Victoria Traffic Accident Analysis

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SUMMARY

Traffic accidents remain a significant public health and safety issue in Victoria, Australia. Despite numerous efforts to improve road safety, the state continues to grapple with high road tolls, serious injuries, and the socio-economic impacts of road accidents. This project aims to conduct an in-depth data analysis of traffic accidents in Victoria, employing multiple traffic accident-related data sources from VicRoads, Victorian Government Data Directory, and Kaggle. The project's scope is to leverage advanced data analytical tools and techniques to identify key hidden patterns, trends, insights, and correlations in Victoria's traffic accident data, converting these key insights into actionable insights, enabling us to provide data-driven recommendations to mitigate traffic accidents – amounting to less deaths and numerous benefits. Additionally, utilizing data mining methods to build predictive models to aid in guiding recommendations for accident prevention and determining the best algorithm for such a task. Ultimately, by completing a thorough data analytics process, we can achieve our goal of providing actionable improvements for overall road safety in Victoria.

INTRODUCTION

In the last five years, approximately 1,200 people have been killed on Victorian roads – an average of 236 people each year (*Transport Accident Commission*, 2024). Currently in 2024 alone, there have been 121 fatalities on Victorian roads up to May 30th. Over the past few years, the road toll has fluctuated, with 2023 seeing a total of 285 deaths, a 4% increase from 274 in 2022, which could be attributed to increased traffic volumes post-pandemic as the return of pre-pandemic levels have returned – further vehicles on the road, which subsequently increases the likelihood of traffic accidents (*Transport Accident Commission*, 2024). In addition to fatalities, serious injuries also pose a major concern. In 2023, there were 5,972 serious injuries on Victorian roads (*Australian Institute of Health and Welfare*, 2024). These serious injuries often result in long-term physical and psychological injuries, significantly affecting the victims and their families. Road crashes in Victoria amount to 3-4 billion dollars every year (*ABC*, 2017). These alarming statistics emphasize the persistent challenges in improving road safety, reducing fatalities, and minimizing serious injuries. The socio-economic impacts are profound, with each fatality and serious injury contributing to emotional distress, healthcare costs, and economic burdens. The Victorian government's proposed solution to address these on-going traffic accident-related issues was to launch 'Victoria's Road Safety Strategy 2021-2030' – a road safety strategy improvement program with the primary goal of halving fatalities by 2030, as well as the ambitious future goal of eliminating deaths on Victorian roads by 2050 (*Transport Accident Commission*, 2024). My proposed solution to optimally accelerate this campaign as efficiently as possible is to harness the capabilities of data analytics and data mining algorithms. Implementing the Victoria Road Safety program as soon as possible is of paramount importance as it directly mitigates death and serious injury on our roads. By

extension, this approach coincides with our main purpose of enhancing overall road safety by conducting data analytics to drive data-driven decision-making for accident prevention on Victoria's roads. My proposed solution is achieved by conducting our scope: the data analytics process. Specifically, data collection, data cleaning, exploratory data analysis, feature engineering/selection, and modelling. By leveraging the power of data analytics and data mining algorithms on Victoria's traffic accident-related data, we can identify valuable key insights such as: accident hotspots, common causes, influential factors that contribute to the severity of accidents, and hidden patterns & features associated with traffic accidents in Victoria; data mining algorithms can then build upon these correlated insights/features, facilitating the forecast of traffic accidents in Victoria – enabling us to provide data-driven recommendations for overall road safety, with the ultimate goal of creating a safer road environment for all Victorians in mind.

Conducting a comprehensive traffic accident data analysis offers a multitude of expected overall benefits and outcomes.

Main benefits:

1. **Improved Road Safety:**
    - **Identifying Hotspots:** Data analysis can identify locations with high accident frequencies, allowing for authorities to target these areas for safety improvements, such as better signage, traffic calming measures, or road design changes.
    - **Predictive Insights:** Predictive models can help anticipate where and when severe accidents are likely to occur by identifying patterns that are strongly associated with severe accidents, leading to the facilitation of pre-emptive measures to avert accidents; by understanding these patterns, authorities can implement targeted solutions (e.g., stricter speed controls in high-risk areas, improved road signage, and better lighting) to mitigate the risk of severe accidents.
    - **Guided Infrastructure Improvements:** Understanding the types of accidents and their contributing factors can aid in the design of safer roads and intersections. For example, if many accidents occur in poorly lit areas, improved street lighting could be prioritized and implemented.
2. **Resource Allocation:**
    - **Efficient Use of Funds:** Insights from the data analysis can guide where to allocate funds for infrastructure improvements, ensuring that resources are used where they can have the most significant impact on reducing accidents.

