OPTIMIZING URBAN MOBILITY USING LSTM AND GRU

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AUTHOR'S DECLARATION FOR ELECTRONIC SUBMISSION OF A MAJOR RESEARCH PROJECT (MRP)

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ABSTRACT

Urban mobility optimization is crucial for enhancing traffic management and reducing congestion in cities, directly impacting travel times, emissions, and quality of life. This study applies advanced neural network architectures—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—to predict traffic volume, leveraging their ability to model temporal dependencies in sequential data. The dataset, incorporating temporal and weather-related features, is analyzed through comprehensive exploratory data analysis (EDA) to uncover patterns and prepare the data for modeling. LSTM and GRU networks are rigorously trained, with model parameters fine-tuned for optimal performance. The results demonstrate that these models effectively capture complex, non-linear patterns in traffic data, offering significant potential for improving urban traffic management and forecasting.

Keywords: Urban Mobility Optimization, Intelligent Transportation Systems (ITS), Traffic Volume Prediction, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Neural Networks, Temporal Dependencies, Sequential Data, Exploratory Data Analysis (EDA)

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1. INTRODUCTION

1.1 BACKGROUND

Urban mobility optimization is a critical aspect of intelligent transportation systems aimed at enhancing traffic management and reducing congestion. Efficient urban mobility ensures the smooth movement of people and goods, which is essential for the functioning of cities, impacting daily life, economic activities, and overall quality of life.

Traffic congestion remains a significant challenge in urban areas, leading to delays, increased pollution, and higher stress levels for commuters. Addressing these issues is crucial for sustainable urban development, and accurate traffic flow predictions play a vital role in this endeavour. Predictive models can help in better planning and real-time adjustments, ultimately improving road safety and traffic flow.

1.1.1 Significance of Traffic Flow Predictions:

Accurate traffic flow predictions enable city planners and traffic management authorities to make informed decisions, optimizing traffic signal timings, deploying traffic enforcement officers, and providing real-time updates to drivers. These measures contribute to reducing congestion and improving travel times, thereby enhancing the overall efficiency of urban transportation systems.

1.1.2 Challenges of Traffic Congestion:

Traffic congestion poses several challenges, including delays, increased pollution, and higher stress levels for commuters. These issues not only affect the quality of life but also have economic implications, such as increased fuel consumption and economic losses due to wasted time. Addressing traffic congestion is essential for ensuring the smooth functioning of urban areas.

1.2 RESEARCH QUESTION

The primary research question addressed in this study is: “How can advanced neural network models, specifically LSTM and GRU, be utilized to predict traffic volume using temporal and weather-related features?”

This research question guides the exploration of the capabilities of LSTM and GRU models in capturing complex patterns in traffic data. It aims to determine whether these advanced neural network architectures can provide accurate traffic volume predictions, which can be used to enhance urban traffic management.

1.3 INDEPENDENT/DEPENDENT VARIABLES

1.3.1 Date and Time:

Traffic volume is influenced by the time of day, day of the week, and time of the year. For example, rush hours typically see higher traffic volumes compared to other times of the day. Similarly, traffic patterns differ between weekdays and weekends. Additionally, seasonal variations and holidays can impact traffic volume.

1.3.2 Weather Conditions:

Weather plays a significant role in traffic volume. Factors like temperature, rain, snow, and cloud cover can affect driving conditions and, consequently, traffic volume. For instance, extreme weather conditions such as heavy rain or snow can reduce traffic volume as people may choose to stay indoors.

1.3.3 Holiday Information:

Traffic patterns can vary significantly on holidays compared to regular working days. For example, traffic volume might be lower on holidays due to reduced commuting. Special events or long weekends can also impact traffic flow.

1.3.4 Previous Traffic Volume:

Historical traffic volume data is crucial for predicting future traffic volumes. By analyzing past traffic patterns, we can identify trends and make more accurate predictions. Previous traffic volume serves as a key indicator of expected future traffic flow.

2. LITERATURE REVIEW

Traffic flow prediction has evolved as a crucial aspect of transportation engineering and urban planning, aiming to enhance the efficiency and safety of transportation systems. Early research in this domain relied heavily on traditional statistical models like the AutoRegressive Integrated Moving Average (ARIMA) model, which became a standard tool for short-term traffic forecasting. ARIMA models utilize historical traffic data to predict future trends by identifying and extrapolating linear patterns within the data. However, despite their utility, these models have limitations, particularly when faced with non-stationary data or abrupt changes in traffic behavior, which are common in dynamic urban environments [1], [2].

Recognizing these limitations, researchers began to explore machine learning techniques that could offer more robust and flexible prediction capabilities. One such technique is the Random Forest model, an ensemble learning method that improves prediction accuracy by combining the results of multiple decision trees. When applied to traffic flow prediction, particularly using data from GPS, Random Forest models have been shown to outperform traditional statistical approaches. These models, however, require substantial computational resources and careful tuning of parameters to achieve their full potential [3], [4].

Another machine learning approach that gained prominence is the Support Vector Machine (SVM). SVMs are particularly adept at capturing non-linear relationships in data, which are often present in traffic patterns. Their ability to model complex, non-linear trends makes them highly effective for traffic flow prediction. However, the computational demands of SVMs and the need for precise parameter selection can pose challenges, particularly in real-time traffic management scenarios where speed and efficiency are critical [5].

The introduction of deep learning has further revolutionized traffic flow prediction, particularly with the development of advanced neural network models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. LSTM networks, which are designed to capture long-term dependencies in sequential data, have been particularly successful in modeling the temporal dynamics of traffic flows. These networks excel at handling time-series data, where understanding the order of events is crucial for accurate predictions. Studies have demonstrated that LSTM models significantly outperform traditional methods by effectively capturing the complex, non-linear patterns inherent in traffic data [6], [7].

While LSTM networks are powerful, their complexity can make them computationally expensive. To address this, GRU networks were developed as a more streamlined alternative. GRUs simplify the architecture of LSTMs by merging some of the gates, thereby reducing the computational load while

maintaining a similar level of performance. This efficiency makes GRUs particularly attractive for scenarios where faster model training is necessary, without a significant trade-off in accuracy [8], [9].
In addition to these sequential models, Convolutional Neural Networks (CNNs) have also been explored for traffic prediction, especially in capturing spatial dependencies within traffic networks. CNNs are highly effective at processing grid-based spatial data, which makes them well-suited for modeling the spatial distribution of traffic across urban networks. However, their ability to capture temporal dynamics is limited unless they are combined with models like LSTMs or GRUs that are designed for sequential data processing [10], [11].

To harness the strengths of different neural network architectures, researchers have developed hybrid models that integrate various approaches. For example, by combining CNNs with LSTMs, it becomes possible to capture both the spatial and temporal dependencies in traffic data, leading to more accurate predictions. These hybrid models have proven particularly effective in improving the overall performance of traffic flow prediction systems by addressing the specific limitations of each individual model [12], [13].

More recently, Graph Neural Networks (GNNs) have emerged as a novel approach for traffic flow prediction, particularly in complex urban environments. GNNs are designed to model both spatial and temporal dependencies within traffic networks, making them highly suitable for urban traffic prediction. However, despite their potential, challenges related to the implementation and scalability of GNNs have hindered their widespread adoption [14].

Incorporating real-time and crowdsourced data into traffic prediction models has also gained importance in recent years. Real-time GPS data and crowdsourced information from platforms like Waze offer valuable insights that can enhance the accuracy and timeliness of predictions. However, these data sources present challenges such as data sparsity, privacy concerns, and the need for effective integration methods to ensure that the predictions remain reliable and accurate [15].

3. EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) is a fundamental step in any data-driven project, providing an in-depth understanding of the dataset, revealing hidden patterns, and guiding the model development process. For this study, EDA was conducted on the Metro Interstate Traffic Volume dataset, which offers a rich collection of hourly traffic volume records along with temporal and weather-related features. The analysis helped uncover the dynamics of traffic behaviour on an interstate highway, shedding light on how various factors influence traffic flow.

3.1 DATASET OVERVIEW

The Metro Interstate Traffic Volume dataset is extensive, comprising **48,204 hourly entries**. Each entry captures the number of vehicles passing a specific point on the interstate, accompanied by a rich set of features that include date-time information, weather conditions, and environmental factors. This dataset is well-suited for exploring how traffic volumes fluctuate over time and in response to different weather scenarios.

The dataset's breadth allows for a detailed examination of traffic patterns over several years, capturing both short-term variations, such as daily rush hours, and long-term trends, including seasonal changes. Understanding these patterns is crucial for developing predictive models that can accurately forecast traffic volumes, aiding in better urban traffic management.

3.2 INITIAL DATA CLEANING

Before delving into deeper analysis, the dataset underwent a rigorous cleaning process to ensure that the data was consistent, reliable, and ready for subsequent modelling. One of the first steps was to check for missing values—a common issue in large datasets that can skew analysis and lead to biased model predictions. Fortunately, this dataset was found to be **free of missing values**, which allowed for a smooth transition into the exploratory phase without the need for data imputation or the exclusion of records.

```
temp                   0
rain_1h                0
snow_1h                0
clouds_all             0
weather_main           0
weather_description    0
date_time              0
traffic_volume         0
dtype: int64
```

Missing values

Additionally, the dataset was scanned for outliers—extreme values that might distort the overall analysis. While some outliers were present, particularly in traffic volumes during unusual weather events or holidays, these were retained as they represent real-world scenarios that the models should be able to handle.

3.3 TRAFFIC VOLUME ANALYSIS

The first major focus of the EDA was on understanding the distribution and characteristics of traffic volume, the primary variable of interest. Traffic volume, representing the number of vehicles passing a specific point on the interstate each hour, exhibited a clear distribution pattern:

- **Peak Traffic Volume**: The distribution of traffic volumes showed a pronounced peak around **4,000 vehicles per hour**. This peak corresponds to periods of high demand, likely during morning and evening rush hours when commuters are traveling to and from work. These peaks are critical as they represent the times when traffic management is most challenging and when accurate predictions are most valuable.

- **Low Traffic Volume**: At the other end of the spectrum, the dataset recorded instances where traffic volumes dropped close to **zero vehicles per hour**. These instances typically occurred during late-night hours or during extreme weather conditions, such as heavy snow or ice storms. Understanding these low-traffic periods is equally important, as they can inform strategies for road maintenance or emergency response planning.

