

traffic volume

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Class BO-3

Agenda

- INTRODUCTION
- THOUGHT & PROBLEM
- DETAILS
- RESULTS

INTRODUCTION

In today's fast-paced world, understanding and predicting traffic patterns is crucial for efficient transportation planning, traffic management.

our project aims to tackle this challenge by leveraging the power of Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTMs) and Gated Recurrent Unit (GRU) models, to forecast traffic volume.



Accurately predicting traffic volume is essential for various applications, such as route planning, traffic signal optimization, and resource allocation. However, the task is often hindered by factors like weather conditions, events, and the complex interactions between different roads and intersections. Developing an effective model that can reliably forecast traffic volume is crucial for improving transportation system efficiency and enhancing the overall commuter experience.

THOUGHT

Traffic volume prediction is a complex task that requires the ability to capture the inherent temporal and sequential nature of traffic data. Traditional forecasting methods may struggle to account for the dynamic and non-linear patterns present in traffic data. RNNs, LSTM, GRU with their unique capability to remember and process sequential information, hold the potential to uncover the underlying relationships and trends within the traffic volume data.

Dataset overview

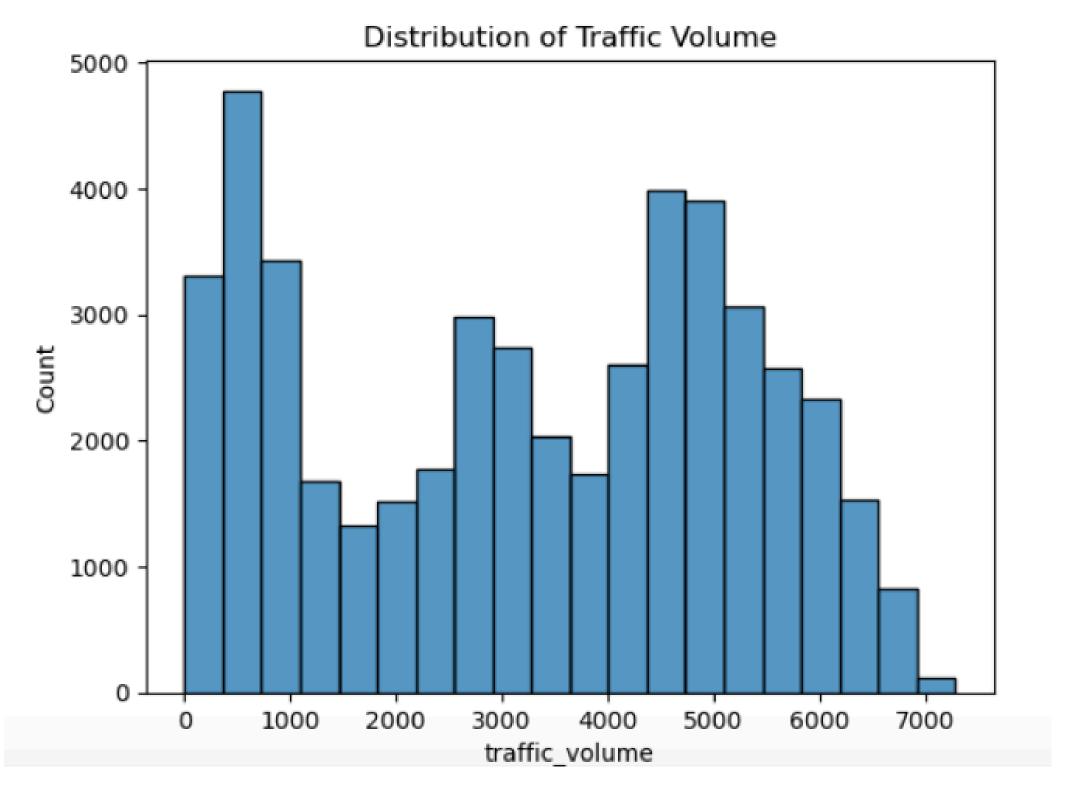
	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time	traffic_volume
0	NaN	288.28	0.0	0.0	40	Clouds	scattered clouds	2012-10-02 09:00:00	5545
1	NaN	289.36	0.0	0.0	75	Clouds	broken clouds	2012-10-02 10:00:00	4516
2	NaN	289.58	0.0	0.0	90	Clouds	overcast clouds	2012-10-02 11:00:00	4767
3	NaN	290.13	0.0	0.0	90	Clouds	overcast clouds	2012-10-02 12:00:00	5026
4	NaN	291.14	0.0	0.0	75	Clouds	broken clouds	2012-10-02 13:00:00	4918



We have used these three model types for comparison, and which one gave me the best performance and which one was the least?

