected one hour before
	clouds_all	Percentage of cloud cover
	weather_description	Longer textual description of the current weather
	Rainfall	amount in **mm** of rain that occurred in the hour
Traffic details	Vehicle flow	Number of vehicles passing through source and destination.
Holiday details		US national holidays + regional holidays of Minnesota State

Table 1: attribute information

B.Exploratory data analysis

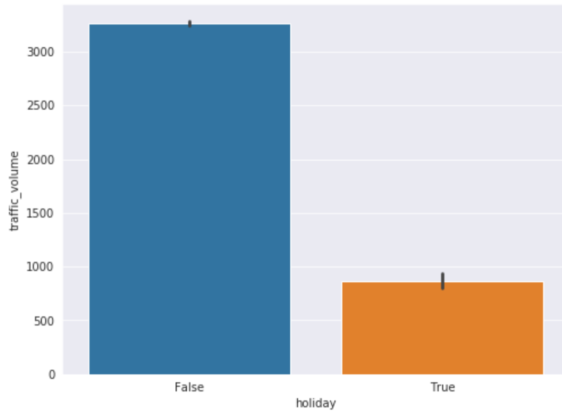

Figure 1. Holiday Vs Traffic volume

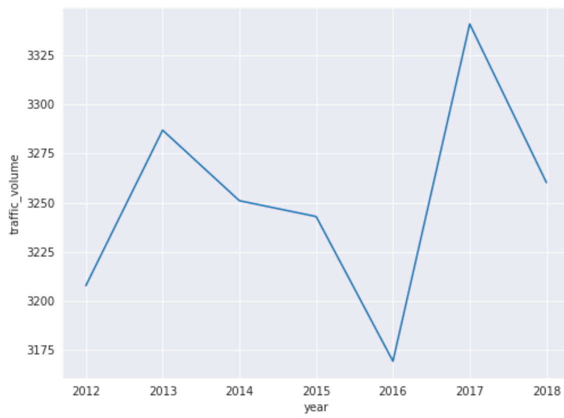

Figure 2. Year vs traffic volume

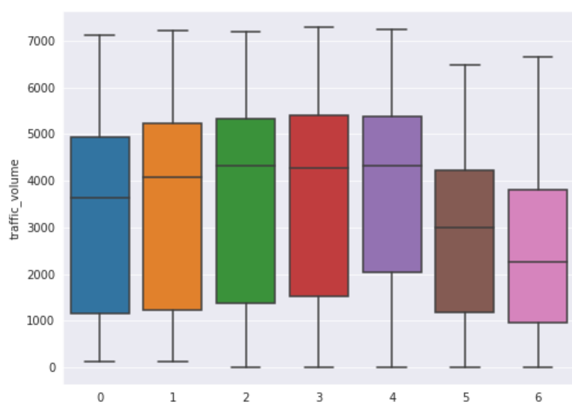

Figure 3: weekday vs traffic volume

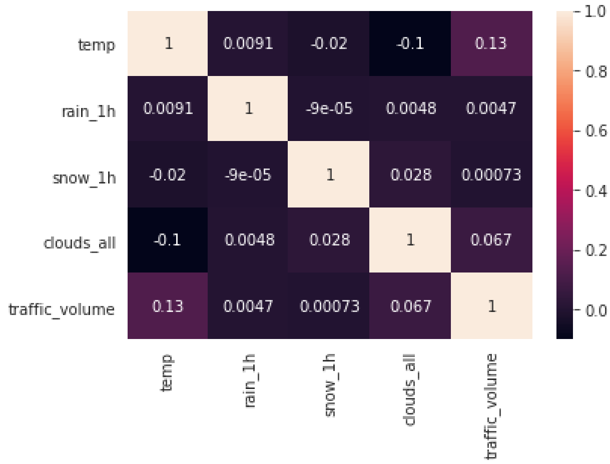

Figure 4: Heat map of temperature and traffic volume.

In this figure 1, illustrates the relationship between how holiday is making an impact in predicting traffic flow. Figure 2 illustrates the traffic flow among number of years. Figure 3 explains how traffic flow is measured during weekdays.

Model	**MAE**	**MSE**	**RMSE**	**accuracy (%)**	**training time(s)**
Linear regression	16.03	33.67	18.27	76.84	52
polynomial regression	17.67	35.6	17.2	82	186
Decision trees	18.92	36.9	19.6	73	187
Random forest	17.2	29.2	18.2	79	223
LSTM	18.3	25.7	19.1	88	180
Convolutional LSTM	17.6	22.6	18.92	82	204
Improved fuzzy convolutional LSTM	**12.25**	**16.72**	**8.92**	**94**	**253**

B. Evaluation metrics

Root Mean Square Error (RMSE): RMSE is a quadratic equation which measures the average magnitude of the error. It is the square root of the average of squared differences between prediction and actual observation.

$$\text{RMSE}=\sqrt{1/n\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$$

where y_i is the actual expected output and $\hat{y}_i$ is the model's prediction.

Mean Square Error (MSE): It is a metric used for regression evaluation. It is the average of square of difference between prediction and actual observation. It is defined by the equation.

