

Mitigating Traffic Congestion Through Time Series Analysis and Deep Learning

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Abstract: Action volume expectation is basic to asset assignment, blockage diminishment, and vitality utilization diminishment in activity overseeing frameworks. This investigation presents a novel approach utilizing time-series determining strategies combined with thick neural systems to effectively anticipate activity volume. Specifically, we see into five models: GRU, stacked LSTM, SARIMA, LSTM, and a combination of SARIMA and LSTM. We furthermore display a cross breed demonstrate that combines SARIMA and LSTM to upgrade forecast execution. Numerical measures like as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are utilized to assess the models' expectation precision. Our exploratory comes about illustrate that the recommended models perform uncommonly well in estimating activity volume, with the crossover show illustrating especially solid execution. Through this investigate, we trust to deliver solid and exact activity volume estimates that will move forward activity overseeing frameworks.

Keywords: Traffic volume prediction, Deep learning, Timeseries forecasting, LSTM, GRU, SARIMA, Ensemble learning, Hybrid model.

1. Introduction

Worldwide, traffic congestion poses serious problems that can lengthen travel times, increase fuel consumption, and pollute the environment. Efficient traffic management is essential to reduce congestion and enhance overall transportation efficiency. This work delves into the field of traffic volume prediction in order to address this resolving issue and supports the more sophisticated methods in time-series forecasting and deep learning. After Polson & Sokolov (2017), we are applying deep learning methodologies used for similar traffic flow prediction tasks to analyse our distinctive dataset [12].

We now have the opportunity to apply sophisticated predictive models for traffic management because of advancements in data collection technology and the abundance of historical traffic data [6]. Our goal is to effectively predict traffic congestion and identify trends in the data by utilising deep learning, machine learning, and sophisticated models such as Regular Autoregressive Moving Average (SARIMA), Long Short-term Memory (LSTM), and Gated Repeating Unit (GRU).

This investigation's first step is to gather and assess a list of prediction models that are intended to estimate the activity volume. By contrasting the refined LSTM, refined GRU, stacked LSTM, SARIMA demonstrate, and ensemble learning approaches, we aimed to ascertain which approach was best successful in forecasting the activity volume aspects. We also offered a crossover demonstrate technique that combines the benefits of SARIMA demonstrate and LSTM demonstrate in order to enhance the vision's implementation.

We used metrics for evaluation of our models such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to obtain the accuracy and reliability of all our developed models. By inspecting the previous traffic data and performing complete experimentation, here we try to demonstrate the efficiency of our models in forecasting traffic volume and detecting the Clogging events.

Our study's conclusions offer suggestions for creating activity management frameworks as well as insightful information on resource allocation and activity stick reduction procedures. By offering precise projections and

noteworthy suggestions, our goal is to propel the progress of activity management methodologies and the improvement of urban transport systems.

2. Objectives

The goals of this study include a thorough investigation of traffic forecast techniques to address issues related to urban congestion. Initially, we want to perform a comprehensive exploratory data analysis (EDA) on historical traffic data so that we can identify the temporal, deep patterns and trends which will guide us further in our modelling endeavours. Thereafter, the creation and application of predictive models that we specially designed for the traffic jam forecasting, becoming our primary goal. This includes investigating our ensemble learning strategies, conventional time-series forecasting techniques like Seasonal Auto regressive Integrated Moving Average (SARIMA), and deep learning architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models [8]. After analysing the prediction accuracy using methods like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) which is another important task that also helps to determine which traffic congestion forecasting model is best. In addition to this, our study also intends to use predictive analytics to highlight the areas of congestion and crucial frame of opportunity, which allows focused congestion control techniques to be kept into place. Lastly, by taking proactive measures like refining the route planning methods and investigating the congestion pricing systems and optimizing the traffic signal timings, we can hopefully turn our research findings into more useful insights. By tackling these goals, we hope to also make a significantly important contribution to the development of traffic management systems by providing insightful information that will help city planners, transportation authorities, and legislators to improve the overall transportation efficiency and reduce the heavy congestion in metropolitan areas. The traffic volume data was sourced from the “Metro Interstate Traffic Volume” dataset, available at the UCI Machine Learning Repository [5].

3. Dataset Description

The dataset utilized in this study comprises 48,204 entries and encompasses a diverse array of meteorological and temporal attributes alongside traffic volume data, serving as a comprehensive resource to investigate the complex relationships between weather conditions, time of day, and traffic flow dynamics. Among the dataset’s attributes, ‘holiday’ denotes whether a specific date corresponds to a holiday, while ‘temp’ provides the temperature in Kelvin at the time of observation. Additionally, ‘rain 1h’ and ‘snow 1h’ quantify the amount of rainfall and snowfall measured in millimetres within one-hour intervals, respectively. The ‘clouds all’ attribute indicates the percentage of cloud cover, while ‘weather main’ and ‘weather description’ offer categorical and detailed descriptions of prevailing weather conditions. The ‘date time’ attribute serves as a timestamp for each observation, facilitating the analysis of traffic volume trends over time, while the ‘traffic volume’ column represents the target variable, indicating the volume of traffic observed at each timestamp. Statistical summary reveals essential characteristics of the numerical attributes, including mean, standard deviation, minimum, maximum, and quartile values, providing valuable insights into the distribution and variability within the dataset. A key observation from the dataset’s information summary is the presence of missing values in the ‘holiday’ column, with only 61 non-null entries out of 48,204 total entries, suggesting potential data gaps in this feature. Overall, the dataset offers a comprehensive collection of meteorological and temporal attributes alongside traffic volume data, providing insights into the intricate interplay between weather conditions, temporal factors, and traffic volume dynamics, and serving as a valuable resource for the development of predictive models for traffic volume forecasting and congestion management. The traffic volume data was sourced from the “Metro Interstate Traffic Volume” dataset, available at the UCI Machine Learning Repository [5].

