Computational Engineering and Physical Modeling 5-3 (2022) 50-63

Contents lists available at CEPM

Computational Engineering and Physical Modeling

Journal homepage: www.jcepm.com

Study of Traffic Forecast for Intelligent Transportation System

Abhishek Prakash Paswan[1], Priyam Kapri[2], Indrajeet Singh[1], Ritu Raj[3], S. Anbukumar[4], Rahul Kumar Meena[5*]

1. Ph.D., Student, Civil Engineering, Delhi Technological University, Delhi, India
2. U.G. Student, Civil Engineering, Delhi Technological University, Delhi, India
3. Assistant Professor, Civil Engineering, Delhi Technological University, Delhi, India
4. Professor, Civil Engineering, Delhi Technological University, Delhi, India
5. Assistant Professor, Civil Engineering, Punjab Engineering College, Chandigarh, India

Corresponding author: *rahulmeena@pec.edu.in*

https://doi.org/10.22115/CEPM.2023.360823.1221

ARTICLE INFO

Article history:
Received: 06 September 2022
Revised: 29 January 2023
Accepted: 20 April 2023

Keywords:
ITS;
Traffic forecast;
Prediction;
Accuracy;
Development.

ABSTRACT

The number of cities, particularly those with advanced infrastructure, is increasing rapidly. There has been a steady increase in the number of automobiles on the road, which has led to severe congestion and wasted time and money. Increasing the number of roads or lanes available is a costly solution to traffic congestion. The primary objective of this research was to examine the traffic pattern using machine learning technologies, which is the optimal method in such situations. The primary objective was to compare the LSTM and ARIMA algorithms across 15-minute intervals, which is confirmed by calculating the observed error. The data obtained was then normalized and filtered to meet the requirements of this study, and machine learning methods are used to make predictions about traffic volume and average speed. Predictions from regression models can be utilized for decision-making. A prediction is a statement about how a variable will change or stay the same. A decision, on the other hand, is what to do in response to a prediction. The LSTM model has less error from the start of the project, while the ARIMA model performance improves with time or at the latter stage. The percentage error of the LSTM model is about 15% less than that of the ARIMA model, hence it can conclude that the LSTM model will perform better than the ARIMA model.

How to cite this article: Paswan AP, Kapri P, Singh I, Raj R, Anbukumar S, Meena RK. Study of traffic forecast for intelligent transportation system. Comput Eng Phys Model 2022;5(3):50–63. https://doi.org/10.22115/cepm.2023.360823.1221

1. Introduction

Under infrastructure limitations, urban transportation networks are unable to deal with on-going increases in road traffic [1]. Growth in accidents, emission of toxic, overcrowding, speed breaches, and other undesirable outcomes result are due to the uncontrolled rise in the number of road transport [2]. Some different studies described the further problems related to overcrowding. Surveillance footage is a common technology for measuring and managing traffic movements [3]. Essentially, road video cameras are employed to record traffic offences. The Intelligent Transport System (ITS) [4,5] layout of transportation infrastructure and products, as well as designing, funding, and governing, are all dependent on a transportation planning process that is closely linked to travel demand forecasting. When there is an increase in traffic and visits in the future, forecasting models in transportation planning are extremely important to consider. Finding the relationship between visitors counting's that leave from a neighbourhood from origin vacation location (O-D) survey result and distinct freelance variables of macro-degree in a very specified zone is the goal of the web site guests production modelling [6]. This prompted the application of space analysis to seek for the matrix origin-vacation point of traffic production over a period of twenty-four hours, which was treated as a random variable. Machine learning is the training of techniques that allow computers to simplify the creation and development of information models and algorithms by methodically identifying clinically important patterns within the data [7,8]. Although machine learning approaches are becoming more common, the very first effort to create a machine that simulates the behaviour of a biological thing.

