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LONG SHORT-TERM MEMORY RECURRENT NEURAL NETWORKS FOR SHORT-TERM TRAFFIC PREDICTION AT ROAD INTERSECTIONS

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ABSTRACT

The ability to predict short-term traffic designs enables Intelligent Transport Systems to proactively address potential events before they occur. Given the exponential growth in the volume, quality, and granularity of traffic data, novel techniques are necessary to effectively leverage this information to yield better outcomes while accommodating the ever-increasing data volumes and expanding urban areas. This study proposed a Long Short Term Memory (LSTM) Recurrent Neural Network for traffic prediction at road junctions was proposed and designed for short-term road traffic density prediction utilizing Long Short-Term Memory (LSTM) recurrent neural networks in implementation. The model was trained using the following dataset, vehicle ID, time of the day, vehicle type, weather condition, vehicle type and vehicle condition, obtained from road junctions and kaggle online dataset. The model was evaluated using the stated evaluation metrics, RMSE, SSE, R-Square, and R-Square Adjusted. The following results were obtained; RMSE was 0.128, SSE was 11.406357765197754, R-Square was 0.8670005614171354, and Adjusted R-Square was 0.8570256035234206.

Keywords: Proactive, Traffic design, Junctions, Prediction, Model

INTRODUCTION

The issue of maintaining smooth traffic flow in urban areas remains persistently a major challenge, as the demand for road infrastructure continues to outpace the rate at which cities are expanding and urbanization. This surge in demand results in traffic congestion, which has a direct and negative impact on society in various ways, including reduced traffic safety, increased pollution, wasted fuel and time, and increased costs for businesses.

Traffic congestion can greatly reduce accidents on the road if they are properly managed, and also help in increasing the road capacity, road systems for commuters, and making sure that individuals safely travel. Currently, there are several reasons why traffic is congested. Additional usage of cutting-edge technology, such as the Internet of Vehicles (IoV), would aid in predicting the pattern of fluctuations in traffic flow that is anticipated to occur in the future. Research on traffic movement forecasting can benefit greatly from the vast amount of data available in the Internet of Vehicles (IoV) (Zhang, L. and Li, 2020).

The IoV location consist of traffic flow information, this could help in traffic prediction and could also be relevant in traffic controlling units to understand the traffic position on time, convey appropriate traffic flow control strategies, and drastically manage traffic movement, in other to advance traffic resources and enhance traffic situation. As an alternative, it may promptly designate a way that would allow other commuters to avoid clogged roads and save time on their journey. Furthermore, traffic movement data in the Internet of Vehicles (IoV) environment are quickly becoming a major issue in computer vision due to the growing demand for intelligent transportation (Zhao *et al*., 2020). In the meanwhile, rapid and effective traffic movement statistics can assist in resolving issues with traffic congestion and reducing the risk of accidents, which in turn lowers the density of urban traffic. Therefore, creating a reliable, accurate, and consistent traffic movement forecast model is essential for enhancing the traffic of the Internet of Vehicles route system.

Deep learning methods power LSTM's capabilities to completely employ its present fine-grained and high-resolution data, and offer a challenge in training a single LSTM-based architecture above the total road network due to the major rise in system parameters. Hence, an LSTM model was proposed to address this challenge at junctions on road networks using LSTM model, with data streaming from cameras at those partitions; Ma et al. (2015); Zhao et al. (2017) and Fouladgar et al. (2017).

In the context of the Internet of Vehicles (IoV), Tian (2018) presented a model for journey time prediction based on support vector machines (SVM) and artificial neural networks (ANN). The findings showed that the least square SVM trip time predictor model performed satisfactorily.

Philip *et al.* (2018) devised a data-driven methodology that demonstrated improved precision in estimating trip time in situations when traffic data was scarce and highly variable. Using information gathered over an 11-week period from Bluetooth sensors positioned along an urban arterial corridor in Chennai, India, urban commute times were estimated. This data-driven method used the Support Vector Regression (SVR) model. When it came to performance, the SVR model beat the ANN.

Oh *et al*. (2018) did a research on the difficulties with the data-driven strategy, this was the major place-specific and susceptible to variations in characteristics linked with a certain location. Due to these constraints, the data-driven method was less resilient to changes in geometry.

An intelligent congestion prediction architecture combining data fusion and ANN was proposed by Elleuch *et al*. (2016). This method took into account both past GPS data and current unanticipated occurrences, such accidents, that affect traffic jams.

