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RESEARCH ARTICLE **ARTIFICIAL INTELLIGENCE**

Machine Learning-Based Traffic Flow Prediction for Enhanced Traffic Management

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A B S T R A C T

Accurate traffic flow prediction is crucial for effective traffic management strategies, enabling dynamic signal control, congestion mitigation, and improved transportation efficiency. Traditional traffic prediction methods often rely on historical data and fixed traffic patterns, failing to capture the dynamic nature of traffic flow and its susceptibility to real-time events and incidents. In recent years, machine learning (ML) has emerged as a powerful tool for traffic flow prediction, offering the potential to analyse complex traffic data and identify patterns that traditional methods may overlook. This paper presents a novel approach to traffic flow prediction using ML techniques, aiming to enhance traffic management and reduce congestion in urban areas. The proposed approach employs a combination of ML algorithms, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, to capture the temporal dependencies and long-range relationships within traffic data. The ML models are trained on a comprehensive dataset of historical traffic data, incorporating various factors such as traffic volume, vehicle speed, and weather conditions. The trained ML models can then predict future traffic flow patterns based on real-time traffic data collected from sensors embedded in the road infrastructure.

التنبؤ بتدفق حركة المرور القائم على التعلم الآلي لتحسين إدارة حركة المرور

مبروكة فضل [1,*]، ناصر أبوهمود [1]

الملخص

يعد التنبؤ الدقيق بتدفق حركة المرور أمرًا بالغ الأهمية لاستراتيجيات إدارة حركة المرور الفعالة، وتمكين التحكم الديناميكي في الإشارات، وتخفيف الازدحام، وتحسين كفاءة النقل. غالبًا ما تعتمد طرق التنبؤ بحركة المرور التقليدية على البيانات التاريخية وأنماط المرور الثابتة، وتفشل في التقاط الطبيعة الديناميكية لتدفق حركة المرور وقابليتها للأحداث والحوادث في الوقت الفعلي. في السنوات الأخيرة، ظهر التعلم الآلي (ML) كأداة قوية للتنبؤ بتدفق حركة المرور، مما يوفر إمكانية تحليل بيانات حركة المرور المعقدة وتحديد الأنماط التي قد تتجاهلها الطرق التقليدية. تقدم هذه الورقة نهجًا جديدًا للتنبؤ بتدفق حركة المرور باستخدام تقنيات التعلم الآلي، بهدف تحسين إدارة حركة المرور والحد من الازدحام في المناطق الحضرية. يستخدم النهج المقترح مجموعة من خوارزميات التعلم الآلي، بما في ذلك الشبكات العصبية المتكررة (RNNs) وشبكات الذاكرة القصيرة المدى الطويلة (LSTM)، لالتقاط التبعيات الزمنية والعلاقات طويلة المدى داخل بيانات حركة المرور. يتم تدريب نماذج التعلم الآلي على مجموعة شاملة من بيانات حركة المرور التاريخية، مع دمج عوامل مختلفة مثل حجم حركة المرور وسرعة المركبات وظروف الطقس. يمكن لنماذج التعلم الآلي المدربة بعد ذلك التنبؤ بأنماط تدفق حركة المرور المستقبلية بناءً على بيانات حركة المرور في الوقت الفعلي التي تم جمعها من أجهزة الاستشعار المضمنة في البنية التحتية للطرق.

الكلمات المفتاحية

التعلم الآلي
الشبكات العصبية المتكررة
كفاءة النقل
حركة المرور في المناطق الحضرية
نماذج محاكاة التعلم الآلي

Introduction

Traffic flow prediction plays a crucial role in the development of Intelligent Trans portation Systems (ITS), which rely on accurate traffic forecasting to support control and management over a wide range of traffic conditions. The prediction models aim to provide insights into vehicle density and average speed at specific locations, enabling better decision-making for traffic management authorities and road users alike [1]. Traditional model-based approaches for traffic prediction have been exten sively developed over decades, while recent advances have increasingly focused on leveraging machine learning (ML) and deep learning (DL) techniques [1,2]. the utilization of machine learning (ML) and deep learning (DL) methodologies is increasingly prevalent. Intelligent Transportation Systems (ITS) provide an abundance of high-caliber traffic data that can be harnessed in empirically-driven traffic flow prediction strategies [2]. The emergence of machine learning and deep learning as branches of artificial intelligence (AI) has engendered considerable progress within the domain. These methodologies have demonstrated substantial efficacy in forecasting traffic flows through the examination of patterns derived from historical datasets and extrinsic variables [3]. For example, research employing a regression framework executed with libraries such as Pandas, Numpy, Matplotlib, Keras, Sklearn, and Tensorflow adeptly forecasted the forthcoming year's traffic data based on the data from preceding years [3]. This