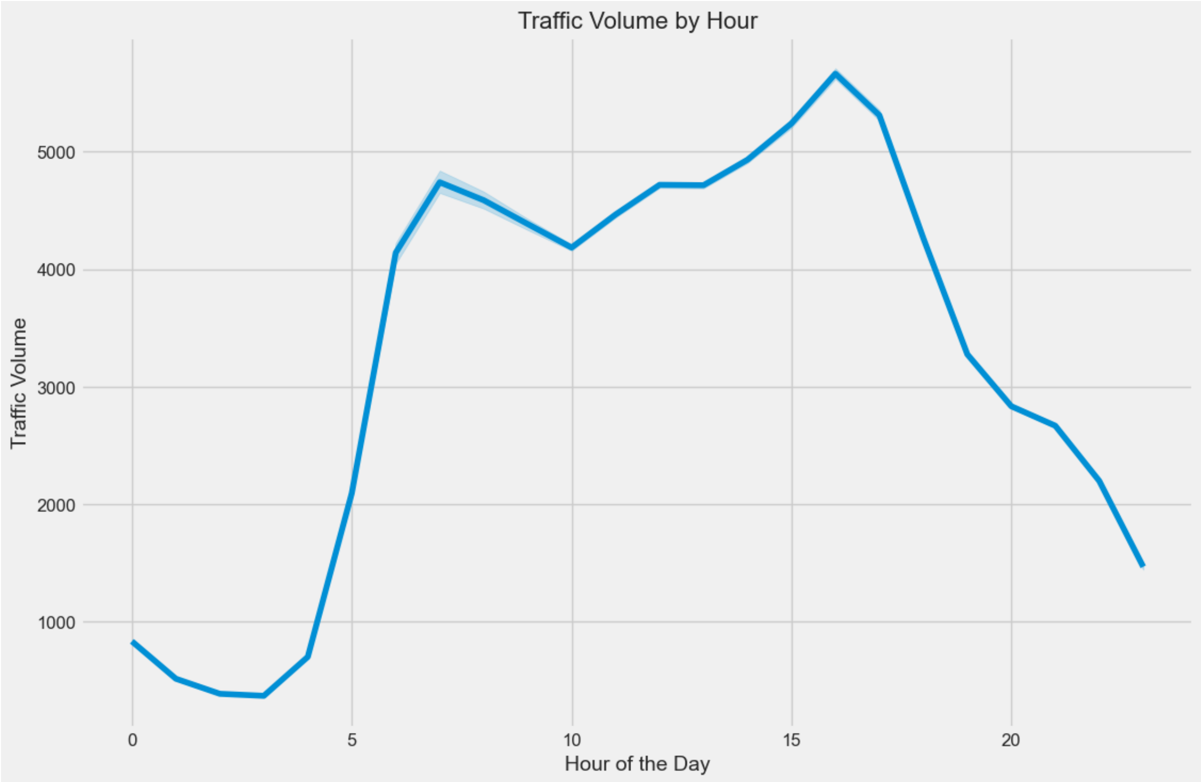
The overall distribution of traffic volume was slightly skewed, with more frequent occurrences of higher traffic volumes during peak hours, reflecting the dataset's urban setting where high traffic is the norm during certain times of the day.

3.4 TEMPORAL ANALYSIS

Given the nature of traffic data, temporal factors were expected to play a significant role in shaping traffic patterns. The EDA explored several temporal features to understand their impact on traffic volume:

- **Hour of the Day**: The analysis revealed a strong diurnal pattern in traffic volumes, with distinct peaks observed during the morning (7-9 AM) and evening (4-6 PM) rush hours. These rush hour peaks are driven by commuter behaviour, with significant increases in traffic as people travel to and from work. The **lowest traffic volumes** were recorded during the late night hours (around 3-4 AM), when most people are off the roads. This clear hourly pattern underscores the importance of including time-of-day as a critical feature in predictive models.

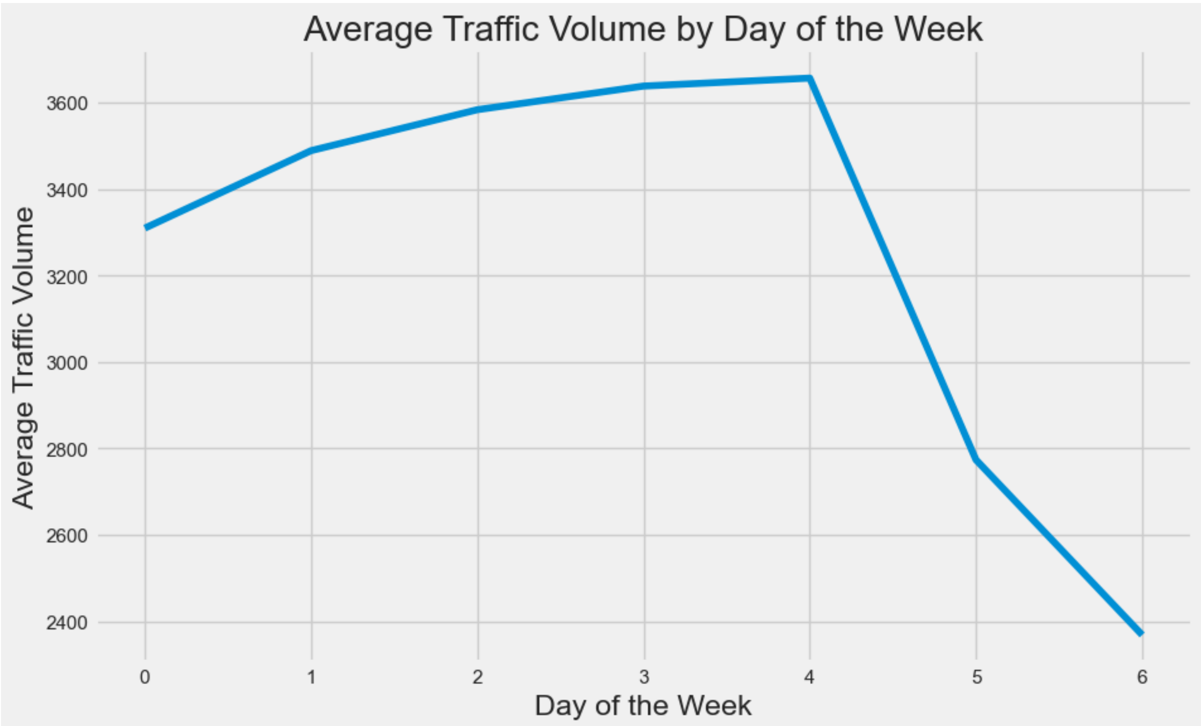
- **Day of the Week**: The data showed a marked difference in traffic volumes between weekdays and weekends. **Weekdays** consistently recorded higher traffic volumes, reflecting the typical workweek commuting pattern. **Fridays** saw the highest traffic volumes, possibly due to a combination of end-



Hour of the day

of-week commutes and early departures for weekend activities. In contrast, **Sundays** recorded the lowest traffic volumes, as fewer people are on the roads.

- **Month and Season**: The analysis extended to seasonal variations, revealing that traffic volumes were generally higher during the summer months. This trend is likely due to increased travel during



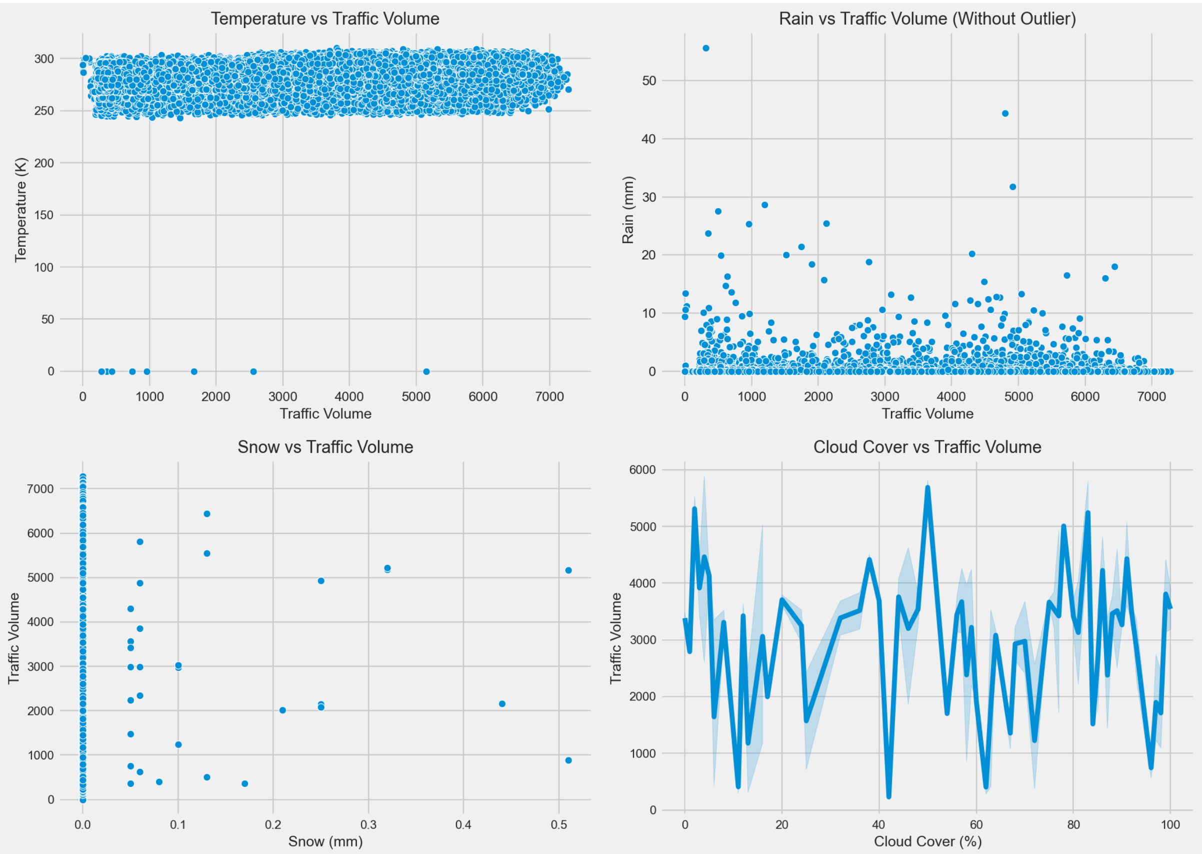
Day of the week

holidays and vacations, as well as generally favourable driving conditions. Conversely, traffic volumes dipped during the winter months, particularly in December and January, which could be attributed to colder weather, shorter daylight hours, and the holiday season when many people stay home or travel less frequently.

3.5 WEATHER CONDITION ANALYSIS

Weather conditions are known to influence driving behaviour, and the dataset provided a rich set of weather-related features, including temperature, rain, snow, and cloud cover. The EDA examined these features to determine their impact on traffic volume:

- **Temperature**: The correlation between temperature and traffic volume was moderate but significant. The analysis showed that traffic volumes tend to increase with rising temperatures, peaking at around **50°F to 60°F**. These temperatures likely represent ideal driving conditions—neither too cold nor too hot—leading to increased road usage. Extreme temperatures, particularly very cold conditions, were associated with lower traffic volumes, possibly due to hazardous driving conditions or reduced travel demand.



Temporal Pattern

- **Rain and Snow**: Precipitation, particularly in the form of rain and snow, had a noticeable dampening effect on traffic volume. Days with **heavy rain or snowfall** saw significant drops in traffic, as adverse weather conditions likely discouraged people from driving. This effect was more pronounced in snowfall, where traffic volumes could drop dramatically during heavy snowstorms. These findings highlight the importance of including weather variables in predictive models, as they can significantly impact traffic volumes.