- **Emergency Response Planning:** Predictive models can identify areas with high accident frequencies and severity which can help optimize the placement of emergency services to ensure quicker response times and treat car crash patients more effectively. For example, predictive models will help in enhancing emergency response strategies; by knowing which types of accidents are likely to be more severe, classification models can greatly aid emergency services to prepare and respond more effectively, ensuring that the right resources are deployed efficiently to potentially life-threatening situations.

- **Resource Allocation Optimization:** Predictive modelling can help prioritize and maximize resource allocation by predicting high-risk severity, times and locations for accidents, allowing for more efficient deployment of police, emergency services, and road maintenance crews. For example, if a classification model identifies that certain road conditions or times of day are associated with higher accident severity, resources can be directed towards improving those conditions or increasing patrols during those times.

3. **Policy and Decision Making:**

    - **Policy Development:** Insights gained from data analysis can inform policy decisions and the development of road safety strategies. For example, if traffic-related data shows a high incidence of accidents involving old drivers at night, policies could be developed to address this specific risk.

    - **Regulatory Improvements:** Understanding traffic accident patterns can lead to the development of new traffic regulations or the modification of existing ones to enhance safety.

    - **Data-Driven Decisions:** Policymakers can use the key insights gathered from data analysis to draft evidence-based regulations and policies aimed at improving road safety.

    - **Predictive Insights**: Insights gained from predictive models can inform policy decisions. For example, if the model shows a high correlation between certain types of road users (e.g., unlicensed drivers) and accident severity, policies can be designed to address these issues, such as stricter licensing checks and penalties for driving without a license.

4. **Public Awareness and Education:**

    - **Community Engagement:** Engaging with the community about the data analysis findings can foster a collaborative approach to road safety, with input from local residents and stakeholders.

- **Targeted Awareness Campaigns:** Data analytics can identify key risk factors and demographics most at risk, enabling the development of targeted public awareness campaigns and educational programs to address specific issues like drunk driving, speeding, or distracted driving.

Associated Benefits:

- **Supporting Victoria's Road Safety Strategy 2021-2030 Initiatives:**
  - **Data-Driven Strategy:** Comprehensive data analytics aligns with goals like those in Victoria's Road Safety Strategy 2021-2030, which aims to reduce fatalities and serious injuries. Its ultimate ambitious goal is to reduce fatalities to zero by 2050. Data-driven insights can track progress toward these goals and refine strategies as needed.

- **Enhanced Urban Planning:**
  - **Infrastructure Development:** Insights from the data analysis can be used to improve urban planning, ensuring that new developments incorporate road safety considerations.
  - **Traffic Management:** Better understanding of traffic flow and accident patterns can lead to improved traffic management strategies, reducing congestion and enhancing safety.

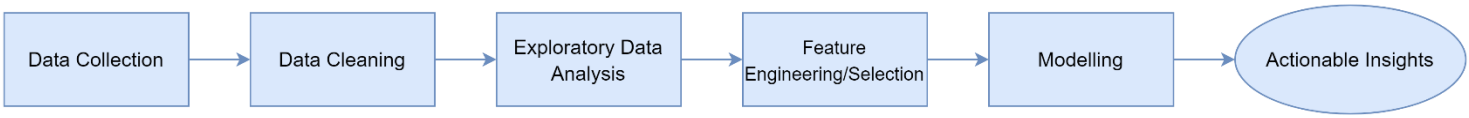
- **Economic Benefits:**
  - **Cost Savings:** Preventing accidents through informed interventions can lead to significant cost savings in healthcare, emergency response, and infrastructure repair. Reduced accident rates also lower economic burdens related to productivity losses and insurance claims.
  - **Insurance Premiums:** A lower incidence of accidents can result in lower insurance premiums for individuals and businesses, leading to overall economic savings for the community.

- **Technological Integration:**
  - **Smart City Initiatives:** Integrating Victoria's traffic accident data with other smart city technologies can lead to innovative solutions, such as real-time traffic monitoring and dynamic traffic control systems.

