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.

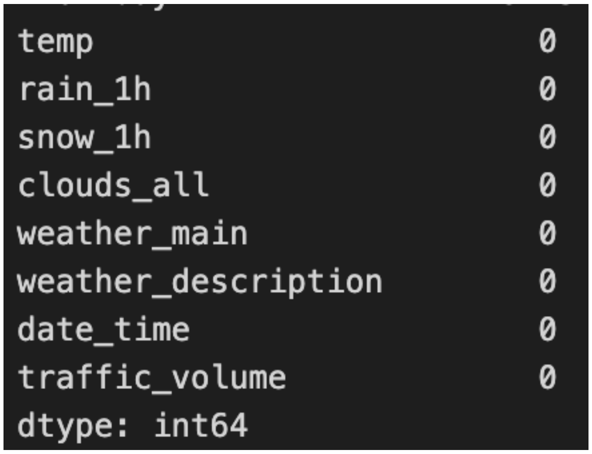
3.1 DATASET OVERVIEW

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.

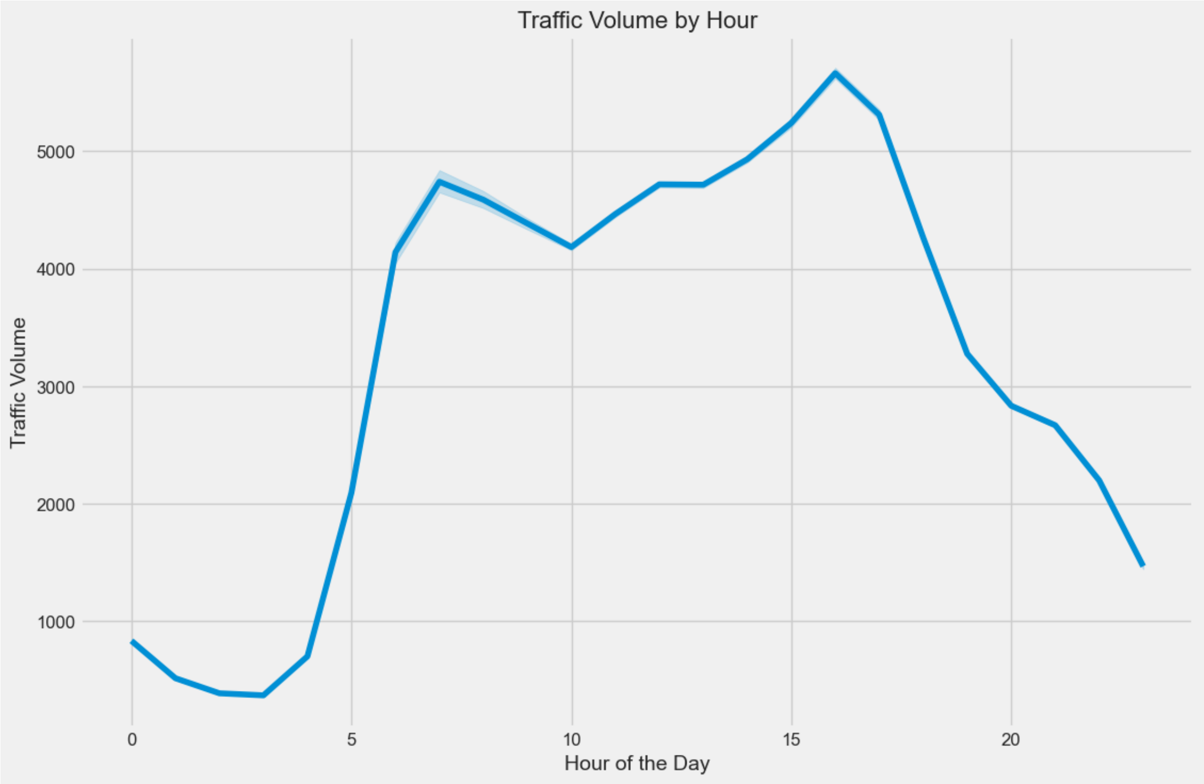
- **Low Traffic Volume**: At the other end of the spectrum, the dataset recorded instances where traffic volumes dropped close to **zero vehicles per hour**. These instances typically occurred during late-night hours or during extreme weather conditions, such as heavy snow or ice storms. Understanding 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