- RNNs Model
- LSTMs Model
- GRUs Model

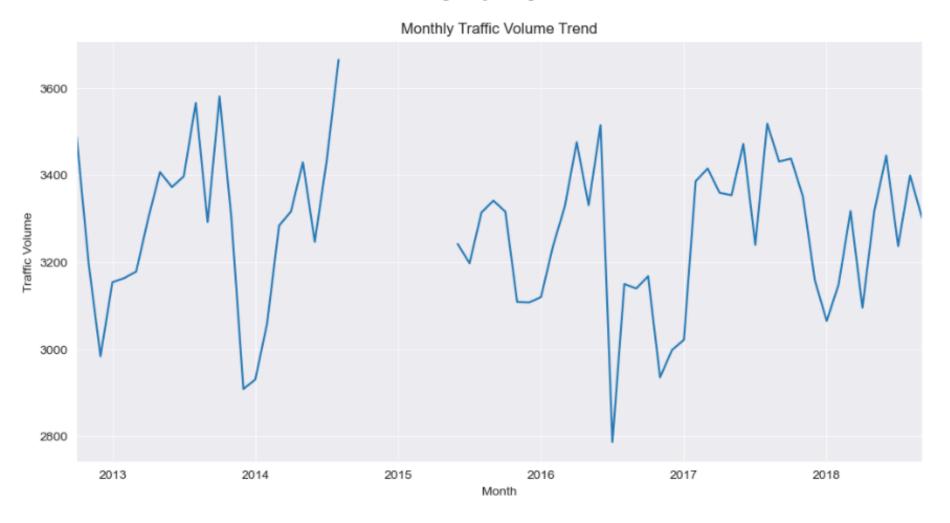




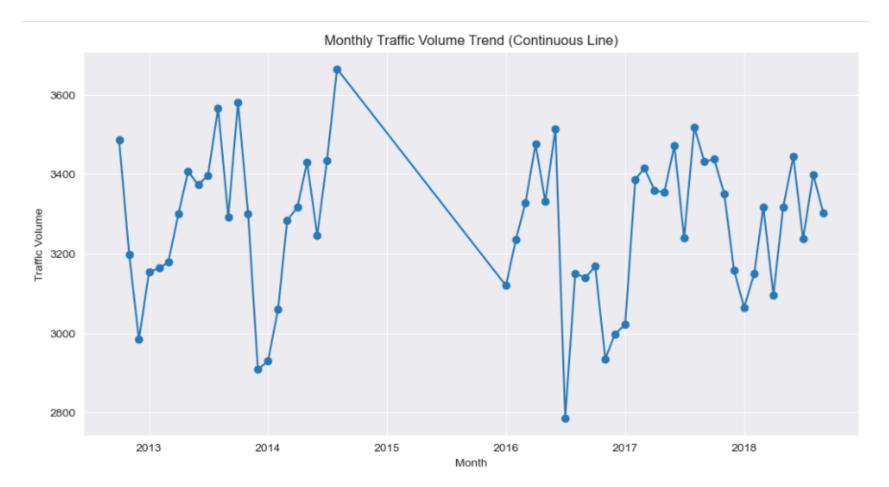


traffic volume trend

Before



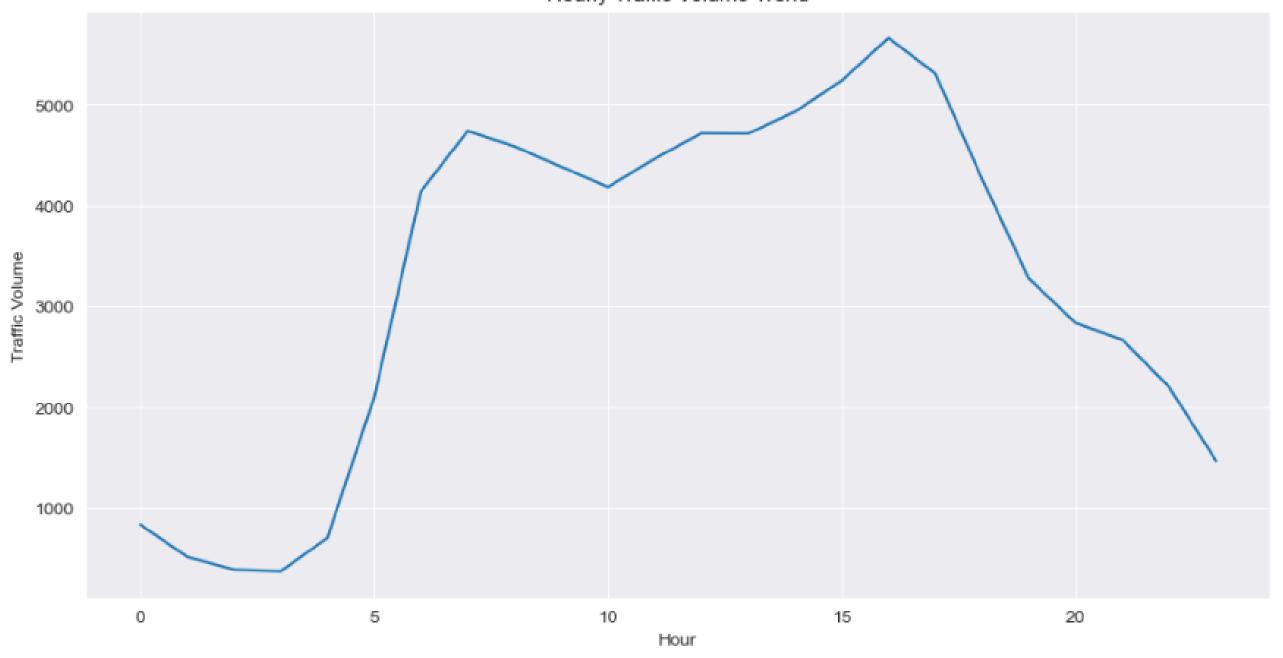
After





Hourly traffic volume trend







RNN Model

Recurrent Neural Networks (RNN) are a type of neural network designed to handle sequential data, such as text, time, or temporal signals (like time series). The key feature of RNNs is their loops that allow information to be passed from one time step to the next, enabling them to "remember" previous data and use it in current computations.

RNNs are especially useful for tasks that depend on sequences, such as machine translation, text analysis, time series prediction, and speech recognition. However, RNNs can struggle with long sequences due to the vanishing gradients problem. To address this, improved versions like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units) were developed to better handle long-term dependencies.



