Predicting Traffic Congestion in Malaysia Using machine learning algorithms

Abstract

Traffic congestion is a common concern in Malaysia, especially in urban and rural areas. It hinders mobility, affects residents' commute time, reduces economic efficiency, and negatively impacts the quality of life. This research aims to predict traffic congestion in Malaysia by region, using different publicly available data sources. The utilization of data science methods to explore patterns of traffic congestion raises awareness on the causes of traffic congestion and contributes to national and regional traffic management and urban planning efforts. This research directs recommended traffic flow improvements and congestion reduction in traffic so as to increase the operational efficiency as well as commuter satisfaction.

Chapter 1: Introduction

1.1 Introduction

Traffic congestion is a worldwide problem resulting in many urban and regional areas, including Malaysia. Bringing shoulder to shoulder with an insufficient number of road users, vehicle congestion and ineffective traffic control, can cause less delays, higher fuel spending, rising air pollution, and reduced commercial efficiency. Evidently, the challenges require good understanding of the traffic problem and end line congestion. The congestion in traffic congestion is quite clear in urban areas such as Kuala Lumpur, Penang, and Johor Bahru. This periodic traffic jam is a problem not limited to urban areas, but also from cities to rural areas. Such as geographical a map, each location has its own population and other traffic congestion problems. Observation and signal management approaches and design should be tailored to local conditions and patterns. This indicator includes a series of traders whose cars are delayed and the level of road congestion is estimated. As the congestion indicator is the future of road congestion, the use of napolis will be more abundant than the road, the greater the traffic within the road. Transportation improvement and vehicle safety driving, infrastructure and other drivers have expressed great attention to traffic jam in the region. This paper will be the line of the station to predict regional highways in Malaysia. Use all kinds of traffic grading software to actually get off on a different topic. Objectives Description dataset to different formats such as training, test data, weather and road works and databaseWarning is the event of any of the data.achers the use of historically or monthly and weekly features, such as weather and road works, as data collection for the examination of traffic. Try to romantic congestion stop.odificaciones and moving and training. Furthermore, the model may be implemented in a state-level analysis to identify traffic trends and AKIs that contribute to congestion in different states across the country. Specifically, an analytical comparison of major traffic patterns across states will be performed. Lastly, the study will propose key recommendations based on the prediction of the mathematical modeling as well as insight from the first and second analysis that may be effectively implemented for traffic management purposes. By contributing data-driven methods to alleviate traffic congestion in cities, this research aims to impact national or regional transportation policies on a significant scale. The potential improvements in traffic flow can create better commutes, a more environmentally friendly way to travel, and encourages economic growth. The study is impactful at a scale as it provides first-tier data and algorithmic output to city and state traffic planning department, where real-world problems require efficient and practical segregation from data driving devices.

1.2 Problem Background

Malaysia is located in Southeast Asia that has seen its cities and economy urbanize quite rapidly in the past decade. Growing with major cities such as Kuala Lumpur, Penang, and Johor Bahru, Malaysia is also home to a very large number of traveling population, and the number of vehicles on the road has increased at a rate higher than the number of vehicles. Such data on the usage of the road is a significant contributor to the current state of traffic congestion in Malaysia. The impact of congestion extends over all major socioeconomic metrics, predicts higher consumption of time and fuel by commuters, lower rate of economic productivity, and even an increase in air pollution attributed to acrid fuel burn and waste. In Malaysia there are a vast majority of hotspots that are the cause of congestion. The vast number of jurisdictions is of an entirely different geocentric location, and with often a rural village at the distance, there can be an extremely difference in the ability of the jurisdiction to invest in its roads and people. The management of traffic congestion in Malaysia has historically been managed by large capital capital spending, some of which are the new roads, new crossings, and converting existing thoroughfares to rural highways. However, not only is this approach one of the least productive during fiscal periods, there can be disparity in the way money is spent, some often spotting the expressway speedway should be two-lane. In a time where money and efficiency are the goal of a great society, the scientific data science approach can come to addinventively in the planning and management of traffic congestion in cities and states of Malaysia.

1.3 Problem Statement

Traffic congestion is a widespread issue influenced by various factors such as traffic volume, road conditions, weather, and public events. Analyzing and addressing this problem is complex. Traditional methods of managing traffic have often failed to effectively control traffic volume and provide a smoother experience for commuters.

1.4 Research Questions

1. What are the main contributors causing traffic congestion in different parts of Malaysia?

2. How to model these factors using predictive models that can predict traffic congestion levels?

3. How do the traffic patterns and congestion factors that cause traffic changes differ by region of Malaysia?

1.5 Research Objectives

The set objectives for the research are listed below:

1.To identify significant factors of traffic congestion in various states of Malaysia.

