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)

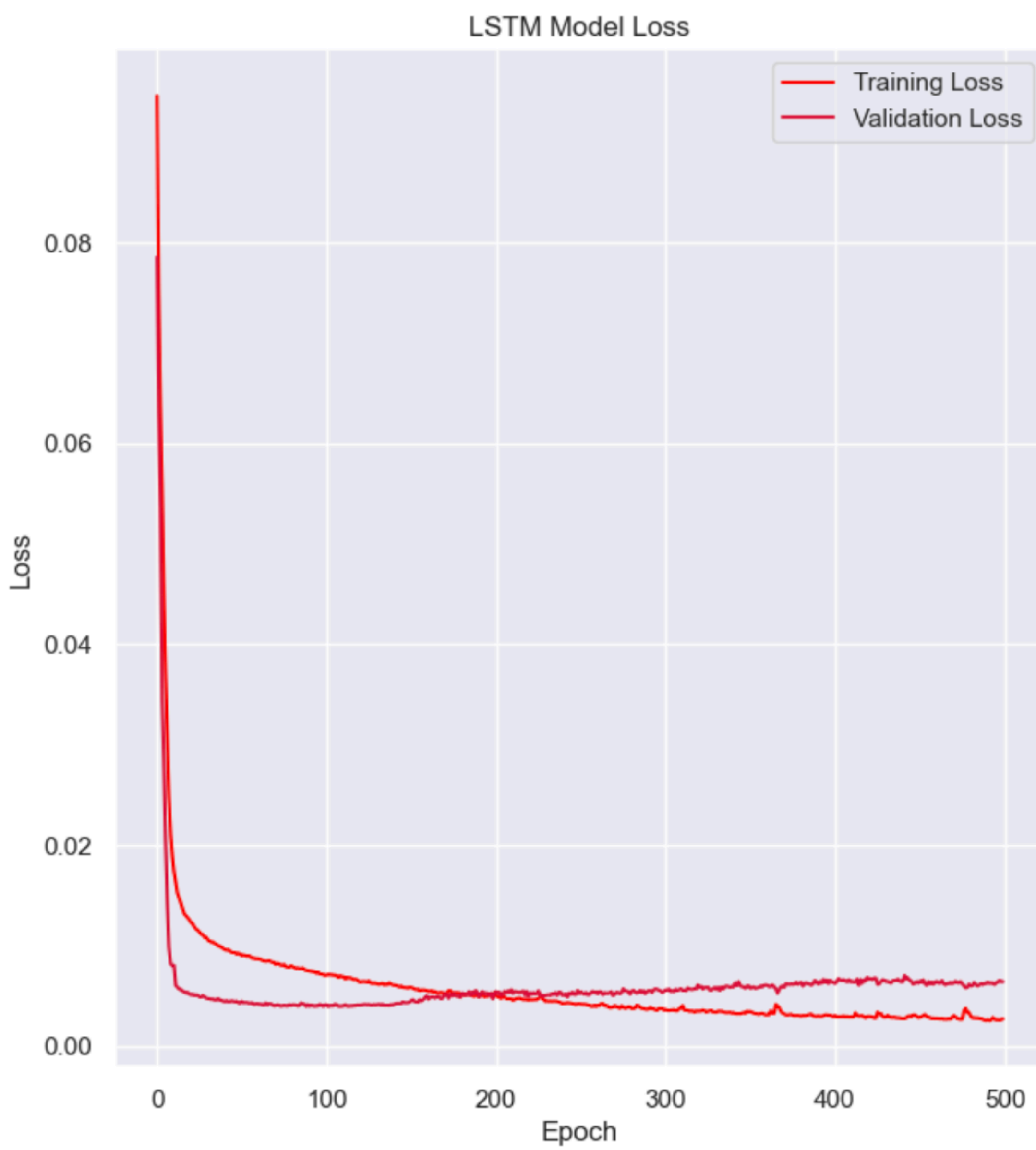
The steady decrease in the training loss indicates that the LSTM model is continuously improving its predictions on the training data.

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.

