Traffic Flow Prediction Using Long-Short Term Memory Technique for Connected Vehicles in Smart Cities

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Abstract. An intelligent transportation system is an advanced application that aims to improve the efficiency and safety of various modes of transportation. It works by providing innovative services related to different modes of transportation and traffic management. Machine and deep learning have become an integral part of improving the efficiency of traffic flow prediction. In this study, we proposed a traffic flow prediction using Long-Short Term Memory (LSTM) technique to improve a traffic flow prediction. Our experimental design and algorithm to investigate the accuracy of traffic flow prediction are presented in this paper. For data simulation, the VISSIM simulator is utilised to generate data for classification training and testing. Validation will be done by applying other techniques discussed in the literature. This study will serve as a confirmatory study for traffic flow prediction using LSTM.

Keywords: Traffic flow · Congestion prediction · Machine learning · Deep learning · Long-short term memory

1 Introduction

Recently, developments emphasized making the planet a "smarter" place by implementing smart technologies such as smart cities, smart industry, smart transportation, and others with the rise of IoT technology. The Intelligent Transportation System (ITS) is a ground-breaking technology that is a component of intelligent transportation. ITS helps to lessen traffic issues especially, traffic congestion and, to improve traffic quality. The establishing transportation networks to facilitate the connectivity and mobility of travellers within a given location allows the most use of the networks. The establishment also offers an array of cost-effective, accessible travel alternatives, monitors collisions and congestions, and offering the highest quality of support to road users and travellers [1, 2]. Connected vehicles (CV) are part of ITS implementation which allows travellers

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to arrive at their destination safely, cost-efficient, and quickly [3]. Besides communicating with other cars, CV technology also enables connectivity with roadside facilities, providing critical warning and information.

One of the central concerns that researchers seek to address with the CV progress and growth is congestion [4]. The prediction of traffic flow and congestion has been the subject of several works and studies. Even though information sharing in congested areas is critical, the invention of the CV has made it much easier to disseminate the information. The use of Artificial Intelligence (AI) technologies, particularly Machine Learning (ML), to create and generate traffic flow predictions is innovative. It gives a more accurate technique of developing and generating traffic flow predictions [5]. DL is a subcategory of ML which are closely related to each other in AI methods. As a result, a comprehensive analysis of traffic flow prediction for connected vehicles using machine learning will be conducted in this study. The implementation of CV encouraged the use of ML methods to enhance the capability of the technology through the generation of vast amounts of data which demand a better and faster analysis of data that could not be performed well by traditional methods [6]. One of the main applications of ML in CV is for traffic flow prediction.

Several research questions have been raised and discussed to lead and inspire this study of Traffic Flow Prediction using LSTM Technique in Connected Vehicles. Several studies are currently underway examining the congestion prediction model in CV using the LSTM technique, with differing results and consequences. This study aims to review studies that implement the LSTM technique for traffic flow prediction and based on the review, to propose and come out with a conceptual model for traffic flow prediction using the LSTM technique.

2 Related Works

2.1 Smart City

The emergence of the Internet of Things (IoT) has led to developing Smart City. This concept is composed of various elements such as education, healthcare, transportation, and infrastructure. Sensors, cameras, mobile phones, high-speed wireless Internet, and emerging new technologies that are part of the Internet of Things are the leading technologies in Smart City. These devices create large amounts of data that can be used in Smart Cities for various purposes. Big data is defined as information that is large in volume, diversity, velocity, and validity [7]. As a part of smart cities development, the Intelligent Transportation System (ITS) advancements can change how people commute. Different types of transportation, advanced infrastructure, traffic and mobility management technologies are all available with ITS [2].