- **Cloud Cover**: The impact of cloud cover on traffic volume was relatively minimal compared to other weather conditions. The analysis suggested that overcast conditions alone do not deter drivers to the same extent as precipitation does. However, in combination with rain or snow, cloud cover could contribute to a reduction in traffic volumes by signalling worsening weather.

3.6 HOLIDAY AND SPECIAL DAY ANALYSIS

Holidays and special days often disrupt regular traffic patterns, and the EDA explored how these events impacted traffic volumes:

- **Holidays**: The analysis revealed that traffic volumes were generally lower on holidays compared to regular workdays. Major holidays like Thanksgiving, Christmas, and New Year's Day saw a **significant drop in traffic**, as people either stayed home or traveled outside of typical commuting hours. The decrease in traffic volume on these days underscores the importance of including holiday indicators in predictive models, as they represent deviations from normal traffic patterns.
- **Special Events**: While the dataset did not specifically mark special events, inferred impacts could be seen on certain days where traffic volumes deviated significantly from the norm. For instance, traffic volumes around national holidays or during significant weather events suggested a reduction in regular commuter traffic and an increase in non-commuter travel, such as holiday shopping or attending events.

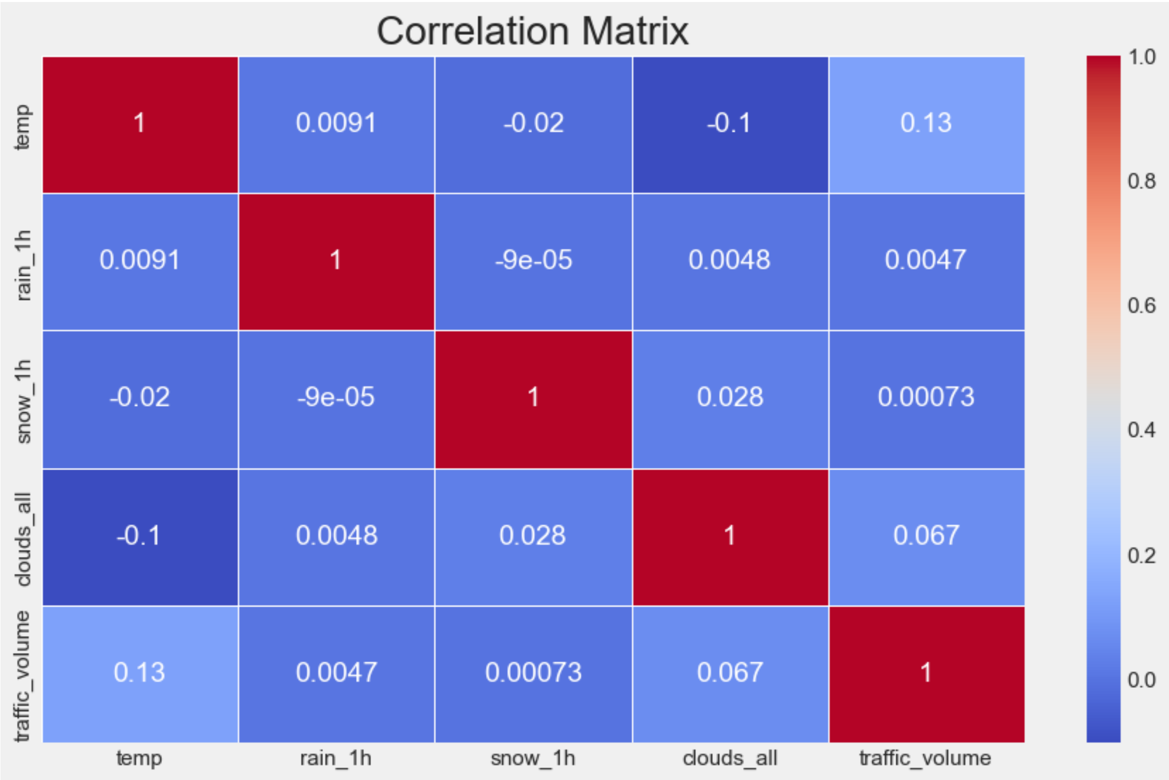
3.7 CORRELATION ANALYSIS

To quantify the relationships between different features, a correlation matrix was generated. This analysis revealed several key relationships that informed the model development process:

- **Traffic Volume and Temperature**: A moderate positive correlation was observed between traffic volume and temperature, with a Pearson correlation coefficient indicating that warmer temperatures are generally associated with higher traffic volumes. This finding aligns with the understanding that clear, warm weather conditions encourage driving.

- **Traffic Volume and Rain/Snow**: Negative correlations were observed between traffic volume and precipitation variables, particularly snow. This confirms the earlier finding that adverse weather conditions lead to reduced traffic volumes, as drivers are likely to avoid traveling in poor weather conditions.

- **Temporal Features**: Among the temporal variables, the hour of the day exhibited the strongest correlation with traffic volume. This reinforces the idea that time-based patterns are the most significant predictors of traffic flow, making temporal features critical in the development of predictive models.



Correlation Matrix

This detailed exploratory analysis provided essential insights into the factors affecting traffic volume on the interstate, laying a strong foundation for the subsequent modelling efforts.

By thoroughly understanding these patterns, the models developed in later stages were better equipped to account for the most influential variables, ultimately leading to more accurate and reliable traffic forecasts.

4. METHODOLOGY

4.1 AIM OF STUDY

4.1.1 Objective:

The primary objective of this study is to explore the use of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models in predicting traffic volume. These models are well-suited for handling sequential data and are known for their capabilities in capturing temporal dependencies, which are crucial for understanding traffic flow dynamics.

The study aims to evaluate how these models might be leveraged to improve urban traffic management by providing accurate traffic volume predictions, thereby aiding in the reduction of congestion and enhancing transportation efficiency.

4.1.2 Significance:

Effective traffic management is a fundamental challenge in urban areas, where congestion can lead to significant delays, increased pollution, and reduced quality of life. The potential of advanced machine learning models like LSTM and GRU to provide more accurate traffic predictions lies in their ability to incorporate both temporal patterns and external factors such as weather conditions.

This study seeks to investigate these capabilities, offering preliminary insights into how these models could contribute to a more robust and efficient urban traffic management system.

4.2 OVERVIEW OF THE MODELS

4.2.1 LSTM Model:

he Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) that has been widely utilized in tasks involving sequential data. LSTM networks are equipped with a unique architecture that includes memory cells and gating mechanisms—specifically, input, forget, and output gates—that allow the model to retain or discard information as necessary.

This structure enables the LSTM to maintain context over long sequences, making it particularly effective in scenarios where long-term dependencies are critical. In this study, the LSTM model is explored for its potential to predict traffic volumes by capturing complex temporal patterns within the data.

4.2.2 GRU Model:

The Gated Recurrent Unit (GRU) model is a simplified variant of the LSTM, designed to achieve similar outcomes with fewer computational requirements. GRUs merge the forget and input gates into a single update gate and combine the cell and hidden states, resulting in a more streamlined architecture. This simplification is hypothesized to make GRUs faster to train while still effectively capturing essential temporal dependencies. The study investigates whether this efficiency might offer advantages in specific contexts, such as when computational resources are limited or when faster model training is desirable.

Both models are applied to historical traffic data to examine their capacity to predict future traffic volumes. The LSTM model's more complex architecture may provide fine-tuned control over memory retention, potentially making it effective in capturing detailed traffic patterns. Conversely, the GRU model's simplified structure is evaluated for its potential to balance performance with computational efficiency.

4.3 RESPONSE (DEPENDENT) AND INDEPENDENT VARIABLE(S)

The study's exploratory nature requires an examination of how various factors influence traffic volume, the primary outcome of interest. Traffic volume is defined as the number of vehicles passing a specific point on the road within a given time frame, and accurately predicting this variable is crucial for effective traffic management. To explore the potential impact on traffic volume, the study considers several independent variables:

- **Date and Time:** Temporal features, such as the hour of the day, day of the week, and month, are hypothesized to play a significant role in determining traffic patterns. Traffic volumes are expected to exhibit cyclical behaviour, with peaks during morning and evening rush hours and differences between weekdays and weekends.

- **Weather Conditions:** Weather-related factors, including temperature, precipitation, and cloud cover, are anticipated to affect traffic behaviour. This study explores whether incorporating these variables into the models can enhance prediction accuracy by allowing the models to account for external environmental conditions.

- **Holiday Information:** Holidays are likely to introduce variations in traffic patterns, deviating from regular working days. Including a binary indicator for holidays is expected to help the models adjust their predictions accordingly.

- **Previous Traffic Volume:** Historical traffic data is expected to be a strong predictor of future traffic volumes. The study examines how well the models leverage past patterns to inform their predictions, particularly in a time-series context where the relationship between past and future data points is critical.

4.4 FACTORS, LEVELS, AND PARAMETERS

This section outlines the key factors and parameters considered in the exploratory phase of this study. These elements are crucial for understanding how the models might perform under different conditions:

4.4.1 Number of Layers:

The number of layers in a neural network determines its depth and complexity. A deeper network has the potential to learn more intricate patterns from the data, which could be beneficial for capturing the complexities of urban traffic flows. The study suggests experimenting with different numbers of layers (e.g., 2, 3, or 4 layers) to find an optimal balance between model complexity and performance.

4.4.2 Units per Layer:

The number of neurons in each layer affects the model's capacity to process and store information. More units can increase the model's ability to capture detailed patterns but also make the model more computationally intensive. The study recommends testing different configurations of units per layer (e.g., 128, 64, 32) to evaluate how these adjustments influence the models' predictive power.

4.4.3 Learning Rate:

The learning rate is a critical parameter that determines how quickly the model adjusts its weights during training. A higher learning rate can speed up training but may lead to overshooting the optimal solution, while a lower learning rate allows for more precise adjustments. The study suggests exploring different learning rates (e.g., 0.001, 0.01, 0.0001) and potentially using learning rate schedules to fine-tune the models over time.

4.4.4 Batch Size:

The batch size, which refers to the number of samples processed before the model's internal parameters are updated, can influence the stability and efficiency of the training process. The study proposes testing a range of batch sizes (e.g., 32, 64, 128, 256) to find an optimal balance, potentially starting with smaller batch sizes for more precise updates and increasing them as the models stabilize.

4.4.5 Activation Functions:

The batch size, which refers to the number of samples processed before the model's internal parameters are updated, can influence the stability and efficiency of the training process. The study proposes testing a range of batch sizes (e.g., 32, 64, 128, 256) to find an optimal balance, potentially starting with smaller batch sizes for more precise updates and increasing them as the models stabilize.

4.4.6 Regularization Techniques:

Regularization techniques such as dropout and L2 regularization are considered to prevent overfitting. The study proposes experimenting with different dropout rates (e.g., 0.2, 0.3) and L2 regularization penalties (e.g., 0.001, 0.01) to evaluate how these adjustments impact the models' generalization ability.

4.4.7 Considerations:

Throughout the experimentation phase, the study remains flexible in tuning these parameters. If early experiments suggest overfitting despite using regularization, the study may revisit the model architecture, potentially simplifying it or increasing dropout rates. Conversely, if the models under-fit, adjustments such as increasing the number of layers or units, or modifying the learning rate, may be considered.