The goal of the device learning a set of rules is to improve the match between outputs and inputs by employing a non-stop feature to help machines understand how outputs change as inputs change. The regression issue may also be foreseen as a difficulty with prediction. Numerous mathematical elements may be used to characterise the connection between output variables and entry variables (linear, nonlinear, and logistic). The machine learning is regressing Mathematical procedures that allow records scientists to anticipate a continuous end outcome (y) solely based on the cost of one or more predictor variables are included in learning (x). Linear regression is the most used type of regression analysis [9] since it is the most straightforward to utilise in predicting and forecasting. It quantifies and is dependent on one or more entry variables (volume), the nature of the relationship between the aim and the enter variables. The equation that yields the lowest difference between all of the measured value and their predicted value is identified using linear regression. R-squared is a goodness-of-suit metric for linear regression models. When the unbiased additives are introduced together, it exhibits the proportion of version withinside the established variable that the unbiased elements account for. R-squared measures the energy of the connection among the version and the established variable on a 0-100% scale.

The greatest amount of fecundity with the least amount of wasted effort or value consumption of street network would answer the difficulties of the visitors. As a result, predicting the exact number of website visitors in a short span of time is a critical area of management and, obviously, an Intelligent Transportation System (ITS). When comparing period-of-time traffic statistics to short-term number of website visitors forecast technology, there are variants. Now-a-days, huge historical guest statistics with a slew of criteria such as guest volume, time-stamp, vehicle speed, and nearby occurrences are readily available and will be recognized on a regular basis. This information can be utilized to increase prediction accuracy and make traffic forecasting more reliable. Regression analysis is a statistical technique in which variables change from one value to another. Formally, regression analysis uses a mathematical function, called a (linear or non-linear) model, to predict the mean outcome from the values of its independent variables. Other uses might include predicting whether new treatments will work better than existing ones; forecasting quantities such as costs, sales volumes and profits; and predicting trends in sales over time. Linear regression is useful in these and many other situations where there is data that can be modeled by linear relationships between input variables and outcomes.

R-squared is used to calculate the dispersion of facts factors across the linear regression line. It's additionally referred to as the coefficient of dedication or the coefficient of several determinations in a couple of regressions. For the identical facts set, better R-squared values advocate much less disparities among measured and expected values.

$$R^2 = \frac{\text{Variance observed from the model}}{\text{Total Variance}} \quad (1)$$

The R-squared number is always in the range of 0 to 100%: A model with a 0% explanatory power explains no variance in the response variable's mean. However, there are several key limitations to this principle, which will go through in both this and the following post fig.1 indicated the linear regression while fig.2 shows that the polynomial regression of study done by different researcher [10].

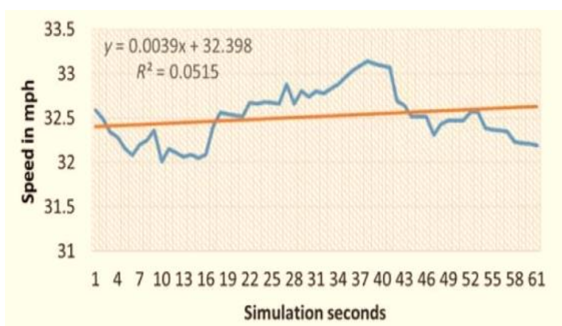


Fig. 1. Linear Regression [10].

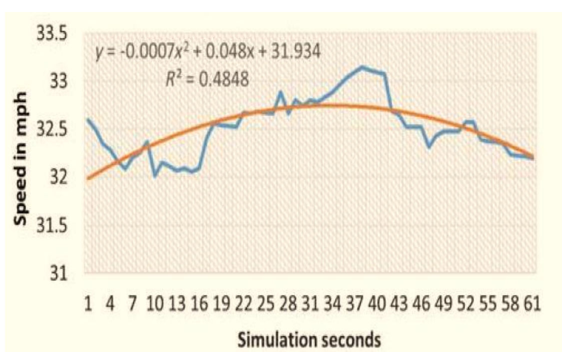


Fig. 2. Polynomial Regression [10].

The standard, nature, and amount of the knowledge are important aspects that influence the precision, effectiveness, and toughness of the device learning rule in both supervised and unsupervised situations. Even though the aim of any device about to grab the appliance is to seize truth and version uncertainty, the known version will normally reflect the actual fact provided the records set rather than the particular international. The flow chart depicts a median step-by-step strategy to improve device learning rules as presented in Fig 3.