2.2 Machine Learning Techniques Approach in Traffic Flow Prediction

Most studies implement or integrate one machine learning approach with various methodologies and systems based on the literature reviewed. A model called SG-CNN is proposed by Tu et al. [8] in which a method of training data is enhanced through an algorithm where road segments are grouped up that make use of the CNN algorithm. A multi-task learning perspective for extracting both temporal and spatial data in numerous cities was demonstrated in [9]. In [10], the authors proposed a combination of distributed LSTM with normal distribution and time window formed on the MapReduce framework. Romo et al. [11] came out with a framework based on machine learning techniques through the conduct of a comparative study of three algorithms XGBoost, LSTM-NN and CNN. An efficient automated system for congestion classification is proposed in [12], which are formed on CNN and concise image representation. Abdelwahab et al. [13] present an LSTM model for IoT traffic forecast according to time series. Another LSTM based model called LSTM_SPLSTM is proposed by Lin et al. [14] to predict traffic flow. Shin et al. used the LSTM model for a prediction formed on absent spatial and temporal data [15]. Elleuch et al. [16], in their study, introduces a neural network model that uses floating car data (FCD) called Intelligent Traffic Congestion Prediction System. Another method called SSGRU is proposed by Sun et al. [17], where the focal point is on various road segments. Zafar and Haq [18] conducted a case study comparing different ML algorithms for the traffic congestion predicting based on the ETA congestion index. Yi and Bui [19] propose a deep neural network model using LSTM for data analysis derived from a Vehicle Detection System. Another study uses LSTM to develop a model called C-LSTM in an end-to-end neural network [20]. A CNN-based model called MF-CNN is introduced in [21] based on spatiotemporal features, capable of conducting a significant network scale prediction of traffic flow. In the study by C. Chen et al. [22], the authors develop a framework named MRes-RGNN, which are formed on various residual repetitive graph neural networks. A comparative analysis study is conducted in [23] to determine the performance of three ML techniques k-NN, ANN and SVR, in predicting traffic flow. Xu et al. [24] demonstrate the use of C4.5 and k-NN algorithms to predict the traffic flow by considering the network status like a video. Kong et al. [25] and Tian et al. [26] proposed a model that utilizes the LSTM technique for traffic flow recommendation.

Based on our observation through the reviews, most of the researchers commonly use CNN and LSTM models, which indicates the capability of the models to perform well to predict traffic congestion.

2.3 Hybrid Machine Learning Techniques for Traffic Flow Prediction

A few studies exhibit the usage of a combination of ML techniques by integrating ensemble and hybrid techniques. As an example, Ranjan et al. [27] introduces a hybrid neural network that involves CNN, Transpose CNN and LSTM, in which they also put forward a systematic strategy for data collection. Liu et al. [28] combine LSTM and GCN techniques in their model of traffic flow prediction. In [29], Chou et al. came up with a deep-stacked LSTM model called DE-LSTM to predict traffic flow during peak and non-peak hours. Study by J. Wang et al. [30] demonstrates the combination of LSTM and CNN that produces a traffic flow prediction for urban areas based on spatiotemporal aspects. Another author, W.Jin et al. [31], also combines LSTM and CNN algorithms that have STRNC, a model capable of capturing temporal dependency simultaneously throughout traffic flow prediction. Duan et al. [32] also utilize the combination of LSTM and CNN for spatiotemporal data extraction to produce a deep neural network model integrated with a greedy algorithm.

2.4 Parameters Involved

Since most studies are for traffic flow prediction, the traffic dataset differs due to the involvement of different countries and cities. Nevertheless, most of the dataset consists of standard variables and parameters used for the analysis of data, and the classification of traffic flow calculations. Based on our findings, the commonly used parameters are traffic speed, volume, density, time and traffic flow. Table 1 is the summary of the listed parameters and their description.

Table 1. List of parameters and description based on other studies.

Parameters	Description	Citations
Velocity (Traffic speed)	Speed of the vehicles	[8, 10–12, 15, 16, 19, 20, 22, 24, 26, 28, 32]
Time	Time of day, periods of time, passage of time, or duration of time	[9, 16, 18, 21, 26, 30, 31, 33, 34]
Traffic flow	The number of vehicles passing through a particular point	[9, 11, 12, 14, 25]
Traffic volume	The number of vehicles crossing a section of road per unit time	[8, 10, 17, 19, 23]

3 Research Design

In this research, we are proposing a research design as shown in Fig. 1. Future traffic conditions are predicted using real-time traffic data and the LSTM algorithm. LSTM is proposed to be used as algorithm to indicate the level of traffic congestion. Due to the nature of machine learning in data mining, it is vital that the data must be collected and analysed in a proper manner [24].

Figure 1 illustrates the research design for the conceptual model proposed for traffic flow prediction in this study. The method of this research consists of several phases to perform the traffic flow prediction.

Figure 2 represents the experimental design illustration, in which the figure graphically depicts the process using a variety of software, techniques, and procedures. The data used in this study are in the form of geographical data, collected from map applications and software such as OpenStreetMap, Google map and others. The location selected will be within urban Kuala Lumpur. The extracted map view will then be set up in VISSIM to run the simulation and collect parameters such as traffic speed, time, traffic density, traffic flow and traffic volume. The collected data then will be analysed using LSTM. A collection of training data is used to provide classification accuracy for future prediction. The result of the prediction will be compared with other ML techniques to determine the accuracy of the performance further.