MSE= $1/n\sum(y_i - \hat{y}_i)^2$

Mean Absolute Error (MAE): It measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

MAE= $1/n\sum_{i=1}^{n}|y_i - \hat{y}_i|$

Table 1: Gives the information about each model ,different metrics, accuracy obtained and training time of each model.

Comparative analysis:

We compare our method with following methods

Linear regression: In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models.

polynomial regression: In statistics, polynomial regression is a form of regression analysis in which the relationship between the independent variable *x* and the dependent variable *y* is modelled as an *n*th degree polynomial in *x*.

decision trees: Decision trees are constructed via an algorithmic approach that identifies ways to split a data set based on different conditions

Random forest: It is a machine learning method for supervised learning approach by constructing many decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Results:

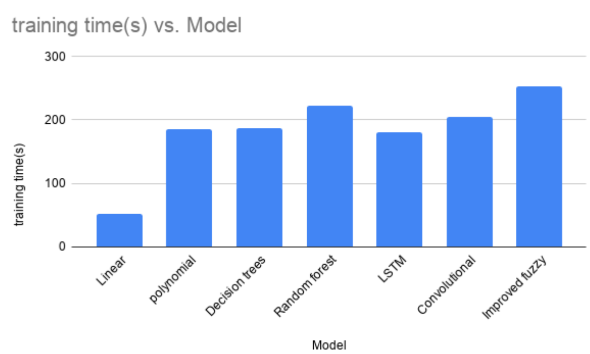

Figure 5: Training time used by different deep learning models (Model vs CT(seconds))

From figure(5), it is understood that improved fuzzy Convolutional LSTM takes more time for training compared to other models

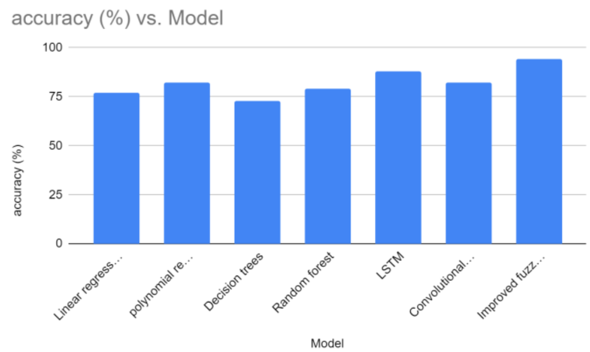

Figure 6:Traffic flow forecasting accuracies obtained by algo(algo vs traffic flow forecasting accuracies(%)).

From the figure(6), it is concluded that proposed model gives more accuracy than other models

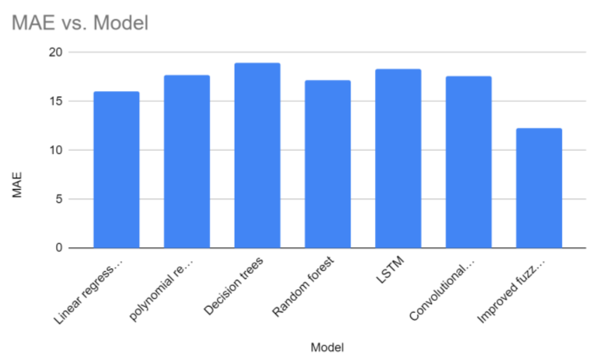

Figure 7: MAE vs Model

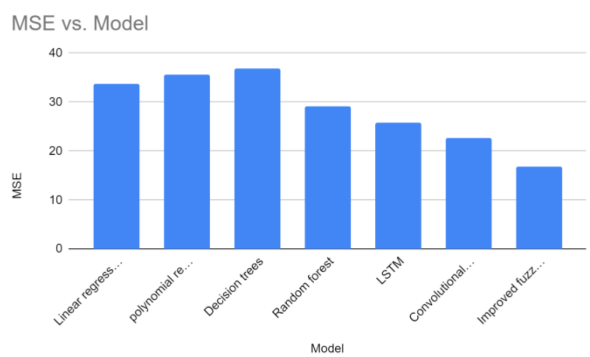

Figure 8 : MSE vs Model

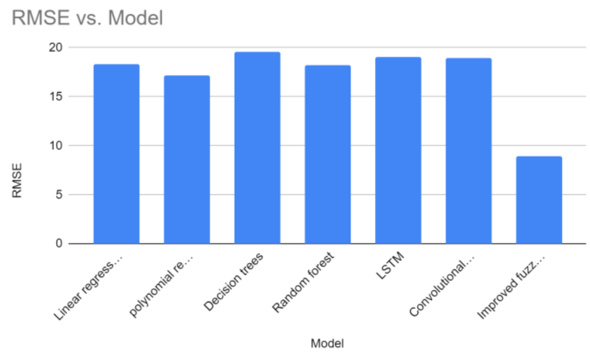

Figure 9: Accuracies for traffic flow forecasting using different metrics.

From figure 7,8,9, it is proposed that the new improved modelachieves less value for metrics(MAE,MSE,RMSE) which is very important for model success.

V. Conclusion:

It concluded that flow prediction is done on google colab with traffic flow data with holiday information and weather information using improved Fuzzy approach**.** It is proved that traffic flow prediction with fuzzy improved result compared to other existing deep learning algorithms.- Further some design constraints can be considered in future like **speed and density information, point of interest, using other activation functions.**

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