4.5 EXPERIMENTAL DESIGN

The experimental design of this study is structured to explore the potential of LSTM and GRU models in predicting traffic volumes. Given the exploratory nature of this work, the design allows for adjustments based on preliminary findings.

4.5.1 Data Preparation:

Data preparation is a foundational step in this exploration, involving the transformation of raw traffic data into a format suitable for model training. The following steps are considered essential for this process:

- **Handling Missing Values:** Missing data can potentially distort predictions, so the study considers techniques like imputation to address any gaps or the removal of incomplete records if necessary.

- **Scaling Features:** Scaling numerical features, such as temperature, is expected to ensure consistency across the dataset, making it easier for the models to process these variables.

- **Encoding Categorical Variables:** Categorical variables, such as weather conditions, are converted into numerical formats using methods like one-hot encoding, enabling the models to incorporate these factors into their predictions.

4.5.2 Randomization (Train/Test Split):

In this study, we aimed to build a robust predictive model for traffic flow using a dataset composed of time-ordered vectors, each representing traffic data for a specific time period. To ensure the accuracy and generalizability of our model, it was crucial to carefully consider how we split the dataset into training and testing subsets.

Given the temporal nature of the data, a simple random split could introduce potential biases, as it might allow the model to “peek” into future trends during training, thereby inflating its performance. To mitigate this risk and more accurately simulate real-world conditions, we employed a sequential, time-based data splitting approach.

Sequential Time-Based Split:

The dataset, spanning several consecutive days of traffic data, was divided based on time. Specifically, the first 70% of the dataset, corresponding to the earlier time periods, was used to train the model. This segment of data represents historical traffic patterns, providing the model with a comprehensive view of how traffic volumes evolved over time.

The rationale behind this approach is to mimic a scenario where the model learns from past data, which is a common practice in time-series forecasting.

By feeding the model data from the first 70% of the time periods, we allow it to recognize patterns, trends, and cyclical behaviours inherent in the traffic data. These insights are crucial for making informed predictions about future traffic volumes.

Testing on Subsequent Data:

Once the model was trained on the first 70% of the dataset, its performance was evaluated using the remaining 30% of the data. This portion of the dataset corresponds to the later time periods that the model had not encountered during training.

By testing the model on this unseen data, we aimed to assess its ability and make accurate predictions in a real-world context, where future traffic conditions are unknown.

This sequential splitting method offers several advantages:

- **Realistic Scenario Simulation:** By training on past data and testing on future data, this closely simulate the conditions under which the model would be used in practice. This approach ensures that the model's performance metrics reflect its true predictive capabilities, rather than being artificially inflated by data leakage.

- A**voidance of Data Leakage:** Randomly splitting the dataset could lead to situations where data points from the same time period are present in both the training and testing sets. This overlap could allow the model to interpolate between closely related points, resulting in predictions that seem highly accurate but do not genuinely reflect the model's ability to predict future trends.

- **Robustness of Predictions:** By focusing the training on historical data and testing on subsequent, unseen data, we ensure that the model's predictions are based on learned patterns and not on the ability to interpolate between known data points. This approach provides a more robust measure of how the model will perform when faced with new, unseen traffic conditions.

4.5.3 Experiment Performance and Revisions:

Throughout the experimental phase, the study conducts multiple rounds of training and testing to refine the models and improve their performance.

Given the exploratory nature of this work, the following steps are considered:

- **Initial Experiment:** The LSTM and GRU models are first trained with default settings over a substantial number of epochs. This initial phase tests various data preprocessing methods to establish a baseline for the models' performance.

- **Model Tuning:** Based on preliminary results, the models were fine-tuned by adjusting key parameters such as the number of layers, units per layer, and learning rate. This tuning process was intended to enhance the models' ability to capture both common patterns and outliers in the traffic data, ensuring that the models could generalize well to new data.

- **Data Imbalance Handling:** Recognizing that traffic data may be imbalanced, with more data points during peak hours compared to off-peak periods, the study explored techniques such as under-sampling and oversampling to address this issue. These methods were applied to create a more balanced dataset, potentially improving the models' ability to predict rare but significant traffic patterns, such as those occurring during late-night hours or extreme weather conditions.

4.5.4 Measuring Classifier Performance:

In this study, evaluating the performance of the LSTM and GRU models is crucial for understanding their effectiveness in predicting traffic volumes. Several performance metrics are employed to provide a comprehensive assessment, with a focus on both accuracy and the ability to handle the nuances of the dataset.

Precision and Recall:

Given the potential imbalance in traffic data, precision and recall were prioritized as key metrics. Precision measures the ratio of correctly predicted positive observations to the total predicted positives, highlighting the model's accuracy in predicting high-traffic volumes.

Recall measures the ratio of correctly predicted positive observations to all observations in the actual class, focusing on the model's ability to identify all instances of high traffic volumes.

Mean Absolute Error (MAE):

MAE is used to measure the average magnitude of errors between predicted and actual values. It provides a straightforward interpretation of prediction accuracy by indicating how much, on average, the predictions deviate from the actual traffic volumes. This metric is particularly useful in scenarios where absolute differences are more critical than relative differences.

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE):

MSE emphasizes larger errors by squaring the differences between predicted and actual values, making it a crucial metric for understanding the model's ability to minimize significant errors. RMSE, the square root of MSE, presents the error in the same units as the original data, offering an intuitive understanding of prediction accuracy.

MSE = (1/n) * Σ (y_i - ŷ_i)^2

where:

- n is the number of data points.
- y_i is the actual value for the ith data point.
- ŷ_i is the predicted value for the ith data point.
- (y_i - ŷ_i)^2 is the squared difference between the actual and predicted values.

Both metrics are essential for assessing how well the models perform in minimizing errors that could have substantial impacts on traffic management decisions.

Application of Metrics:

During the experimental phase, these metrics were applied to both the training and test sets to monitor the models' performance. Precision and recall were closely monitored to ensure that the models could accurately identify high-traffic periods, which are critical for effective traffic management. MAE, MSE, and RMSE were used to gauge the overall accuracy of the models, with particular attention to how well the models handled peak traffic volumes and periods of low traffic.

4.5.5 Algorithm Comparison and Selection:

Both the LSTM and GRU models were implemented to predict traffic volumes. The selection and comparison of these models are essential steps to determine which model provides better predictive performance for urban traffic management applications

Comparison Criteria:

The models were compared based on several performance metrics, including precision, recall, accuracy, MAE, MSE, and RMSE. Each metric offered a different perspective on the models' performance, allowing for a comprehensive evaluation.

The key criteria for comparison were how well each model captured the traffic patterns, particularly during peak hours, and how effectively they minimized prediction errors.

5. RESULTS

5.1 INTRODUCTION

Managing traffic in urban environments is crucial for ensuring smooth transportation and reducing congestion. Accurate traffic volume prediction helps in planning and managing road usage, reducing traffic jams, and enhancing overall urban mobility. This project aimed to predict traffic volume using advanced machine learning models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models.

By forecasting the number of vehicles on the road, urban planners can implement strategies to improve traffic flow and enhance transportation efficiency.

5.2 DATA PREPARATION

The Metro Interstate Traffic Volume dataset served as the foundation for this study. This dataset provided detailed information about traffic patterns over time, including various features such as date-time, temperature, weather conditions, and traffic volume.

5.2.1 Data Cleaning and Feature Extraction

Data preparation began with a thorough cleaning process. The dataset originally contained 48,204 entries, each representing an hour of traffic volume data. Fortunately, the dataset had no missing values, ensuring completeness. To help the models understand temporal patterns in the data, additional features were extracted from the date-time column:

- **Hour of the Day:** Traffic volume varies significantly by hour, typically peaking during morning and evening rush hours.
- **Day of the Week:** Weekdays tend to have higher traffic volumes compared to weekends.
- **Month:** Seasonal variations can affect traffic volumes, with some months experiencing higher traffic due to holidays or weather conditions.

5.3 MODEL IMPLEMENTATION

The heart of the project involved building and training two types of recurrent neural network models: LSTM and GRU. These models are particularly suited for time-series prediction tasks due to their ability to remember patterns over long sequences.

The final model configuration included:

- Number of layers: 4
- Neurons in each layer: 128, 64, 32, 16
- Batch size: 256
- Learning rate: 0.001
-

5.3.1 LSTM Model

The LSTM model was the first to be trained. This model is known for its ability to learn from long-term dependencies in data, making it ideal for predicting traffic volumes based on historical trends. The training process involved feeding the model with past traffic data and tuning its settings to find the optimal configuration.

This included adjusting the number of layers, the number of neurons in each layer, the batch size, and the learning rate. Each of these parameters was carefully selected to ensure the model performed at its best.

The model was trained over 500 epochs, with training and validation losses monitored to ensure proper convergence.

Training Loss (Solid Red Line):

- **Trend:** The training loss decreases steadily over the 500 epochs.

- **Interpretation:** The loss function here is the Mean Squared Error (MSE), which is defined. (refer section 4.5.4)

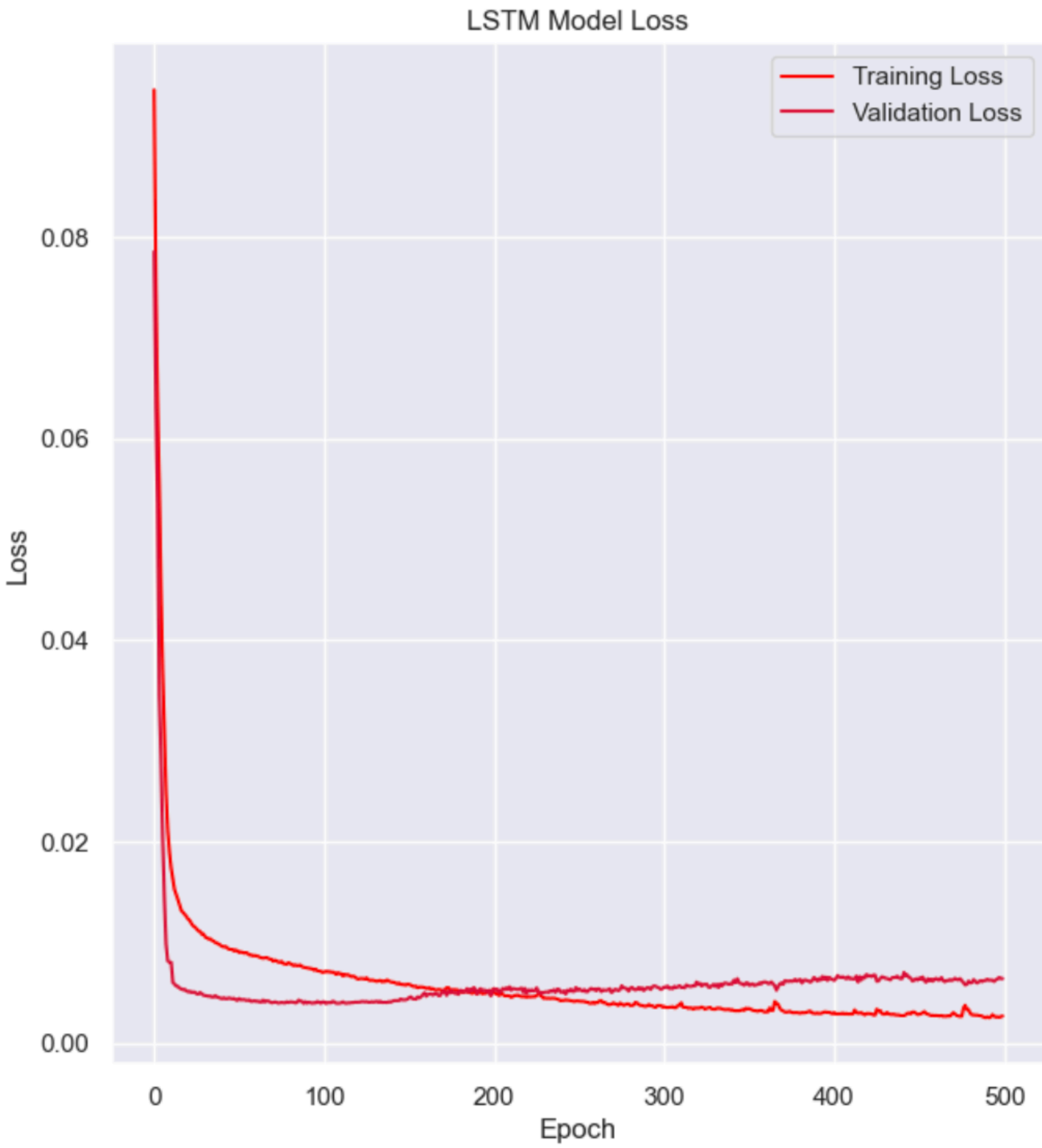
The steady decrease in the training loss indicates that the LSTM model is continuously improving its predictions on the training data.