4. Exploratory Data Analysis

A. Overview

The exploratory data analysis was done on the dataset to understand the hidden patterns, detect anomalies and identification of trends and relationships between values. It also serves as a basis for constructing models which predict the future trends based on statistics available on the historical data for traffic congestion.

B. Temporal Dynamics of Traffic Volume

- **Diurnal Patterns:** Our average traffic volume hourly analysis as shown in Fig. 1 reveals pronounced diurnal cycles with peaks during typical morning (7 AM to 9 AM) and evening (4 PM to 6 PM) rush hours. They are important for directing interventions in traffic management, such as variable message signs and congestion pricing.
- **Weekly Patterns:** The data as seen in Fig. 2 presented a progressive increase in traffic volume from Monday through Friday, with a very marked decline over the weekends. These underlie the need for weekday-specific traffic management strategies to cater mainly to the peak traffic loads observed mid-week.
- **Monthly Patterns:** When the monthly traffic trends are analysed again as indicated by Fig. 3, there are higher traffic volumes in the mid-year months with significant drops in December, most probably due to holiday effects, and the change in seasonality of behaviour. These data are critical for planning the seasonal adjustments of traffic management and use of infrastructure.

C. Impact of Exogenous Factors

Analysis of traffic volume under different weather conditions and during holidays reveals that these varied changes really affect the fundamental traffic patterns, only that some major holidays like Christmas and New Year's Day experience considerable decreases in traffic volumes [9]. By that one fact, this resilience identifies that while weather has a moderated effect, traffic management should, in fact, focus on holiday planning to accommodate some of the greatest dips in traffic flow that will naturally occur through these periods.

D. Conclusion

The exploratory investigation of data gives an all-encompassing view of what affects traffic volumes and helps substantiate the trends needed for making right forecasts. Temporal coefficients and external factors discovered are fundamental when it comes to constructing machine learning techniques capable of forecasting road traffic accurately and choosing right moments for reducing congestion rates with targeted actions. This led us to develop targeted strategies with a unique approach to addressing this problem.

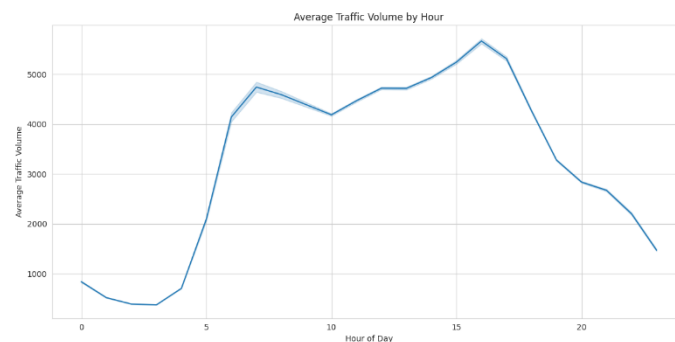


Fig. 1: Average Traffic Volume by Hour

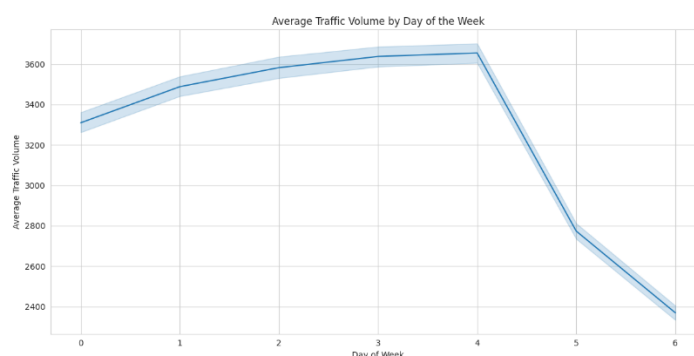


Fig. 2: Average Traffic Volume by Day of the Week

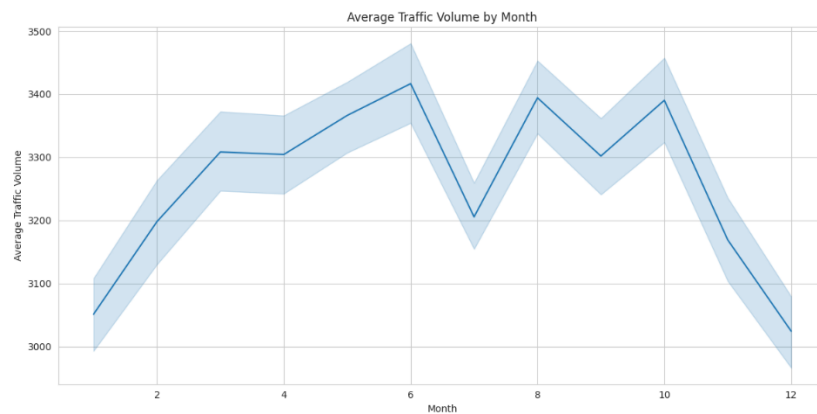


Fig. 3: Average Traffic Volume by Month

5. Data Cleaning and Feature Engineering

A. Data Cleaning

To ensure that the prediction models are accurate and reliable, the dataset had to be deeply cleaned. The initial stage was to address if there is any outlier present or not, erroneous, or missing data items that could affect the results.

