Enhanced Intelligent Traffic Prediction in Junctions Using LSTM

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Abstract: *Big data systems, which can store, retrieve, and analyze huge amounts of data, and Deep learning techniques, which can learn and anticipate complicated sequences, two important technologies that have recently emerged. Together, these technologies offer novel opportunities for utilizing the vast quantities of traffic volume data in order to improve road traffic prediction and the detecting of anomalous traffic patterns. In this an efficient method to make use of urban transportation system more effectively is proposed, as accurate traffic flow forecast is a necessary element in smart city development. An efficient traffic prediction system in the junctions is done using the LSTM algorithm, accuracy obtained is 94.2% and also the analysis of the dataset is done to extract useful inferences from the data.*

Keywords: **Big data, Deep Learning, long short-term memory (LSTM), traffic-flow prediction.**

1. INTRODUCTION

The Intelligent Transportation System becomes the most important element of all as smart cities are developed into digital cities that make life easier for their residents in every way. Transportation is a major issue in any city; whether people are travelling within the city for work, school, or other reasons, they use the transportation system. Smart Transport System can help citizens save time while also making the city smarter. By reducing traffic issues, the Intelligent Transport System seeks to increase traffic efficiency. By providing users with advance notice of traffic, regional comforts, strong running information, it shortens commuters' journey times and improves their comfort and safety. Accurate and real time traffic is a very difficult task to predict by identifying the traffic patterns which are generally non-linear nature.
However, in the recent years many scholars are trying out with many different algorithms for the accurate predictions by identifying the traffic patterns and gathering the data from different sources such as Global positioning system (GPS), sensor data, social media and crowd sourcing. Also, combination of deep learning methods are put into action to solve prediction problems due to which a significant increase in the performance is identified such as LSTM NN and stacked autoencoders [1].

2. LITERATURE SURVEY

A powerful technique for managing a lot of data, deep learning is a part of machine learning techniques. With diverse radio data and large-scale design, DL offers a mechanism for adding intelligences to wireless networks. Use neural network concepts in DL to uncover channel information (such as bandwidth utilization, bottleneck sites, spikes, and traffic obstacles) by utilizing this function. The travel time is the essential aspect in ITS and the exact travel time forecasting also is very challenging to the development of ITS [1]. Long Short-Term Memory (LSTM) is one of the most effective predictors among those which are sort of linear. It is advantageous to prevent overfitting of data. LSTM is not that great for relatively smalldata sets with fewer outliers.

SVM support linear and nonlinear regression that we can refer to as support vector regression, instead of trying to fit the most significant possible roads between two classes while limiting margin violation. Support Vector Regression (SVR) tries to fit as many instances as possible on the road while limiting margin violations. For the purpose of predicting short-term traffic flow, a hybrid machine learning-based model was developed by combining singular frequency analysis and a kernel extreme learning machine. The gravitational search technique was used to optimize the parameters of the presented models. To calibrate and test the model, five days' worth of traffic flow data were gathered at two detector sites along the at 5-min intervals. The Friedman aligned-ranks test, together with the mean average error and root mean squared error, were employed to evaluate the model.

Analyzed stacked autoencoder models to estimate traffic flow during different time windows. They specifically evaluated the model's results on weekdays and weekends, as well as during the day and at night [2]. They claimed that during the daytime, the mean average error and root mean squared error were larger than during the night. For the weekday and weekend projections, the mean average error and root mean squared error were not provided.

In order to account for the effects of rainfall in short-term traffic flow forecast models, research was done on the use of deep belief networks and long short-term memory techniques [3]. The study's findings showed that using meteorological information to make predictions increased their precision.

Based on the gradient boosting decision tree method, a model for predicting traffic flow has been suggested. With a mean average absolute relative error of 9.7 percent, experimental results for the Huangke Interchange demonstrated the effectiveness of a gradient boosting decision tree-based traffic flow forecasting approach [4].

Authors proposed a gradient boosting decision tree-based short-term traffic prediction model. For the purpose of predicting traffic flow at a specific place, both upstream and downstream traffic levels were taken into consideration. The model was created and trained using traffic flow data gathered over a 9-week period on State Route 22 in Los Angeles by 9 loop detectors. The outcomes showed that the prediction error was decreased when traffic conditions on nearby route segments were taken into account [5].