In essence, data analytics can serve as an extremely useful and powerful tool for preventing traffic accidents in Victoria. By applying comprehensive data analytics on traffic accident-related data in Victoria, we can extract valuable key insights to drive data-

driven accident prevention recommendations to mitigate death and serious injury on Victorian roads, as well as bringing numerous substantial benefits such as: Improved road safety, efficient resource allocation, enhanced policy and data-driven decision making, increased public awareness and education, improved economic benefits, data-supported strategy development, and forecasting of severe accidents.

DATA ANALYTICS PROCESS

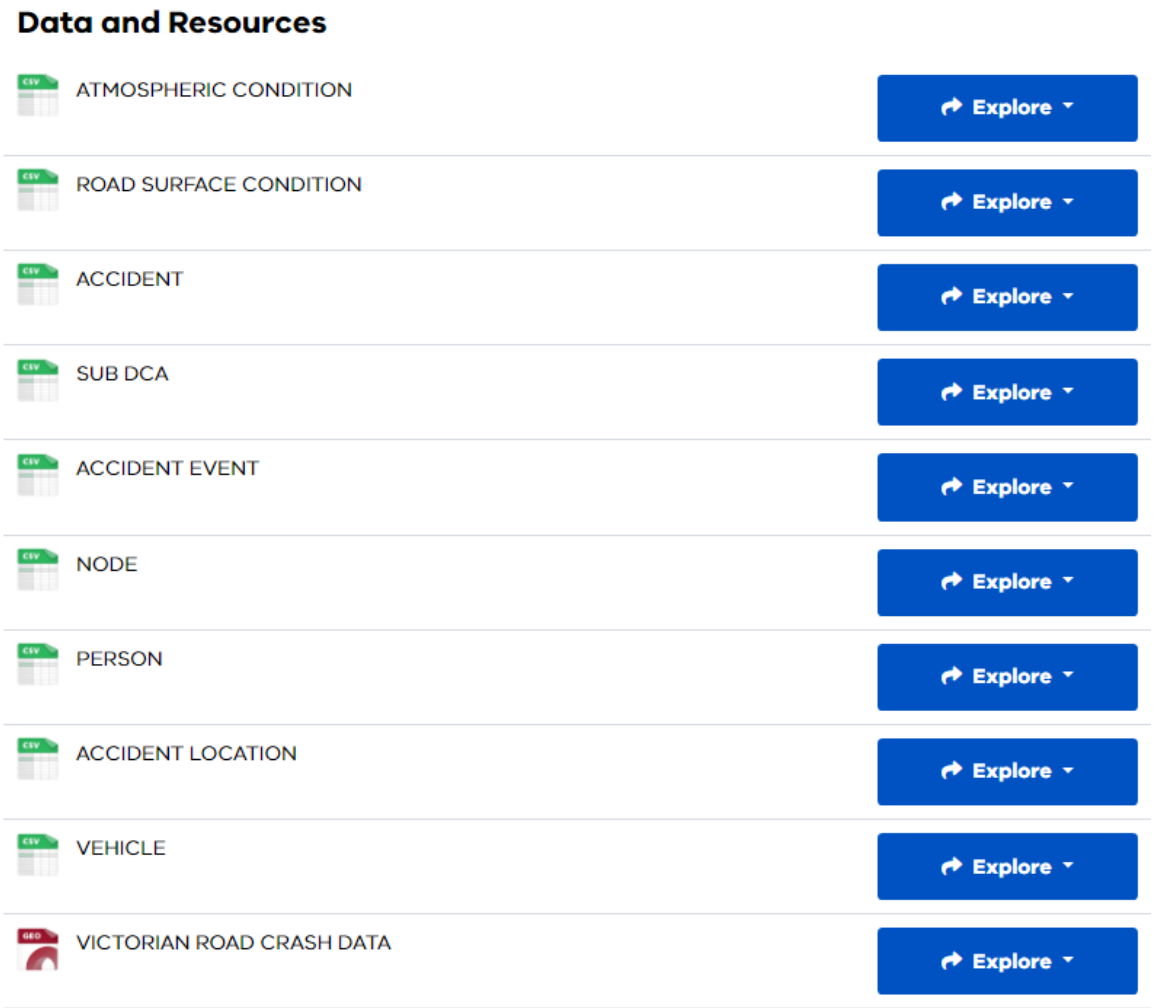


The data analytics process involves several key stages, each critical in their own way for extracting meaningful insights from Victoria's traffic accident-related data.

