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Predictive Traffic Analytics Using Recurrent NeuralNetwork in Conjugation with Long Short-Term Memory

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***Abstract*—**Cities have a significant problem when trying to planfor the future by trying the short term forecast of traffic at aparticular location. Massive volumes of traffic data, such as pastpatterns, present situations, and external variables like weather,events, and construction, must be analysed to accomplish thisjob. Machine learning algorithms have made significant progressin recent years at reliably predicting near-term traffic patterns.These methods use big data, deep learning, and time-seriesanalysis to detect intricate traffic patterns and provide reliable forecasts. Optimal traffic flow, reduced congestion, and increasedtransportation efficiency are all possible outcomes of short-termtraffic forecasting, which may be used by transportation authori-ties to influence decision-making. Nonetheless, there is still a needfor further study to increase the accuracy and dependability ofthese predictions, since problems persist in data quality, modelinterpretability, and scalability. A sophisticated machine learningtechnology that has showed promise in capturing complicatedtemporal correlations in traffic data is LSTM-RNN. To makeshort-term traffic predictions, this method utilises an LSTM-RNN model trained on historical traffic data and then applied tothe present traffic environment and other external parameters.As it considers both types of traffic trends, the LSTM-RNNmodel is able to learn from historical traffic patterns and providereliable predictions. It has been shown that this strategy is moreaccurate and reliable than more conventional approaches likelinear regression and time series analysis. In addition, the LSTM-RNN model may be easily interpreted, providing insights into theelements that drive traffic flow and empowering transportationauthorities to make data-driven choices that increase transporta-tion efficiency and effectiveness. Traffic flow prediction usingLSTM-RNN has the potential to transform the way we runurban transportation systems, despite the fact that there are stillobstacles to overcome in terms of data quality and model tuning.

Keywords: Smart City, Traffic Prediction, Transportation Management, Route Guidance, Neural Network.

I. Introduction

The modern ways of transportation is an innovative component of the concept of "smart cities," where it contributes greatly to the reduction of traffic congestion, air pollution, and incidents of personal injury. The significance of predicting traffic flow has expanded in line with the expansion of it's use and development. The provision of precise and up-to-date information on current traffic conditions is the major objective of traffic flow prediction. This information is intended to be used by passengers, corporations, and government organisations. Yet, due to the complexity of the highway transportation network, external factors like as weather and landforms have the potential to drastically influence the predictability of traffic flow. This is a big obstacle that must be overcome before accurate forecasting can be done [1]. Seeing changes in traffic patterns over time may be thought of as both a temporal and a spatial activity [2].

[3] on the long term, the intermediate term, and the near term The length of the forecast period (δT) determines whether or not it is able to make appropriate forecasts about the flow of traffic. The Highway Capacity Manual

recommends use a short-term prediction interval of fifteen minutes for the purposes of research and assessments [4]. Over the course of the last several decades, scholars have endeavour of trying to forecast short-term traffic flows [5]. The two most common methods for making predictions are referred to as parametric and nonparametric approaches respectively [6]. The first ef- forts to forecast traffic flow made use of time series related models, according to [7]. Parameters of the mathematical frameworks can be calculated from observational evidence us- ing the methodological approach. The most popular parametric approach is the ARIMA model. As an ARIMA formula, it looks like this: The model is denoted as ARIMA(a,b,c), wherea is the order of the vector autoregression polynomial, b is the value of the interconnected polynomial, and c is the value of the moving average polynomial. When [8] attempted to anticipate highway traffic, they used Box-Jenkins time series analysis. The ARIMA with parameters as 0, 1, and 1 was discovered to be the one that provided the best accurate results.The unpredictable and nonlinear nature of traffic flow, which makes analytical equations meaningless, prevents parametric models from providing an appropriate description of the flow of traffic. Because of this, there has been an increase in aca- demics' interest in nonparametric approaches. SVM is a kind of algorithm well regarded for its efficacy and effectiveness inthe area of artificial intelligence-based technology. [9]. Before doing linear regression, the SVM first performs a nonlinear mapping of the data into a high-dimensional feature space.