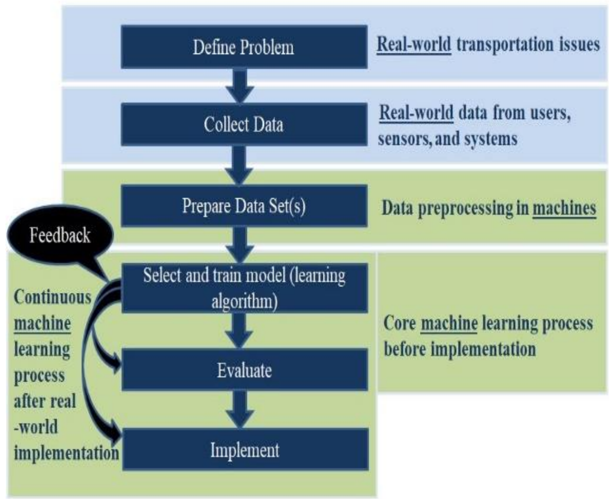


Fig. 3. Working Flowchart.

The aggregate quantity of motor vehicle passing through a particular place in a given time interval can be explained as Traffic Flow (F). The following is a definition of traffic flow prediction [11]: Traffic flow prediction [12] (F) is calculated as eq. 2.

$$\mathbf{F} = \frac{\mathbf{n}}{\Delta\mathbf{T}} \tag{2}$$

Here, the quantity of cars existing at a specific or certain location at a given time is denoted by n. The letter T represents the passage of time [11].

Programs for the traffic forecasting have been created to use a range of methodologies and disciplines. Fig. 3 is indicating the working flow chart adopted in the present study. When assessing traffic prediction results, one must incorporate prior information as well as the present situation of traffic. The road traffic must be linked to a dynamical object. As a consequence, traffic forecasting is strongly reliant on both time and space. By using an LSTM network, it integrates the dynamical relationship for relatively brief traffic forecasting in this research.

What does it mean for data to be linearly related?

Usually, data models consist of many variables, with each variable having different types of possible values. The values of some variables may be highly correlated with one another (i.e. two variables may be related in that changes in one often correspond to changes in the other). For example, if someone needs a new house, they might choose to buy a new car, or vice versa. Since both variables are related, data regarding their values can be modeled by a line. A linear relationship is one where each dependent variable is linearly related to each independent variable.

Simple linear regression analysis is a technique that has been used for more than 100 years as an important tool for analysing data containing relationships between several variables. The model is well suited for situations where independent variables are measured as continuous values (numerals) and dependent variables are measured as continuous values such as time, weight or profits.

2. Methodology

Significance of the study is written as part of the introduction section of a thesis. It provides details to the reader on how the study will contribute such as what the study will contribute and who will benefit from it. It also includes an explanation of the work's importance as well as its potential benefits. It is sometimes called rationale [13].

2.1. Experimental

Mainly Experiment will be based on calculating and comparing analysis on 3 criteria. Some frequently used ones for the evaluation of prediction of traffic are mention below.

- Mean absolute error (MAE)
- Root mean square error (RMSE)
- Mean relative error (MRE)

MEAN ABSOLOUTE ERROR (MAE)

Mean absolute error calculated with the help of pervious literature available in this domain [14] This measure refers to the average absolute difference between the desired and true values [15].

$$\mathrm{MAE} = 1/\mathrm{n}\left(\sum_{i=1}^{n} |x_{i-x}|\right) \tag{3}$$

Where, n= the quantity of errors

Σ= Summation

$|x_i - x|$= the absolute errors

In data interpretation, this kind of an error is a computation of errors between matched data reflecting the alike occurrence. In machine learning, absolute error refers to the difference between an observation's predicted value and its actual value. The average of absolute errors for the whole group is used to calculate the size of mistakes for a set of forecasts and observations.

Importance of Mean Absolute Error- It is one of the widely used essential arithmetic operations for regression issues. MAE [16] aids in the formulation of performance problems as optimization problems, allowing us to readily comprehend the quantitative assessment of mistakes for regression problems.

