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Traffic Flow Prediction using Deeplearning

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***Abstract*— A problem statement like "traffic congestion" has a wide variety of implications on society and the economy. Work is continuously being done in this area to make significant advancements. We have attempted to anticipate the network-wide traffic flow speed using time series analysis and cutting-edge deep learning techniques. For our work, we took into account the historical traffic data for Chicago, which includes the speed of the next time period's 1047 individual road segments. We converted the traffic data into a spatio- temporal matrix and added temporal data for each spatial road segment separately in each column because the traffic data contains time series for each spatial road segment. A RNN model with two layers of LSTM that allots one memory unit to each road segment was created. Using the spatio- temporal training matrix, we trained our model for 50 epochs and then received a vector containing the speeds of each road segment for the subsequent time step. For both the training set and the validation set, the model clearly displayed a learning tendency. Finally, for better visualization, we calculated the MSE and RMSE for the model on the spatio-temporal test matrix and also rendered the prediction as a spatio-temporal image.**

***Index Terms*— RNN model, LSTM, Spatio-temporal analysis, Neural Networks, Classification, Optimization.**

I. INTRODUCTION

A. Overview

Roadblocks caused by excessive traffic are a typical occurrence in most nations, particularly in those with high vehicle and population densities. Such issues cause distress because they have significant economic and social ramifications. Consequently, in light of today's society, traffic management studies are now important. Traffic forecasting is one of those topics. Traffic forecasting can be done using time-series analysis. A statistical tool known as time series is used to examine data points at regular periods of time. Instead of using randomly generated data points, the data point intervals can be fixed at a specific time. Some applications of traffic forecasting include estimating traffic flow rates to calculate travel times or even determining the optimal path to take to avoid traffic as much as possible. Datasets for time series analysis-based traffic forecasting often take the form of traffic data that was collected at regular intervals. Any normal duration, such as an hour, a day, a week, or more, can be used as the fixed time period. This time series dataset is now used as training data for a carefully constructed machine learning or deep learning-based model. Upon training, the model

may provide accurate predictions for a variety of traffic features in the following time step.

B. Objectives

Our goal is to develop techniques for creating multivariate models that can generate the most precise forecasts for a time series of traffic congestion. For forecasting, many statistical models (like ARIMA and VAR) and some common ML models (like SVR and XGBoost) are utilised. Our study will be concentrated on the Deep Learning models. The majority of the time, the so-called multivariate models that are employed in diverse contexts are simply multiple univariate models for each of the covariates in the data. This strategy not only involves a complicated implementation model, but it also neglects to account for the correlation between various variables, which frequently results in models that perform even worse than a straightforward univariate model. Our algorithm will generate predictions using just one deep learning model that considers the most appropriate variables involved and their association to provide the most precise traffic predictions. Since the data is ultimately a time series, our goal is to create a model that can best shed light on the temporal relationships in the data.

C. Motivation

The advent of megacities with intricate road networks has made intelligent traffic forecasting systems extremely important for managing traffic, estimating travel times, locating the optimal routes, etc. Based on past data, these systems predict the traffic situation for a specific road segment. The application of deep learning in this industry has become significantly more important and beneficial due to the meteoric increase in the amount of data collected for this purpose from various widely used mobile devices. In order to produce the most realistic and precise forecast, we intend to create a special deep learning-based model that can fully extract information about the road network and traffic relationships throughout the network from the data.

II. LITERATURE REVIEW

A. Machine learning methods

There have been a few time series analysis-based works for

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the road traffic problem statement before. In [1], a dataset containing hourly data for a whole week at

stretch was fed into multiple time-series forecasting models like ARIMA, SNAIVE, ETS, etc. In [2], some auto-regressive models have been used for forecasting. In [3], integrating time-series data with deep learning has been explored to solve time-series problems. In [4], multivariate STM was explored to develop a traffic forecasting tool. This work explored the conversion from univariate to the multivariate paradigm. In [5], clustering algorithms like DBSCAN was integrated with ARIMA time-series model and other machine learning models like SVR to solve the short-term traffic prediction problem.

B. Deep learning methods

In spatio-temporal applications like time-series traffic forecasting, Generative Adversarial Networks (GANs) have demonstrated promising results and typically outperform other conventional models and techniques. [6] presents the conceptualization of the GAN-based model TrafficGAN that examines traffic predictions at the network level. The use of GAN in traffic forecasting was pioneered by this paper. This research produced an adversarial training-based model that, at the network size, beats the majority of deep learning models used in traffic forecasting. In comparison to previous models like CNN, Graph Convolutional Neural Networks (GCNs) perform better because it makes more sense to represent the roads as weighted digraphs rather than as simple images. GCNs are frequently utilised because they make it easier to better capture spatial patterns and features. In order to account for the spatial properties of the dataset, a graph convolutional recurrent neural network (TGC-LSTM) is proposed in [7]. This network depicts the road network as a graph. This aided in identifying the physical uniqueness of the road network and in creating the required features. The following algorithms performed better in terms of predicting traffic flow, according to reviews of numerous articles [8,9] on the subject:

1) **CapsNet with NLSTM:** They introduced the capsule network (CapsNet)[10] in paper [8] and used a nested LSTM (NLSTM) structure to capture the hierarchical temporal dependencies in traffic sequence data. A system that successively connects CapsNet and NLSTM for generating results is also used to forecast traffic networks. Based on the following steps, this algorithm operates:
   - The traffic network was utilised as an example in the initial stage. Using the traffic status photos, a new CapsNet is used to extract the high-level characteristics and record the spatial dependencies between the highway linkages. Instead of the conventional scalar forms of Neurons, "capsules" in a vector form are used to represent the learnt attributes.
   - An NLSTM structure is employed in the second stage to dynamically capture the hierarchical temporal dependencies in the spatial information that CapsNet has learned.
   - To forecast results, they combined CapsNet and NLSTM in the third step to create a novel framework for network-level traffic prediction.

2) **EnLSTM-WPEO:** The EnLSTM-WPEO model, which combines the long short-term memory neural network (LSTM), no negative constraint theory (NNCT) weight integration, and population extremal optimisation (PEO) method, is described in this research [9].

Based on the following steps, this algorithm operates:
   - For estimating traffic flow in the first stage, LSTMs with various network architectures and time lags are utilised.
   - The predicting results from the first stage are combined in the second stage using NNCT-based weight integration.
   - The weight coefficients of the NNCT weight integration are optimised using PEO in the third stage.

III. IMPLEMENTATION

We take historical traffic flow data of Chicago over 1000 segments, starting in March 2018 of Chicago's arterial streets by monitoring real time traffic flow

A. About the source:

The aforementioned dataset contains historical traffic flow statistics for more than 1000 traffic segments on Chicago's arterial roadways, starting in March 2018, as determined by the observation of actual traffic flow. These statistics were generated by estimating two different types of traffic flow:

1. Based on traffic segments
2. By Regional Traffic

Estimate by traffic segments provides observed speed for a street's first half mile in one traffic direction. The average level of traffic for all arterial street segments within an area is provided via estimation by traffic regions.

B. Data description

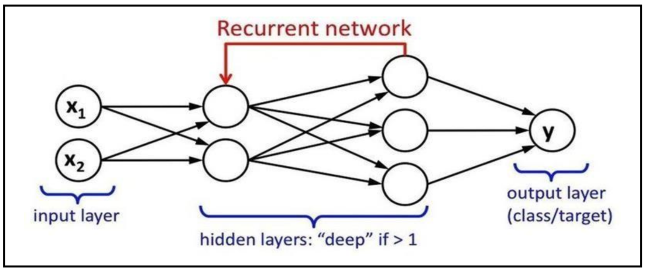
Parameters in the dataset include time and speed. Due to numerous circumstances, including frequent intersections, traffic signals, transit movements, the presence of alternate routes, accidents, short segment lengths, etc., the pace of traffic is very variable. Yet, traffic flow estimation in high-traffic areas lasts for a comparatively longer time.

C. Data preparation

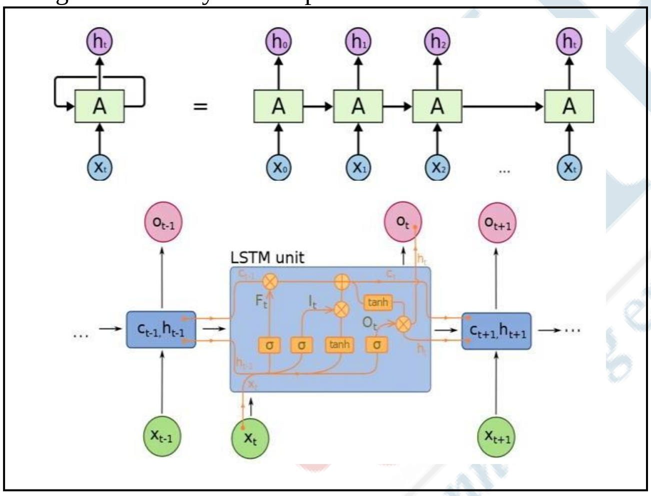
A spatio-temporal matrix was built in order to adequately address the spatial road segments and associated time series data. The data from each road segment was represented by a column in the matrix, and the time steps in the data were represented by a row. This improved the traffic data's visualization.

IV. METHODOLOGY

A finely adjusted recurrent neural network (RNN) model makes up our model. The best method for identifying temporal trends in the data is to use RNNs. They can manage sequential data, such as the traffic data we collect, thanks to their unique feed forward network [11].



Simple RNNs are still insufficient to detect trends across long epochs. LSTM (Long Short-Term Memory) models are therefore better suited for memorising lengthy time sequences [12]. Understanding long-term patterns is crucial for traffic data because the data might be very periodic throughout a variety of time periods.