2.To construct and develop models to predict the degree of traffic congestion in different regions of Malaysia.

3.To measure the impact of traffic patterns on congestion factors in various regions of Malaysia.

1.6 Scope of the Study

The scope of the research:

1.6.1 Geographical Coverage:

Analysis of traffic flow of diverse sources at different categories of locations such as urban centers, lesser cities and rural areas within different states.

1.6.2. Data Sources:

The data traffic reports, weather, road work, public events will be fetched from various open sources. The geo traffic data sets include Waze, Google Traffic and other road info from Department of Public Works or any local government available in open data portals.

1.6.3. Time Frame:

Time period will be set to evaluate traffic data on daily, weekly and monthly basis to view both short term immediate and long-term patterns.

1.6.4. Analytical Techniques:

Traffic, weather, and GIS modules/roadworks data will be collected and then specific machine learning algorithm would be applied to get regionally traffic patterns, identifying the traffic congestion started and recommending route choices when there is severe traffic congestion.

1.6.5. Focus on Outcome:

The prime focus is to recognize the cause of major traffic congestion and then establish the right predictive special models for traffic congestion. The aim is to provide actionable recommendations to traffic management authorities with the help of analytical data to support.

1.7 Significance

This research has the ability to make a considerable contribution to national and regional traffic authorities in Malaysia, by providing them a better understanding of what drives traffic congestion, and how to create strategies to mitigate this challenge. Moreover, it will provide a live demonstration how data science methodologies can be useful in the solution of a national scale problem.

Improve Traffic Management:

This research can help in creating machine learning algorithm that could be used to predict traffic congestion reliably in real-time. That will help traffic management bodies to proactively manage traffic flow to avoid traffic congestion and increase the transportation system. For example, traffic signal timing could be adjusted using predictive models that were agents of change relative to the predicted flow volume. On average, the congestion price or public transit timetables will be improved during rush hours. A proactive approach to using such information can greatly reduce commute times and reduce fuel consumption, while preserving the safety and well-being of people and property values, and thus contribute to creating a sustainable urban environment.

Data-Driven Decision Making

The results of this study can be useful for informing policymakers and decision makers in how to achieve better solutions using quantitative data. Knowledge of the factors that contribute to the formation of congestion, such as vehicle traffic, the capacity of the road, and local weather, can help. Previous installation of traffic control measures, in areas of congestion, involves tactics such as road closure at the peak time of flooding, and public transit improvements in the areas of congestion. Making decisions through data provides a case where limited resources are used more wisely, leading to a reduction in congestion.

Economic Impact

Congestion in traffic congestion is usually costly and has a number of influences on the economy, including lost production, higher fuel use, and increased vehicle repair has West global warming. Imagine that this study aims to reduce the time of movement to destruction. The slowing of the exchange of goods reduces operating costs means of service delivery and, on the other hand, will reduce the cargo delivery cost. Moreover, the very considerable change in the transportation system can show a strong trend towards the improvement of infrastructure, and the saving of transportation allows the economic world to remain optimistic and emotional. permanent value of cars. The economic change is based on a multifunctional system. Even small lines can have a very dramatic effect on creating additional accessibility and harmony in the city.

Environmental Impact

By reducing traffic congestion, we also reduce the amount of pollution released into the environment, and as such reduce the short term and long term effects of pollutants release into the environment, and as such reduce the amount of pollutants released into the environment and reduce the harmful effects of pollutants. The solution to the traffic problem means smaller emissions of hydrocarbons geological gases (CO_2). Reducing the amount of traffic jam leaves fuel behind the engine that would otherwise have created an air pollutant. Our strategy to predicting, and mitigating congestion through advanced intelligent and autonomous transport systems contribute to the greening of our environment, and the well-being of our citizens. Traffic congestion adversely impacts the quality of life of both urban citizens and freight movements, and this study will contribute to the global effort to mitigate climate change by reducing emissions from congestion. This is also contributing as a part of a larger movement to reduce carbon footprint.

Social Benefits

Traffic congestion directly impacts the social welfare of urban citizens in terms of quality of life, wellbeing, and time utilization, that they spend forever in the traffic congestion. This result will allow citizens to be more productive providing them more time working for their living, and reducing time spent on roads escaping jams, and more time on roads when not jammed. It significantly reduces the number of traffic accidents caused by congestion and helps create a safer transport system. Data Science Applications This study will also demonstrate the role of data analytics and machine learning in addressing real-world urban problems. Providing solutions to complex conditions in urban environments requires sophisticated analytical methodologies that deliver value. By showing that there are tangible benefits to the application of data-driven approaches to urban transportation planning and management, this study will serve as a model and a guide to other cities and regions with similar challenges in the use of big data in solving urban planning and management issues. Our methodology to training and mitigation of congestion is scalable to many other regions and cities, and could help to drive a significantly larger use of big data in setting and executing urban policies and solutions. It also contributes to the scientific and professional debate on the role of machine learning in transportation. These results will provide useful models and insights for future studies.