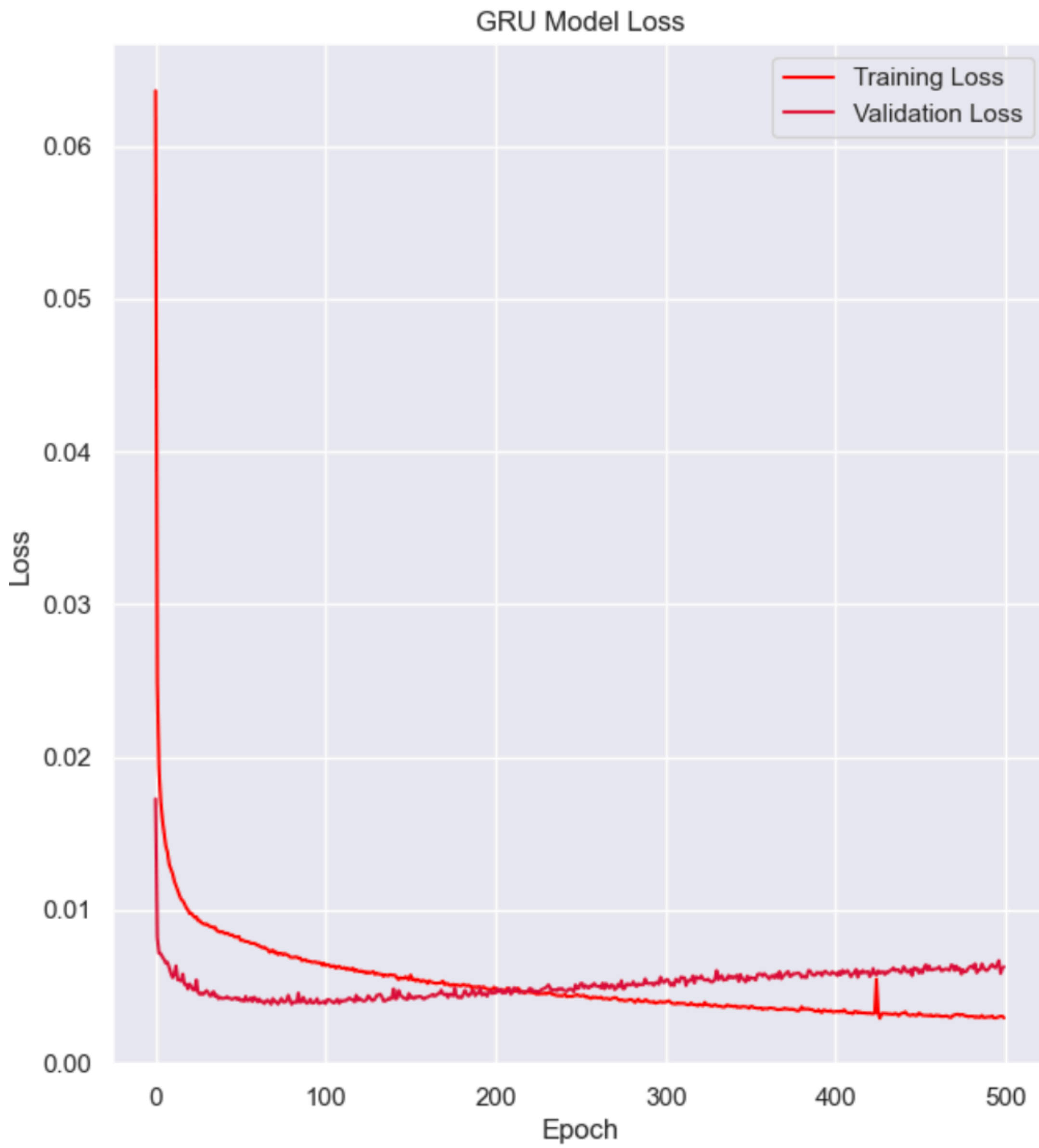


LSTM loss

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

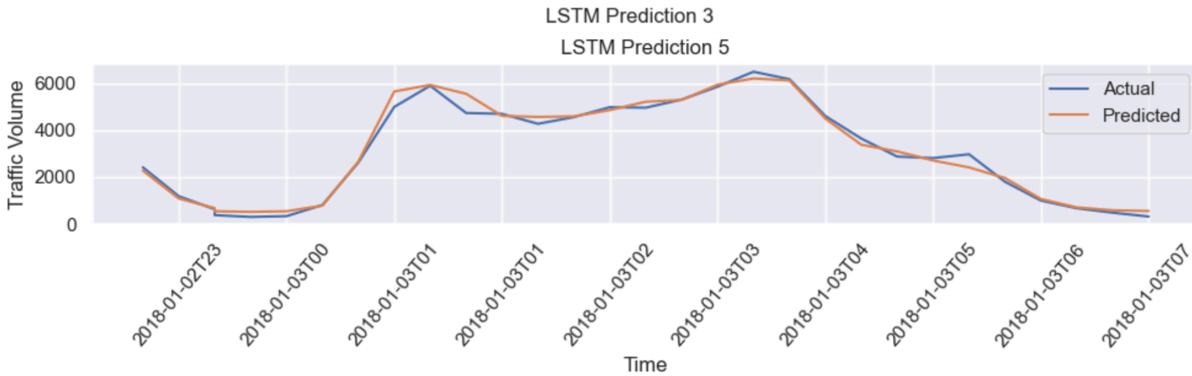
Metrics

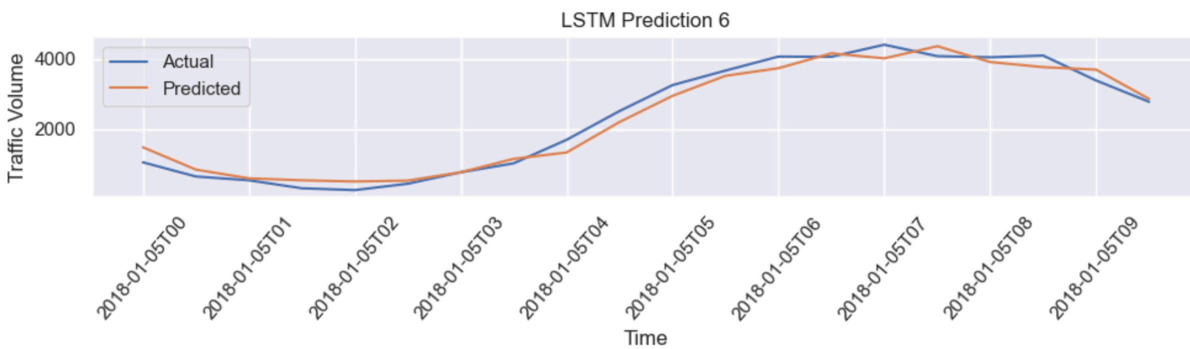
6.1 VISUALIZATIONS

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

6.1.1 LSTM predictions