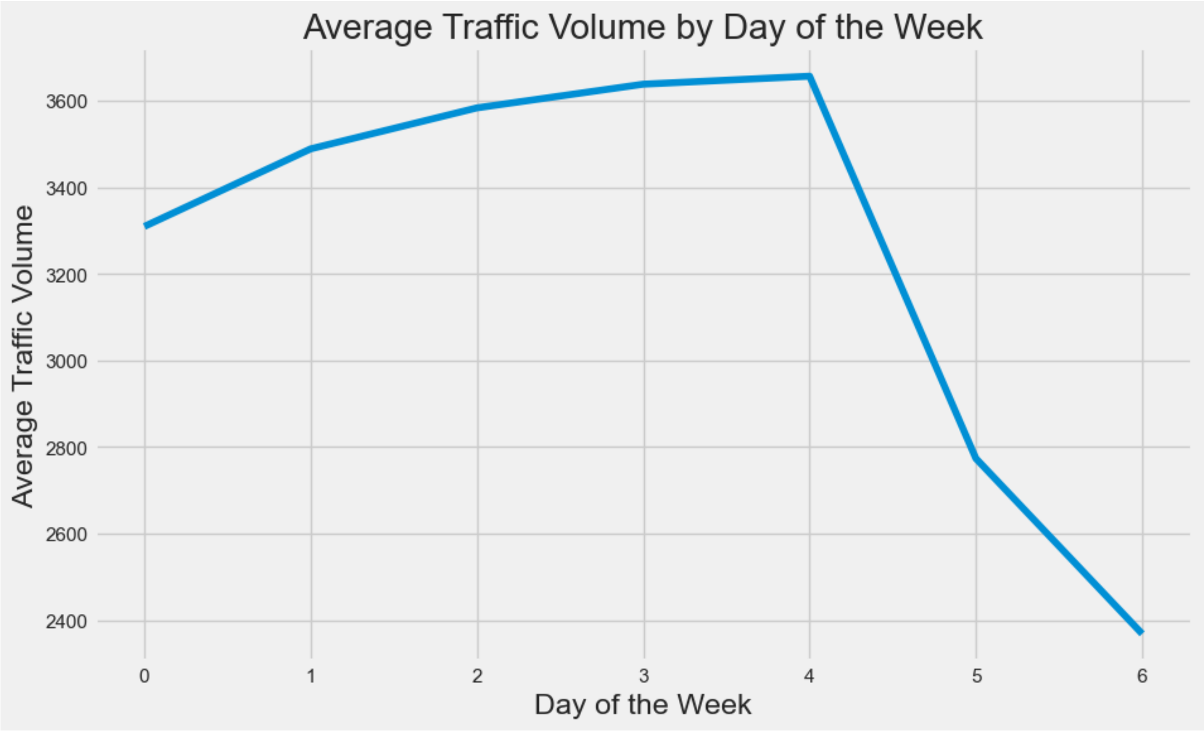


Hour of the day

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-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 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.