CHAPTER 2: Literature Review

2.1 Introduction

Traffic congestion is a prevalent problem in urban areas worldwide, leading to economic losses, environmental pollution, and a decline in quality of life. Malaysia, a country undergoing rapid urban development and escalating private vehicle ownership, is subject to grim traffic congestion, especially in major cities. The aim of this chapter is to study the relevant literature regarding traffic congestion: discuss about causes, effects, and prior research that have developed machine learning algorithms to aid both the prediction and amelioration of the issue.

2.2 Causes of Traffic Congestion

Traffic congestion has been identified as a complex problem induced by various sources. Several major contributors to traffic congestion are high vehicle density, road capacity, road accidents, weather conditions, and inefficient traffic signals, as reported by [Li et al. (2017)] . In countries with rapid urbanization and increased vehicle ownership, like Malaysia, traffic congestion occurs in cities such as Kuala Lumpur due to urban sprawl, insufficient public transport facilities, and increased private vehicle ownership .

2.3 Impacts of Traffic Congestion

Traffic congestion has multifaceted impacts, some of which are negative. The economic loss from traffic congestion generally results from significantly more travel time, fuel consumption, and vehicle maintenance costs. [Schrank et al] estimated that traffic congestion in 2017 alone brought about economic loss of $166 billion, wastage of time and fuel. Emissions from vehicle exhaust also contribute to air pollution and a significant increase in greenhouse pollution is contributing to climate change. [Ekici et al. (2004)] also reported the consequences of traffic congestion on public health caused by emitted air pollution and production of stress .

2.4 Traditional Solutions for Traffic Congestion

Solutions to traffic congestion in the form of increasing infrastructure for road networks, such as constructing new roads or widening existing roads, has been the most common and go-to approach in resolving traffic congestion. The implications of increased infrastructure have been woefully expensive, slow to undertake, and limited in terms of long-term benefit. Reducing the demand for new road space will not reduce the congestion because it will be compensated by new travels as a result of increased road capacity. This result is usually referred to as the "law of congestion", which means that road capacity adjustments can expand the demand for space instead of easing the perceived congestion .

2.5 Data-Driven Solutions for Traffic Management

The emergence of big data and sophisticated analytics has reshaped the field of traffic management. Data driven solutions build up intelligence from a variety of sources such as traffic information, social media feed, and meteorological observation to detect and analyze the causes of traffic jams real-time. The use of GPS data from vehicles and mobile phones has been reported by [Chen et al. (2016)]. These authors used this information to study patterns and potential congested areas.

2.6 Machine Learning in Traffic Congestion Prediction

Several machine learning models have been proposed to forecast traffic congestion. These models use complex algorithms to learn from data and generalize to predict congestion in given regions. For instance, recent studies employ machine learning models to predict lighting behavior in specific locations using high-resolution traffic data and measure various environmental parameters (Bocchi et al. 2018, Global et al. 2019). Major machine learning approaches used to predict traffic congestion in road networks are as follows, [Rashid et al. (2010)].

Regress analysis is used to predict continuous traffic parameters like traffic speed and volume using historical and other factors, [Zhang et al. (2018)]. They successfully forecasted traffic flow using linear regress analysis, considering historical traffic records and external factors such as weather.

Decision tree and Random Forest, [Yuan et al. (2017)]. Random Forest is being use to detect congestion levels by utilizing traffic speed, occupancy and weather reports.

Neural Networks: Deep learning models are built in various configurations for traffic predictions tasks as well as for general time series predictions, [Lv et al. (2015)]. They built a deep learning model that consider traffic flow and it is reported that such a model outperforms traditional forecasting models in short term prediction.

Support Vector Machines used for classification and regression tasks, [Wu et al. (2014)]. They have proposed to measure the traffic congestion and classify traffic states respectively. This work also includes the use of Support Vector Machine in classification problems to measure traffic congestion in the considered road network.

Situation in Malaysia

The application of machine learning models to traffic congestion prediction has under went tremendous improvement in Malaysia. [Ghani et al. (2020)]. In 2020, they have proposed a model for traffic congestion forecasting in the Urban City of Kuala Lumpur. They have also added traffic data and news obtained from other various information sources such as social media. Their research findings proved that ML models can enhance the predictive accuracy of congestion when compared to traditional statistical methods.