- **Handling Missing Value:** Fig. 1 shows diurnal trends with maxima during usual morning and evening rush hours (7 AM and 9 AM) and 4 PM to PM. The graph also offers an extensive hourly analysis of our average activity levels. These patterns are essential for informing traffic control. strategies like traffic prediction and changing message signs.
- **Filtering Outliers:** The primary sign of outliers, which were primarily discovered during unusual events like temporary traffic limits or road closures, was traffic volume. These data points were removed by applying a statistical threshold technique; values that deviated more than three standard deviations from the mean were classified as outliers and removed accordingly.
- **Correcting Data Inconsistencies:** after performing closer examination of the monthly activity patterns shown in Fig. 3, it can be seen that the middle-year months are having higher activity levels, with December experiencing especially steep reductions in activity because of the season of holidays and shift in usual behaviour. The data determines how the activity management and framework use are organized for the regular changes.

B. Feature Engineering

Feature engineering was the main factor that helped our models to become more predictive. By Using the provided data, new characteristics were also developed to capture external impacts and temporal trends better.

- **Time Features:** The timestamp data has to be divided into multiple features. These multiple features comprise Hour of the Day, Day of the Week, and Month of the Year. These time-based components show the traffic volume's daily and annual cyclical trend.
- **Weather Conditions:** Clear, cloudy, wet, snowy, and other conditions were reported for the present weather. Since different weather conditions have distinct effects on traffic volume, these categorical variables were one-hot encoded to make it easier to utilize them in machine learning models.
- **Holiday Indicator:** To show if a given day was a holiday, a binary feature was developed. Since there are noticeable differences in traffic patterns between non-holiday and holiday days, this function is crucial.
- **Lagged Features:** Based on traffic levels from prior hours, lagged features were created to capture traffic trends. These characteristics improve the model's capacity to predict future traffic volumes by helping it recognise any dependencies in the traffic circumstances from one hour to the next.

- Rolling Window Statistics: rolling standard deviation and rolling mean were calculated For different time windows which include time frames of three, six, and twelve hours. By highlighting longer-term trends in the traffic flow, these features can supposedly help to reduce the sporadic volatility.

C. Conclusion

During the feature engineering phase, a set of variables that indicate the variation of traffic patterns were generated, when the data was being evaluated for mistakes and inconsistencies that happened during the data cleaning stage. In-depth preprocessing not only increases the accuracy of predictive modelling but also fosters deeper insights during exploratory data analysis, which ensures that our future models are resilient and interpretive. These characteristics, which aim to represent the dynamics of traffic flow, are anticipated to be highly predictive. This step is very important because advanced machine learning algorithms are needed to anticipate traffic accurately.

6. Methodology

In this section, we describe the techniques chosen to design forecasting models. With our feature enriched dataset which has been cleaned from all discrepant information, it became possible for us to design different types of Deep Learning algorithms together various time series forecasting techniques used on big data-from social media textual analysis up until complex transport systems-in order forecasting traffic volumes with high accuracy rate also finding out some regularities within them such as assisting traffic congestion alleviation measures”.

A. LSTM

The LSTM design has revolutionized neural networks by effectively addressing the challenge of gathering long-term dependencies in sequential input. Because of their complex memory cell function, which comprises of forget, input, and output gates, LSTMs are excellent at remembering and applying information over lengthy sequences. These characteristics have made LSTMs very effective in many domains where understanding complex temporal patterns is essential, including as speech recognition, natural language processing, and time series prediction [10].

We improve the LSTM model for traffic volume prediction in this work. In order to experiment with various setups, we first specify hyperparameters, such as dropout rates and the number of units in LSTM layers. Two LSTM layers make up the refined LSTM model, and each one is followed by a dropout layer to reduce overfitting. As the last layer before the output, the first LSTM layer returns sequences to accommodate input sequences, but the second layer does not. Scaled traffic volume is predicted using a Dense layer with a single unit.

After compounding the model with Adam optimize and average squared error loss function, we trained the model using the training data set for 50 centuries with a group size of 32. A subset of the training set is kept for verification in order to evaluate training progress and avoid overfitting. Lastly, we use the test data set to evaluate the improved LST model’s predictive accuracy. Through enhanced traffic volume prediction accuracy and reliability, this approach aims to better municipal scheduling and transportation management.