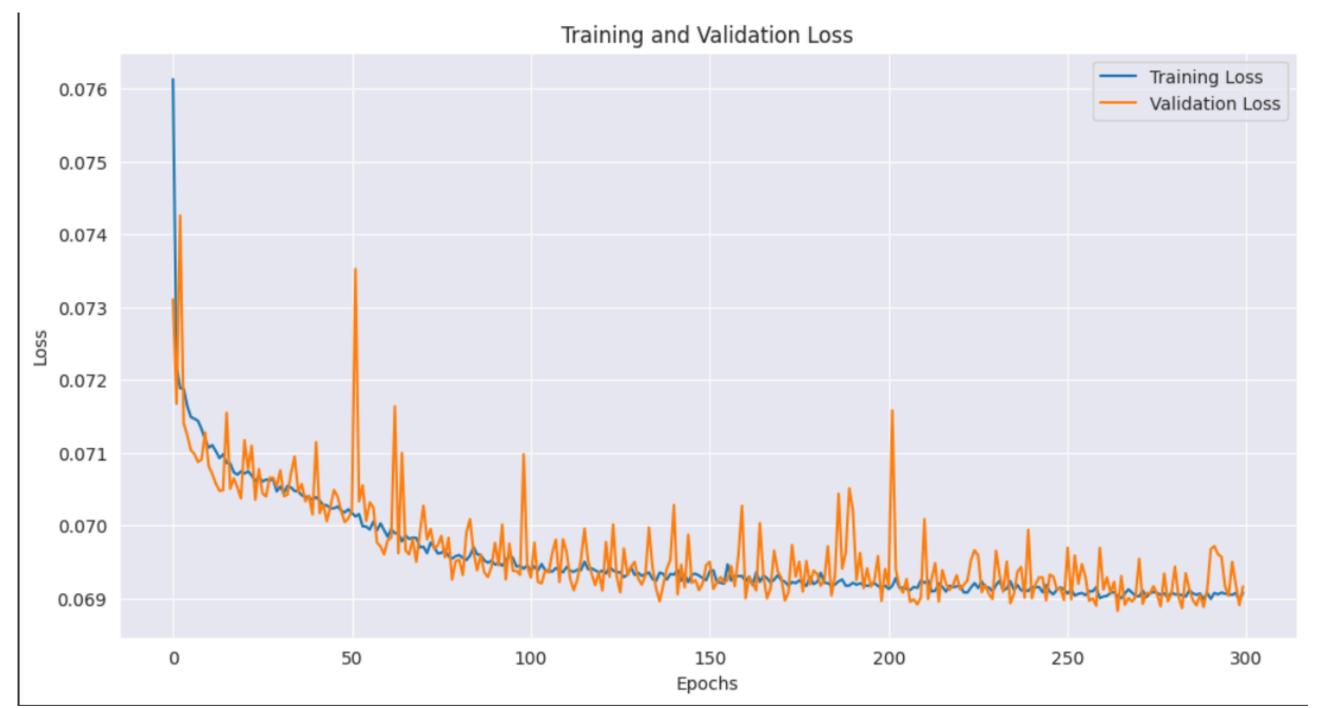
Model structure analysis RNN

del: "sequential"						
.ayer (type)	Output Shape	Param #				
simple_rnn (SimpleRNN)	(None, 50)	2,900				
lense (Dense)	(None, 1)	51				
otal params: 2,951 (11.53 KB) rainable params: 2,951 (11.53 KB) on-trainable params: 0 (0.00 B)						

The model size is relatively small (11.53 KB), making it suitable for use in resource-limited applications.



figure Training and Validation Loss



Loss (0.0691) and Validation Loss (0.0695) are very close to each other. This indicates that the model is handling well and does not suffer from overfitting.