An ANN known as a Jordan's sequential network was created by More *et al*. (2016) to anticipate traffic on roads. In order to predict future traffic flow, our ANN model took into account both aggregated historical values and real-time traffic data. The performance of the network was evaluated based on accuracy and speed, indicating that the prediction relying on both real-time traffic and historical data was more accurate than using historical data alone.

Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is made up of connected neurons arranged in layers, each with an activation function. It performs essential calculations: forward-backward passes. In the forward step, the network processes data from a training set, computes output error, and in the backward step adjusts the weights based on the error. Using the Quasi-Newton BP approach, Zargari *et al.* (2012) employed the MLP algorithm to estimate traffic flow on the Rasht-Quazvin highway in Iran. Hou *et al.* (2015) used sensor data and a multilayer feedforward network to compute traffic flow in building sites in St. Louis, USA.

Xu et al. (2017) predicted traffic flow on a highway using toll data by employing MLP and random forest algorithms. Pamula (2018) trained an MLP/Autoencoder combination using the Levenberg-Marquardt method to forecast traffic flow in Gliwice, Germany.

A further version of MLP is the Back Propagation Neural Network, or BPNN was developed by Xu *et al*. (2018), it used historical vehicle trajectories using BPNN to forecast trip-oriented travel times in metropolitan networks, noting daily and weekly changes in travel times caused by weather and other variables. However, temporal and geographical connections, climatic change, and unidentified random variables generating abrupt shifts made it difficult to anticipate journey times. Convolutional neural networks use convolution to extract picture information and have fewer inputs coupled to neurons, therefore lowering network variables.

The majority of studies used a variety of methodologies and strategies to integrate or apply various machine learning algorithms, Tu *et al*. (2021) devised a technique called SG-CNN. To improve the training dataset, they grouped the road sections together and used the CNN approach Zhang and others (2021). Xia, D. (2020) created a multi-task learning perception for mining spatial and time-based data in various metropolises.

A combination of distributed long short term memory (LSTM) was created by Romo *et al*. (2020) using a period frame and regular distribution that was built on the Map Decrease architecture. They investigated the relative merits of three procedures XGBoost, LSTM-NN, and CNN in order to create a framework based on machine learning techniques. In 2020, Abdelwahab et al. created a computerised system that is effective for classifying congestion. CNN and succinct visual aids were used in its design.

An LSTM model was presented by Abdel-Wahab *et al.* (2020) to estimate IoT traffic using time data. To anticipate traffic flow Lin *et al*. (2020) created a novel LSTM model based on LSTM_SPLSTM. An LSTM model for traffic prediction based on historical and spatially inattentive data was created by Shin *et al*. in 2022. Elleuch *et al*. (2020) presented the Intelligent Traffic Congestion Forecast System, a neural network technique that utilises floating vehicle data (FCD).

A different technique known as SSGRU was developed using the pivotal area on several road sections, Sun *et al*. (2020). Zafar and Haq, (2020) piloted a situation by studying and matching several ML models for traffic congestion forecasting centered on the ETA jamming index.

Yi and Bui (2019) used data analysis from a vehicle detection scheme to create a deep neural network model based on LSTM.

Yang *et al*. (2019) used an end-to-end neural network to create the C-LSTM LSTM model.

A CNN-based technique called MF-CNN was created by Gao *et al*. (2019). Based on spatiotemporal structures, it was able to perform a significant network measure predicting of traffic movement. A model known as MRes-RGNN was created by Chen *et al*. (2019); it was composed of several residual repeating neural network graphs. Bartlett *et al*. (2019) carried out a comparison analysis to determine the effectiveness of three machine learning models k-NN, ANN, and SVR in predicting traffic flow.

Xu et al. (2018) traffic flow may be predicted by employing k-NN and C4.5 models and network positions that resemble videos. (Kong *et al*., 2018 and Tian *et al.*, 2018) proposed a model that references traffic flow using the LSTM approach. Based on our observations of the examined literature, the majority of researchers often employ CNN and LSTM models, indicating the models' capacity to effectively anticipate traffic congestion.

The ANN model‘s hidden layer accepts the weighted sum and applies an allocation function, this functions through the process by summing up each layer. In ANN network, there are several kinds of allocation functionalities, which are log-sigmoid and tan-sigmoid; these transfer function are used for training and testing of datasets. In the procedure, the output layer of the ANN model receives the new weighted sum through the hidden neurons and applies an additional allocation function, the output layer then computes the sum and the transfer function process continues. The input layers of the ANN model are connected to the hidden layers, which is connected to the output layers.