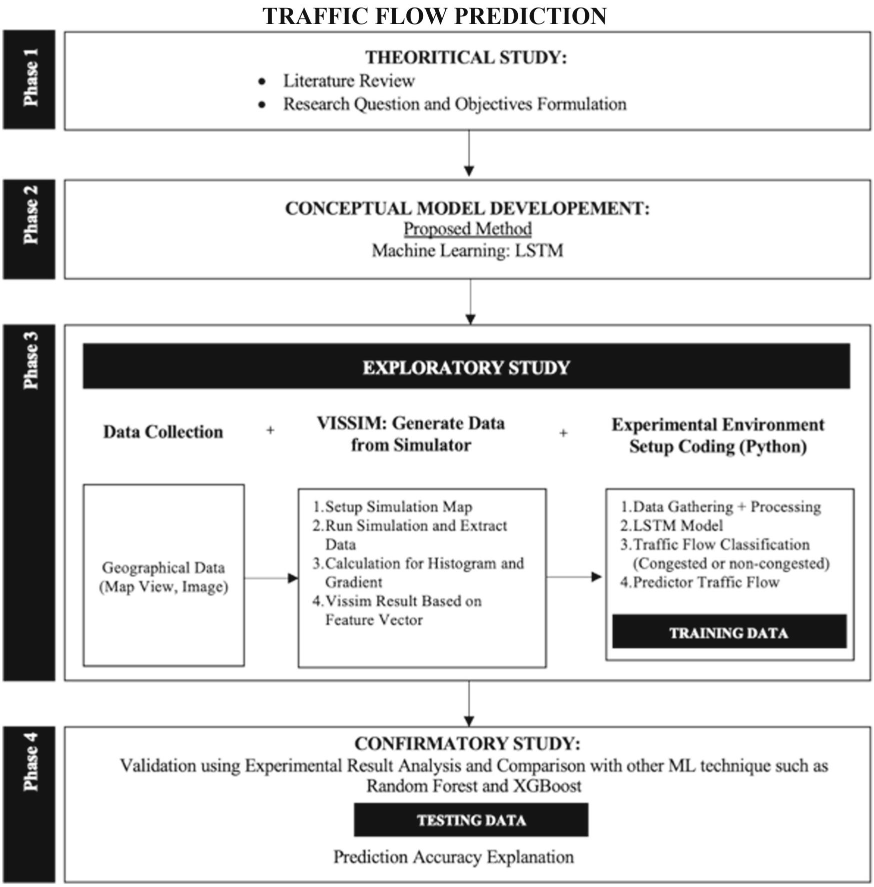


Fig. 1. The research design

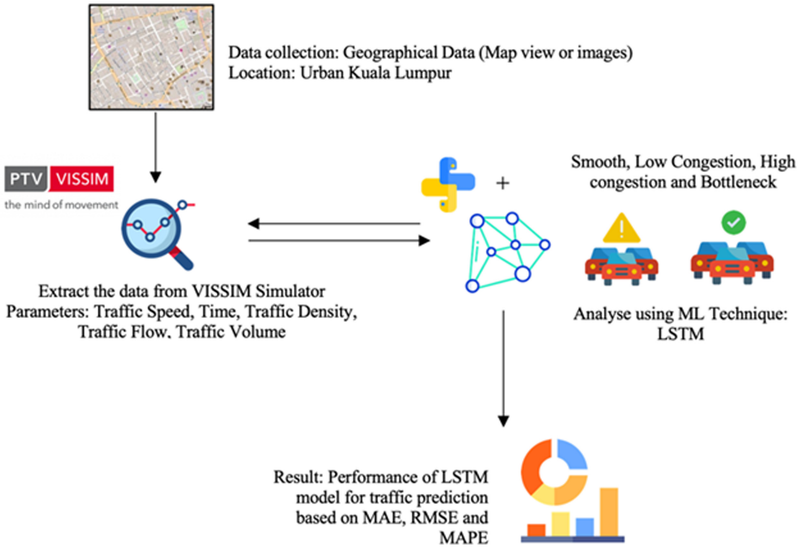


Fig. 2. Experimental design

3.1 Phase 1 – Theoretical Study

Phase 1 is the process of conducting theoretical reviews of literature to further explore the topic. Through these reviews, can produce the formulation of the research questions and objectives. The parameters used for traffic flow prediction are also studied. The outcome of this phase is explained in Sect. 2.