II. Background and Related Work

[10] used dynamic support vector regression to foresee both normal and peak traffic conditions, like vacations and accidents. There has been on-going work on artificial neural networks (ANN) for the purpose of forecasting the traffic. It has great learning and adaptability capabilities, can handle data in a range of dimensions, and has good generalizability. Using a genetic algorithm-optimized neural network allowed for an improvement in the ability to forecast short-term traffic flow [11]. [12] and [13] are two examples of sources that have utilised nonparametric models for the purpose of predicting traffic flow. We have two additional examples of nonparametric models that have been used for this purpose. These nonparametric models, on the other hand, are unable to automatically determine the optimal time delays; as a result, the length of the historical data that is being input into the model must be provided in advance.

TABLE I
Abbreviations used throughout the paper

Sl.No.	Abbreviation	Expanded Form
1	**HVS**	Hidden Vector Sequence
2	**LSTM**	Long Short-Term Memory
3	**RNN**	Recurrent Neural Network
4	**ITS**	Intelligent Transportation System
5	**PeMS**	Performance Measurement System
6	**HCM**	Highway Capacity Manual
7	**ARIMA**	Autoregressive Integrated Moving Average
8	**SVM**	Support Vector Machine
9	**OL-SVR**	Online Support Vector Regression
10	**SAE**	Stacked Auto Encoder
11	**DBN**	Deep Belief Networks
12	**BPTT**	Back Propagation Through Time
13	**FFNN**	Feed Forward Neural Network
14	**RTRL**	Real Time Recurrent Learning
15	**RW**	Random Walk
16	**DNN**	Deep Neural Network
17	**MAPE**	Mean Absolute Percentage Error
18	**RMSE**	Root Mean Square Error

The findings of this study have led to the development ofa cutting-edge model known as the LSTM-RNN. This model excels in accurately predicting the flow of traffic because it better captures the unpredictable and complicated nature of the phenomenon. Because it is endowed with memory blocks that allow it to overcome the problem of back-propagatederror decay, the LSTM RNN has a significant advantage over competing models in the field of long-term time se-ries prediction. This is because the As compared to otherpreviously suggested methods for traffic prediction, LSTM RNN significantly outperforms the competition. The model's capacity to store large quantities of past data and automatically decide the time delays that are most relevant provides even greater precision and accuracy than before when dealing with varying forecast intervals.

A. *List of Abbreviations Used*

III. Proposed Approach

Because of their adaptability, capacity to understand and adapt, and ability to acquire knowledge from novel scenarios, neural networks are rapidly becoming a favourite method for short-term traffic flow prediction. You have the option of usingeither a FFNN or a RNN when trying to forecast upcoming traffic patterns in the near future. Yet, the accuracy of the prediction is directly proportional to the amount of time thatis spent looking at data from the past. Since FFNN is unableto recall past input data or identify suitable time delays, it is only capable of translating the current input vector to an output vector, which results in inferior prediction outputs. This limitation causes FFNN to make inaccurate predictions. Never-theless, RNNs that offer recurrent connections are able to map all of the input data to each output, and these connections also allow the network to retain and make use of the information gained from previous inputs. In a typical RNN, the effect of an input either becomes less significant over time or grows at an exponentially faster rate as it is passed through the recurrent connections of the network.

The LSTM-RNN architecture is an excellent choice forinitial category of traffic flow prediction because it is able to accurately express long-term dependencies and locate suitable time delays for solving problems involving time series. This is crucial since it is not always clear how the length of the historical data used as input impacts the precision of the forecasts, and this is one of the unknowns. The LSTM RNN design has three layers: an input layer, a repeated softmax layer that employs memory blocks in place of conventional neuron nodes, and an output layer. Memory blocks are comprised of subnets, each of which has one or more memory cellsand is also self-connected. In addition, each memory block contains input, output, and forget gates. LSTM cells are able to circumvent the problem of a diminishing gradient thanksto these gates, which allow information to be stored and retrieved over longer periods of time. By opening and shutting multiplicative gates according to the requirements, the LSTM network has the ability to regulate when information that is stored in its memory cells is accessible. Figure 1 presents the architecture of the LSTM RNN prediction model, which only has a single memory block.

Take the provided historical road traffic pattern, $x = (x_1, x_2, ..., x_T)$, to be true. Via a series of iterative equa- tions, the LSTM RNN determines both the HVS $H = (H_1, H_2, ..., H_T)$ and the anticipated traffic flow sequence $y = (y_1, y_2, ..., y_T)$.

$$H_t = \varphi(W_{xH}x_t + W_{HH}H_{t-1} + b_H) \quad (1)$$

$$y_t = W_{Hy}H_t + b_y \quad (2)$$

where,
For weight matrices, we use W, for bias arrays, b, and for hidden layer functions we have used φ.