As the training progresses, the squared differences between the actual and predicted values decrease, meaning that the model is fitting the training data more accurately.

Validation Loss (Dashed Crimson Line):

- **Trend:** The validation loss decreases initially but starts to increase after approximately 200-300 epochs.

- **Interpretation:** The decrease in validation loss suggests that the model is learning generalizable patterns from the training data that also reduce the prediction errors on unseen validation data.

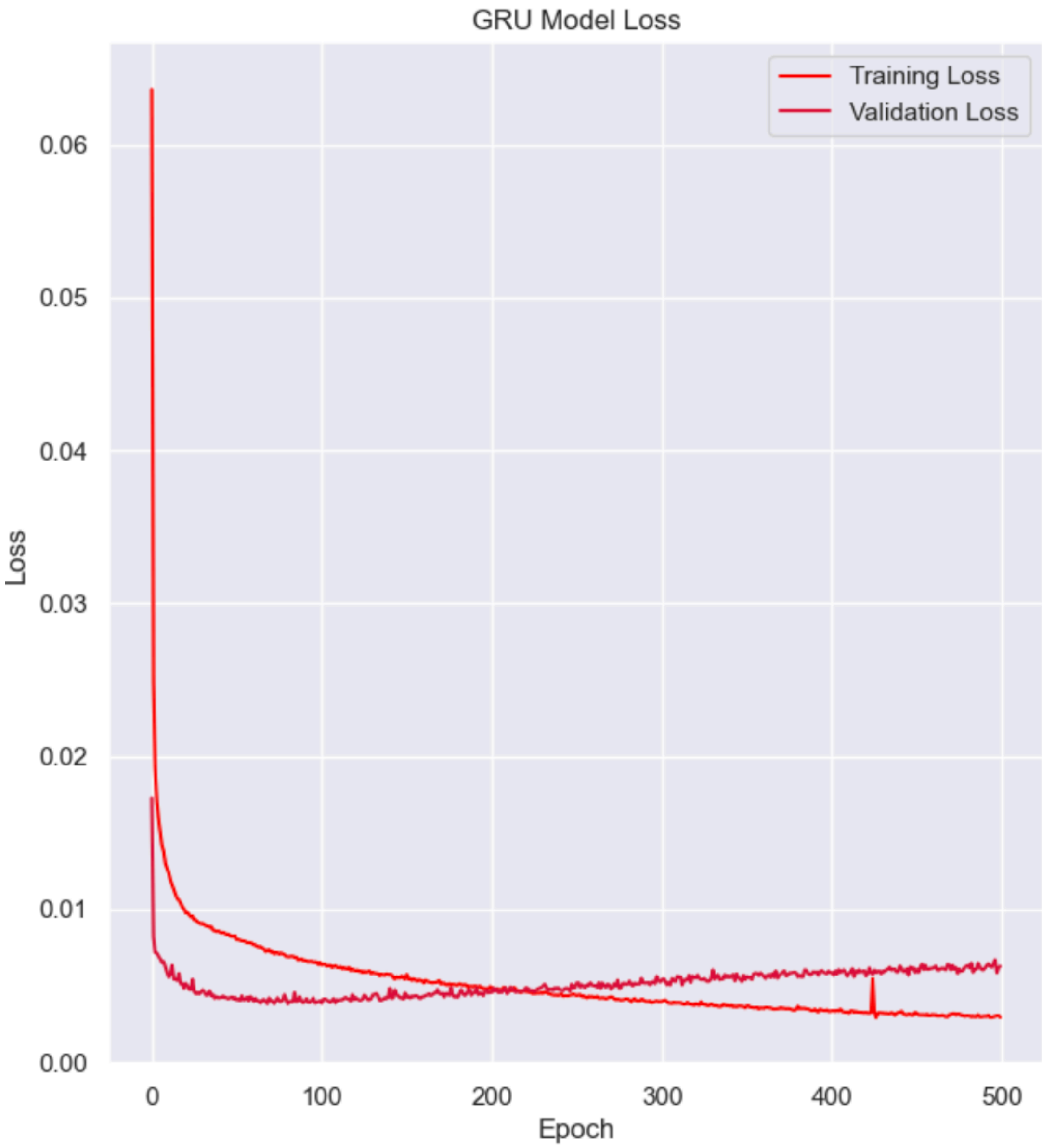


LSTM loss

5.3.2 GRU Model

Next, the GRU model was implemented. While similar to the LSTM model, the GRU is designed to be simpler and faster, making it a strong alternative for prediction. The GRU model underwent a similar training process, where its hyper parameters were fine-tuned similar to LSTM model to improve its accuracy in predicting traffic volumes.

The model was also trained over 500 epochs, with training and validation losses monitored to ensure proper convergence.



GRU loss

Training Loss (Solid Red Line):

- **Trend:** The training loss decreases rapidly in the initial epochs, showing that the model quickly learns the fundamental patterns in the data. The loss continues to decline more gradually as training progresses, indicating further refinement of the model's learning.

- **Interpretation:** The steady decrease in training loss throughout the epochs suggests that the GRU model is effectively learning from the training data. The low final loss value indicates that the model has successfully minimized errors on the training data.

The spike in training loss could be due to an anomaly or instability during the training process, possibly caused by issues such as a sudden change in learning rate, data irregularities, or a gradient explosion. After the spike, the loss returns to near-zero, indicating that the model is able to recover from the anomaly and continue learning effectively.

Validation Loss (Dashed Crimson Line):

- **Trend:** The validation loss also decreases rapidly in the initial epochs, following a similar pattern to the training loss. It stabilizes after around 100 epochs, with only minor fluctuations, indicating consistent performance on unseen data.

- **Interpretation:** The validation loss closely mirrors the training loss, indicating that the GRU model is not overfitting and generalizes well to new data. The slight increase in validation loss towards the end of training could suggest the beginnings of overfitting, but overall, the model maintains good generalization performance.

5.4 OVERALL ANALYIS

The comparison of the LSTM and GRU model loss curves reveals distinct characteristics and strengths in predicting traffic volumes. The LSTM model shows a rapid decline in both training and validation loss during the initial epochs, indicating effective learning, but it begins to exhibit signs of overfitting after around 200-300 epochs, as the validation loss starts to diverge from the training loss. This suggests that while the LSTM is powerful in capturing complex patterns, its ability to generalize to new data diminishes over time. In contrast, the GRU model maintains a closer alignment between training and validation losses throughout the 500 epochs, demonstrating strong generalization and stability.

The GRU model's consistent performance, with minimal divergence between losses, highlights its resilience and effectiveness in avoiding overfitting, making it a more reliable choice for scenarios where robust and consistent predictions are crucial. While the LSTM may be better suited for capturing long-term dependencies, it requires careful management to prevent overfitting, whereas the GRU offers a more balanced and stable approach, making it particularly well-suited for real-time traffic prediction tasks where reliability is essential.

6. EVALUATION

When evaluating the performance of the LSTM and GRU models through key metrics, a nuanced picture emerges, highlighting both the strengths and subtle differences between the two models. The Mean Squared Error (MSE) is a critical measure of a model's accuracy, representing the average of the squares of the errors between predicted and actual values. For the LSTM model, the MSE is recorded at 179,189.4908, while the GRU model achieves a slightly lower MSE of 178,980.8104. This marginal difference indicates that both models are highly effective in minimizing prediction errors, but the GRU model demonstrates a slight edge, suggesting it is marginally more accurate in capturing the overall patterns in the data.

The Root Mean Squared Error (RMSE), which provides a measure of the standard deviation of the prediction errors, further reinforces this observation. The LSTM model has an RMSE of 423.3078, whereas the GRU model records a slightly lower RMSE of 423.0612. This consistency in RMSE between the two models indicates that both are performing similarly in terms of error distribution, with the GRU model again showing a slight advantage. The lower RMSE for the GRU model implies that it is better at minimizing larger errors, which is crucial for maintaining predictive accuracy, especially in applications where even small deviations can have significant consequences.

In addition to these metrics, the overall loss of each model provides further insights into their performance. The LSTM model records a loss of 0.0041, closely followed by the GRU model with a loss of 0.004. Both models also show identical Mean Absolute Errors (MAE) of 0.043, highlighting that, on average, the predictions of both models deviate from the actual values by a similar amount. The MAE is a direct measure of prediction accuracy and suggests that both models are equally competent in minimizing absolute errors.

However, where the GRU model notably outperforms the LSTM is in the Mean Absolute Percentage Error (MAPE). The MAPE is particularly useful as it expresses prediction errors as a percentage, making it easier to interpret the relative size of errors in the context of the data. The LSTM model records a MAPE of 23,394.4199, which is significantly higher than the GRU model's MAPE of 7,541.0254. This substantial difference indicates that the GRU model is far more effective in handling percentage errors, which is crucial in scenarios where relative accuracy is important, such as predicting traffic volumes or other time-series data where the magnitude of the error in relation to the actual value matters.

The lower MAPE in the GRU model suggests that it can provide more reliable predictions, particularly in real-world applications where understanding the proportion of error relative to the actual values is critical. This makes the GRU model more suitable for tasks requiring precise percentage-based predictions, ensuring that even small percentage errors are minimized.

In summary, while both the LSTM and GRU models perform exceptionally well across various metrics, the GRU model's slight edge in MSE, RMSE, and its significant advantage in MAPE indicate that it may offer better overall accuracy and reliability. The GRU model's ability to handle errors more effectively, particularly in terms of minimizing relative percentage errors, makes it a stronger candidate for applications that demand high precision and consistent performance across diverse scenarios.