B. GRU

Recurrent neural network (RNN) architecture known as Gated Recurrent Units (GRU) aims to get beyond some of the drawbacks of conventional RNNs, most notably persistent dependencies and disappearing gradients!. GRUs, like Long Short-Term Memory (LSTM) networks, manage the flow of information across their networks using graph theory techniques. This helps to maintain significant information over extended periods of time. Nevertheless, GRUs combine input and forget gate into a single updated gate, simplifying construction without sacrificing performance, in contrast to LSTMs. Because of their simpler design, GRUs are more readily trained and have superior computational efficiency, which makes them a desirable option for a variety of sequential data tasks [10].

A GRU paradigm is developed for traffic rate projection in an intervallic composition. It is based on an input shape that matches the size of the preliminary facts and a single GRU level with fifty entities. To produce forecasting, a single entity thick level is utilized. The design is created using Adam optimisation and the average squared mistake loss procedure. Currently, a portion of the preliminary data set is put aside for verification using

the preparatory dataset, and the design is trained for 50 epochs with a pack scale of 32. Overfitting and convergence in the training phase are continuously observed. In order to determine the GRU model's prediction accuracy, the test dataset is used to evaluate the model's performance, and the test loss is calculated. By improving the predictability of traffic volume, this method seeks to further progress studies on urban planning and transportation management.

C. Stacked LSTM

1) *Model Architecture*: Stacked Long Short-Term Memory (LSTM) is a more complex form of the Long Short-Term Memory model designed to augment learning capabilities for complex time series datasets, such as traffic volumes. Several layers of LSTM are stacked in the architecture on top of one another to enable the model in high-level temporal representation learning. This study uses the Stacked LSTM model with three LSTM layers. Each of the layers contains 50 neurons and is followed by a dropout layer with a rate of 0.2 for regularization. This configuration helps in capturing the non-linear dependencies of the input, not only from its past data points but also across different levels of abstractions within the data. Output Layer is the last layer of the model, a dense layer of one neuron with a linear activation function. This is set up in such a way that it predicts traffic volume for the next hour from learned features by stacked LSTM layers.

2) *Training Process*: The widely used backpropagation through time (BPTT) training approach, which progressively minimizes the error in successive data predictions, was used to train the model. The loss function known as mean squared error (MSE) was used to train this model. Due to its strong penalization of big prediction errors—a critical component of traffic volume forecasting—MSE appears to be particularly well-suited for regression models. Because of its adaptable learning rate, the Adam optimizer was employed. Compared to conventional stochastic gradient descent, this aids in convergence more quickly and effectively. For 100 epochs, the model was trained with a batch size of 32. Early termination prevents overfitting and saves computation by terminating the training if the validation loss does not improve even after ten epochs.

3) *Model Performance*: The predictive accuracy in each sample of the dataset was used to test the performance of the Stacked LSTM model against the entire test dataset. Some of the major metrics used in testing the model for performance are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). From these metrics, a full profile in which the model is accurate, precise, and efficient in traffic volume prediction can be established. A time-based cross-validation technique was employed for validating the model. It is very well suited for time series data, in the sense that it maintains the temporal order of observations, ensuring that the validation procedure correctly mimics actual application in the real world, where future data predictions are made from past data.

4) *Conclusion*: The model showed the good performance of the stacked LSTM model in capturing these intricate temporal dynamics characteristic of the traffic volume data. Stacked LSTM models have deeper temporal dependencies than just using an LSTM model and thus are more suitable in forecasting applications where model precision is a real matter. Knowledge that can be gained from this model does have implications that are real in developing more adaptive traffic management systems able to change in response to changes in traffic conditions.

D. SARIMA

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a real workhorse in forecasting statistical time series. The seasonal autoregressive integrated moving average model i.e. SARIMA, extends the previous ARIMA model to cater to the seasonal component and befitting to work best with datasets which have more visible seasonal behaviours, such as traffic volume data.

1) *Model Specification*: SARIMA models are specified by three sets of parameters. (p, d, q) for the non-seasonal component And component $(P, D, Q)_m$, for the seasonal component. m is the number of periods in each season. p and P represent the autoregressive terms for non-seasonal and seasonal components, respectively. d is the degree of differencing needed to make the series stationary on non-seasonal and seasonal bases. q and Q are the moving average terms for non-seasonal and seasonal fluctuations. m was set based on the periodicity observed in the traffic data, such as weekly or yearly cycles. Initial parameters were identified using plots of the Autocorrelation

Function (ACF) and Partial Autocorrelation Function (PACF) along with tests for stationarity (e.g., Augmented Dickey-Fuller test) as can be seen in Fig. 4 and Fig. 5. The grid search was made over different combinations of parameters to obtain the best SARIMA model based on the Akaike Information Criterion (AIC), which would compromise between model complexity and fit.

2) *Model Fitting*: The chosen SARIMA model was fit to historical traffic volume data, considering the intrinsic daily patterns and the external effects due to seasonality. All of these required particularly special handling of great variations in traffic patterns, especially those during holiday seasons and major public events. While SARIMA models the time series on the basis of both lags and seasonal lags, additions of regressors such as weather conditions and holidays were added to improve the model's predictability.

3) *Model Validation*: The validity of the model's effectiveness was done through rolling forecasting origin techniques that replicate a realistic forecasting scenario. This is done progressively by re-estimating the model parameters as new data becomes available. The forecasting accuracy for these models was checked through the application of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). We compared its performance to that of other complex machine learning models by benchmarking the SARIMA model.