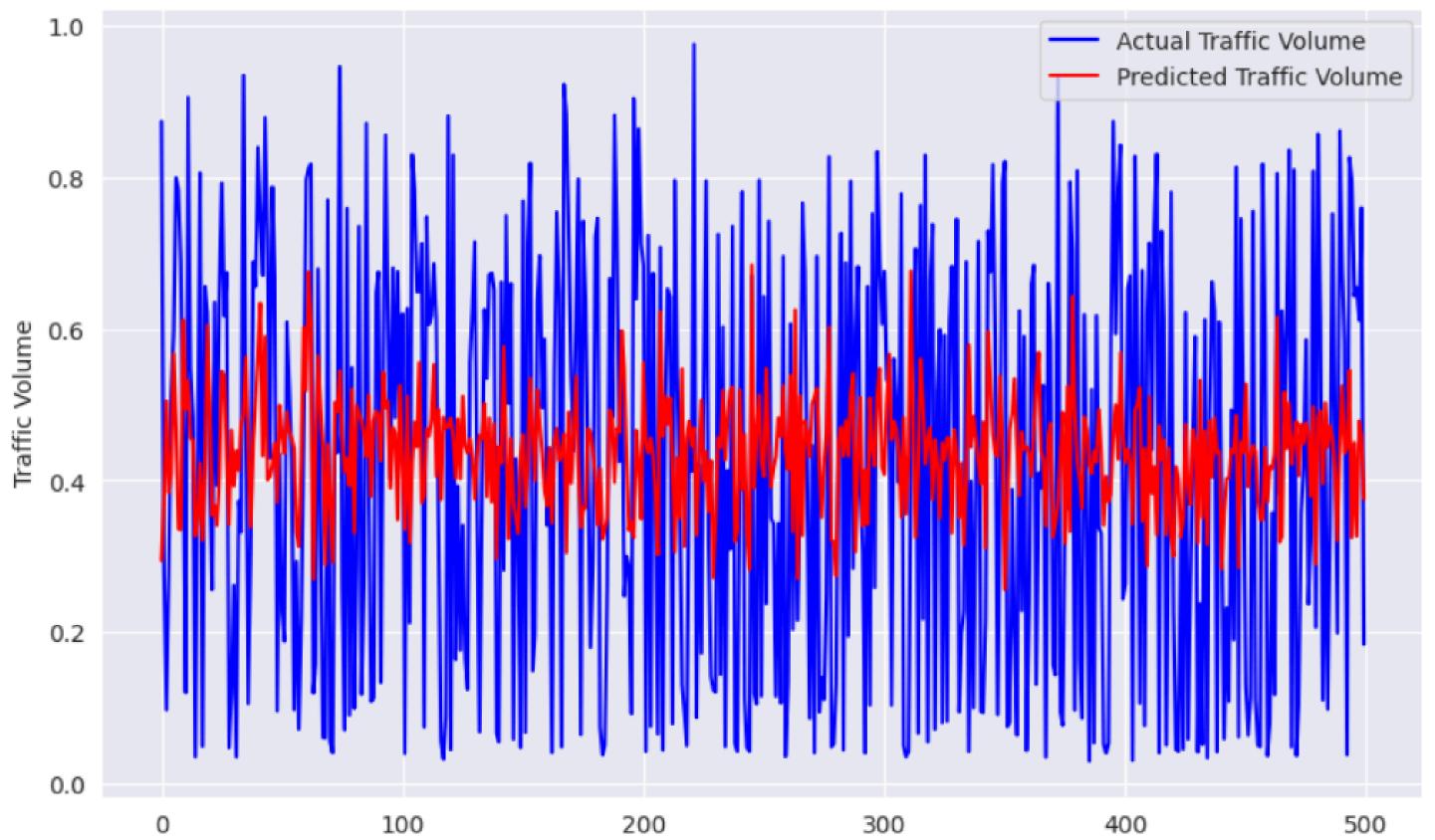
compare actual values to forecasts and rescale to original range

Actual values	Predicted values	
0.874	0.329	



Traffic Volume Prediction vs Actual Values

Traffic Volume Prediction vs Actual Values (First 500 Data Points)