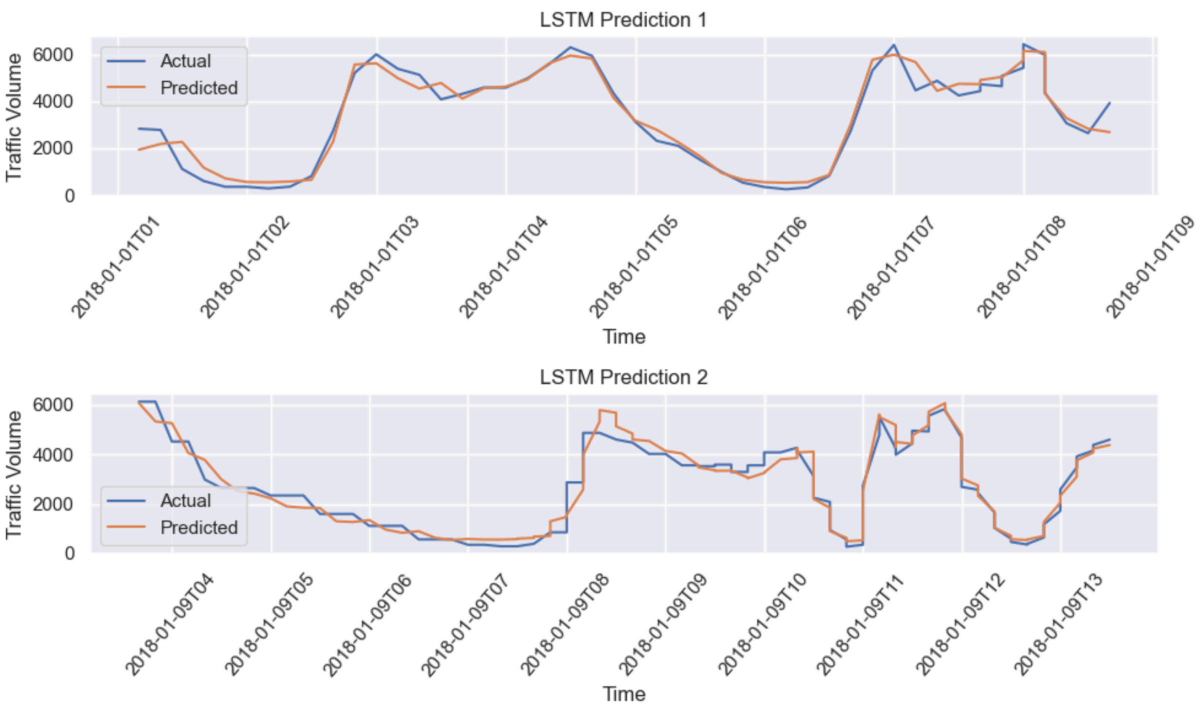
MODEL	LOSS	MAE	MAPE	MSE	RMSE
LSTM	0.0041	0.043	23394.4	179189.4	423.3
GRU	0.004	0.043	7541.02	178980.8	423.06

Metrics

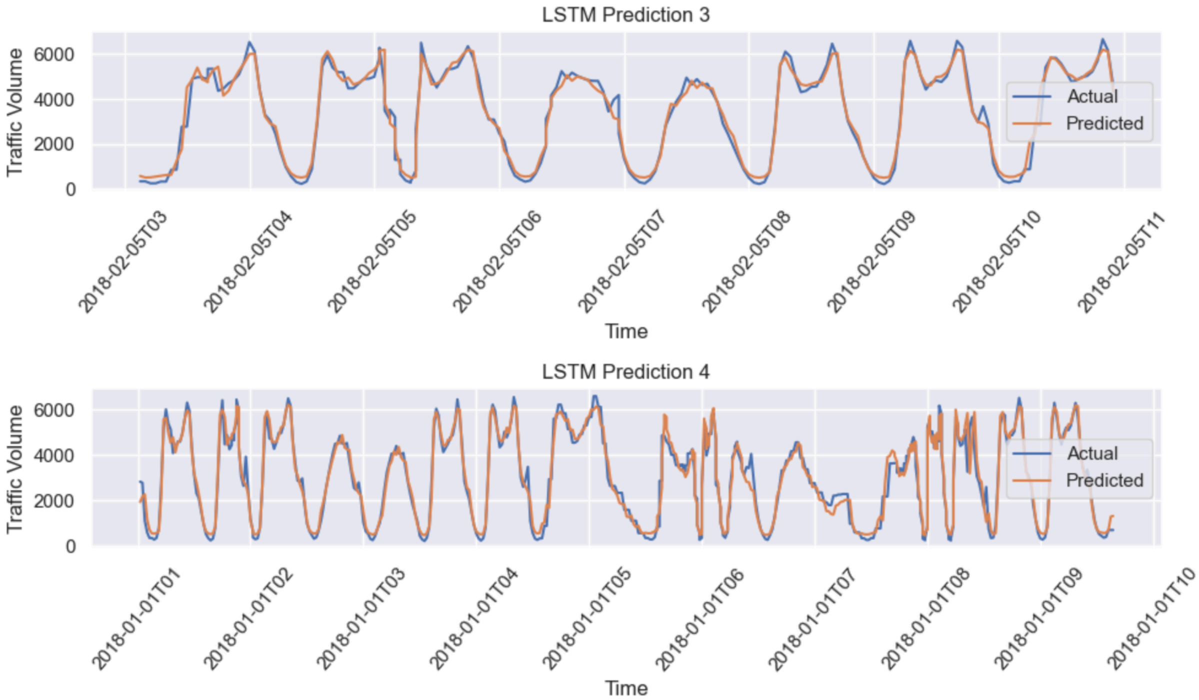
6.1 VISUALIZATIONS

To better understand the models' performance, various visualizations were created.

6.1.1 LSTM predictions

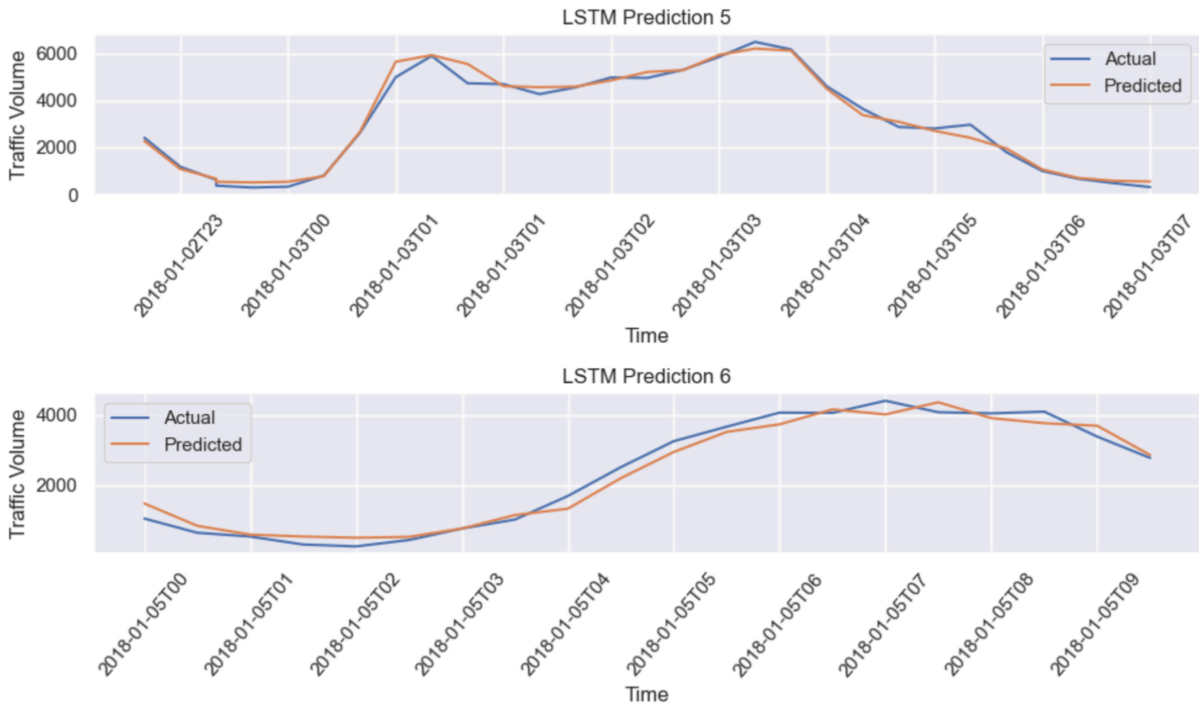


LSTM prediction 1-2



LSTM Prediction 3-4

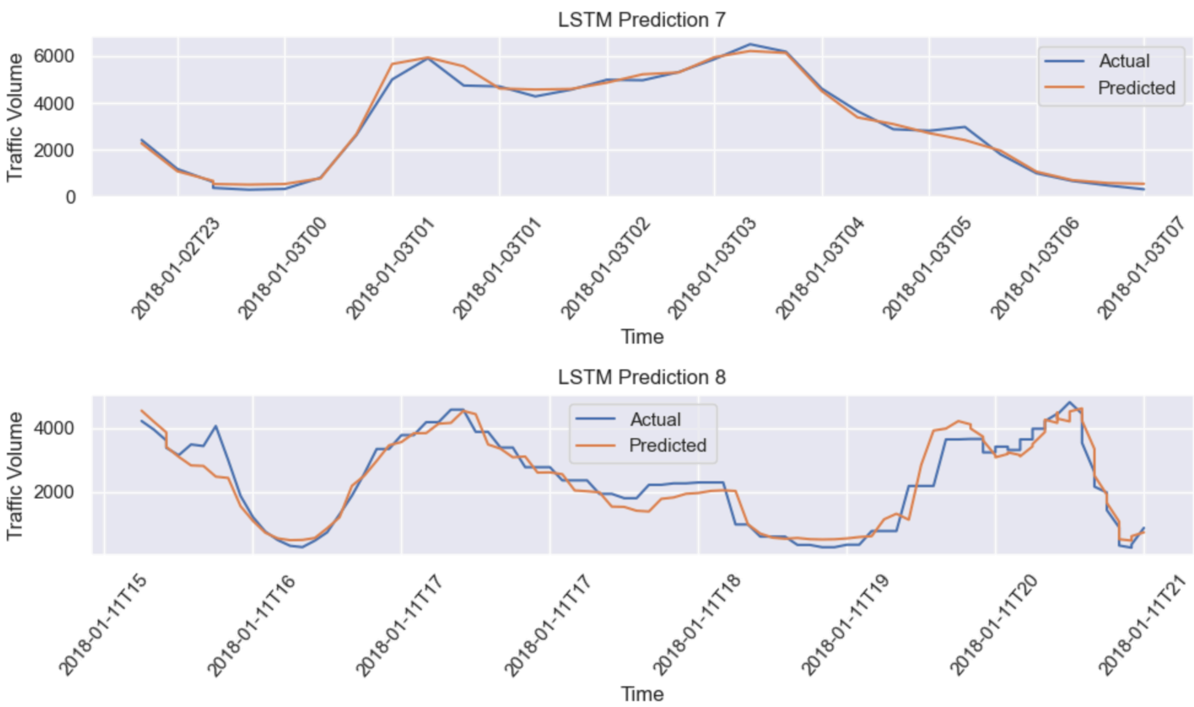
The LSTM model's performance across the eight predictions demonstrates its ability to closely align with actual traffic volumes, capturing the daily cyclical patterns and nuanced fluctuations with considerable accuracy. The analysis of these predictions, accompanied by specific values from the plots, provides a detailed understanding of the model's strengths and areas for improvement.