By considering each road segment in the data as an independent memory unit, we created our RNN model. Our model has 1047 segments and the same amount of memory units based on the data segment that was chosen from the dataset. With each layer having a dropout ratio of 0.2, we used 2 LSTM layers [13]. This means that after training in each layer, 20% of the trainable parameters are set to zero. In turn, this decreases the likelihood of overfitting and thins the network during training, allowing for a reduction in training time. The graphic above shows our model's whole structure. After developing the network, we train the model on the training set, from which we also create the validation set. For 50 epochs, the model is trained. The validation set is used to evaluate our model using the mean square error (MSE) metric after each epoch. Adam, a model optimizer, has been included to help us minimise model losses. The AdaGrad and RMSProp algorithms are used in the Adam optimizer [14], which is employed because it is the best adaptive optimizer[17].

V. RESULT AND DISCUSSION

Data from 10 August 2022 to 25 August 2022, a period of 15 days, is used to train the model. As a test dataset, the data from the following two days, or up until August 27, are used. Our implementation's training and validation loss was determined to be as follows using MSE as the validation metric. Now, we tested our model on the testing set of the data. The scores obtained are as follows:

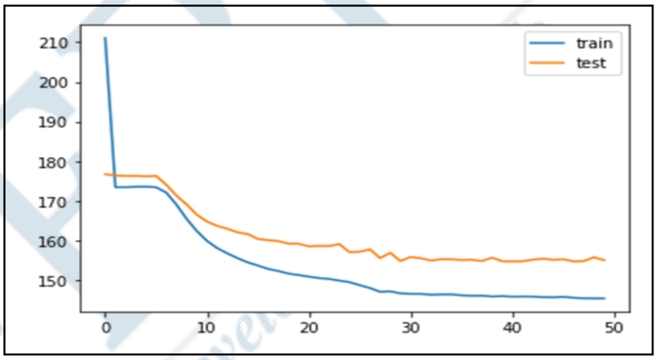


Fig. 1. Testing set of data on model

Mean Squared Error (MSE) = 180.83473204069207
Root Mean Squared Error (RMSE) = 13.447480509

$$\text{Relation Mean Squared} = \frac{\sum_{n=1}^{N}\left(\frac{y_n - \hat{y}_n}{y_n}\right)^2}{N}$$

Relative MSE score was 121.48064669673566.

Although relative MSE is a great metric, in our situation it is not particularly dependable. The primary cause of this was that many entries in the data were missing, and relative error values for those missing entries were calculated by assuming that they were zero. So, in our situation, normal mean square errors are more trustworthy. We created a 2D spatio-temporal image to represent 6 hours of the testing data because our dataset comprises both spatial and temporal relations. The timestamp is represented by one dimension, while each road segment is represented by the other. At each coordinate, the traffic density is depicted by a different color. In this approach, the predictions our model produces are easier to see. The resulting diagram is as follows:

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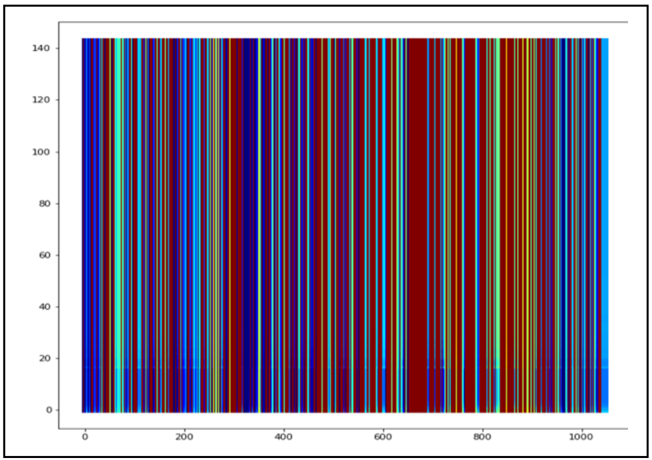

Fig. 2. Spatio-temporal analysis of traffic data

Each coordinate in this diagram indicates the traffic density, which is determined by dividing the average speed by the free flow speed. Higher-valued, or darker-colored, pixels indicate higher traffic densities. For the charting of this image, random road segments were chosen. As a result, the values of the x-coordinate do not match the number of the road section.

VI. CONCLUSION

Our RNN-based model has been successfully tested using historical traffic data from Chicago. Although our work is still in its early stages, the model exhibits strong data- driven learning. The scores on the testing set are also encouraging and comparable to the scores obtained on the training data, indicating that the model fits the training data well without overfitting. The spatio-temporal forecast generated by our algorithm is diagrammatically represented, which allows for a fantastic visual examination of the road network across time. The results nevertheless indicated some improvements that can be made to the model even after carefully developing our current methodology. CNNs can be utilized to more accurately capture the spatial relations in the data according to our findings and the methodologies mentioned in the literature study.

Moreover, GCNs are found to be effective at comprehending the road network. The performance of the model can most definitely be improved by a deep learning model that completely incorporates the properties of all these techniques. The evaluation metric has room for improvement in another area as well. The missing data or times when there are no vehicles on the road are not taken into account by our present relative evaluation approach. As a result of employing zero where appropriate, the scores for our model are drastically lowered.

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