3.2 Phase 2 – Conceptual Model and Algorithm Development

Phase 2 is involving the process of developing a conceptual model, as well as an algorithm for the operation of traffic prediction using LSTM.

Standard Measurement for Congestion Status. To express the status level of traffic, speed performance index (*SPI*) is used, where SPI can evaluate urban traffic conditions [35]. *SPI* value ranges from 0 to 100, which is defined by the ratio of vehicle speed with the maximum speed limit as shown as below:

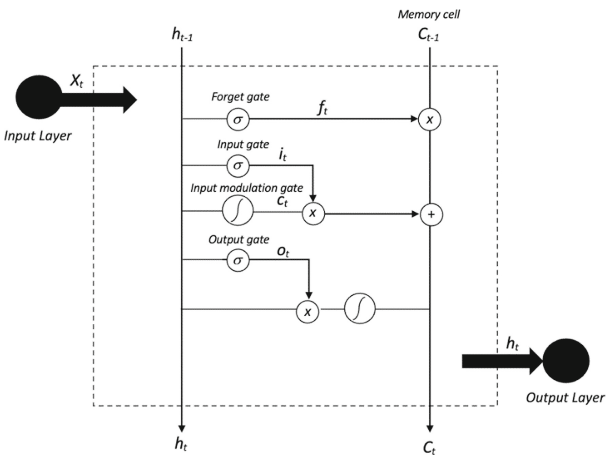
$$\mathrm{SPI} = \left(\upsilon_{\mathrm{avg}} / \upsilon_{\max}\right) \times 100 \tag{1}$$

Where υ avg is average vehicle speed, and υ max is the maximum speed limit. SPI adopts three thresholds value consisting of 25,50 and 75 as the classification criteria for level of traffic congestion. The classification includes smooth, low congestion, high congestion and bottleneck. Table 2 below enlists the ranges of SPI, their levels of traffic congestion and description.

Table 2. Level of traffic congestion based on *SPI*

Traffic congestion level	SPI	Description
Bottleneck	0–25	If average speed is low = Road traffic state is poor
High congestion	25–50	If average speed is lower = Road traffic state is weak
Low congestion	50–75	If average speed is higher = Road traffic state is better
Smooth	75–100	If average speed is high = Road traffic state is good

LSTM Structure Model. In this research, the chosen deep learning technique for this study is Long short-term memory (LSTM). This technique is selected based on the literature review conducted and the performances in different studies, which will further explore in this study. LSTM is a variation that comes from RNN, where RNN solves the issue of other traditional neural networks in handling sequential data [13]. Traditional neural networks are only able to process current time-series information. they could not use its historical information to good use, in which RNN can retain information from the history and use it for the calculation of the current sequence. But RNN Could not effectively utilize the length of historical details [13, 25].



$$\boldsymbol{f_t = \sigma(W_f \cdot [h_{t-1}, x_t]) + b_f}$$
$$\boldsymbol{i_t = \sigma(W_i \cdot [h_{t-1}, x_t]) + b_i}$$
$$\boldsymbol{o_t = (W_o \cdot [h_{t-1}, x_t]) + b_o}$$
$$\boldsymbol{C_t = tanh(W_c \cdot [h_{t-1}, x_t]) + b_c}$$
$$\boldsymbol{C_t = f_t \times C_{t-1} + i_t * C_t}$$
$$\boldsymbol{h_t = o_t \times \tanh(C_t)}$$

Fig. 3. LSTM structure and formula [13, 25].

LSTM is an extension of RNN, with the inclusion of a memory unit or cell which is used to hold historical information. The memory unit uses a "gate" to add or remove information to the cell state. There are three main gates in an LSTM Structure: input gate, output gate, and forget gate as illustrated in Fig. 3 and the calculation formula.

Where σ is the sigmoidal function, $b_j$is the bias, and W is the matrices weight. The main component of LSTM is the cell state, where C_{t-1} or memory from the preceding block runs to C_t, the memory from the actual block. x_t is the current input, and h_{t-1} is the former output. For a traffic flow prediction, the information to the LSTM structure includes traffic time, traffic speed, traffic density, traffic volume, and traffic flow. The outputs of the LSTM structure are the predicted state of current traffic flow, whether it is congested or non-congested.