ROOT MEAN SQUARE ERROR (RMSE)

The root mean square error (RMSE)[17] is the residuals' standard deviation [18] (prediction inaccuracy). RMSE [14,18] is a computation of the amount of data points vary from the regression line, and the remaining are a estimation of how far they spread. To positioned it any other way, it explains how intently the records is collected across the best-healthy line. In climate forecasting, aerology, predictions, and regression analysis, root suggests rectangular mistakes are broadly wield to assess observational interpretations. A typical measure for calculating a model prediction error is the Root Mean Square Error (RMSE). Its formal definition is as follows:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{4}$$

Where, $\hat{y}_i$ = forecasted value

y_i = observed value

n = quantity of observations

Importance of Root Mean Square Error-RMSE is only helpful for evaluating classification error of dissimilar replicas or dummy arrangements for a single variable, not in between of the variables, because it is scalar reliant.

MEAN RELATIVE ERROR (MRE)

It refers to the ratio of a measurement's absolute error to the measurement itself when used as a precision metric. To put it another way, the size of the object being measured influences the type of error that will be made. The Mean Relative Error [14]has no units and is expressed as a percentage.

$$\mathrm{MRE} = \frac{\text{Absolute Error}}{\text{Measurement being taken}} \tag{5}$$

Traffic Flow

For weekdays, according to ample of vehicles predicting composition, traffic sticks to a highly specific pattern. The traffic is building in the morning and ultimately attains a apex (hurry hour). Following that, vehicle concentration gradually reduces all over the period, later gradually surges one more time in the evening time because individuals drive to their residences (hurry hour). There are two types of correlations to consider when dealing with traffic predictions. Fig. 4 (a) depicts the traffic flow while fig. 4 (b) indicates the terrific velocity curve.

Temporal Correlations: Temporal correlations are relationships between historical traffic flow data and present or future measurement. To put it another way, time-dependent correlations.

Spatial Correlations: It will be able to merely ponder/review previous vehicles movement coming through the corresponding road section when estimating vehicles movement on a sole roadway division. It is practicable feasible, though, traffic metrics (movement or velocity) through surrounding roadway divisions are also strong forecasters.

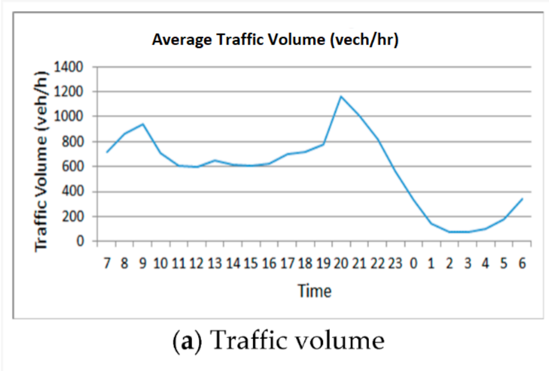


Fig. 4(a). Traffic volume Curve.

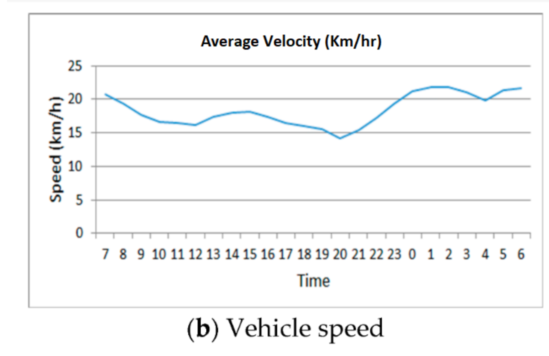


Fig. 4(b). Traffic Velocity Curve.

Predicting

Forecasting upcoming events have always remained a component of people character, dating back to dawn of time. Humans have an advantage over other species because of the ability to predict future events and respond proactively. Predicting predator positions or food and water location, for example, are the one of the critical factors for the sustenance of human being. During study of a paragraphs, for example**,** these are common factors that are able to foresee how the sentence will conclude since it follows a familiar structure. This is made feasible by having prior information as to authorize some to provide accurate predictions regarding the forthcoming time.