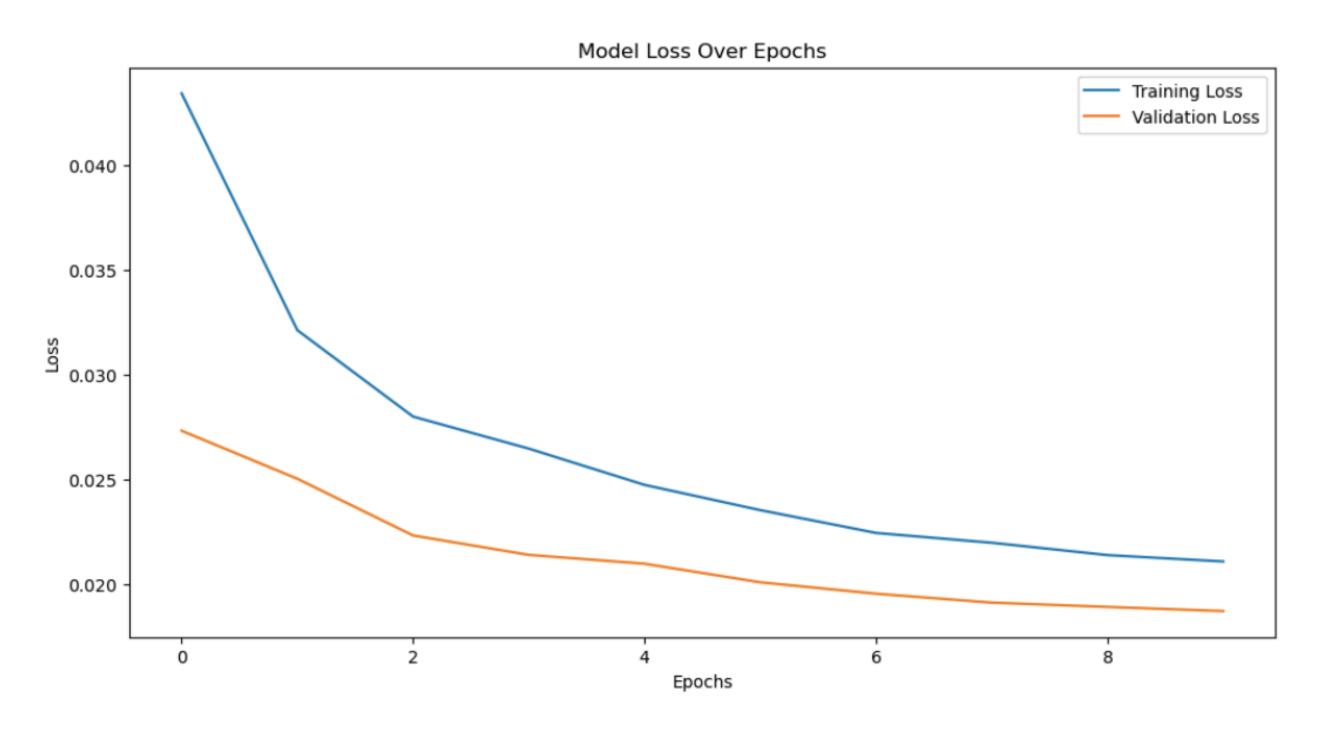


LSTM Model

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) architecture designed to handle sequence data and overcome the limitations of traditional RNNs, particularly the problem of vanishing gradients. LSTMs are well-suited for tasks that involve long-term dependencies, such as time series prediction, natural language processing, and speech recognition.