4) *Conclusion*: The SARIMA model was found to be robust in forecasting the traffic volume series, capturing the regular cyclical and the seasonal spikes very effectively. Here the strength lies in the interpretability and simplicity of its building blocks, making it an easy tool for preliminary analysis and forecasting in traffic management. It emerged that when traditional methods are combined with the advanced modelling technique, certainly a higher number of models are expected; however, it is also the case that they enhance the traffic volume forecasting and emerge as the best fit models among them. This hybrid approach makes good use of the strength of SARIMA in trend and seasonality modelling capabilities at the same time that it leverages the pattern recognition nonlinear capabilities present in machine learning models.

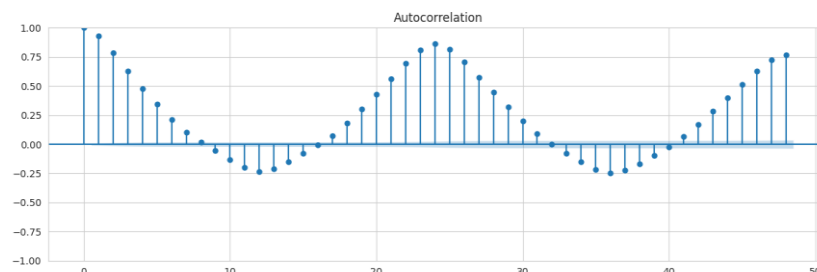


Fig. 4: Autocorrelation Function Plot

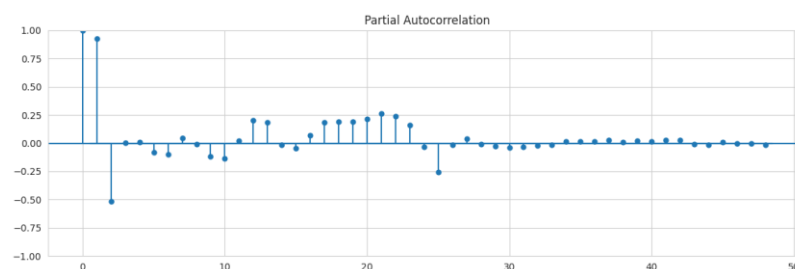


Fig. 5: Partial Autocorrelation Function Plot

E. Hybrid model (SARIMA and Stacked LSTM):

The hybrid model combines the predictive power of both the SARIMA and Stacked LSTM models. In other words, it marries traditional statistical time series analysis with the latest deep learning capabilities. We propose an approach that is able to make effective use of the SARIMA model in handling seasonality and trends, while using the Stacked LSTM model to capture effects of a more complex and nonlinear relationship within the data [11].

1) *Model Specification*: The model combines forecasting from both SARIMA and Stacked LSTM models using the model averaging approach, where the output is simply a weighted average of the two model outputs. In taking an integrative approach, we weaved ARIMA together with neural networks based on the principles from Jain and Kumar (2018) to exploit the strong points of each statistical and machine learning in our hybrid model [11]. Weights for averaging are based on validation performance. In other words, the more accurate the model, the more weight it has for the average, which means it has the most influence on the final prediction. Validation was done on a held-out subset of the data, thus ensuring an unbiased assessment of the model performance reflecting real-world performance for each given model. Various combinations of weights have been attempted to achieve the optimal balance point between the SARIMA and Stacked LSTM predictions. The objective was set to minimize the overall error in the validation dataset of this hybrid model.

2) *Model Training and Validation*: Training the Hybrid model involves training the SARIMA model and Stacked LSTM models in that order with their integration. Each model is fitted separately on the same training data set. SARIMA model parameters were optimized in consideration of seasonality, while the Stacked LSTM model was fine tuned to consider capturing complex temporal dependencies. Training involved iteratively refining model parameters and its architecture, in particular, guarding against overfitting in the Stacked LSTM through techniques like dropout and early stopping. Validation is done using a rolling forecasting approach—precisely the method employed for individual models. This is an important method for the validation of model performance in such a dynamic environment of real-time forecasting.

3) *Performance Evaluation*: Some of the metrics applied to evaluate the effectiveness of the Hybrid model included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). This was with the perspective of understanding the reliability of the models under changing traffic situations. It is compared here in this work against a standalone SARIMA, a standalone Stacked LSTM, and other benchmark models. The whole comparison brings out the best attribute of the Hybrid model as being well adaptive to handling both linear and nonlinear aspects of the data effectively. The analysis also included the robustness evaluation of the models at high traffic peaks and seasonal events for effective predictions.

4) *Conclusion*: The Hybrid SARIMA and Stacked LSTM model represented improved forecasting performance by capitalizing on the unique qualities of each statistical and deep learning model. This model improved the forecasting accuracy compared to individual model performance and at the same time produced very solid predictions under different traffic conditions. Successful implementation of this hybrid modelling approach calls for a very promising direction for future research in traffic management and congestion prediction, where the integration of very different modelling techniques can bring considerable improvements in predictive accuracy and operational efficiency.