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highlights the considerable promise of ML and DL in augmenting the precision of traffic forecasting. One common approach involves integrating multi-modal information to capture spatial and temporal attributes. Spatial attributes are derived from nearby Points of Interest (PoIs) within various proximity ranges, ensuring comprehensive coverage of diverse spatial influences on traffic patterns [4]. Temporal information, including the day of the week, specific hour, and holidays, is also integrated into the model, enriching its contextual reasoning and predictive capabilities [4]. Research has investigated a multitude of machine learning and deep learning frameworks for the purpose of forecasting traffic flow, including the CNN-LSTM architecture and models predicated on Cellular Automata [1]. Furthermore, spatio-temporal neural networks that integrate matrix factorization methodologies have been employed in the context of urban flow prediction, thereby illustrating the adaptability and resilience of these sophisticated approaches [5]. highlighting the adaptability and resilience of these sophisticated methodologies. Notwithstanding the achievements, numerous obstacles remain in the implementation of machine learning (ML) and deep learning (DL) techniques for traffic forecasting. Challenges such as the variability of traffic data, the necessity for extensive datasets, and the intricate computational demands of training deep learning models constitute significant hindrances. Nevertheless, ongoing scholarly inquiry persistently seeks to tackle these difficulties, with the objective of enhancing and optimizing predictive models for real-world applications [1,6].

Fig.1: Traffic Stakeholders

In Figure 1, transportation networks are employed with greater safety and intelligence [7], [8]. The effectiveness of these systems is contingent upon the quality of traffic data; only under such conditions can an Intelligent Transportation System (ITS) achieve success. As indicated in the World Health Organization's (WHO) 2018 report concerning the global status of road safety, fatalities due to road traffic accidents continue to escalate, with 1.35 million deaths documented in 2016, thus rendering the study of traffic forecasting an invaluable approach for alleviating congestion and promoting safer, more economically viable travel [9,10]. The advantages of traffic flow forecasting are depicted in Figure 2.

Machine learning

Traffic flow forecasting utilizes an array of machine learning methodologies owing to the inherently stochastic and nonlinear characteristics of traffic data. These methodologies can be extensively classified into conventional machine learning algorithms and sophisticated deep learning frameworks [11]. Traditional machine learning models are categorized into three primary types based on the learning techniques they utilize: supervised learning, unsupervised learning, and reinforcement learning (RL) [12].

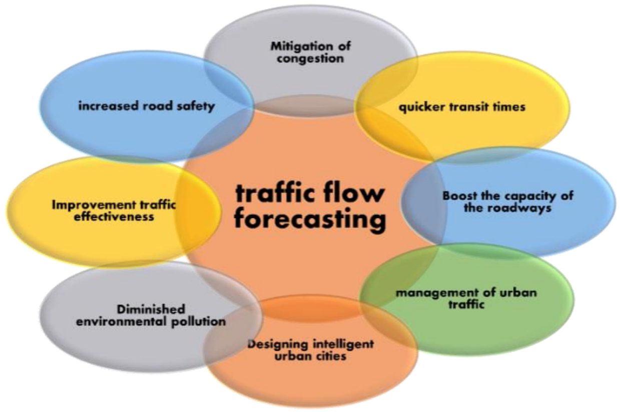


Fig.2: Traffic flow prediction advantages

Support Vector Machine (SVM)

Support Vector Machines (SVMs) are employed in traffic flow prediction due to their robustness in handling high-dimensional data and their capability to find an optimal separating hyperplane for classification tasks. SVMs are effective for problems in volving many features relative to the number of training cases, making them suitable for traffic data, which often includes multiple variables [6,13].

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is an unsupervised machine learning technique used to reduce the dimensionality of the dataset. PCA transforms the data into new variables called principal components, which are orthogonal and account for most of the variance in the data. This reduction helps in efficient computation and reduces the risk of multicollinearity [6].