2.2. Data collection

Forecasting methods are also divided into many categories. The key difference is that the non-parametric method is constant. A collection of attached length parameters is common in parametric learning models. It accepts any information you enter but does not change the parameter size [14][18]. Constant methods are easier, faster, and may work with less statistics because of the fixed-size parameters. The statistic technique, on the other hand, does not adhere to specific restrictions regulating the shape of the mapping feature. The number of factors in statistical methodology expands as the size of the education set grows. They will be successful in adapting to a variety of mapping capabilities. The drawbacks of statistical techniques are they need more information; thus, they are slower than constant strategies. In terms of educational records, it's a better threat of outfit. The Autoregressive integrated moving average (ARIMA) variant of constant methodology is a well-known constant methodology. The most common framework for constructing a website visitor forecast model is ARIMA. Over the last few years, ARIMA has collaborated with a number of researchers. Researchers have been paying attention to the use of deep gaining data of algorithms in recent years due to its adjustive nature with the quantity of parameters [14]. SAE, CNN, and LSTM are the three most widely utilised methods. Some researchers devised a system for accurate traffic forecasting that looked at the relationship between guests and traffic flow and climate conditions. They also forecast weather and traffic statistics separately once each result is unified for better outcomes.

Vehicle Volume Figures

Traffic API applied to obtain number of figures on NH9 from Delhi to Haldwani car traffic also the google map is presented in fig. 5 .[16] This was accomplished by making an HTTP request for traffic statistics in the area depicted. The data is returned in BSON format, which allows the relevant parameters to be preserved. In the database, the parameters were divided into two categories: Roadway and Vehicle Amount. Roads collection keeps the fixed variables of each ways and there portions under a certain distance. Every road contains a defined number of divisions that contain information namely the title and line-up of coordinates that form the road shape.

Fig. 5. Map of NH 9 road network from Delhi to Haldwani (https://goo.gl/maps/uFu9nQvztfUNn6KB9).

Based on the velocity thresholds, a simple selection tree is used to classify interstate facts into driving force behaviour (slow, ordinary, and competitive). One of the most appealing features of decision bushes is how simple they are to comprehend. If one recognises speed and tour mode for every motorist from interstate traffic statistics, it may be described that motive force as gradual, regular, or competitive. First and foremost, The AI will choose the primary inquiry, which will be labelled as the kind of vehicle. Second, it will classify the type of that specific vehicle's velocity. Similarly, it will respond (selection) based on the previous facts' inputs. As a result, categorising from the trip mode to the aggression of their operating speeds will be easier. Table1 and 2 shows the prediction by LSTM and applying decision on some specific data presented in the table.

Table 1
Example for predicating the speed by LSTM method.

Predicted Speed by LSTM	
True Speed	**Predicted Speed**
31.70	31.50
30.50	30.25
32.60	31.30
30.25	31.85
31.60	32.45
33.00	30.95
31.30	32.16
30.40	30.25
30.30	31.25
30.60	32.50

Table 2
Example for predicating the speed by applying Decision.

Predicted speed by Decision	
True Speed	**Predicted Speed**
30.40	30.455
33.50	32.500
33.20	30.050
34.25	30.255
30.65	31.555
30.15	32.850
32.09	30.230
30.75	31.005
31.85	30.250
32.95	33.255
Prediction Accuracy	0.75
Prediction Error	0.2850

The efficiency of 3 machine learning approaches in prediction of highway velocity is shown in table-1 and 2 with an example. The forecast speed, machine learning techniques Decision tree, and LSTM were utilised. Training and testing patterns were created using the data and presented in the fig. 6 with flow charts.

The figure 7 and 8 shows the speed created from the available data respective for decision tree and LSTM method. This data indicates that the speed is fluctuating between 31 and 33.5 miles per hour.