It offered a cutting-edge methodology for predicting traffic flows that largely focuses on these irregular traffic flows. After identifying these outliers in the traffic flow data, they run a spatiotemporal correlation analysis to determine their relationship to one another [11]. These correlations help us track the background of the outliers and identify the relevant components for our OE-LSTM prediction model.

The authors' proposed research looked into the feasibility of performing traffic prediction using CCTV footage. To extract traffic information, the video is automatically analyzed using object detection and object tracking algorithms. Following that, both Multi-layer Perceptron (MLP) and Long Short-term Memory are used to model the traffic data (LSTM) [12]. To obtain the most accurate representation of the data, Root Mean Squared Error (RMSE) is used to assess model performance.

Authors predict short-term traffic flow using Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) neural network (NN) approaches [13] Experiments show that RNN-based deep learning methods, such asLSTM and GRU, outperform the auto regressive integrated moving average (ARIMA) model.

Work explores and assesses the application of hierarchical temporal memory (HTM) for short-term traffic flow prediction over real-world Sydney Data about arterial highways in the Adelaide metropolitan area, South Australia, from the Coordinated Adaptive [14].

Traffic System. Results from long-term and short-term memory are compared (LSTM). In comparison to earlier LSTM and other deep learning techniques used for

short-term traffic flow prediction, extensive testing with LSTM network topologies in both batch learning and online learning modes yields results with higher predictive performance.
Authors suggests using a combination of the stack auto-encoder (SAE) and long short-term memory network (LSTM) to estimate traffic flow, with SAE used to gather spatial characteristics and LSTM to extract temporal features [15]. The traffic flow status is then predicted using a combination of the features from SAE and LSTM. The effectiveness of the suggested strategy is assessed using statistics on the current traffic flow from Beijing. The performance of the suggested strategy is superior than some well-known prediction models, according to experimental findings.
To perform those duties successfully, it has been suggested that an accurate TM prediction approach is necessary. Fortunately, advances in computer technology like the GPU and TPU have helped Artificial Intelligence (AI) advance rapidly. This presents a chance to integrate AI with TM prediction techniques [16]. The distributed control and constrained local view of network nodes present challenges when employing machine learning techniques in conventional networks. A centralized control architecture, such as Software-defined Network (SDN), is a potential option for this purpose. The TM prediction mechanisms of an SDN architectural network are implemented in this research using Long Short-Term Memory (LSTM) and its two versions, Bidirectional LSTM (BiLSTM) and Gate Recurrent Unit (GRU).

3. PROPOSED SYSTEM

The proposed system was developed to predict traffic in junctions using LSTM:

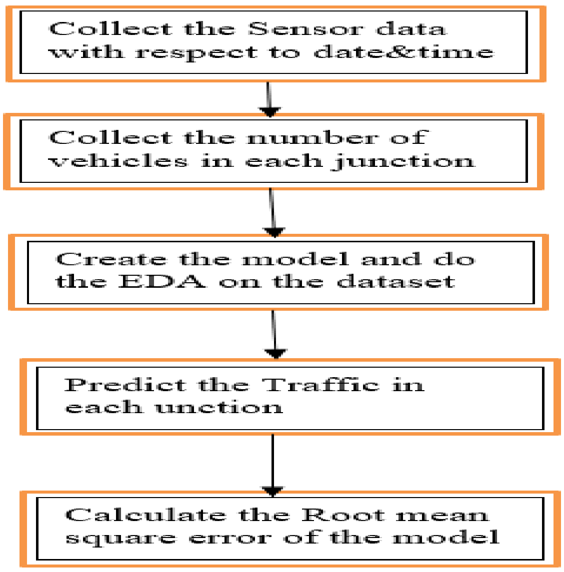

Fig: 1 System Architecture

It is found that fig 1 shows the sequential flow of the process this algorithm is very efficient and it can obtain the model which gives the higher accuracy of the deep learning model than the other algorithms as the LSTM is very efficient algorithm. It is simple to train the deep network by using the methodology with the gradient-based improvement strategy. Sadly, it should be mentioned that models developed using this method function alarmingly. Using alternative procedures would not be a prudent decision due to the minimal number of characteristics in the produced dataset and the fact that its enormous dimensions have been reduced.