LSTM Prediction 5-6

LSTM Predictions 1 through 8 consistently show that the model is adept at forecasting peak traffic periods, with actual volumes often reaching around 6,000 vehicles per hour, as seen in **Prediction 1** and **Prediction 4**.

During these high-traffic periods, the LSTM model's predictions align closely with the actual data, indicating its reliability in scenarios where managing peak traffic is critical. For instance, in **Prediction 4**, the model accurately predicts the peak volume at approximately 6,000 vehicles per hour and the subsequent decline, showing only minor deviations.

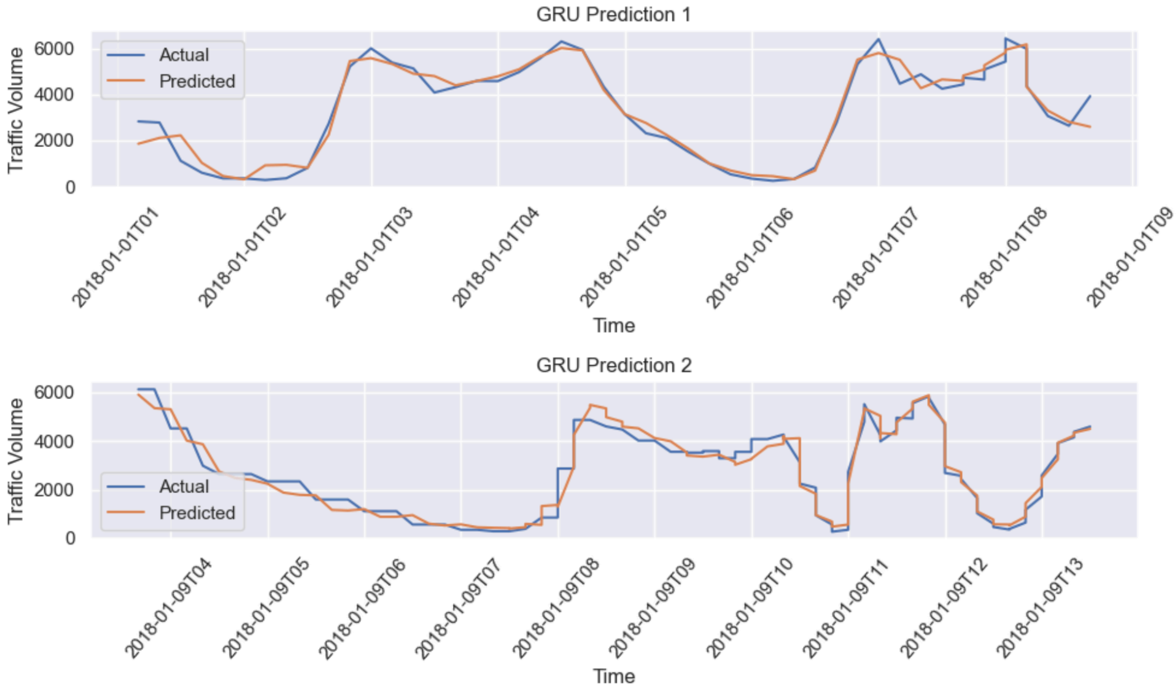


LSTM Prediction 7-8

In **Prediction 5**, the LSTM model captures the transition from low traffic volumes in the early morning hours, around 1,500 vehicles per hour, to a peak of approximately 5,500 vehicles per hour as the day progresses. This prediction illustrates the model's ability to handle the rising phase of traffic, although it slightly underestimates the volume during the peak's decline.

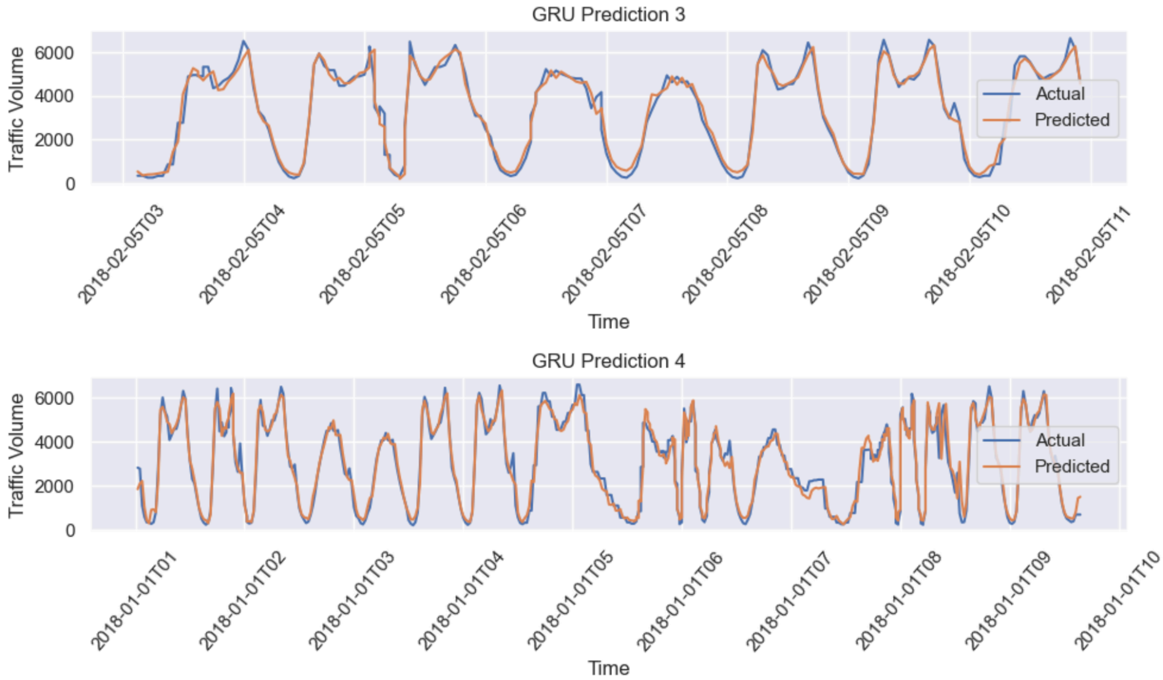
Predictions 6 and 7 further highlight the model's capability, with predicted traffic volumes closely matching actual values, particularly during the transition from peak to off-peak hours. For example, in **Prediction 6**, the model predicts a peak of around 4,000 vehicles per hour, which aligns well with the actual recorded volumes. However, minor deviations are observed during the decline phase, where t

6.1.2 GRU predictions



GRU Prediction 1-2

The GRU model's performance across the eight predictions showcases its effectiveness in predicting traffic volumes, closely aligning with actual data while handling fluctuations and peak traffic volumes

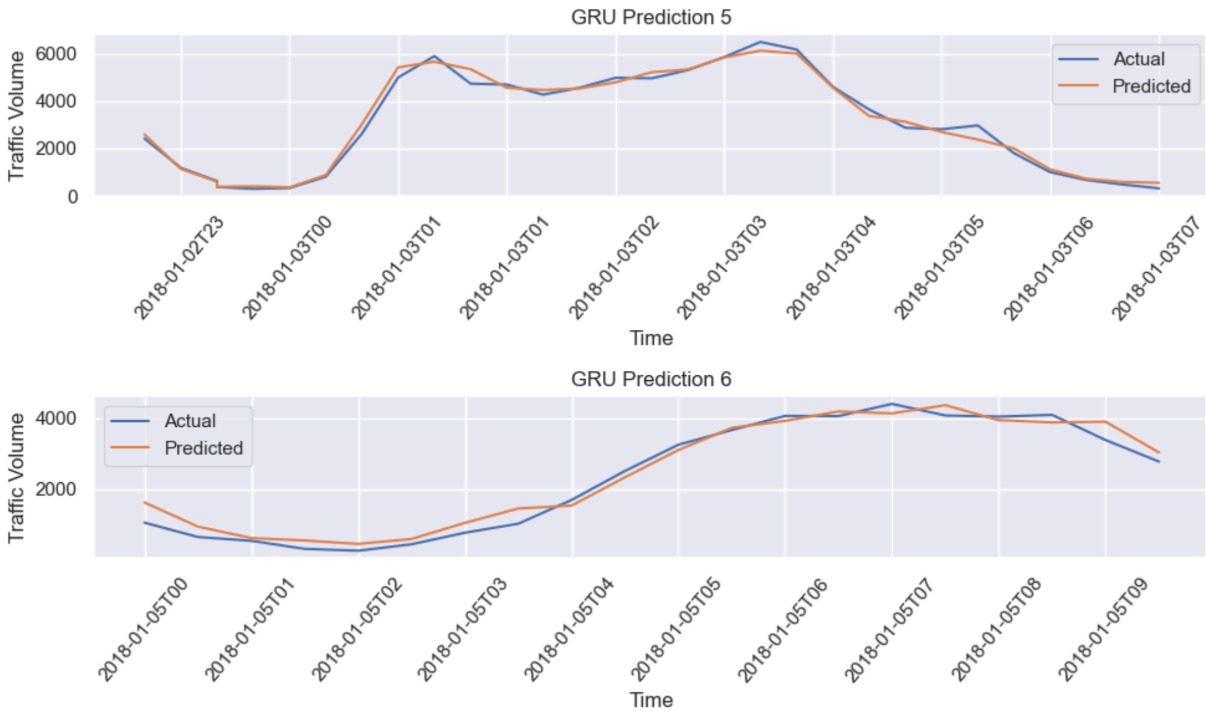


GRU Prediction 3-4

with precision. By examining the predictions collectively, we can observe the model's strengths, especially in capturing cyclical traffic patterns, and identify areas where minor deviations occur.

GRU Predictions 1 through 8 consistently demonstrate the model's ability to track the rise and fall of traffic volumes throughout the day.

The plots reveal that the GRU model effectively predicts peak traffic periods, often reaching around 6,000 vehicles per hour, as seen in **Prediction 1** and **Prediction 3**. This strong alignment during high-traffic times suggests that the GRU model is well-calibrated for capturing the critical periods of urban traffic flow, which are essential for planning and congestion management.