Result from LSTM Model

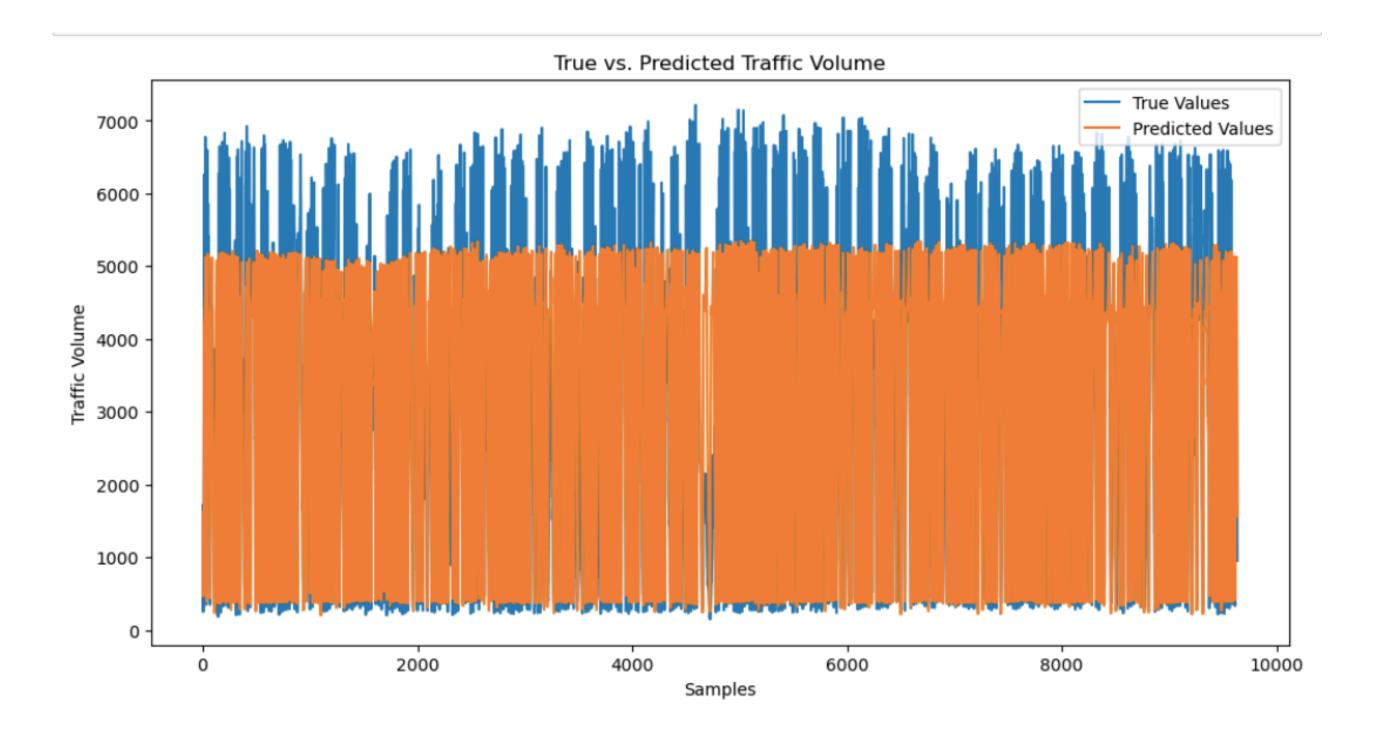


loss: 0.0214 - val_loss: 0.0187

RMSE: 996.1544965982981