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 3-4

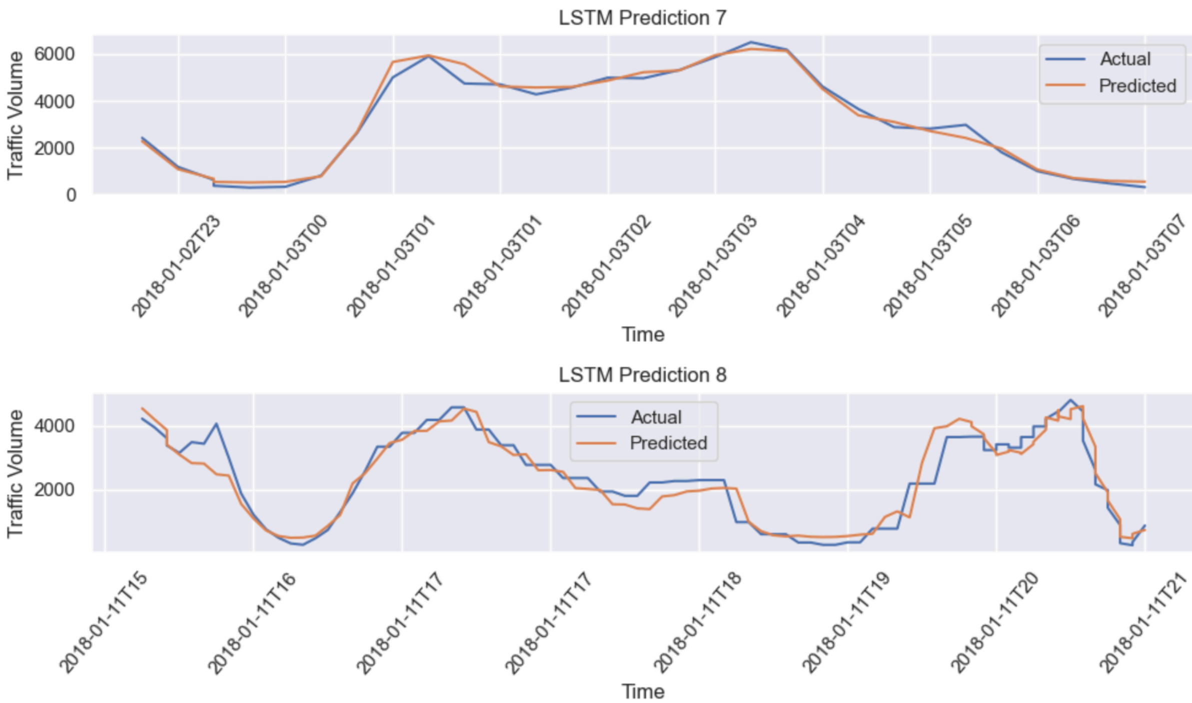
LSTM Prediction 5-6

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.

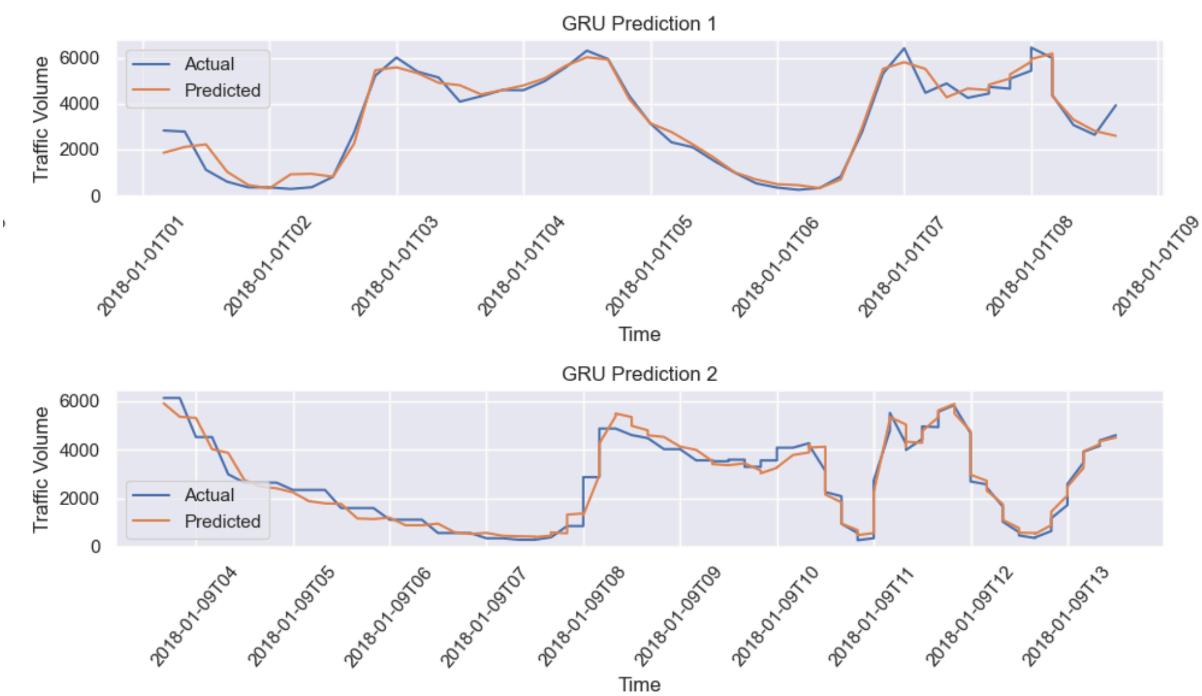
In **Prediction 5**, the LSTM model captures the transition from low traffic volumes in the early morning hours, around 1,500 vehicles per hour, to a peak of approximately 5,500 vehicles per hour as the day progresses. This prediction illustrates the model's ability to handle the rising phase of traffic,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