Subsequently, deep learning (DL) surfaced as a powerful machine learning (ML) approach, demonstrating significant effectiveness across various application domains [14]. Deep Learning (DL) represents an artificial intelligence paradigm that has attracted significant attention from the academic community and has shown greater potential compared to traditional methods [15]. DL is a more efficient, supervised, time-intensive, and cost-effective technique than Machine Learning (ML). It not only serves as a specialized approach to knowledge acquisition but also adapts to diverse methodologies and contexts, making it advantageous for addressing a wide array of complex issues. This approach learns the illustrative and differential characteristics in a relatively diverse manner [16,17]. The process of ML and DL is illustrated in Figure 3.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) are extensively utilized in the domain of traffic flow forecasting owing to their proficiency in feature extraction from unprocessed input data via convolutional layers and max-pooling mechanisms [18]. CNNs demonstrate significant efficacy in identifying spatial patterns within traffic datasets, an aspect that is imperative for achieving precise predictive outcomes [1]. Figure 4 illustrates the architecture of a Convolutional Neural Network (CNN).

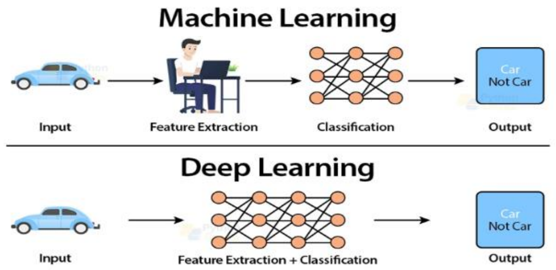


Fig.3: ML versus DL [16]

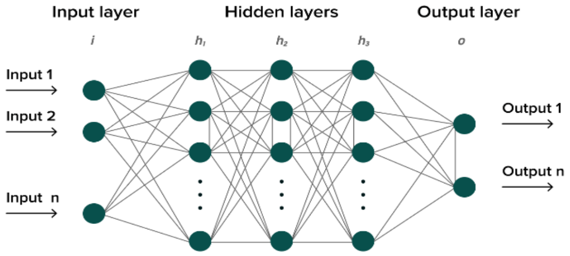


Fig.4: Architecture of a CNN [19].

Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are utilized due to their proficiency in processing sequential data and retaining information from antecedent inputs. RNNs exhibit substantial efficacy in the analysis of time series data, rendering them adept at forecasting future traffic patterns predicated on historical datasets [1]. They incorporate feedback loops within hidden layers to archive and leverage prior information, thereby augmenting the accuracy of predictions [20]. For a designated sequence of inputs, an illustrative representation of an unfolded recurrent neural network (RNN) is exhibited in Figure 5.

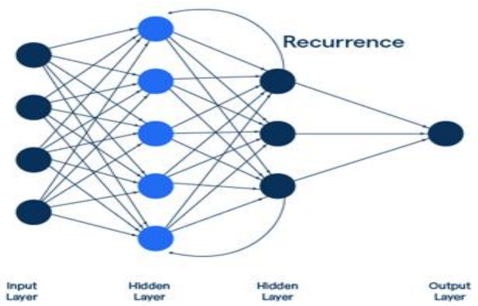


Fig.5: RNN diagram [21].

Long Short-Term Memory (LSTM)

LSTM networks, which represent a specific class of recurrent neural networks (RNN), have been developed to address the inherent challenges faced by conventional RNNs through the implementation of memory cells that are capable of preserving information over extended durations [22] . The efficacy of LSTMs in predicting traffic flow is notably pronounced, attributable to their proficiency in acquiring long-term dependencies within traffic behaviour patterns [6].

A rudimentary recurrent neural network (RNN) cell illustrated in Figure 6 has been augmented through the incorporation of a memory block, which is regulated by multiplicative gates for both input and output [23].

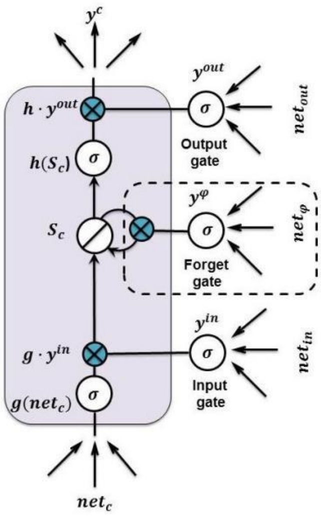


Fig.6: An original LSTM unit architecture [23]