BPTT is often used to train RNNs [1]. A RNN is a kind of neural network that can make predictions based on past data. In BPTT, the RNN is unfolded over time, and a chainof identical, connected copies of the network is formed, one for each time step. Given that all of the replicas of the network have the same configuration, the network may pickup on temporal patterns and relationships. The network is”trained” by providing it with a sequence of inputs and then comparing the outcomes to an ideal set with the use of a loss function. The gradients of the loss with respect to the network parameters are then calculated by applying backpropagationto each time step in reverse order. Backpropagation is usedto accumulate the gradients over time, which are computed individually at each time step. By modifying its parametersin response to the errors it encounters at each time step, the network is able to improve its output prediction. BPTT may be used to train many distinct RNN designs, such asgated recurrent units, long short-term memory networks, and standard recurrent networks. Its application has helped solve a number of issues, including as language modelling, speech recognition, and machine translation.

In order to solve the vanishing gradient issue that plagues RNN, a new kind of RNN architecture known as a LSTM was developed. When applied to sequential data, like language or voice, the LSTM architecture is able to capture long-term dependencies. There are several parts that make up an LSTM cell, including the cell state, the input gate, the forget gate, and the output gate. The ”memory” of the LSTM is the cell state, which stores information for a very long time. The gates regulate the entry and exit of data into and out of the cellular state. The cell state is dependent on the information from the current input, and this is decided by the input gate. The forget gate decides what details from the previous cell state may be forgotten. The present state of the LSTM cell is evaluated by the output gate to decide what data should be sent out.The LSTM cell receives fresh input at each time step, atwhich point the state of the cell and its gates are modified accordingly. It is the current input and the previous outputthat are used to calculate the input gate, while the currentinput and the state of the cell are used to determine the forget gate and the output gate, respectively. The current input, the state of the input gate, the state of the forget gate, and theprior state of the cell are then used to calculate the new state of the cell. Finally, the LSTM cell's output is calculated using the current state of the cell and the output gate. Itsoutput is either piped into the next available LSTM cell orsent out as the network's final output. The LSTM may recall or forget information selectively over lengthy periods of time because to the input gate, forget gate, and output gate. This enables it to produce reliable predictions by capturing long- term relationships in data that is collected sequentially [14].

IV. Experimental Results and Conclusion

A. Data Insights and Experiment Framework

In this study, we used the data from the PeMS for both the training and assessment of the models [15]. The PeMS dataset, which is used for traffic flow prediction, is created by collecting data at 30 second intervals from a large number of individual detectors that are dispersed over the roadway networks of the state of California. These detectors may be found across the state. When the information has been gathered, it is first organised into 5-minute chunks for each detector, and then it is made accessible online to the general public for study and for use as an aid in navigation. The data on traffic flow clearly follow a daily cycle, and the patternsof traffic on weekdays and weekends are quite distinct from one another. Since traffic management during the weekdaysis so important, this study only focuses on predicting how 30 much traffic will be on the roads throughout the day. In 2014, there were a total of 249 workdays, and in order to collect data on traffic volumes, we conducted random sampling at observation locations spread out throughout 6 highways in PeMS. The first 200 workdays' worth of data served as the basis for our training set, while the data from the subsequent 49 days made up the test set. The raw data on traffic flow fromPeMS has to be aggregated into the appropriate time period in order to comply with the studies' 15-minute, 30-minute, 45- minute, and 60-minute interval forecast intervals, respectively.Take note that we only utilised data on traffic flow as the inputfor the forecast, neglecting other factors such as weather and accidents as well as other traffic metrics (such as density and speed) that may be connected to traffic flow.

The application of the LSTM RNN model that was developed for short-term traffic flow prediction has been supported by a number of studies. The four classic prediction models selected for comparison are the RW, SVM, FFNN, and SAE. It has been determined to adopt RW as the simplest baseline model possible. This model forecasts the traffic flow of the future time step based on the value of the traffic flow at the current time step, which can be expressed as $(hatf(T+1) = f(T)$. A SVM is a model that has been shown to be effective in both classification and regression problems. It achieves this by generating a hyperplane in a high-dimensional feature space using a kernel technique. SVMs have been shown to be useful in both of these types of problems. The RBF kernel is used in the SVM prediction model that we have been working with; this has been how we have been making our predictions upto this point. In our experiments, we make use of a single hidden layer FFNN, which is one of the oldest and mostused models for neural networks. For comparison, we trainthis model using the conventional BP approach. DNN models have recently acquired favour as a result of their greater effectiveness; similarly, we opt to employ SAE to forecast near-term traffic trends. Before employing the BP approach forfine-tuning, the model is pre-trained by unsupervised learning at the greedy layer level. This is done before the BP techniqueis used.