GRU predictions 5-6

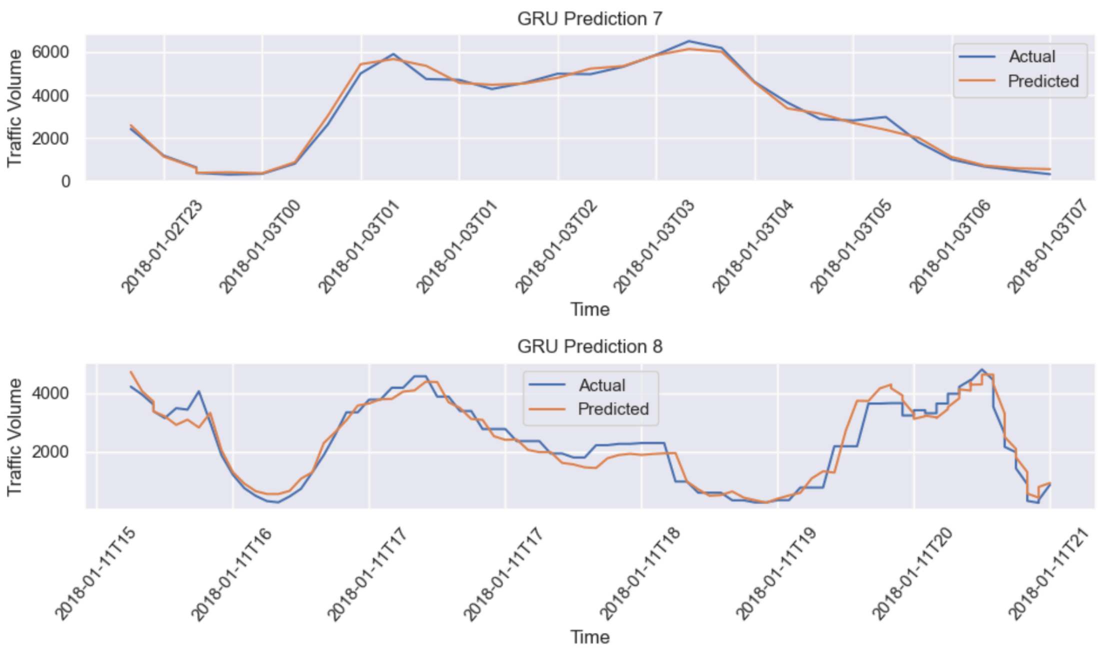
In **Prediction 2**, the GRU model captures the transition from a high traffic volume, approximately 5,500 vehicles per hour, to a significantly lower volume, reflecting the model's capability in predicting both the peak and off-peak hours.

However, small deviations are observed where the model slightly underestimates the troughs and overestimates the recovery periods. These deviations, though minimal, indicate a slight smoothing effect, similar to the LSTM model, where the GRU tends to average out sharp transitions.

Predictions 4 and 5 further highlight the GRU model's performance, with predicted volumes closely matching actual data during both high and low traffic periods. In **Prediction 4**, for instance, the model accurately tracks a series of rapid traffic volume fluctuations, suggesting the GRU's robustness in handling volatile traffic conditions. The model's ability to maintain accuracy during these rapid changes is particularly noteworthy, given the complexity of predicting such dynamic patterns.

In **Predictions 6 and 7**, the model continues to demonstrate its effectiveness by closely mirroring actual traffic volumes during both gradual and rapid transitions.

For instance, in **Prediction 6**, the GRU model captures the morning rise in traffic, reaching about 4,000 vehicles per hour, and maintains accuracy through the peak. This prediction underscores the model's capability in handling both steady and abrupt changes in traffic volume.



GRU Predictions 7-8

The final prediction, **GRU Prediction 8**, exemplifies the model's ability to manage more complex traffic patterns, particularly during periods of erratic volume changes.

While the model continues to perform well, minor deviations occur during the sharp transitions between peaks and troughs.

These discrepancies are relatively small and reflect the model's slight tendency to smooth out rapid fluctuations, a common characteristic observed across different time periods.

6.2 PRACTICAL IMPLICATIONS

6.2.1 For Peak Traffic Prediction and Precision:

The LSTM model is likely to perform better in scenarios where high precision is required, particularly during peak traffic periods. Its slightly superior ability to minimize large errors makes it more suitable for applications where accurate prediction of high traffic volumes is critical, such as in congestion mitigation strategies during rush hours.

This model would be the preferred choice when the primary goal is to achieve the highest possible accuracy in forecasting traffic patterns.

6.2.2 For Real-Time Applications and Computational Efficiency:

The GRU model, on the other hand, is better suited for real-time applications due to its lower computational demands. It performs comparably to the LSTM model while being faster and more efficient, making it ideal for scenarios where rapid updates and predictions are necessary.

This includes real-time traffic flow optimization, dynamic signal control, and situations where quick response times are crucial, such as in emergency management or during unexpected traffic disruptions.

Final Decision:

For applications that require the highest level of accuracy, particularly in managing peak traffic periods, the LSTM model is recommended. However, if the system demands quick, real-time predictions with slightly less emphasis on minimizing every prediction error, the GRU model is a strong contender.

Both models have their strengths, and the choice should align with the specific goals and constraints of the traffic management system.

7. CONCLUSION

When comparing the LSTM and GRU models, the analysis reveals that both models demonstrate strong capabilities in predicting urban traffic volumes, each with its own distinct strengths. Both models effectively capture the cyclical nature of traffic flow, especially during peak periods, with predictions that closely align with actual recorded volumes. However, there are subtle differences in their performance that can influence their application in traffic management systems.

Accuracy and Alignment:

Both LSTM and GRU models perform remarkably well in aligning with actual traffic volumes, particularly during high-traffic periods where volumes reach approximately 6,000 vehicles per hour.

The LSTM model tends to show slightly better performance in terms of minimizing errors during peak periods, maintaining a tighter fit to the actual data as evidenced by its Mean Squared Error (MSE) of 179,189.4908 and Root Mean Squared Error (RMSE) of 423.3078. On the other hand, the GRU model, with an MSE of 178,980.8104 and RMSE of 423.0612, shows comparable accuracy, with a slight edge in handling smaller fluctuations.

Handling of Fluctuations:

One of the key differences between the two models lies in their handling of rapid transitions between traffic peaks and troughs. The LSTM model exhibits a slight smoothing effect during these transitions, occasionally underestimating or overestimating traffic volumes as the flow changes rapidly. This smoothing effect is also present in the GRU model, but to a slightly lesser extent, which allows the GRU model to capture more abrupt changes with greater fidelity, as seen in the GRU prediction plots.

Error Metrics:

When considering the overall error metrics, both models show similar performance with negligible differences in their Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The LSTM model recorded a Loss of 0.0041, an MAE of 0.043, and a MAPE of 23,394.4199, while the GRU model exhibited a slightly lower Loss of 0.0040, an identical MAE of 0.043, and a considerably lower MAPE of 7,541.0254. The lower MAPE for the GRU model suggests that it handles relative errors more effectively, particularly during periods of lower traffic volume.

Computational Efficiency:

In terms of computational efficiency, the GRU model generally requires less time and resources for training due to its simpler architecture compared to the LSTM model. This makes the GRU model more suitable for real-time applications where speed is crucial, although the difference in performance is minimal. The LSTM model, with its more complex architecture, tends to be slightly more computationally expensive but offers marginally higher accuracy in predicting larger traffic volume changes.

Generalization and Robustness:

Both models generalize well across different time periods and traffic conditions, maintaining strong performance even during off-peak hours where traffic volumes are lower and more variable. The LSTM model, with its superior performance in minimizing large errors, may be better suited for applications where precision is critical, such as in peak-hour traffic management. Conversely, the GRU model's ability to handle rapid changes and its lower computational demands make it a strong candidate for real-time traffic prediction and management scenarios.

Overall Recommendation:

The choice between LSTM and GRU models ultimately depends on the specific requirements of the traffic management system. If the application demands the highest possible accuracy, particularly in minimizing large prediction errors during peak traffic periods, the LSTM model is recommended. However, if computational efficiency and the ability to handle rapid fluctuations with slightly lower error metrics are more critical, the GRU model would be the preferred choice. Both models, however, are highly effective and could be leveraged together to create a more robust and versatile traffic forecasting system.

Future works:

The successful application of LSTM and GRU models for urban traffic prediction opens up several opportunities for future research. Key areas include integrating additional data sources like social media and IoT sensors to enhance prediction accuracy, and developing hybrid models that combine the strengths of both LSTM and GRU. Expanding these models for long-term traffic forecasting and improving their interpretability are crucial next steps. Moreover, their application in autonomous vehicle networks could optimize routing and coordination. Future work should also explore dynamic learning capabilities, enabling models to adapt in real-time, and consider scalability for deployment in smart cities. Lastly, comparative studies with other advanced models, like Transformer models or Graph Neural Networks, could further enhance their utility.

Appendix A: Model and Algorithm

Model Architectures:

LSTM Model:

- Number of Layers: 4
- Neurons per Layer: 128, 64, 32, 16
- Batch Size: 256
- Learning Rate: 0.001
- Activation Function: ReLU
- Loss Function: Mean Squared Error (MSE)

GRU Model:

- Number of Layers: 4
- Neurons per Layer: 128, 64, 32, 16
- Batch Size: 256
- Learning Rate: 0.001
- Activation Function: ReLU
- Loss Function: Mean Squared Error (MSE)

Algorithm Description:

LSTM:

The Long Short-Term Memory (LSTM) network is designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs. The model incorporates memory cells to store information, and gating mechanisms to control the flow of information.

GRU:

The Gated Recurrent Unit (GRU) is a variant of the LSTM network, designed to be more computationally efficient while still capturing temporal dependencies. It uses a simpler architecture by combining the forget and input gates into a single update gate, making it faster to train.

Appendix B: GitHub Repository

GitHub Repository Link:

The complete implementation of the LSTM and GRU models, including data preprocessing, training, and evaluation scripts, is available on GitHub.

GitHub Repository: [https://github.com/NAS-510/Optimizing-Urban-Mobility]

This repository contains all the necessary code and dependencies to reproduce the results discussed in this study.

Appendix C: Dataset

Dataset Description:

Source: The dataset used in this study is the Metro Interstate Traffic Volume dataset, dataset includes a variety of features that influence traffic flow, such as temporal data (date and time) and weather-related factors (temperature, rain, snow, and cloud cover).

Structure:

Number of Entries: 48,204

Key Features:

- **Date_Time:** The timestamp indicating the date and hour of the traffic volume recording.
- **Traffic Volume:** The number of vehicles passing through a specific point on the Interstate during the recorded hour.
- **Temperature:** The temperature in Kelvin during the recorded hour.
- **Rain:** A binary indicator of whether there was rain during the recorded hour.
- **Snow:** A binary indicator of whether there was snow during the recorded hour.
- **Cloud Cover:** The percentage of cloud cover during the recorded hour.
- **Holiday:** Indicates whether the recorded day was a holiday.

Modifications:

- **Data Cleaning:** The dataset was checked for missing values, outliers, and inconsistencies. Any necessary cleaning steps, such as filling missing values or removing outliers, were applied to ensure data integrity.

- **Feature Engineering:** Additional features were derived from the Date_Time column, such as extracting the hour of the day, day of the week, and month to better capture temporal patterns in traffic flow.

Dataset Access:

The Metro Interstate Traffic Volume dataset used in this study is publicly available and can be accessed from [UCI Machine Learning Repository](https://archive.ics.uci.edu/ml/datasets/Metro+Interstate+Traffic+Volume).

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