Related works

In [24], the authors established a machine learning (ML)-oriented paradigm for predicting traffic flow, utilizing a regression model that was executed through various computational libraries including Pandas, Numpy, OS, Matplotlib, Keras, Sklearn, and Tensorflow. The process of traffic prediction within this investigation entails forecasting the subsequent year's traffic data predicated on historical traffic data, thereby ultimately yielding metrics of accuracy and mean square error. The traffic data was forecasted based on a temporal resolution of one hour. The data utilized in this research was sourced from the Kaggle dataset. Two distinct datasets were procured, one of which encompasses the traffic data from the year 2015, containing variables such as date, time, vehicle count, and number of junctions. The second dataset comprises the traffic data from 2017, possessing identical specifications to facilitate straightforward comparison without ambiguity. This research necessitates an exploration of additional variables that influence traffic flow prediction and the integration of alternative predictive methodologies such as deep learning and big data analytics.

In [25], a proposal was made to develop a traffic prediction system utilizing four deep learning methodologies: Deep Autoencoder (DAN), Deep Belief Network (DBN), Random Forest (RF), and Long Short-Term Memory (LSTM). This approach is primarily employed to forecast traffic flow in densely populated areas. The key parameters considered in this research included zone classification, weather conditions, day of the week, road capacity, and types of vehicles. However, the dataset utilized in this study is not specified.

In [26], a short-term approach for forecasting traffic flow was introduced, utilizing a recurrent mixture density network that combines elements of recurrent neural networks (RNN) and mixture density networks (MDN). The dataset employed in this research consisted of traffic flow data collected from sensors installed on road networks in Shenzhen, China. This dataset was segmented into two distinct time frames: from January 1, 2019, to March 31, 2019, and from October 1, 2019, to December 21, 2019. The relatively small size of the dataset presents a significant challenge in this study.

In [27], the authors introduced a method for creating a traffic congestion index through the extraction of free-stream speed and flow data. They proposed the Traffic

Congestion Index (TCI), which effectively synthesizes variations in traffic flow and speed to evaluate congestion levels, and elaborated on its generation process. Acknowledging the correlation characteristics of road links within the network, the authors implemented a technique for grouping these links based on sub-graphs to pre-train the deep learning model, facilitating information sharing among road links. They also proposed a traffic congestion prediction model named SG-CNN, which integrates traffic data features with the CNN framework, enhancing the training process through a road segment aggregation approach. To improve the accuracy of the TCI, the authors emphasized the need to incorporate additional factors such as weather conditions, pedestrian activity, and road status that influence traffic congestion. Moreover, the development of a more efficient algorithm that considers the time complexity associated with the segment aggregation method presents an interesting area for further exploration.

Methodology

A systematic and comprehensive methodology is adopted,to develop a robust machine learning-based traffic flow prediction model, which includes stages such as data collection, preprocessing, model selection, training, evaluation, and deployment. In this research, traffic flow in Sebha city was improved using a set of traffic influencing factors such as time of day, day of week, season, weather, road volume, nearby schools, and local events, by integrating Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to better handle temporal patterns in traffic flow data. LSTM networks are suitable because they are able to handle long temporal dependency, which is important for predicting traffic flow based on past patterns.

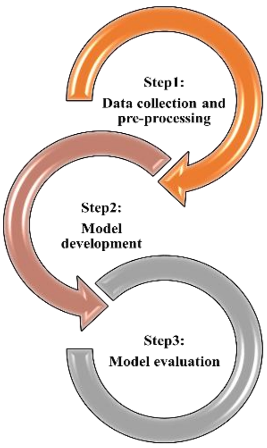


Fig.7: Research Method Steps

Data Description:

In this research, the data set of Hail city was used in Saudi Arabia as the city closest to Sabha in terms of climate. population and geographical area, both cities have a dry desert climate with hot summers and mild winters, More importantly, social habits such as working hours and the reliance of the majority of the population on private vehicles to move around and get children to school, Hail also has a population of about 400 thousand, which is relatively close to Sabha's population of about 200 thousand, and in terms of geographical area they are somewhat similar as Hail and Sabha are medium-sized cities within wide geographical ranges with vast deserts. The data were obtained from the website of the National Traffic Management Centre of the Ministry of Transport and Logistics when they were sent in particular [28]. The data were collected using high-resolution cameras in highways to record traffic continuously. These cameras send data to the control centres, where images are analysed to determine traffic density, congestions, and traffic accidents. The database covers many aspects of road traffic, such as average vehicle speed and traffic volume at intersections. Historical traffic flow data is used to predict future traffic flow. The data were collected at 15-minute intervals, and the data extracted on the main highway was measured in the nine months from November 2023 to July 2024.