LSTM Algorithm for Traffic Flow Prediction

Algorithm for Machine Learning Traffic Flow Prediction using LSTM

1. Load Training set from VISSIM
    traffic_data ← load(data.csv)
2. Input:
    Training data X = {X, X, ….,X_i)
    X ← traffic_data[‘Traffic Speed’’Traffic Volume’‘Time’’Density’’Traffic Flow’]
3. Output:
    MAE, MAPE and RMSE
    The Result of the Test Set {Congested or Non-Congested}
4. Initialize:
    A pre-trained model
5. Create Arrays of Training and Test Set:
    80% training and 20% testing data
    X_train,X_test,
6. Normalize the dataset (X_i) into value from 0 to 1
7. Define:
    LSTM Structure Model
8. For *n* epoch and batch size to
    Train the LSTM model
9. End for
10. Execute Prediction using LSTM()
11. Calculate using SPI to define smooth, low congestion, High congestion and bottleneck
12. Calculate the performance error using MAE, MAPE and RMSE
13. Predict the Result of the Test Set
    Prediction ← Predict(X-test)

Fig. 4. Algorithm for traffic flow prediction using LSTM

Figure 4 above is the algorithm for traffic flow prediction using LSTM, which will be used in this research. In this algorithm, first, a training data set is loaded and used as the input, which contains data such as Traffic Speed, Traffic Volume, Traffic Density, Traffic Flow and Time. The expected output from the LSTM model calculation is the value of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to determine the performance of the prediction classification, which will be calculated as below:

$$\mathbf{MAE} = \frac{1}{\mathbf{n}}\sum_{\mathbf{i}=1}^{\mathbf{n}}|X_t - F_t| \;\; \mathbf{MAPE} = \frac{\sum \frac{|X_t - F_t|}{X_t} \times 100}{n} \;\; \mathbf{RMSE} = \left[\frac{1}{\mathbf{n}}\sum_{\mathbf{i}=1}^{\mathbf{n}}(X_t - F_t)^2\right]^{\frac{1}{2}}$$

Then, a pre-trained model is initialized, and an array of training data and testing data is created, and data is split into 80% training data and 20% testing data. The series of size, train and test are determined. The dataset is then normalized into values between 0 and 1. The LSTM structure model is then defined and trained for *n* epoch and batch size classification. After all, process is done, the prediction using LSTM model is run, and from the output, the performance is calculated through metrics MAE, RMSE, and MAPE.

3.3 Phase 3 – Exploratory Study

Phase 3 is the process of conducting the experiment, which starts with data collection, where geographical data such as the chosen area or location in urban Kuala Lumpur for the experiment will be taken from map view images generated from existing map providers such as OpenStreetMap and Google Maps. The data will then be used in traffic simulator applications such as VISSIM. The simulator will run a simulation and extract parameters such as traffic speed, traffic flow, traffic density, traffic volume and time. The data extracted from VISSIM will then be processed with the LSTM technique through Python and classified whether congested or non-congested. The result of this classification will act as training data.

3.4 Phase 4 – Confirmatory Study

The final phase of this research focuses on validating the outcome of the experiment through the analysis of experimental results and comparing the performance of the LSTM with other ML models and techniques, such as Random Forest and XGBoost. Testing data will be used to compare the results with the training data. Based on the outcome of the prediction, the accuracy will be further explained during this phase.

4 Conclusion and Future Work

Recent growth in the development of smart cities as a part of IoT technologies contributes to new innovative ideas and technologies, including the advanced development of ITS for smart transportation. Researchers and academicians have proposed various methodologies to enhance transportation experience and resolve traffic problems that contribute to a negative effect on the environment and community, such as safety and traffic congestion. Along with the introduction and growth of CV technology, various ideas have been thrown out and proposed to solve traffic problems, especially traffic congestion. In this study, a conceptual model is proposed for traffic flow prediction using a ML technique which is the LSTM. The model was developed based on the review of several related literatures which uses ML techniques for traffic flow prediction. Even when other reviewed literature shows that CNN is one of the most used techniques, in this study, we decide to exclude it due to the characteristic of CNN, which takes input from image data, where our analysis does not include. The chosen parameters, evaluation methods and evaluation metrics are also thoroughly discussed. The research design of the conceptual model with the experimental setup is illustrated and explained simply. In the future, the conceptual model will be implemented in an experiment to test the capability of finding the prediction accuracy performance of using ML techniques for traffic flow prediction.

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