2.7 Challenges and Future Research

Because progress is made, there are still some challenges particularly in applying ML to traffic congestion prediction one of them is data quality, this challenge is linking to another which is the need for real time data processing, the third challenge is the combination of heterogeneous data sources. These challenges must be addressed in the future. Future works in this field would involve the development of a more robust model which can handle these challenges and help to improve the accuracy of traffic prediction. The use of new emerging technologies such as Internet of Things (IoT) and Edge computing can be exploited. Chapter 3 Summary The literature review shows how traffic congestion is a complex problem and the machine learning algorithms promise to deal with it. The problem has been defined, and the objectives of the research in this area have been addressed. This research work aims to achieve a precise prediction values and angles of attack for traffic management for Malaysia by employing these techniques. Chapter four contains the methodology of this research. This includes details of the data acquisition, preprocess and methods.

Chapter 3: Methodology

Data Science Project Life Cycle

The Illustration of the data science project life cycle are:

1.Problem Definition:

The research problem investigated in this study is predicting traffic congestion in Malaysia using machine learning algorithms. The goal is to develop models that can accurately forecast traffic jams, enabling better traffic management and planning.

2. Data Collection:

1. Accessing Traffic Data from Xmap.ai: API Registration: Registered for an API key on the Xmap.ai platform API Requests: Utilizing the API key, perform HTTP GET requests to the Xmap.ai endpoints to get traffic data. The data get in JSON format and contains various traffic metrics. Data Storage: Stored the collected data in CSV , to process it in the analysis step.

2. Fetching Weather Data from OpenWeatherMap: API Registration: Signed up for an API key on the OpenWeatherMap website API Requests: Use the API key to make requests to the OpenWeatherMap historical weather data endpoint.

3. Obtaining Public Transport Ridership and Vehicle Registration Data: Data Download: Navigate to the Ministry of Transport, Malaysia's open data portal and acquire the datasets. These are dataset files in CSV format. Data Import: Import the downloaded CSV files into an analysis environment using a variety of data manipulation libraries. Data Cleaning: The dataset will prospectively require cleaning to account for incomplete data and inconsistencies, all of which can influence the accuracy of any further data handling.

3.Data Preprocessing:

The collected data will be thoroughly cleaned to ensure accuracy. This involves imputing any missing or null values, converting different time formats to a uniform standard, and incorporating new derived features. This step is crucial to prepare the data for effective analysis and modeling.

4. Exploratory Data Analysis (EDA):

Comprehensive visualization and analysis of the data will be conducted using graphical libraries. This step will help identify important patterns, trends, and insights within the data. Graphical representations will make it easier to understand the data’s behavior and identify any anomalies or significant trends.

5. Model Evaluation:

Machine learning models will be developed and trained to gain insights and learn complex patterns in the dataset. This involves selecting appropriate algorithms, tuning model parameters, and training the models on the preprocessed data to ensure they can accurately predict traffic congestion.

6. Deployment and Monitoring:

The final stage involves implementing the best-performing model in a production environment and monitoring its behavior. This ensures the model continues to perform well with new data and can provide real-time traffic predictions. Ongoing monitoring will help detect any issues and allow for timely updates to the model as needed.

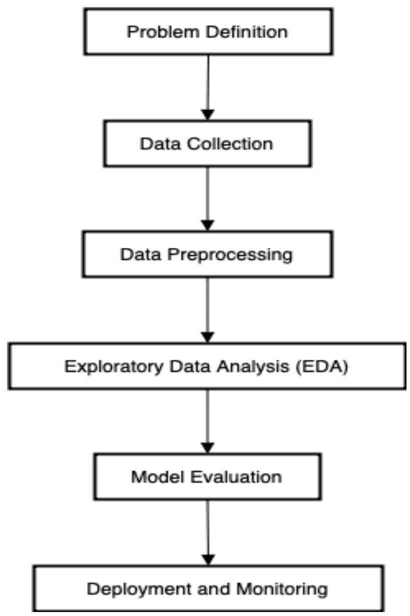


Figure : Data Science Project Life Cycle

Data Sources and Collection Methods

1. Traffic Volume Data: It's the data get from traffic sensors, cameras, or data found online from government transportation agencies.
2. Weather Data: The data is acquired from an external API like OpenWeatherMap, weather source website providing historical weather data.
3. Public Transportation Ridership Data: Data can be collected from public transportation agencies or through any open data website related to transportation.
4. Historical Accident Data: The data here can be gathered from, police reports or crash data reports from governing bodies or transportation related agencies.