MATERIALS AND METHODS

Model Design

In this study, an long short- term (LSTM) Recurrence Neural Network will be applied on the traffic flow datasets that will be obtained from road intersection in Edo and Delta State (Benin City and Abraka), road system. For the generation of the LSTM RNNs model, road parameters to be used are as follows: road Junctions, VehiclesID, Weather condition, Road infrastructure, State of vehicle, Number of vehicles, Timestamp, the corresponding vehicles identity will be inserted in the required format in the Python environment. For this study, a thousand datasets—which were split into 90% and 10%, were gathered through the use of cameras to capture traffic data from the Delta State (Benin City and Abraka) and Edo road systems and online kaggle dtaset. 90% for LSTM RNN model training and 10% each for testing and cross-validation. Network Inputs: Vehicle identification is represented by the number, time, and speed of the vehicles. Additionally, the system was verified using a Kaggle dataset.

The Long Short Term Memory Design

a) The representation: wij denotes the weight of the connection from unit i to unit j.

b) at i, the network input to a specific unit j at time t.

c) bt I represent the value of the same unit after the activation function has been applied.

d) I denotes the input gate, φ represents the forgotten gate, and ω denotes the output gate.

e) C represents the set of memory cells of the block.

f) St c represents the state of cell c at time t, i.e., the activation of the linear cell unit.

g) f represents the activation function of the gates; g represents the cell input activation.
Functions, and h represents the cell output activation functions.

h) I represent the number of inputs, K represents the number of outputs, and H represents the number of cells in the hidden layer.

The architecture of LSTMs

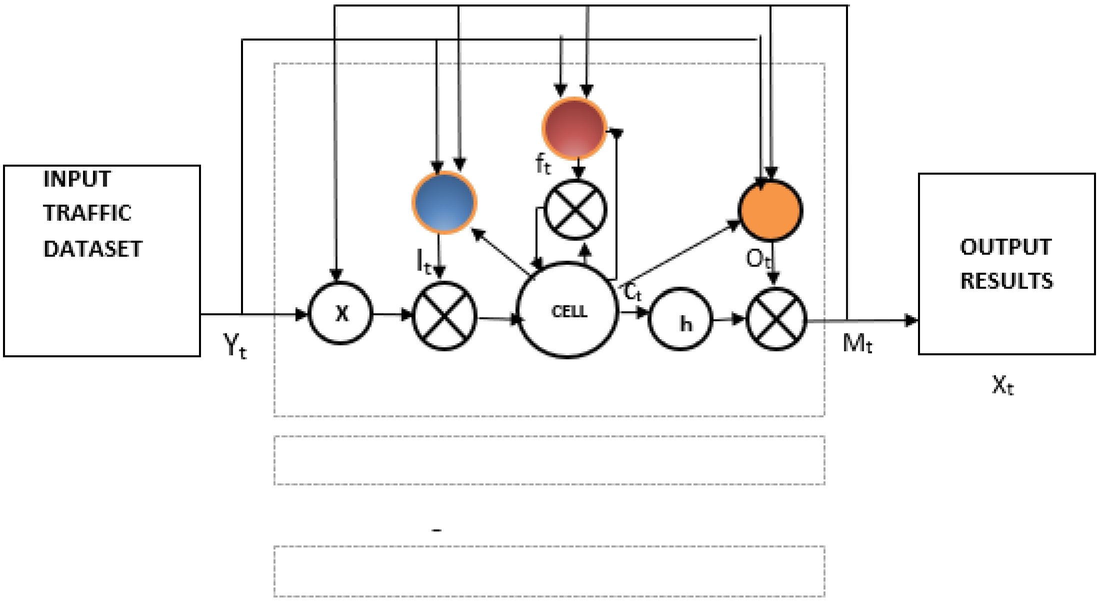

Figure 1: The architecture of LSTMs

The LSTM Network Process

Step 1: Input the data and initializing the input sequence
Step 2: Feature Scaling (Pre-processing of data)
Step 3: Split the dataset for train and test (for prediction)
Step 4: Converting features into array (using the Gated)
Step5: iteratively feeding the input sequence into the trained model and
Step6: Reshaping the array into a shape accepted by the LSTM model
Step7: Updating the input sequence with the predicted output for the next time step.

The basic LSTM architecture consists of three layers: input, LSTM, and output layers. The input layer feeds data to the LSTM layer, where it recurrently flows and updates the memory cells based on input, output, and forget gates. The output unit then sends data to the output layer.