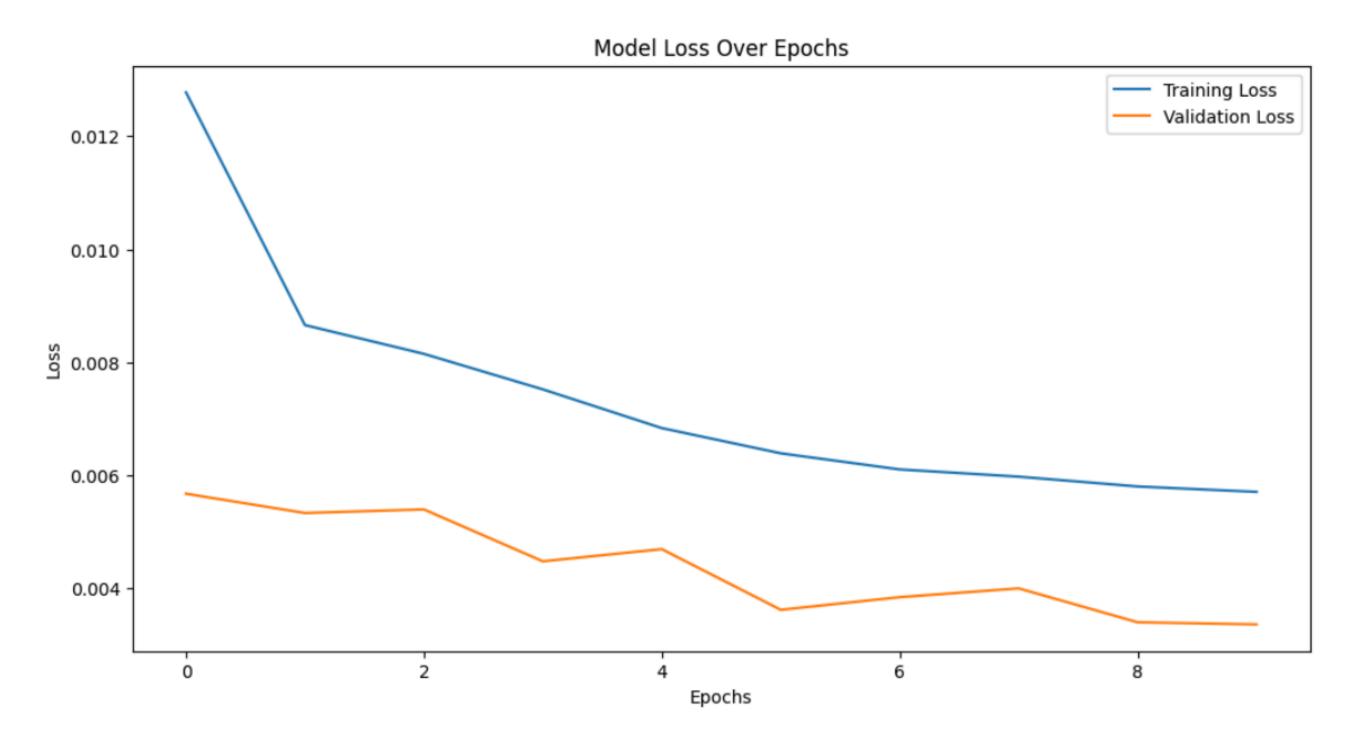


Result from LSTM Model





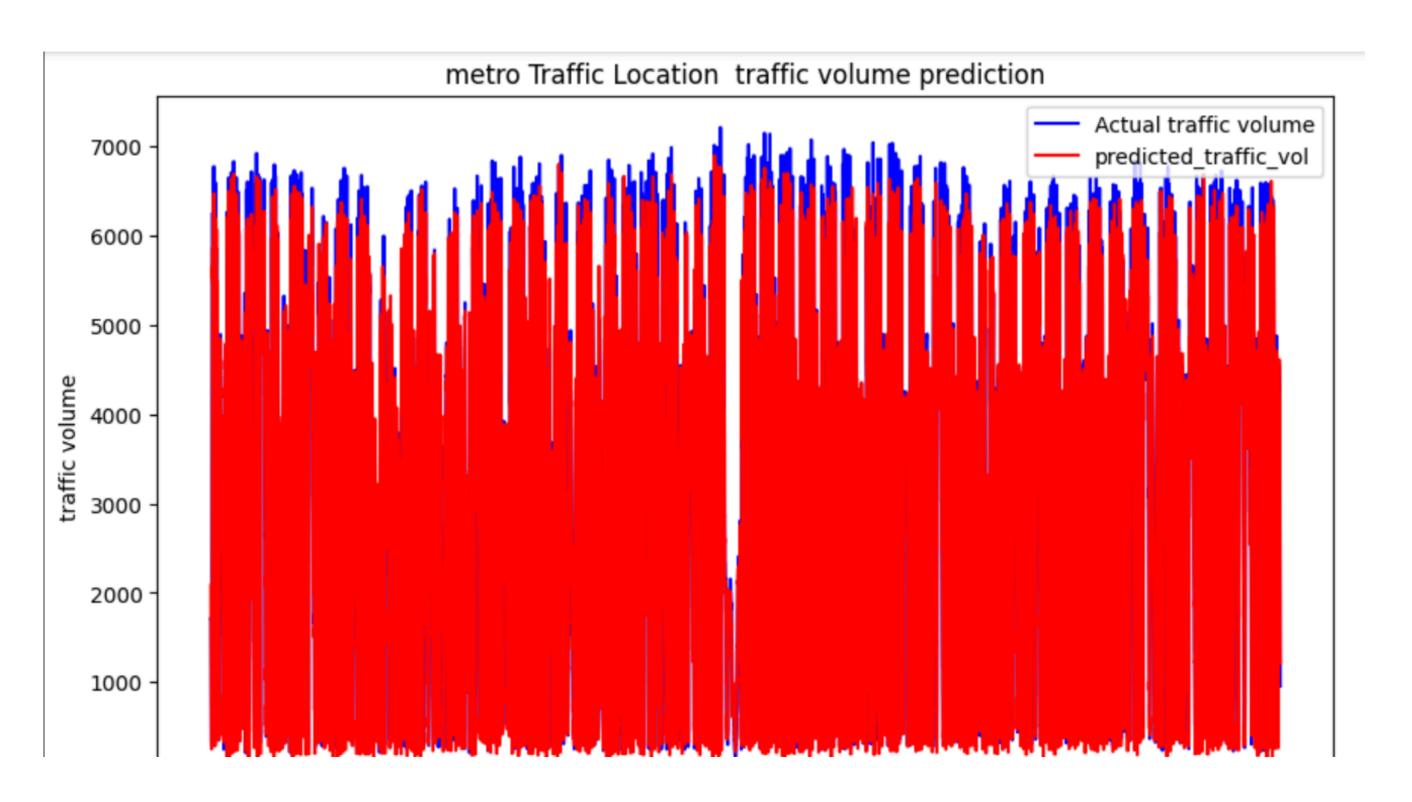
Result from GRU Model



loss: 0.0056 - val_loss: 0.0031



Result from GRU Model





MODEL	LOSS	RMSE	
RNN	0.06	0.26	
GRUs	0.005	5.7	
LSTMs	0.02	996.15	