Experiments were carried out to demonstrate that the proposed model is superior to the models described above, with a particular focus on three characteristics of the LSTM RNN: the accuracy of the predictions made, the capacity to store an extensive amount of historical data, and the ability to generalise over a range of different prediction intervals. A synopsis of the results obtained from our experiment may be seen here.

B. Performance Evaluation of Prediction Models

Two widely used metrics can be used to evaluate the accuracy of short-term traffic flow prediction: MAPE and RMSE. MAPE measures the relative error as shown in equation 3, while RMSE measures the absolute error as shown in equation 4.

$$MAPE(f, \hat{f}) = \frac{1}{n} \sum_{i=1} \frac{|f_i - \hat{f}_i|}{f_i} \tag{3}$$

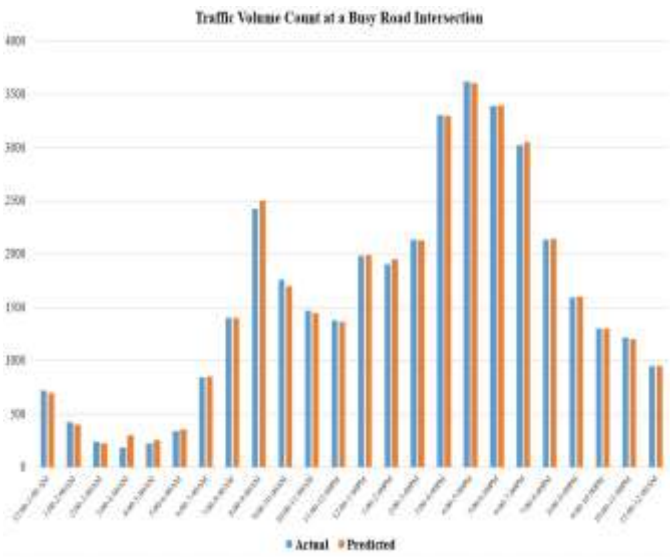

Fig. 1. An Observed Vs Predicted count of vehicles at a busy intersection

$$RMSE(f, \hat{f}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{f_i - \hat{f}_i}{f_i}\right)^2} \quad (4)$$

In the context of traffic flow prediction, "f" refers to the observed value of traffic flow, while "$\hat{f}$" refers to the predicted value.

A comparison of the actual number of automobiles travelling through a busy intersection with the predicted number is depicted in figure 1, which can be found here. The LSTM RNN model has the ability to capture the majority of the variances and produces prediction results that are quite accurate. The results of the predictions as well as the optimal model parameters are shown in Table II for all five models. The input size is denoted by nInput, the number of hidden layers is denoted by nHiddens, and the number of units included in each hidden layer is denoted by nUnits. The LSTM RNN model exhibits the lowest MAPE and RMSE values, when contrasted with the other four models. The MAPE values of 6.29 and 6.48, respectively, for LSTM RNN and SVM demonstrate thatthe two models' performances are quite comparable to one another. In spite of this, SVM is the more advanced model, with an optimal input size of 8 in comparison to LSTM RNN's

TABLE II
PREDICTION RESULTS

Model	Used Metric		Optimal Parameters		
	MAPE	RMSE	nInputs	nHiddens	nUnits
RW	10.28	80.98	1	–	–
SVM	6.40	52.89	7	–	–
FFNN	9.32	64.10	8	1	40
SAE	7.58	55.77	9	4	40
LSTM-RNN	6.77	51.22	1	1	30

input size of 1. When the complexity of SVM is similar to that of LSTM RNN, i.e. when the input size of SVM is 1, the MAPE and RMSE of SVM are 10.32% and 81.66%, respectively, which is considerably behind the performance of LSTM RNN when the complexity of SVM is equivalent to that of LSTM RNN. Finally, the LSTM RNN model is helpful for short-term traffic flow prediction due to its capacity to remember large amounts of historical data and its capacity to achieve high forecast accuracy despite having a very basic model structure. These two features combine to make theLSTM RNN model useful for this application.

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