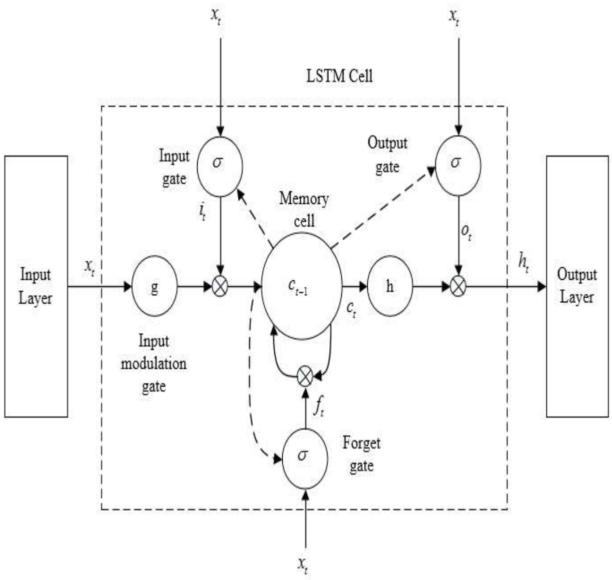

Fig : 2 Structure of LSTM Neural Network

An enhanced RNN, or sequential network, called a long short-term memory network as shown in the fig 2 , permits information to endure. It is capable of resolving the RNN's vanishing gradient issue. RNNs, also referred to as recurrent neural networks, are utilized for persistent memory.

By using LSTM, long-term temporal dependencies may be efficiently captured without facing many optimization challenges. This is applied to solve complex issues. Indeed, LSTM networks, as depicted in fig. 2, are superior to RNNs since they can accomplish anything RNNs would be able to with much more dexterity. Although they can be frightening, LSTMs do offer superior outcomes and represent a significant advancement in deep learning.

Recurrent neural networks RNNs have a difficulty with long-term dependencies, which LSTM networks were specifically designed to solve . In contrast to more traditional feed-forward neural networks, LSTMs have data modification. This trait allows LSTMs to handle whole data sequences without having to consider each point in the sequence separately and instead simply keeping track of previous data. First, at a fundamental level, an LSTM's output at a given moment depends on three factors: The network's present long-term memory is referred to as the cell state.

- The prior concealed state, or the output at the previous instant,
- The input information for the present time

LSTMs use a series of ‘gates’ which control how the information in a sequence of data comes into, is stored in and leaves the network. There are three gates in a typical LSTM; forget gate, input gate and output gate. These gates can be thought of as filters and are each their own neural network.

4 Experimental Analysis and Results

The experimental analysis conducted on various phases of the project suggest incremental increase in the accuracy as compared all the other algorithms implemented by various authors and researchers. The data prediction on all the junctions is done accurately on the real time traffic data collected.

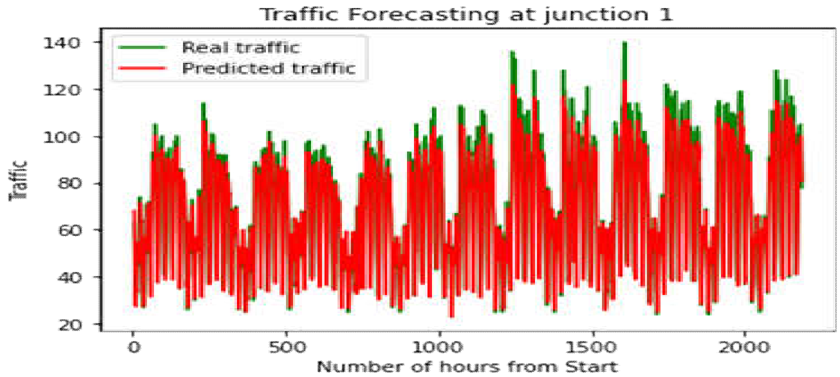

Fig:3 Traffic prediction on Junction 1

The above snapshot fig:3 predicts the traffic at junction 1 of all the junctions taken in the model for the prediction so it shows the real traffic and predicted traffic.