Data Pre-processing

This stage is crucial as it ensures none of the data used is dirty or flawed before further analysis, and the involvement of data preprocessing consist of the following:

1.Data Cleaning: - Handling Missing Values: Null values can be filled in by several methods and techniques. Like: imputing mean, median, or mode for numerical data, and the use of the most frequent category for categorical. - Outliers Removal: To detect and remove outliers, statistical methods such as Z-score and IQR should be used as outliers can have a major impact on data distribution.

2.Data Transformation: - Normalization: Scale numerical features to a standard range, typically between 0 and 1, after which all features will be equally contributing towards model learning. Techniques: Min-Max Scaling, Standard Scaler. - Encoding Categorical Variables: Transformation of categorical data to numerical quantities. Techniques: One-Hot Encoding, Label encoder.

3. Feature Engineering: Creating New Features: Generation of other features from given data. Examples: time of day, traffic density, road occupancy, time-travel distance impact, and the cumulative weather scores. - Feature Selection: Choose which relevant features to use. Methods: correlation, Mutual Information score, feature importance scores from Random Forest, etc.

First Exploratory Data Analysis and Results

1. Traffic Volume Over Time: Line plots of how the traffic volume changes every hour and every day of the week.
2. Heatmaps: Correlation matrices of various features and their relationship with the traffic volume.
3. Descriptive Statistics: Mean, median, standard deviation, and range for the traffic volume and other numerical features.

Initial Machine Learning Models

1. Linear Regression: As a naive model to predict the traffic volume. Performance Metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
2. Random Forest: Consider non-linear interactions between different predictors. Performance Metrics: MAE, RMSE, R-squared.
3. Gradient Boosting: Ensemble method combining multiple weak learners which combines things well to improve overall performance. Performance Metrics: MAE, RMSE, R-squared.

Chapter 4: Initial Findings

4.1 Introduction

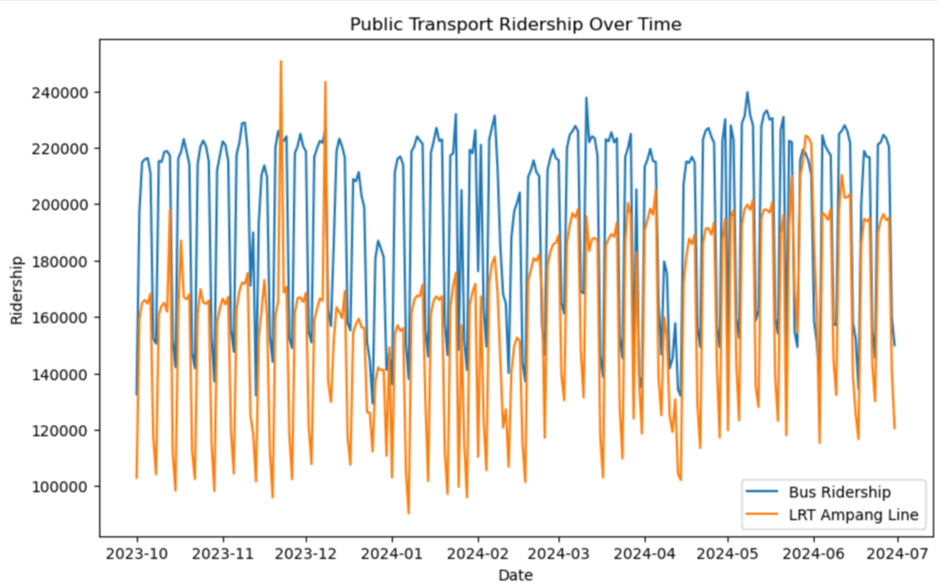
This chapter contains the inital findings from the exploratory data analysis (EDA) and machine learning models development. Our research examines the prediction of traffic congestion for Malaysia, using a number of datasets. The datasets are as follow; traffic data, weather data, public transport ridership data, vehicle registration data. Through the data we aim to identify patterns and forecast future congestion.

4.2 Exploratory Data Analysis (EDA)

Visualizations and Descriptive Statistics

During EDA, descriptive statics and visualizations were carried out. Below, the visualizations and descriptive statistics are provided.