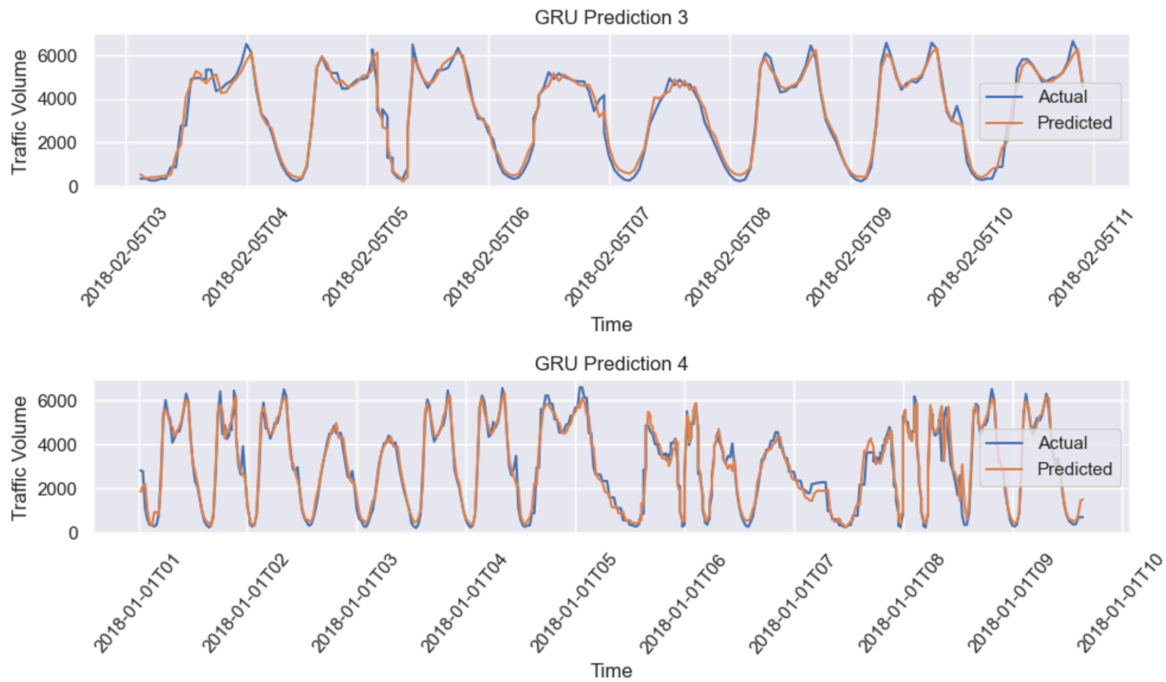
LSTM Prediction 7-8

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



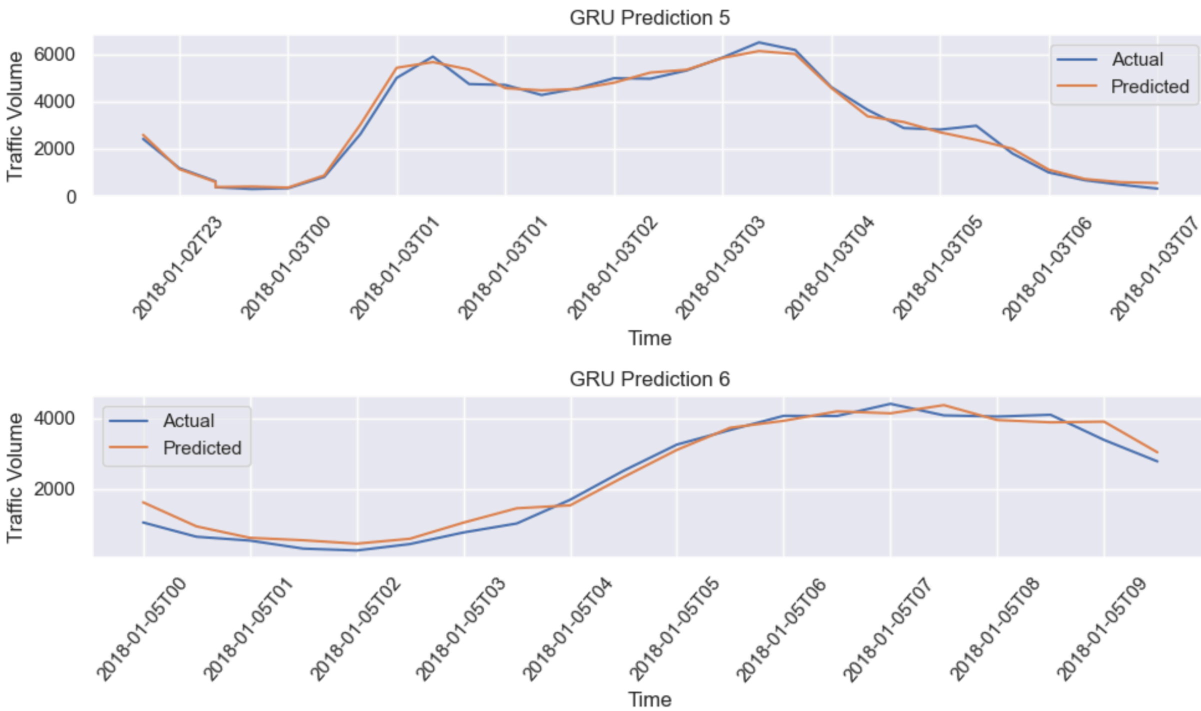
GRU Prediction 3-4