Long Short-Term Memory (LSTM) Network

A specific kind of Recurrent Neural Network (RNN) called Long Short-Term Memory (LSTM) is intended to identify long-term relationships while preserving the recursive properties that make RNNs unique. LSTM is especially good at managing time series data and reduces problems that standard RNNs often have, including gradient vanishing and exploding. An input gate, an output gate, a forget gate, and a memory unit make up the LSTM architecture. The input gate i_t processes incoming data and modifies the memory unit's state based on the context, Based on predetermined standards. the forget gate f_t decides what data should be removed, based on a certain condition. Ultimately, the output gate determines what data will be displayed based on the memory unit's current state as well as the input data.

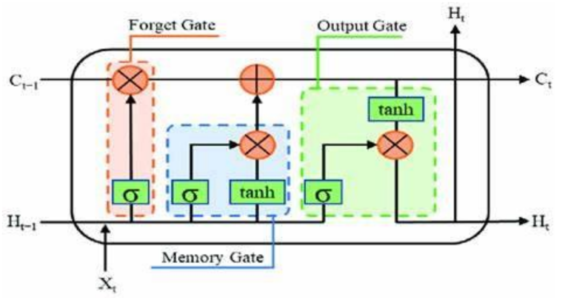


Fig.8: Structure of the LSTM network

At every instant, the forget gate f_t receives the hidden layer state and the current state from the previous instant. It then passes this information through the activation function σ to output a value of [0,1]. The output of the forget gate (f_t) is coupled with the input gate i_t transformed nonlinear function input to obtain the updated memory unit. Ultimately, the output gate o_t can constantly control the LSTM's output h_t in accordance with c_t following the execution of a nonlinear function. Equations (1), (2), and (3) show the formulas for the forget gate, input gate, and output gate, respectively.

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (1)$$

$$f_t = \sigma\left(w_f[h_{t-1}, x_t] + b_f\right) \quad (2)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (3)$$

In this context, σ(.) denotes the sigmoid function; w_i, w_f, w_o, alongside bf, bi, bo, signify the weight matrices and biases associated with the forget gate, input gate, and output gate, respectively, which govern the final output of the LSTM's output gate and unit state control. Subsequently, the values of c_t and h_t are derived through the application of Equations (4), (5), and (6).

$$c_t^{\cong} tanh(w_c[h_{t-1}, x_t] + b_c) \quad (4)$$

$$c_t = f_t * c_{t-1} + i_t * c_t^{\sim} \quad (5)$$

$$h_t = o_t * tanhc_t \quad (6)$$

Where w_c and b_c denote the weight matrix and the bias associated with the candidate state $c_t^{\sim}$ respectively, * signifies the operator for element-wise multiplication.

Recurrent Neural Networks RNN

The predictive model is constructed utilizing a singular recurrent neural network (RNN) layer, succeeded by a dense layer comprising a solitary neuron. Our empirical analysis indicates that this uncomplicated architectural design yields optimal performance for the specified dataset. The RNN layer functions as an autonomous computational unit wherein the output generated at the current time step is reintroduced as input for the subsequent step. The configuration of a fundamental RNN model is exemplified in Figure 9. In this context, x denotes the input variable, y represents the output variable, h signifies the transfer function, and c corresponds to the cell state.

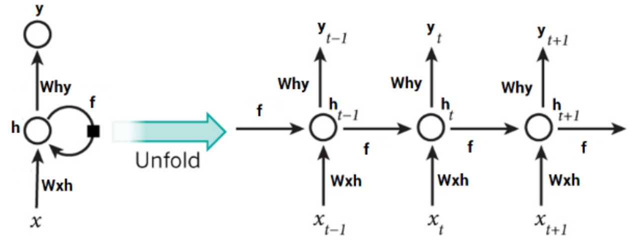


Fig. 9 basic model of RNN

Simple RNN:

Within the framework of the simple RNN architecture, the transfer function h functions solely as an activation mechanism. In the present investigation, the *"tanh"* activation function has been employed, as illustrated in Figure 9. The *"tanh"* activation function guarantees that the resultant output is constrained within the range of -1 to 1. The simple RNN framework operates based on two fundamental equations, specifically equations 7 and 8. The model receives inputs in the form of x_t and c_{t-1}, while its outputs are represented as y_t and c_t.