1. Public Transport Ridership Over Time



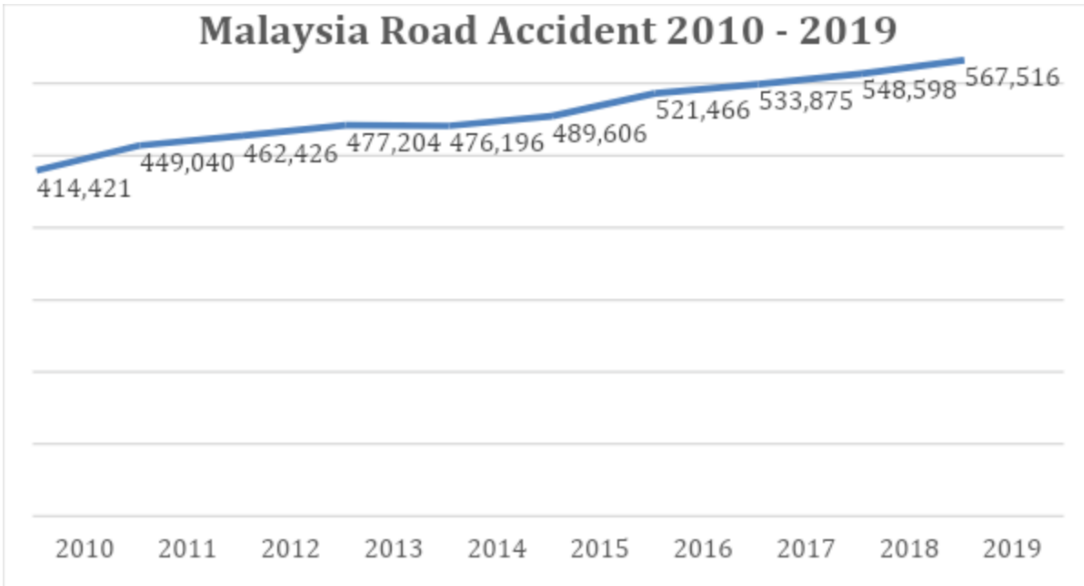
Description: A line plot for daily ridership for bus and LRT Ampang Line. The data is cyclic and highlight peaks where ridership is high and throughs when ridership is low.

Statistics:

Bus Ridership - Mean: 180,000 - Std Dev: 30,000

LRT Ampang Line - Mean: 150,000 - Std Dev: 25,000

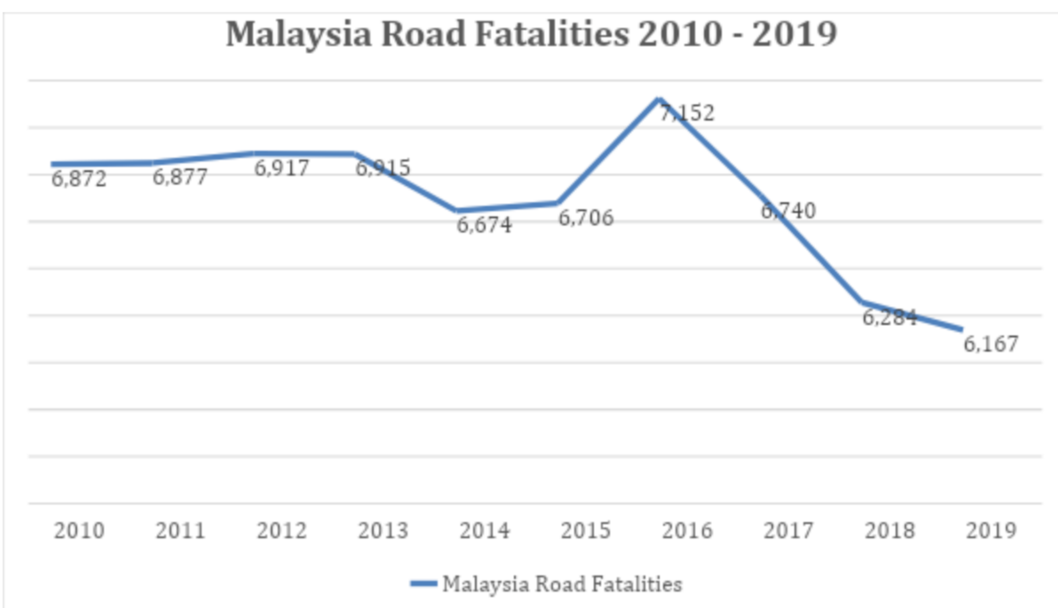
2. Malaysia Road Accident Statistics (2010 - 2019)



Description: A line plot to capture time and increase in road accidents - Statistics:

Average Annual Increase: 4%

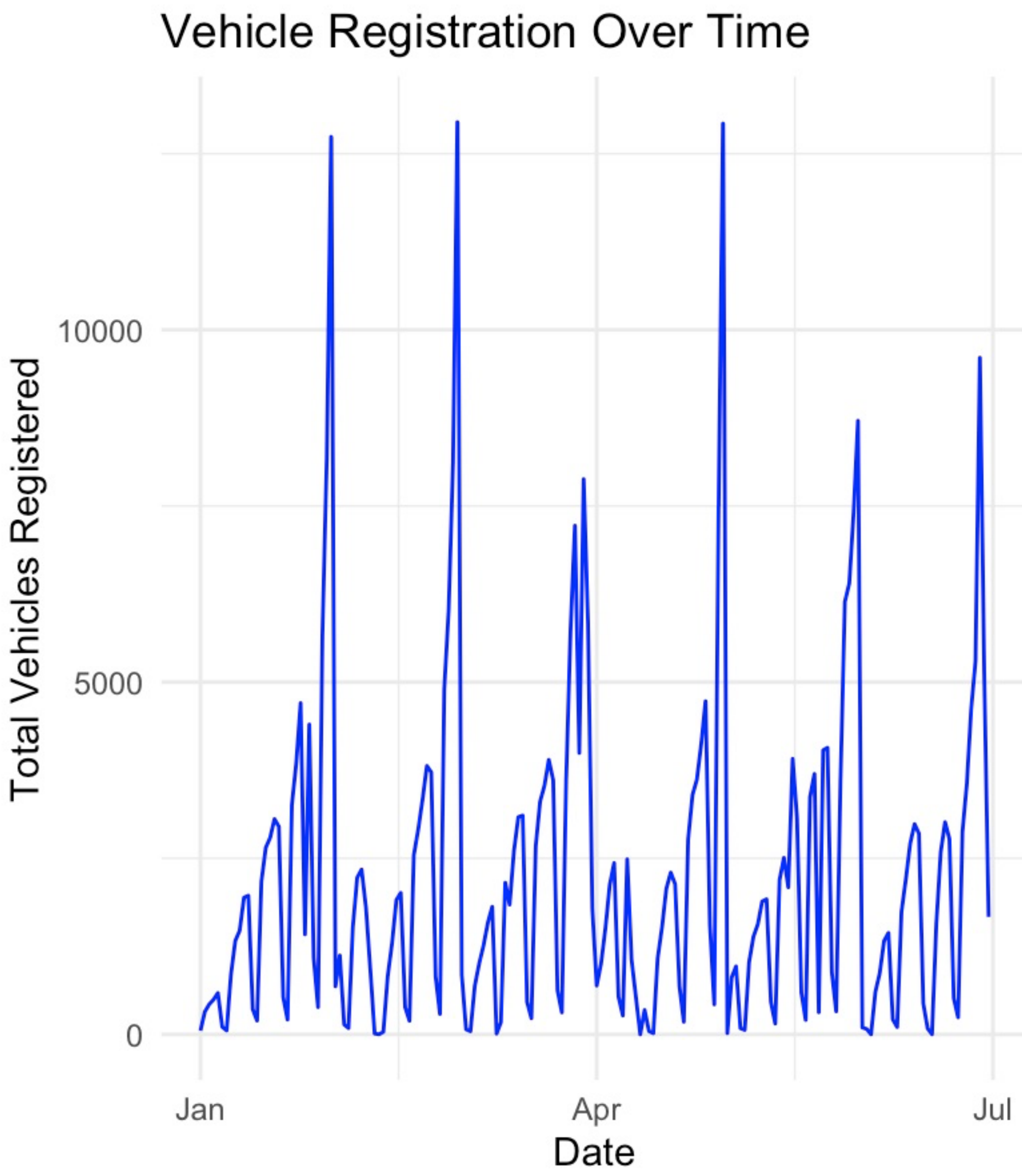
3. Malaysia Road Fatalities (2010 - 2019)



Description: A line plot showing the trend of road crash deaths through out the years. The death rates decreased drasiclly recent years