The traffic datasets was obtained from roads and junctions, in (Benin City), Edo State and (Abraka), Delta State. This traffic data is obtained using cameras from road junctions, as shown in appendix a below. The datasets utilized in this study were gathered in Benin, Abraka Edo, Delta State, and at road junctions as well as from the Kaggle online dataset. In order to conduct the simulation and traffic variables were used, such as road Junctions, VehiclesID, Weather condition, Road infrastructure, State of vehicle, Number of vehicles, Timestamp, the retrieved dataset was transformed into a CSV file. Next, LSTM was used to assess the dataset. In order to offer classification accuracy for upcoming predictions, a set of training data is utilized.

The LSTM Flow Chart

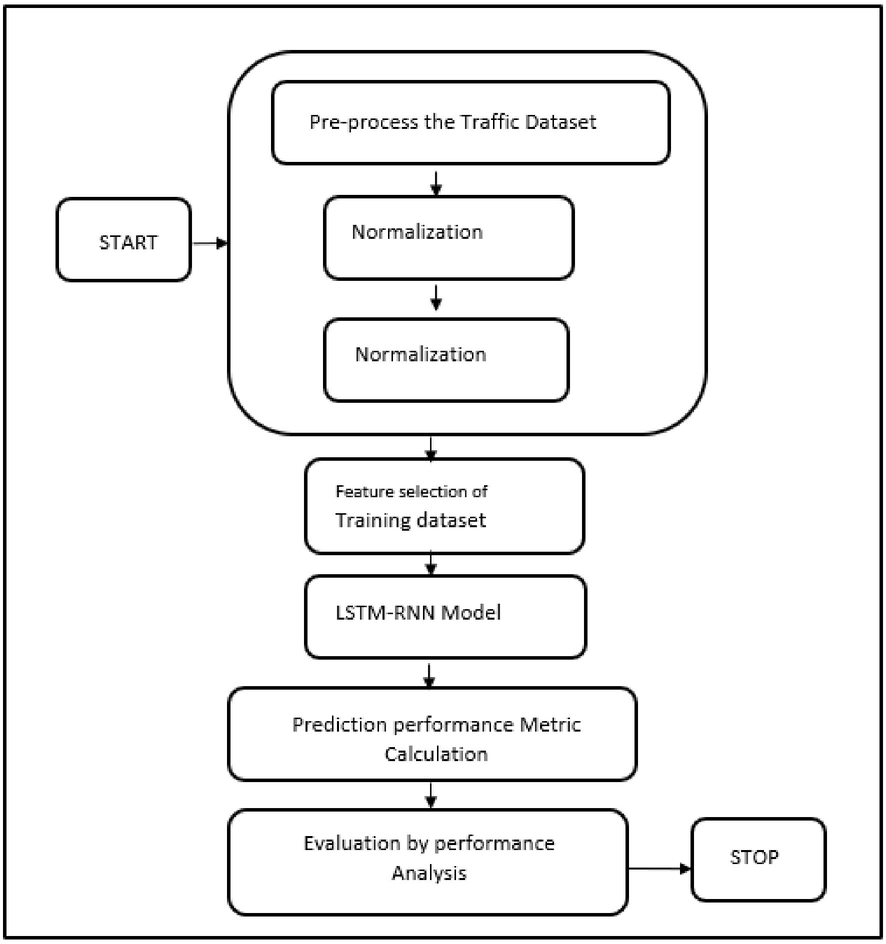

Figure 2: LSTM Model

From Figure 2 above, the traffic dataset is obtained from intersections from the road using cameras, (traffic parameters such as road Junctions, Vehicles ID, Weather condition, Road infrastructure, State of vehicle, Number of vehicles, Timestamp), there after the dataset is pre-processed, then normalized. Feature selection is done, 90% is used for training and 10% for testing, this is modeled using the LSTM model, and then the evaluation metrics (RMSE, SSE, R-Square, and Adjusted R-Square) is now used to evaluate the model performance.