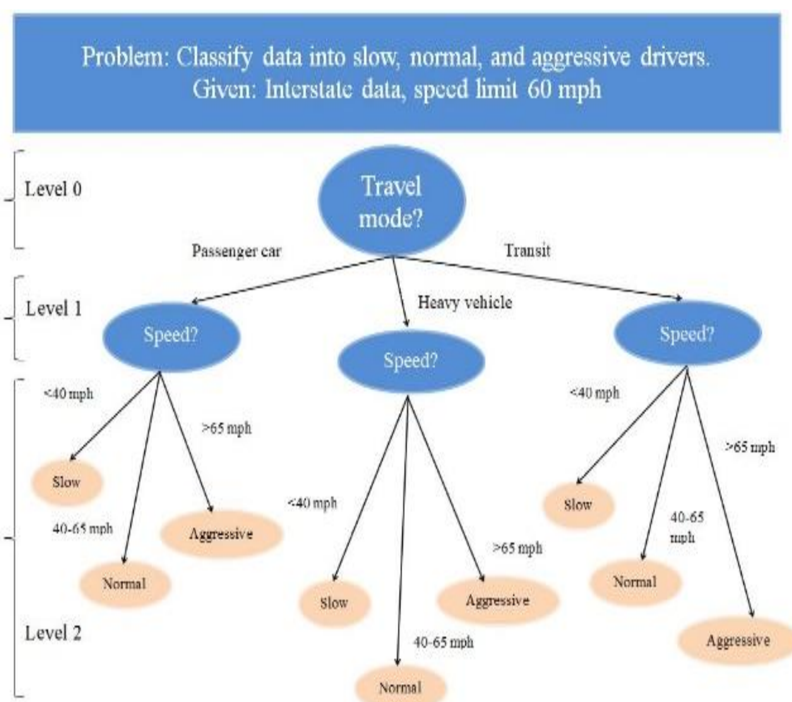
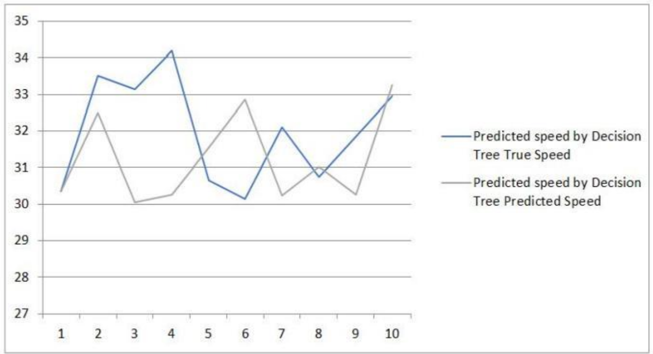
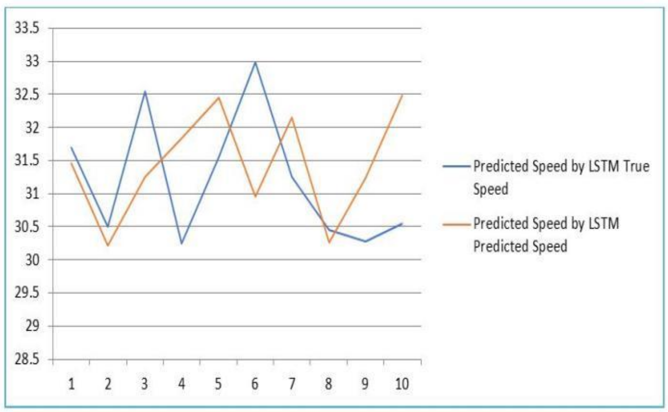


Fig. 6. Flowchart on working methodology.



Comparing the true speed with the predicted speed by Decision Trees.

Fig. 7. Predicted Speed by decision tree.



Comparing the true speed with the predicted speed by LSTM.

Fig. 8. Predicted Speed by LSTM.

3. Result and discussion

3.1. Simulation results

Because this domain is still in its early stages of development, there haven't been many open sources for data collection. The information came from three-month research. In the street areas, incredible sensors, CCTVs, surveillance cameras, and GPS were already installed. Now, this equipment will generate a big number of visitor records with a high density of data entry. There's also the possibility that some of the data won't be usable for the machine learning algorithm. After that, the data must be filtered appropriately.

3.2 Evaluation for forecast result

The simulation result for the algorithm is attached below. The Fig.9 and 10 suggests that the traffic/ visitors on weekends (i.e. Saturday and Sunday) are comparatively very less with respect to the moving weekly average. The factors that traffic flow is dependent upon were parameters that are considered as the input like date, drift, the period, its average journey time, its average velocity, weekends/ weekdays, link duration and sometimes other variables.

Tables 3 show the forecasting accuracy of each model for each experiment, using MAE as the precision measure observed in the present study to predict the decision adopted in the present study.

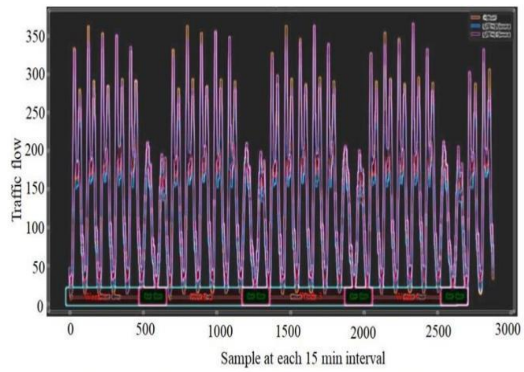


Fig. 9. Actual Vs Predicated [ARIMA and LSTM] for 15 min ahead predication.