$$y_t = tanh\{(W\}_y x_t + U_y c_{t-1} + b_y) \quad (7)$$

$$c_t = tanh(W_c\}x_t + U_c c_{t-1} + b_{\{y\}}) \quad (8)$$

GRU:

The input and forgets gates are combined into a single update gate in the GRU, which is a more straightforward variant of the more intricate LSTM unit. In order to operate more quickly, it then combines the concealed and cell states. The GRU neurons' internal mathematical activities are delineated in equations 9 through 11. The GRU neuron is in the intermediate states zt and rt, respectively. In Figure 9, the terms used in the equations are listed. Figure 10 displays the GRU basic diagram.

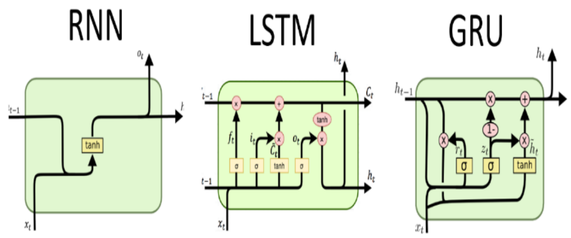


Fig.10: Transfer function for repeater blocks in each model

Neural Network Model Construction:

Data configuration or Preparation for LSTM:

As the LSTM network takes data in 3D format (number of samples, number of time steps, number of features), input data has been reconfigured to add one time step, then the training and testing group data has been standardized, where standardization helps improve the training process and reduce deviation.

LSTM model construction:

A model that includes LSTM layer was built with 64 nerve units and is designed to detect time patterns in data, and at the end of LSTM There is a dense layer containing 32 nerve units with activation function, and this last layer has one cell to anticipate traffic flow. and then the model was assembled and trained using the improver Adam in MATAB R2024a and the loss function Mean Squared Error (MSE).

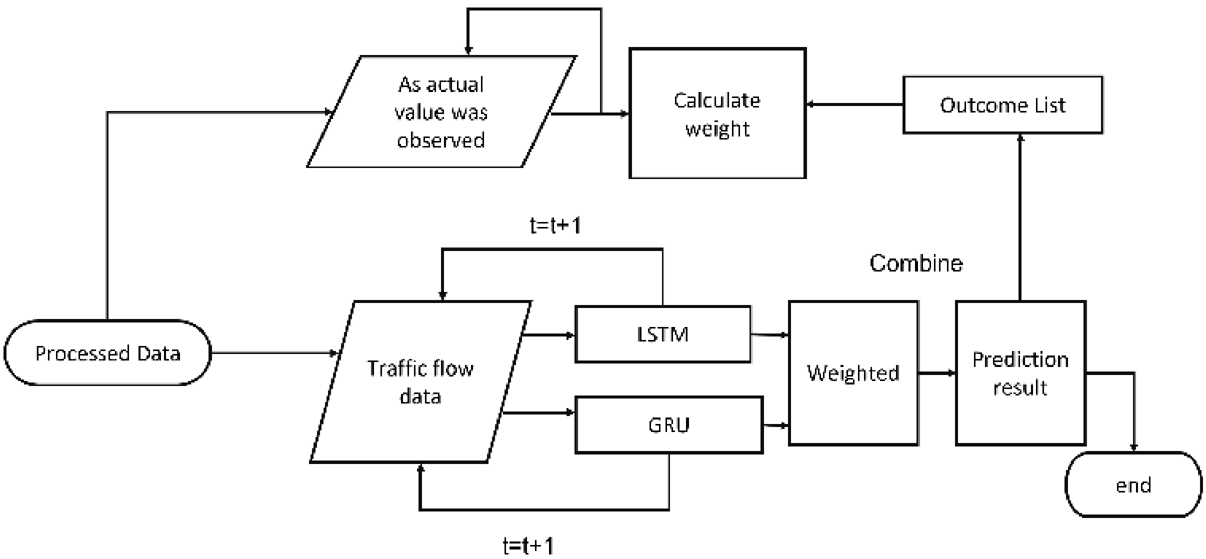


Fig.11: The architecture of combine model

Model training:
The model was trained for a number of different (epochs) 50, 200, 500 , clearly LSTM network error decreases by increasing the number of iterations until it essentially disappeared after 500 iterations of training.