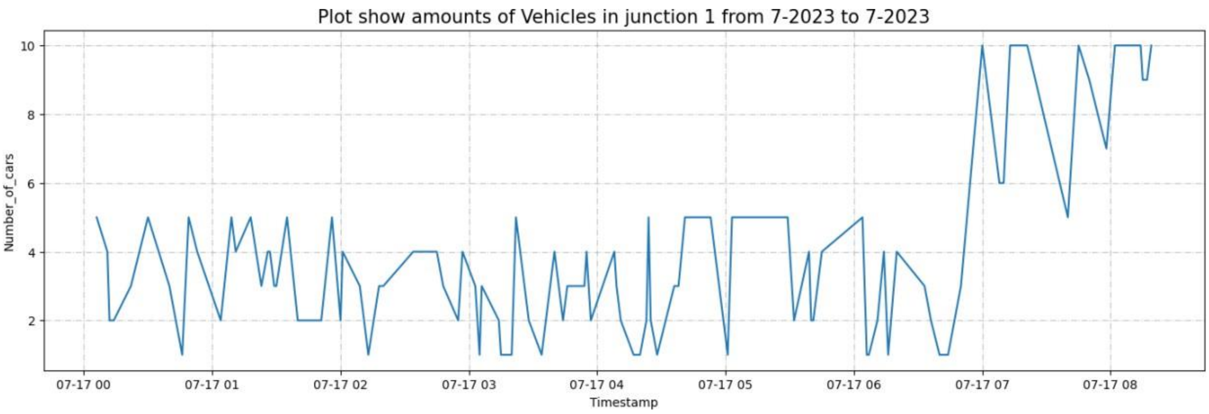

Figure 3: Plot of vehicle at junction 1

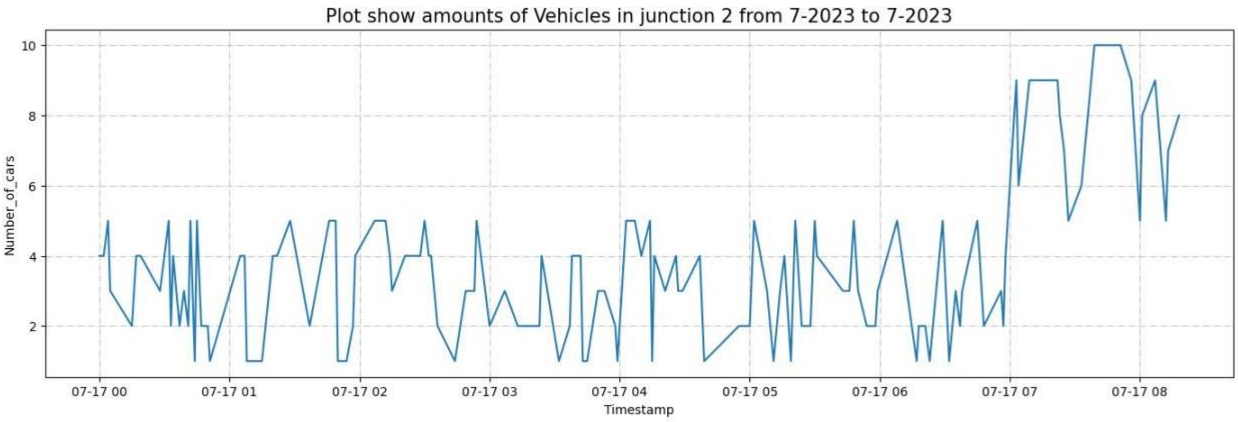

Figure 4: Amount of Vehicles at junction 2

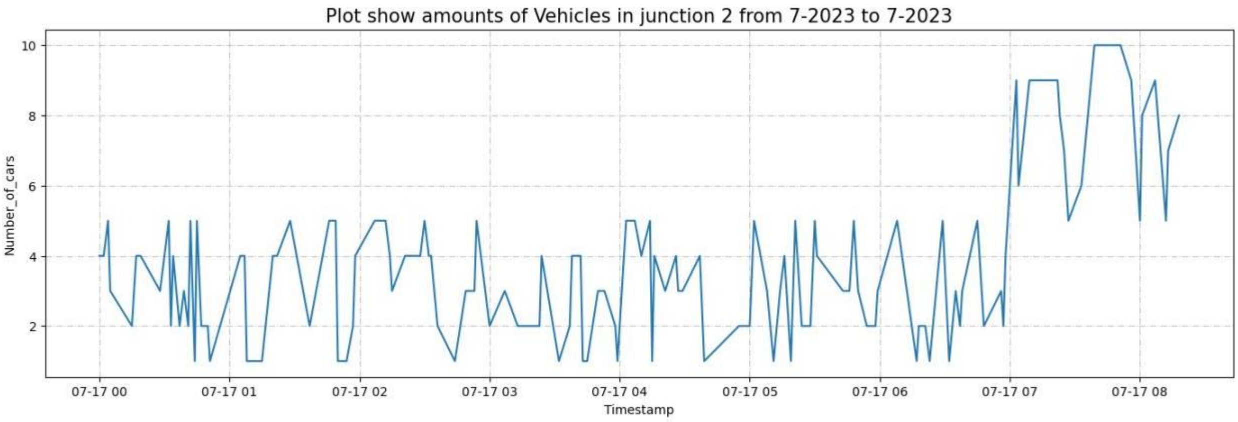

Figure 5: Amount of Vehicles at junction 3

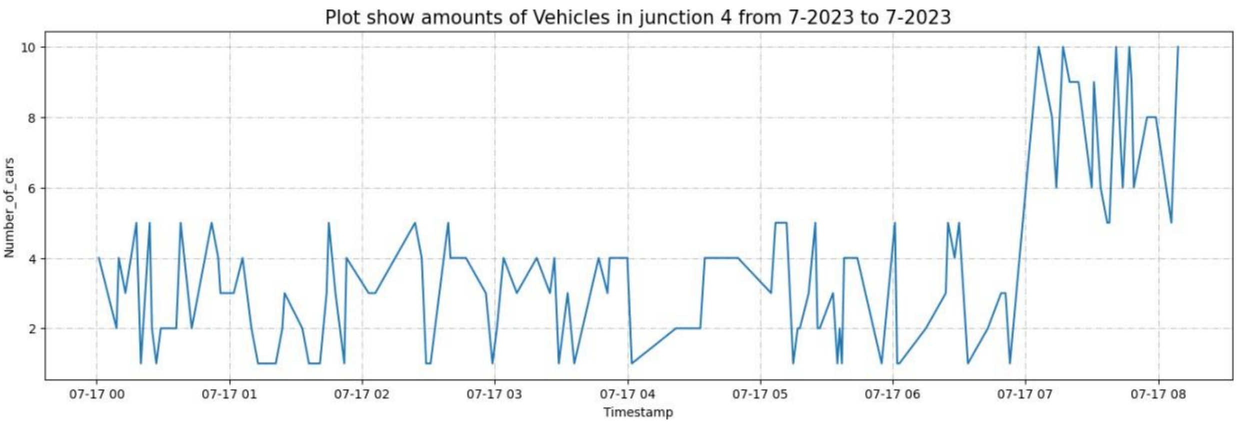

Figure 6: Amount of Vehicles at junction 4

Figure 3 to Figure 6, shows plot of vehicles at junction 1 to junction 4, from a certain period of time.

RESULTS AND DISCUSSION

Result of the Evaluation Metrics

Table 1: Summary of the results of the different metrics applied for accuracy prediction

		Gated Recurrent Units (GRU)	Long Short-term Memory (LSTM)
1	Root Mean Square Error (RMSE)	0.378	0.128
2	Sum of Squared Errors (SSE)	12.442073822021484	11.406357765197754
3	R SQUARED (R^2)	-0.16060791298582178	0.8670005614171354
4	Adjusted R-squared (Adj R^2):	-0.24765350645975848	0.8570256035234206

Evaluation Metrics

The evaluation of our models was based on the following metrics:

The precision of the prediction models was assessed by computing the Root Mean Square Error (RMSE), Sum of Squared Errors (SSE), R SQUARED (R2), and Adjusted R-squared (Adj R2), between the predicted and actual traffic density time series.

Discussion

The experimental results gotten from this study shows that the LSTM yielded a better performance when compared to GRU, from Table 1, with better prediction accuracy. This is attributed to the fact that the recurrent neural network, when provided with a greater amount of information, enables the model to better understand the performance of traffic flow. The readings obtained from the different junctions provided an indication of the traffic conditions that will propagate towards traffic congestion.

In essence, the model is able to acquire more information for the middle and exit sections, resulting in better predictions for these areas as opposed to GRU, which perform better with fewer dataset. Furthermore, we also observed that, with an increase in road parameters and databases, the model can learn better due to its memory units and gated cell cells, which lead to improved prediction and execution time.

CONCLUSION

The model was developed using traffic dataset obtained from road intersections, using traffic variables such as road Junctions, VehiclesID, Weather condition, Road infrastructure, State of vehicle, Number of vehicles, Timestamp. And was simulated using python environment, using LSTM model. The LSTM model prediction level was better compared to the GRU model from Table 1 above, using the different evaluation metrics, SSE, R-Square, R-Square Adjusted and RMSE.

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Appendix I: Data collections of vehicles at road intersections