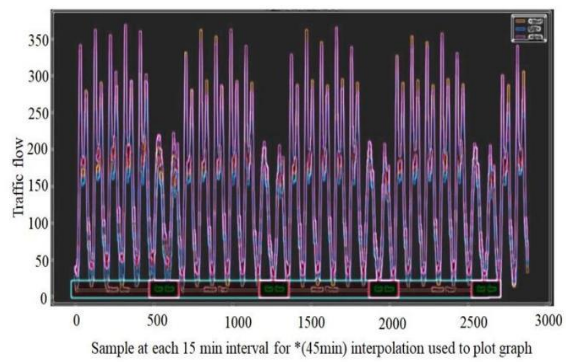


Fig. 10. Actual Vs Predicated for 15 min and 45 min ahead predication for LSTM.

Table 3
Forecasting accuracy of each model for each experiment, using **MAE** as the precision measure.

Algorithm	Mean Square Error	Mean Absolute Error	Mean Relative Error	Algorithm
ARIMA for 15 min	363.002	**13.477**		ARIMA for 15 min
LSTM for 15 min	252.682	**11.004**	2.473	LSTM for 15 min
LSTM for 45 min	695.031	21.586	8.109	LSTM for 45 min
Linear Regression (15 min)	1539.255	29.425	22.948	Linear Regression (15 min)
Linear Regression (45 min)	2989.407	48.483	38.006	Linear Regression (45 min)
Log Regression (15 min)	1792.700	22.501	9.024	Log Regression (15 min)
Log Regression (45 min)	5057.470	38.405	24.928	Log Regression (45 min)

The findings of experiment (1), that included entire time sequences, considering the days off.

The findings of experiment (2), where holidays were excluded from the time series.

The findings of experiment (3), which included geographical correlations.

In each experiment, the MAE value in bold corresponds to the model that produced the best outcome for a specific horizon. The MAE number that is highlighted corresponds to the model that produced the best results across all experiments for a specific horizon.

4. Conclusions

A quick and accurate traffic forecast might be critical for intelligent transportation system (ITS) analysis. In this study, the LSTM method was compared to the already existing ARIMA method. Multi-timeframe analysis is effective for decreasing noise and unwelcome variation. For a detailed comparison and visitor/traffic flow projection, two timeframes of 15 minutes and 45 minutes were used.

- The major goal was to compare the LSTM and ARIMA algorithms over 15-minute intervals, and calculated the error. The error for LSTM models the unique autos that entered each road had their lowest, maximum, mean, deviation, frequency, deviation, and average velocity retrieved. The acquired data was then standardized and filtered according to the features in the required machine learning algorithms in order to forecast the mean speed and traffic volume.
- The LSTM model has a 15% lower percentage error compared to the ARIMA model across the 15-minute interval data, indicating that the LSTM model is more accurate in time series forecasting.
- From the beginning to the end of the project, the LSTM model prediction performance improves but not as much as the ARIMA model. Based on the results of this study, the ARIMA model is the superior alternative for late-stage project performance.
- When comparing linear regression over 15 and 45 minutes, the mean relative error is 72 percent higher for the 45-minute timeframe, whereas the rise over 15 minutes in log regression is 166 present increases for 45-minute time frame.
- The LSTM model displays lower levels of inaccuracy right from the beginning, but the ARIMA model outperforms the LSTM model after undergoing training.

Acknowledgments

The recognition goes out to the Delhi Technological University in Delhi for offering the research faculties, as well as the bachelor of technology students like Pulikt Shakya and Saurabh Shekhar who are working on this project.

The Punjab Engineering College, Chandigarh resources are also valuable to complete the research on time. The authors would like to express their gratitude to the editor for including their work in the highly regarded publication. The authors would also like to extend their gratitude to the reviewers for their insightful remarks on the text.

Funding

The author of this research was awarded an institutional fellowship, however the research itself did not receive any special funding.

Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

APP, PK,IS : Conceptualization; RKM,APP, PK,RR: Data curation; PK,RR,SA: Formal analysis; PK,IS,SAK,APP: Investigation; RR,SAK : Methodology; PK, RKM: Project administration; SA: Resources; SA,PK,RR: Software; SA,RKM: Supervision; RKM, RR,SA: Validation; PK,IS,RR: Visualization; PK,RR,SA: Roles/Writing – original draft; APP,PKRR,SA: Writing – review & editing.

References

[1] Olivier JGJ, Peters JAHW. Trends in Global CO2 and Total Greenhouse Gas Emissions:2019 Report. PBL Netherlands Environ Assess Agency 2020;2020:1–70.

[2] Shepelev V, Aliukov S, Nikolskaya K, Shabiev S. The capacity of the road network: Data collection and statistical analysis of traffic characteristics. Energies 2020;13:1–18. https://doi.org/10.3390/en13071765.

[3] Bickel PJ, Chen C, Kwon J, Rice J, Van Zwet E, Varaiya P. Measuring traffic. Stat Sci 2007;22:581–97. https://doi.org/10.1214/07-STS238.

[4] Zhang J, Wang FY, Wang K, Lin WH, Xu X, Chen C. Data-driven intelligent transportation systems: A survey. IEEE Trans Intell Transp Syst 2011;12:1624–39. https://doi.org/10.1109/TITS.2011.2158001.

[5] Smith R. Directive 2010/41/EU of the European Parliament and of the Council of 7 July 2010. Core EU Legis 2015:352–5. https://doi.org/10.1007/978-1-137-54482-7_33.

[6] Pun L, Zhao P, Liu X. A Multiple Regression Approach for Traffic Flow Estimation. IEEE Access 2019;7:35998–6009. https://doi.org/10.1109/ACCESS.2019.2904645.

[7] Samuel AL. Some studies in machine learning using the game of checkers. IBM J Res Dev 2000;44:207–19. https://doi.org/10.1147/rd.441.0206.

[8] Rumelhart DE, Hinton GE, Williams RJ. Learning Internal Representations by Error Propagation. Readings Cogn Sci A Perspect from Psychol Artif Intell 2013:399–421. https://doi.org/10.1016/B978-1-4832-1446-7.50035-2.

[9] EPA. This is a reproduction of a library book that was digitized by Google as part of an ongoing effort to preserve the information in books and make it universally accessible . Biol Cent 2004;2:v–413.

[10] Bhavsar P, Safro I, Bouaynaya N, Polikar R, Dera D. Machine Learning in Transportation Data Analytics. Data Anal Intell Transp Syst 2017:283–307. https://doi.org/10.1016/B978-0-12-809715-1.00012-2.

[11] Lonare S, Ravi B. New Trends in Computational Vision and Bio-inspired Computing. Cham: Springer International Publishing; 2020. https://doi.org/10.1007/978-3-030-41862-5.

[12] Wang Y, Zhang D, Liu Y, Dai B, Lee LH. Enhancing transportation systems via deep learning: A survey. Transp Res Part C Emerg Technol 2019;99:144–63. https://doi.org/10.1016/j.trc.2018.12.004.

[13] Gray T. Publish and Flourish: Write well and revise rapildly. Work. by Gray—She's anything but gray, New Mex. State Univ., 2003.

[14] Atanasova V, Duraku R, Angjelevska B, Krstanoski N, Sciences T, Ohridski K, et al. Traffic production model using multiple regression analysis. Int Sci J " Mach Technol Mater 2017;594:591–4.

[15] Elhenawy M, Rakha H. Spatiotemporal traffic state prediction based on discriminatively pre-trained deep neural networks. Adv Sci Technol Eng Syst 2017;2:678–86. https://doi.org/10.25046/aj020387.

[16] Aronsson L, Bengtsson A. Machine learning applied to traffic forecasting 2019.

[17] New Trends in Computational Vision and Bio-Inspired Computing - Selected Works Presented at the ICCVBIC 2018. New Trends Comput Vis Bio-Inspired Comput - Sel Work Present ICCVBIC 2018 2020.

[18] Abdullah S, Robert MI, Fuqian B. New Trends in Computational Vision and Bio-inspired Computing. Cham: Springer International Publishing; 2020. https://doi.org/10.1007/978-3-030-41862-5.