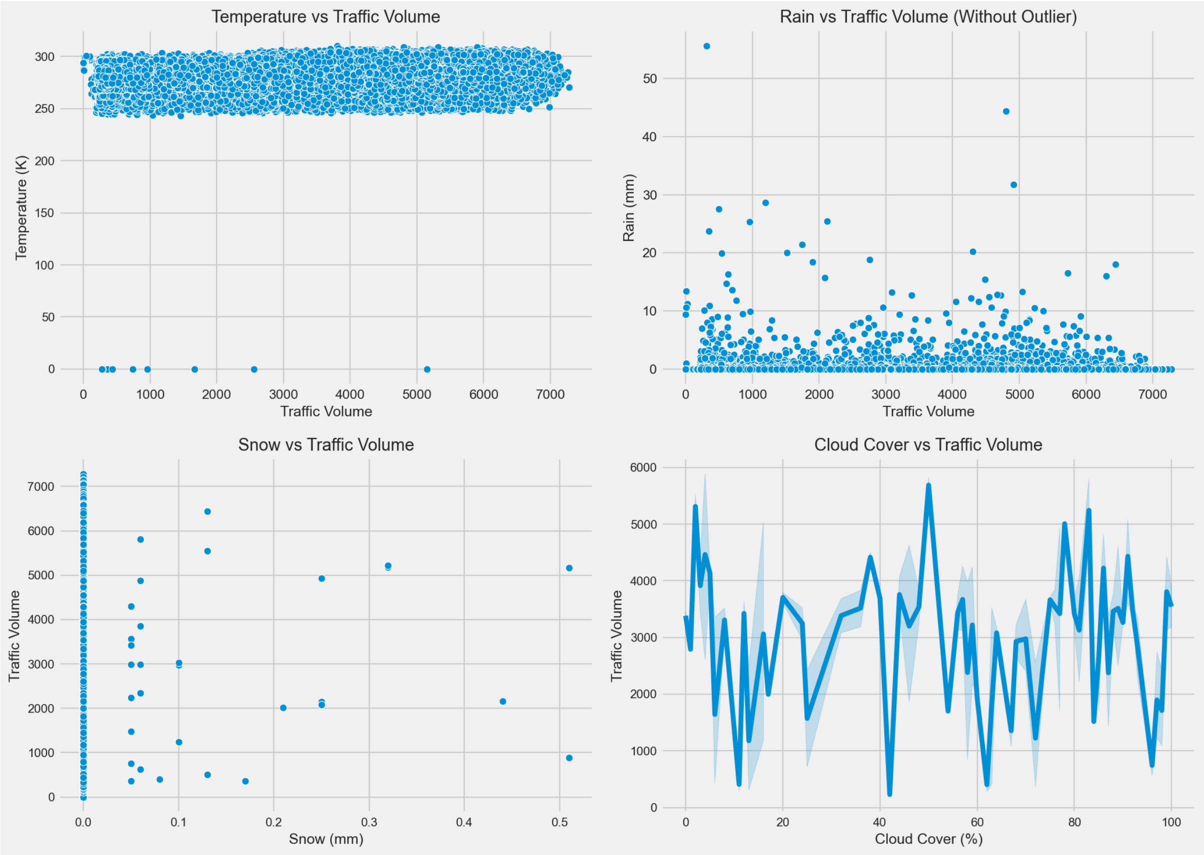


Day of the week

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.
- **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.



Temporal Pattern

- **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:

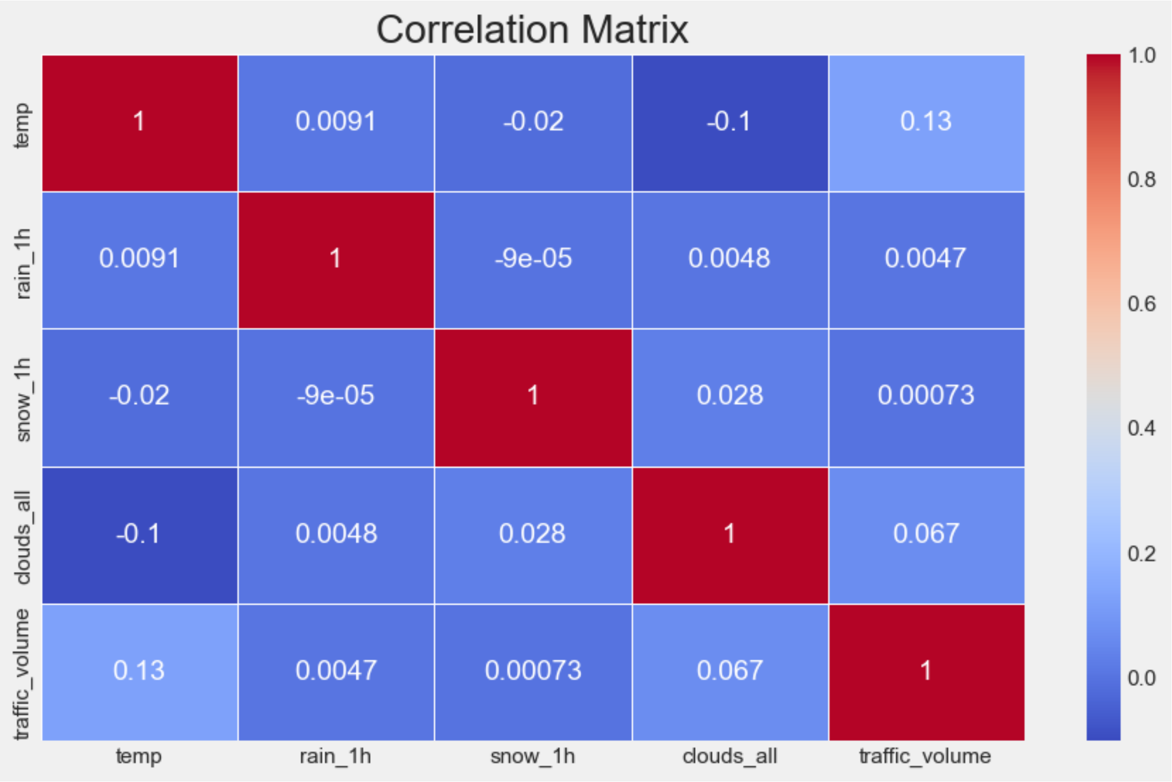
- **Traffic Volume and Temperature**: A moderate positive correlation was observed between traffic volume and temperature, with a Pearson correlation coefficient indicating that warmer temperatures are generally associated with higher traffic volumes. This finding aligns with the understanding that clear,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

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.



	temp	rain_1h	snow_1h	clouds_all	traffic_volume
temp	1	0.0091	-0.02	-0.1	0.13
rain_1h	0.0091	1	-9e-05	0.0048	0.0047
snow_1h	-0.02	-9e-05	1	0.028	0.00073
clouds_all	-0.1	0.0048	0.028	1	0.067
traffic_volume	0.13	0.0047	0.00073	0.067	1

Correlation Matrix

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