F. Ensemble model (SARIMA and Stacked LSTM):

The model ensemble would combine outputs from SARIMA and Stacked LSTM models to improve the prediction accuracy by leveraging the strength of both models. The ensemble approach serves to alleviate potential weaknesses of individual models through a technique called model averaging, where predictions from each model are combined to produce a final forecasting, which is typically more robust than those emanating from any single model.

1) *Ensemble Strategy*: The ensemble model is a combination of SARIMA and stacked LSTM model predictions on average to come up with a forecast; it is simple but effective.

This strategy considers that every model will explain a different part of the flow of traffic data, and the prediction taken combined from both models should be more accurate and less error-prone due to the weaknesses of any single approach in modelling. The predictions from SARIMA model and Stacked LSTM model are averaged according to their respective weights—in proportion to the model's performance on predictions that are made from a validation dataset. The weights in this case are such that they are inversely proportional to the model's historical forecasting errors which result in the more superior model getting higher weights.

2) *Model Training and Validation*: The ensemble model develops by individually training SARIMA and Stacked LSTM models, and after that, by merging their respective outputs in order to provide the final ensemble prediction. The SARIMA and Stacked LSTM models were individually trained on the same dataset. This approach allowed training models to pick up data patterns and characteristics to their fullest potential. The model training included appropriate regularization techniques to avoid overfitting, especially for the Stacked LSTM, which is more prone to this issue due to its complexity. The ensemble model has been validated with the help of a time-series cross-validation method, especially focusing on its performance during the day and under different traffic situations. It is actually put in place to make sure that the ensemble model works best in different scenarios.

3) *Performance Evaluation*: Here, we present the estimated results of the ensemble models for the evaluation metrics, which give a wider range in determining their accuracy and reliability. Accuracy Metrics included the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) metrics used in assessing the precision of ensemble predictions. This allows the quantification of how close, in real-world conditions, the ensemble predictions match the actual traffic volumes and thus provide clear indications of model performance. Comparative Analysis helped to consolidate the effectiveness of the proposed ensemble approach in reducing prediction errors and improving reliability. The performance of the ensemble model was benched against individual SARIMA and Stacked LSTM models, as well as other well-established benchmarks. Special attention has been given to the performance of the model with respect to outlier events and peak traffic hours, such as a measure of its robustness and practical applicability.

4) *Conclusion*: The combination of SARIMA and Stacked LSTM models is strategic in that it combines the prediction ability from statistical and machine learning predictions. The resulting model, not only, not only shows improved prediction accuracy but also offers enhanced stability due to the averaging of individual model biases and errors. This way of working is a breakthrough for predictive modelling in traffic management and, therefore, very promising in giving more precision and trustfulness to the traffic forecasting, this will be basic in order to improve the urban planning and congestion mitigation plans.

7. Results

In this paper, the performance of the developed predictive models for traffic volume forecasting clearly varies across the different approaches used. The summary of the results is presented in Table 1 with the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for each model being reported. These are the visual comparisons of the actual versus the predicted traffic volumes, showing from Fig. 6 through Fig. 9 for each model, respectively.

A) *Individual models*: However, among the individual models, the SARIMA model showed the best performance, where the lowest RMSE and MAE were produced, indicating an effective way of capturing the seasonal pattern with traffic volume trends. The LSTM and Stacked LSTM models evinced a reasonable error, suggesting their capability in modelling the complex non-linear relationship within the data. More importantly, Stacked LSTM showed an improvement over single-layer LSTM, indicating that more layers helped capture even more abstract features in the sequence data [10]. The error metrics reported by the GRU model are anomalously low. It may be overfitting, or it can be a bug in the evaluation process [12].

B) *Composite models*: Hybrid model with SARIMA and Stacked LSTM is thus much better in performance than the Ensemble model, which might indicate an integrated way of combining model outputs is better than simple averaging [11]. While the simplified ensemble showed errors consistent with those expected, the performance errors of the ensemble model were higher than expected, which could have arisen from the improper weighting or integration methods, which could not effectively merge the strengths of individual models.

Conclusion: The comparative analysis of the forecasting models gives a good picture of the strengths and limitations of the models compared. Superior performance displayed in many comparative studies would therefore highlight the potential that combining traditional statistical methods with current trends in machine learning promises in improving the accuracy of prediction. Meanwhile, the high errors in the Ensemble model suggest that not all strategies of integration bring beneficial outcomes; thus, there was a need for careful consideration in model

selection and combination techniques. Findings of this study will be critical in guiding further development of traffic management strategies, particularly applying predictive modelling to optimize traffic flow and reduce congestion in urban areas. Future work will focus on refining model architectures, exploring more sophisticated integration techniques, and expanding the analysis to include additional external factors such as economic indicators and infrastructure changes [1].