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.

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.



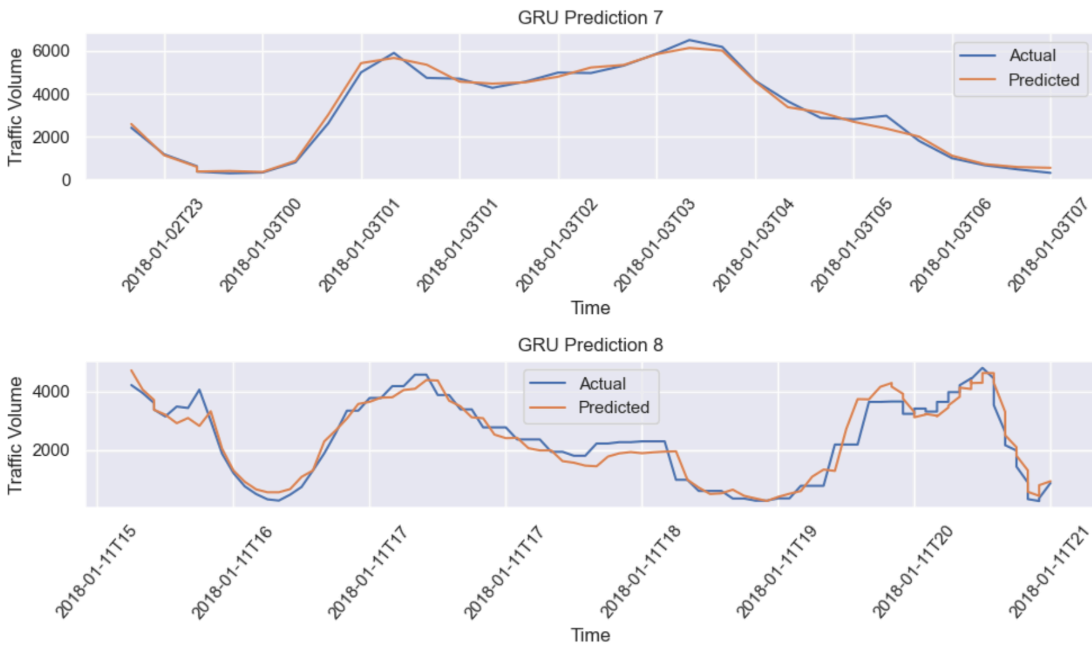
GRU predictions 5-6

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.