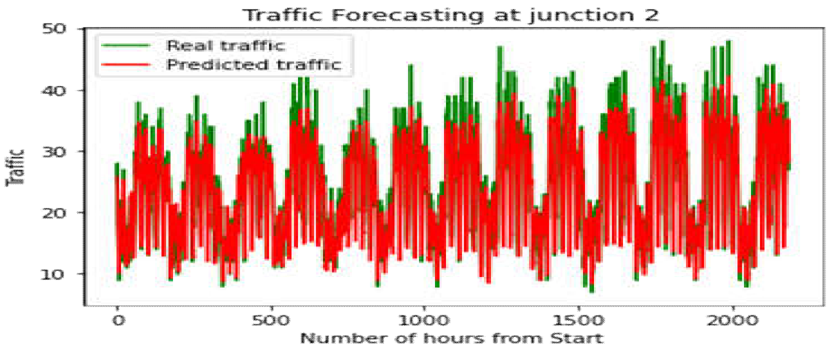

Fig:4 Traffic prediction on Junction 2

The above snapshot fig:4 predicts the traffic at junction 2 of all the junctions taken in the model for the prediction so it shows the real traffic and predicted traffic.

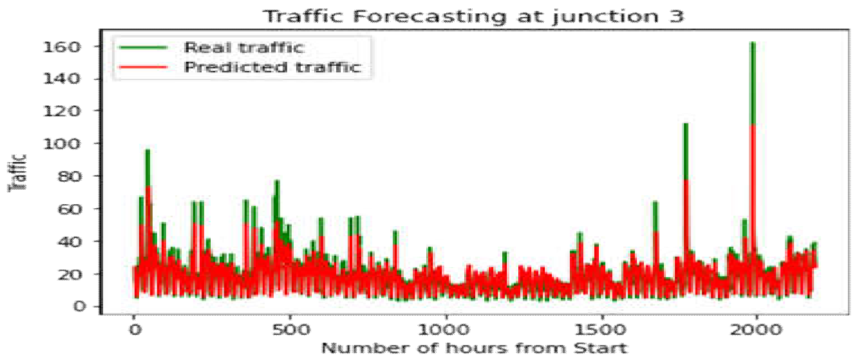

Fig:5 Traffic prediction on Junction 3

The above snapshot fig:5 predicts the traffic at junction 3 of all the junctions taken in the model for the prediction so it shows the real traffic and predicted traffic.

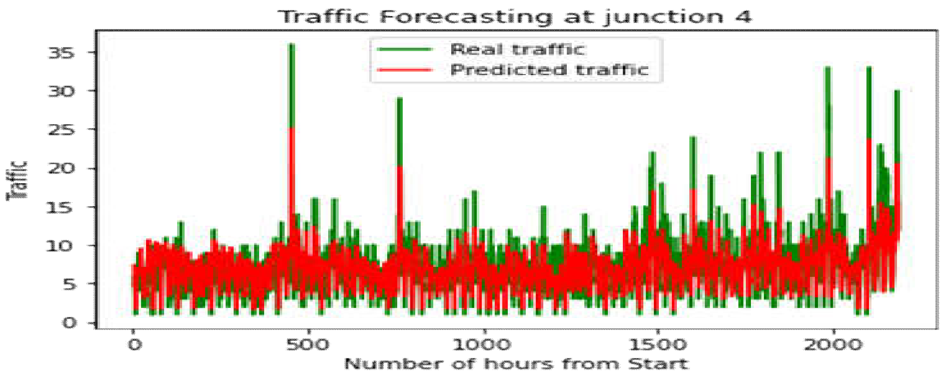

Fig:6 Traffic prediction on Junction 4

The above snapshot fig:6 predicts the traffic at junction 3 of all the junctions taken in the model for the prediction so it shows the real traffic and predicted traffic.

Fig: 7 Snapshot of the Model created

The above snapshot fig:7 depicts the creation of the model used in the traffic prediction and the activation functions, optimizers used in the model and training the model.

Algorithm used	RMSE Obtained
SVM	6.8
Random Forest	5.7
CNN	5.1
LSTM	2.8

Table: 1 Snapshot of the RMSE of the model

The final model result is depicted in the aforementioned snapshot in Table:1 . Root-Mean-Square-Error, or RMSE, is one of the most often used metrics to gauge how accurately our forecasting model's projected values compare to the real or observed values during model training and here a rmse valuse of 2.8 is observed with LSTM and the rmse value is higher for other algorithms.

5 Conclusions

Although deep learning and genetic algorithms are significant issues in data analysis, the ML community has not addressed them in any detail. The proposed model seeks to benefit traffic management in a smart city. This project is really helpful because it is based on enactment that is popular and influential. The suggested approach improves the complexity issues throughout the dataset and provides more accuracy than the current algorithms. It is obvious that LSTM has a lot of potential for forecasting time series. Attempting the same tests while examining more complicated versions of the used models would be interesting for future investigation.

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