Performance and prediction evaluation measures:
To examine the prediction performance of the proposed model, three performance (measures) metrics were used to predict traffic flow on the test set. The mean squared error (MSE) was calculated, which is a measure of the difference between the predicted and actual values, as well as the R^2 (R-squared) calculation, which is a measure of the model's quality in interpreting the variance in the data, and the accuracy, which is calculated from R^2 and gives the percentage of prediction accuracy.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \quad (9)$$

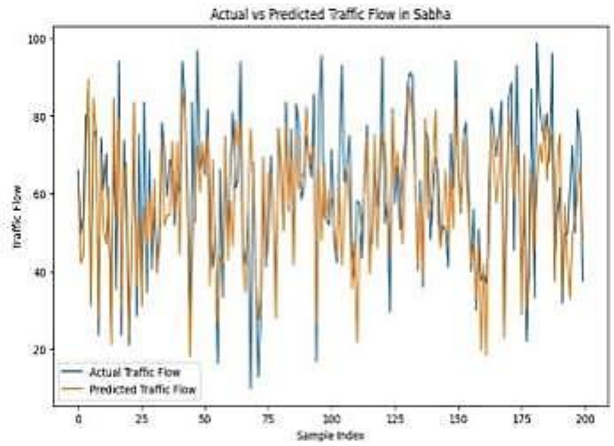
$$R^2 = 1 - \frac{(y_i - \hat{y})^2}{(y_i - \bar{y})^2} \quad (10)$$

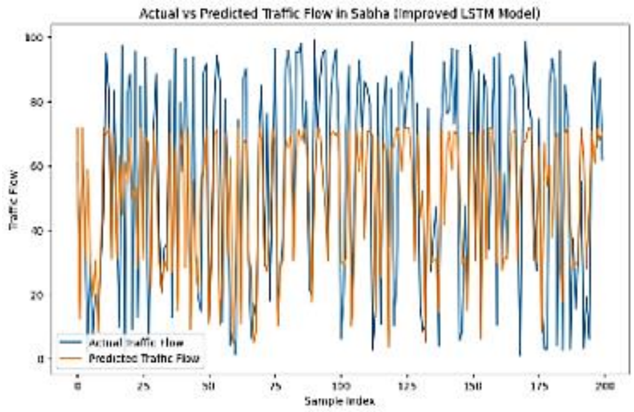
Results and discussion

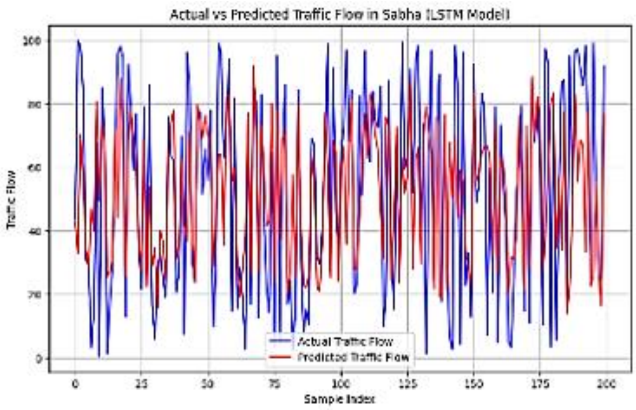
The effectiveness of the proposed model was examined through performance metrics or measures and also by plotting the actual traffic flow versus the predicted flow on the test set to compare the results. The values of the performance metrics were as shown in Table 1, where the MSE value = 4.0043, the mean square error, which represents the average square differences between the actual values and the expected values. It is known that a low MSE value indicates that the model makes predictions close to the actual values, and its value depends on the size of the data used. Here we have 1000 samples, Therefore this MSE value indicates that the model is able to predict traffic flow with high accuracy. Determination coefficient R^2 Score = 0.96749, the coefficient of determination reflects the model's ability to interpret the variance in the data and its value ranges from 0 to 1, whenever the R^2 value is high (close to 1), this indicates that the neural model is able to accurately predict and can explain the factors affecting traffic flow, this means that the R^2 value recorded in this model is able to explain the variance in the target variable (traffic flow) by the features. Accuracy = 96.749 and is represented as R^2 multiplied by 100, and it gives an idea of how good the model is at predicting. If the accuracy is high, this means that the model has good predictive capability, whereas if the accuracy is low, this indicates the need to improve the model, as we can see here, the accuracy of the model is considered high and therefore has the ability to predict traffic flow accurately. As for the graphical representation of the data (actual results vs. expected results), a comparison was drawn between the actual traffic values (real values) and the expected values that the model outputted as in Figure (12), where the line representing the predicted values closely followed the line representing the actual values, meaning that the model provides accurate predictions, and then we made improvements to this model by adding new features, Road Size: The greater the road is the likelihood of traffic congestion. Nearby Schools: If there is a school nearby, this may cause increased traffic. Local Events: If there is a local event, it can increase road congestion, and we have also increased the number of (epochs) where it makes the model learn better over longer training periods, as shown in the figure 12. After these additions, we noted an improvement in the model's performance by an increase in the matching rate between actual and projected data R^2, where the recorded value was 0.98725 while the MSE value was slightly changed, as it presented in Table 1.