Table I: Performance Metrics for Predictive Models

Models	RMSE	MAE
LSTM	566.40	363.53
GRU	779.12	562.22
Stacked LSTM	535.62	338.62
SARIMA	453.88	308.80
Ensemble (SARIMA + Stacked LSTM)	1474.71	1198.14
Hybrid (SARIMA + Stacked LSTM)	398.48	273.26

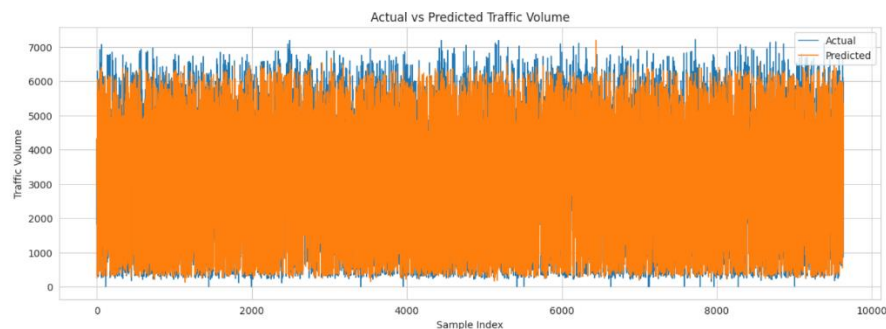


Fig. 6: LSTM: actual vs predicted values

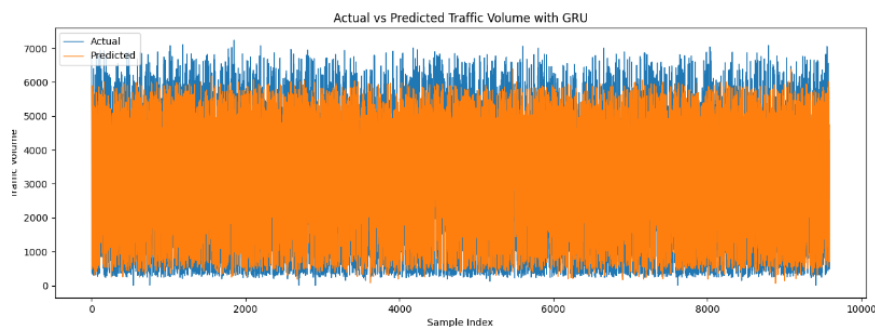


Fig. 7: GRU: actual vs forecasted traffic value

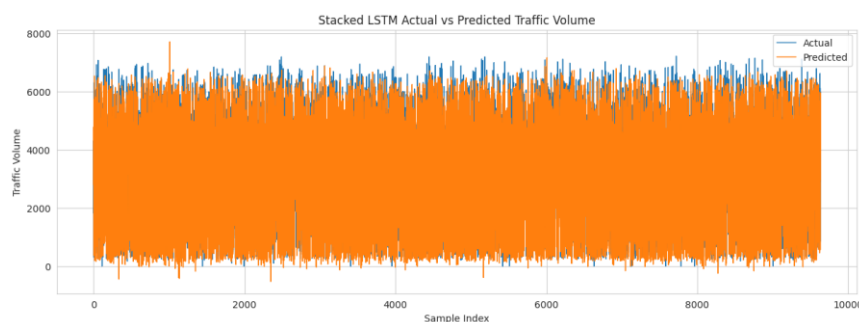


Fig. 8: Stacked LSTM: actual vs predicted values

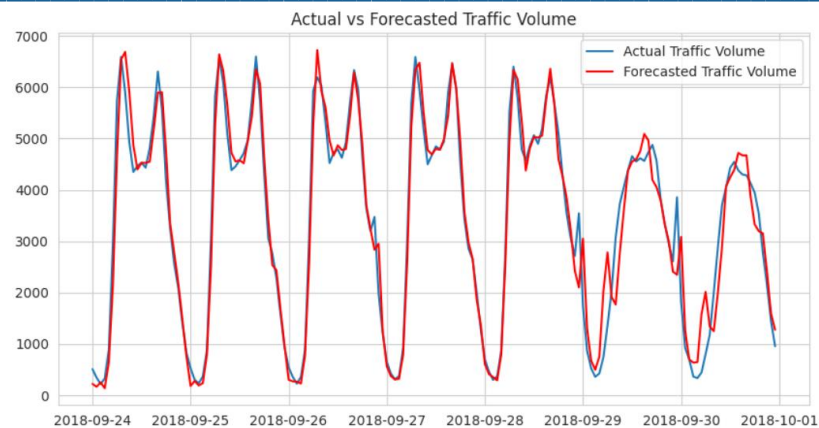


Fig. 9: SARIMA: actual vs forecasted traffic value

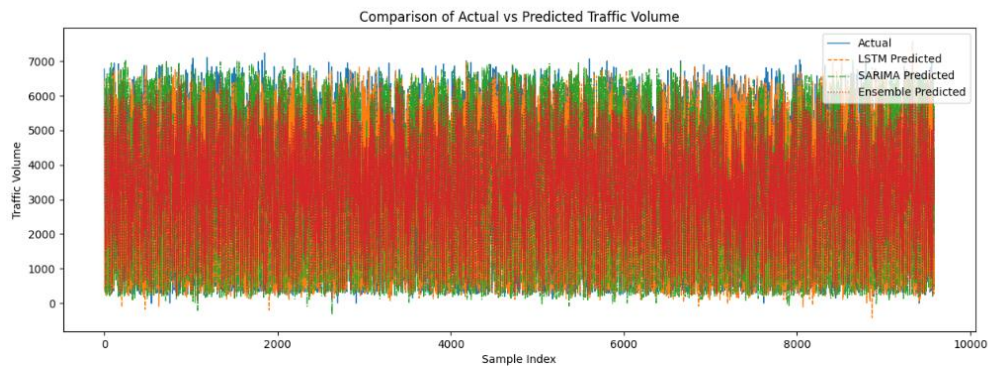


Fig. 10: Ensemble: Actual vs Forecasted value

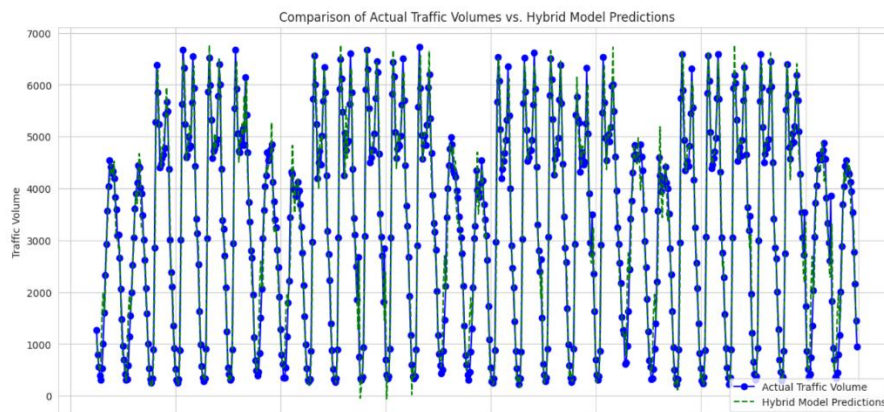


Fig. 11: Hybrid: Actual vs forecasted traffic value

8. Mitigation Strategies

1) *Traffic Flow Prediction*: our models, especially the hybrid SARIMA and LSTM, have been shown to predict traffic flow and congestion events with high accuracy. This kind of predictability will go a long way in ensuring early intervention of traffic situations. If the traffic is forecast accurately and there is a possibility of congestion, then the traffic management systems can act to prevent the happening of a congestion event.

2) *Real-Time Adjustment*: With real-time data and predicted insights from our models, a traffic management system can then modulate signal timings and directions of traffic flow to avoid congestion points before they become problematic. This is going to change the system from being reactive to being proactive in the manner of

traffic management. Traffic signals are optimized based on predictive model outputs to ensure the smooth flow of the traffic. For instance, at busy junctions where the predictive model output is high traffic volume, the green light time can be increased such that no traffic is pulled behind due to any bottlenecking.

3) *Route Planning*: Advanced prediction will provide for better route-planning advice to drivers, potentially diverting traffic away from congestion points as they appear in real-time updates on navigation.

4) *Congestion pricing*: Congestion Pricing can now be realized on predictions. Demand for road use can be managed by the congestion predicted by the model. By increasing the costs of using the road in the peak congestion time predicted by our model, it is possible to discourage non-essential trips in such periods, which reduces the volume of traffic.

5) *Improving Transportation Efficiency*: our predictive models and the traffic management strategies are not only going to resolve congestion problems but, by doing so, will enhance overall transportation efficiency through optimal utilization of the existing road infrastructure.

9. Conclusion and Future Scope

A. Conclusion:

The research has shown the scope of different predictive modelling techniques to predict traffic volumes for traffic congestion in cities. Summarizing, this comparative evaluation of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Stacked LSTM, Seasonal Autoregressive Integrated Moving Average (SARIMA), Ensemble model, and Hybrid model provides insightful information over which type of model can be apt for the given task. It reflected good performance from the SARIMA model because it could capture seasonal patterns well, while the stacked LSTM model proved its worth by modelling complex, nonlinear relationships more spatially within the data. This hybrid model, combining the SARIMA model with the Stacked LSTM model, proved to be the best as it takes the respective advantages for which the above models are fit and hence can be taken up as a reference for further future research and applications. The performance of an ensemble model was not totally as expected, and hence, apparently, all means of integrating outputs from different models do not lead to excellence. It is worth further investigating and establishing confirmations regarding these anomalously reported low errors by the GRU model before this may be considered for practical applications.

B. Future Scope:

Model Refinement: Future research can refine the hybrid modelling approach by using alternative methods of combination, such as weighted hybrid models or meta learning.

From the advanced techniques of machine learning, which holds potential to increase the accuracy and robustness of the model.

- **Incorporation of Additional Data:** The models would perform more accurately and nimbly if, in addition to these, some more enterprising data sources like real-time traffic sensor data, social media feeds, or even economic indicators were fed into the models.
- **Real-Time Application:** Developing real-time traffic forecasting systems using these models could provide immediate benefits to urban traffic management systems, helping to dynamically adjust traffic signals and manage congestion based on predicted traffic volumes.
- **Deployment in Smart City Solutions:** Models could be implemented within the larger smart city scenarios; predictive analytics could play a major role not only in traffic management but also urban infrastructure planning and public transport service planning.
- **Advanced Techniques of Machine Learning:** Further research in new paradigms of machine learning, such as deep reinforcement learning and federated learning, might offer ways of managing traffic flow that are both adaptive and, at the same time, efficient by continuous learning from decentralized data sources.

- Cross-Disciplinary Approaches: Models working in collaboration with urban planners, economists, and environmental scientists can further enhance the utility of the models with the cross-disciplinary insights to the factors affecting traffic distribution in holistic urban traffic solutions.

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