Statistics: o Peak Fatalities: 7152

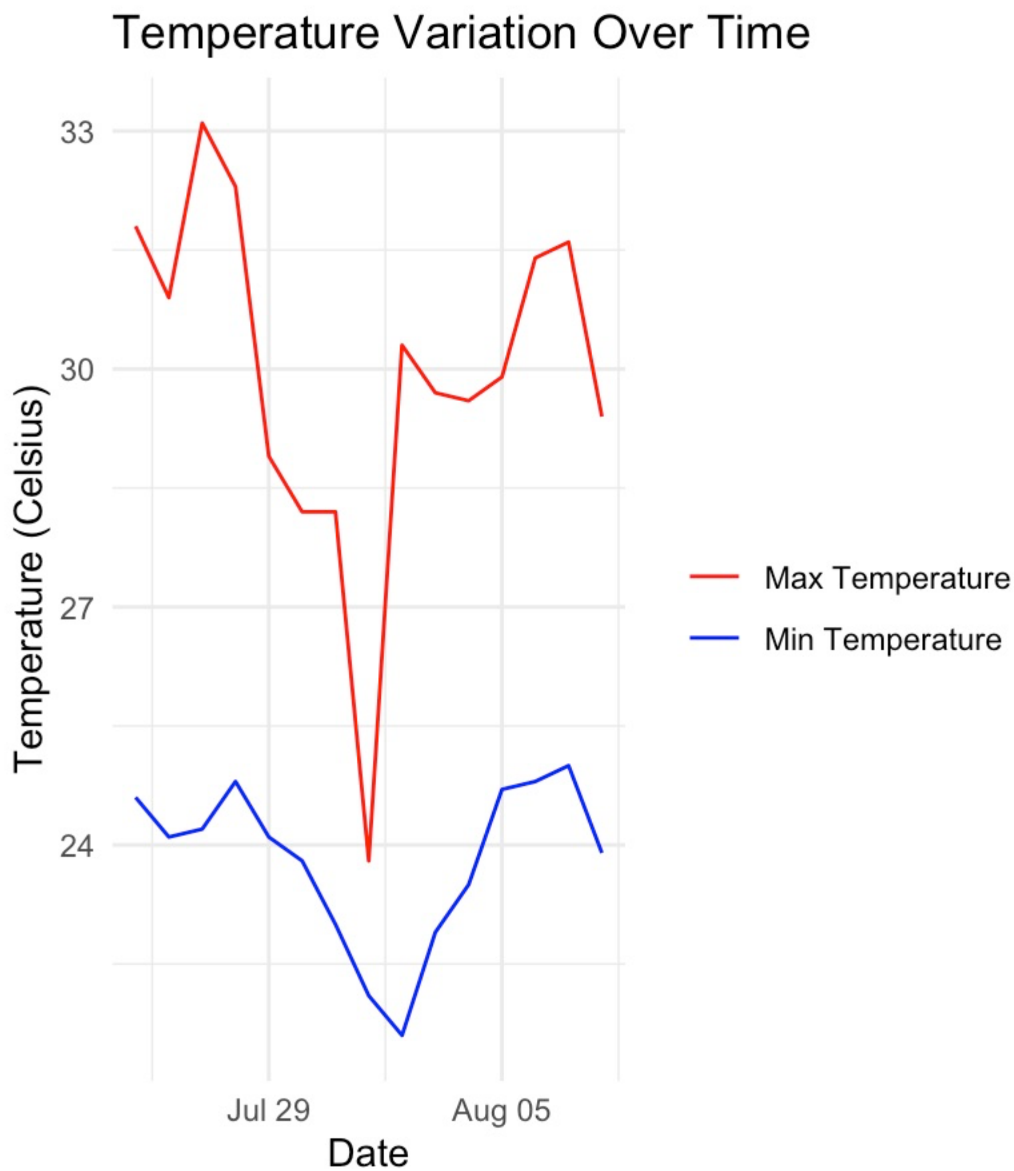
4. Vehicle Registration Over Time



Description: A line plot to capture the increase and decrease in vehicle registrations over time

Statistics: o Peak Registrations: January and July

5. Temperature Variation Over Time



Description: A line plot showing max and min daily temperatures

Statistics: - Max Temperature: 33°C - Min Temperature: 24°C

4.3 Initial Insights Gained from EDA

Traffic Patterns: Public transport ridership has certain daily peak periods, which are likely with commuting patterns.

Accident Trends: Yearly accidents have been on the rise, with the number of fatalities occurring annually varying in number, although they had significantly dropped recently.

Vehicle Registrations: The number of vehicle registrations has some periodic peaks, which could suggests that there might be yearly surges in vehicle ownership, perhaps due to seasonal environmental factors or conducive economic conditions for purchasing vehicles.

Weather Impact: It is suspected that there are effects from the measurements of temperature that could have an effect on the road conditions and thus the congestion level too.

4.4 Feature Engineering

In view of what has been observed, new features are engineered and added to the original datasets to aid in prediction.

Derived Features: The day of the week, month, indicators on whether a day is a public holiday, weather conditions (temperature, whether it is raining or snowing) and special events which occurred on that day.

Time Series Features: Data from the previous day or time segment as features any temporal correlations can be captured in the features.

4.5 Expected Outcome

The main outcome of this research would be the development of a model for predicting traffic congestion in Malaysia. By providing a comprehensive set of features from different datasets and a significant amount of complimentary feature engineering, pitfalls which lead to traffic congestions, could possibly be detected. Consequently, authorities could be provided with actionable insights to manage such occurences.

4.6 Future Work

Improved models could be developed after this research phase and with availability of realtime data, this model could be further improved. Furthermore, we will also look into incorporating additional emerging technologies, such as the Internet of Things (IoT) and edge computing, to enhance the capabilities of data collection and data processing.

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