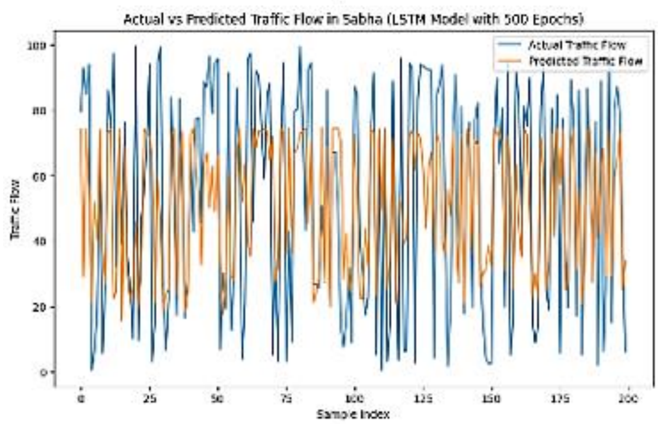
Table 1: Models and the corresponding assessments

Model	MSE	R^2	Accuracy
Lstm (epochs 50)	4.0043	0.96749	96.74
Lstm (epochs 200)	4.0567	0.97352	97.35
Lstm (epochs 500)	4.1795	0.98725	98.25









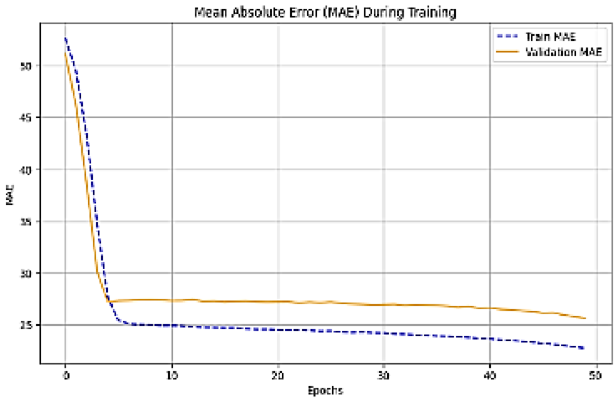


Fig.12: Traffic flow prediction performance for lstm models

Conclusions and recommendations

This paper proposes a method for predicting traffic flow using recurrent neural networks (LSTM), where the model showed good performance in predicting traffic flow in the city of Sabha. The model was evaluated using several metrics, where the mean square error (MSE) was low, indicating the accuracy of the prediction. The coefficient of determination (R^2) was also high, indicating that the model is able to explain a large proportion of the variance in the data. By comparing the predicted values with the actual values, it can be observed that the model captures the general trends of traffic flow, reflecting its ability to learn from temporal patterns and various influencing factors such as time of day, day of week, and climatic conditions. Independent variables such as "time of day", "day of week", "weather", and "presence of local events" play a pivotal role in determining traffic flow. This highlights the importance of incorporating these factors into prediction models to improve the accuracy of the results. The results can be used to improve traffic management and reduce urban congestion in Sabha. The model can contribute to the development of more effective forecasting systems, helping in urban planning and transportation management. The model can be improved by adding more data, such as historical traffic data for years, geographical data, and economic conditions. Furthermore, more complex models, such as deep neural networks or other machine learning models, can be explored to enhance the accuracy of predictions. In conclusion, the study shows that using LSTM can be an effective tool for traffic prediction, contributing to improved traffic management and reduced congestion. Future research needs to explore additional aspects to improve the model and enhance it with available data.

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