I will be using Python and its sophisticated libraries, such as GeoPandas, Pandas, and Scikit-learn, to complete the data analytics process. To facilitate this, I will employ Jupyter Notebook; a powerful tool specifically designed for conducting comprehensive interactive data analysis and is widely used in the data science field.

DATA COLLECTION

For data collection I have utilized multiple Victorian traffic accident-related data sources and merged them. Specifically, I have collected road accident-related datasets in Victoria from Discover Data Vic and Kaggle. Discover Data Vic is an open repository for data related to Victoria, owned by the State Government of Victoria, ensuring accurate and high-quality data. Kaggle is a platform that serves as an open hub for data science, providing a repository of datasets across different domains – very popular in the data science landscape. *Victoria Road Crash Data* (*Discover Data Vic*, 2024) will be my primary source of data as there is a plethora of relevant traffic accident-related datasets available. The data has been compiled from reports by Victoria Police and hospital injury records, then verified and enhanced to offer a thorough and detailed perspective on road crashes and injuries throughout Victoria (*Discover Data Vic*, 2024). This data contains information like accident locations, accident times, weather conditions, vehicle types, driver demographics, etc. Basically, the data holds every single attribute related to traffic accidents.



Victoria Road Crash Data. Discover Data Vic. *(2024).*

As we can observe, there is a multitude of relevant datasets available. The GEOJSON file: *Victorian Road Crash Data* will be my main dataset as it is a combination of all the datasets. Also, since it is in GEOJSON format, it enables us to conduct spatial analysis, which will be very beneficial in the Exploratory Data Analysis (EDA) phase. However, I have thoroughly analyzed all the datasets and identified that not every attribute in the other datasets is found in the Victorian Road Crash dataset. Specifically, I have discovered multiple desirable features that I want to consolidate from the other datasets into the main dataset:

Victoria Road Crash Datasets

- **ATMOSPHERIC CONDITION**: ATMOSPH_COND_DESC
- **ROAD SURFACE CONDITION:** SURFACE_COND_DESC

- **ACCIDENT EVENT:** EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC
- **PERSON:** PERSON_ID, SEX, AGE_GROUP
- **ACCIDENT LOCATION:** ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT
- **VEHICLE:** VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC

These are the several features I want to aggregate from the *Victoria Road Crash Data,* courtesy of Discover Data Vic (2024). Additionally, I have also discovered other beneficial features I intend to merge into my main dataset; from another dataset sourced from Kaggle: the *Victoria State Accident DataSet* by G. Chauhan (2020) – this dataset is compiled from VicRoads and contains Victoria's traffic accident statistics from 2013-2020. Specifically, I am only interested in merging these particular features into my main dataset:

Kaggle Dataset

- **Victoria State Accident DataSet:** ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENESED

Now that I have vigorously identified all the datasets and their respective features to be merged into the main dataset, we can proceed with implementing the code to achieve this integration. By correctly combining all of these features into the main dataset, we will create a comprehensive and robust dataset with a vast array of influential features related to traffic accidents in Victoria to analyze. This integrated dataset will enable us to perform detailed Exploratory Data Analysis (EDA) and uncover valuable insights into patterns and trends correlating with traffic accidents in Victoria. Ultimately, this refined dataset will also provide an excellent foundation for predictive modelling and the development of effective strategies for improving overall road safety in Victoria. Once the data collection process is finalized, I will thoroughly introduce the refined dataset.

First, I need to import the necessary packages for data pre-processing:

```
#Packages
import numpy as np
import geopandas as gpd
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
```

- **NumPy** - NumPy is a fundamental package for scientific computing with Python. It is essential to import NumPy before using other key data science libraries, as many of them are built upon NumPy's foundation.
- **GeoPandas** - GeoPandas is a Python library that extends the capabilities of Pandas to handle geospatial data. It builds on top of Pandas, allowing for the manipulation and analysis of spatial data. It is necessary to import this package as it enables us to use and manipulate our main dataset to its upmost potential.
- **Pandas** - Pandas is a powerful data analysis and manipulation library for Python. It provides essential data structures and functions to seamlessly manipulate structured data. It is necessary to import Pandas for reading and writing all of our CSV datasets we want to consolidate features from – allowing for the aggregation of features from multiple datasets. It is also a prerequisite to perform comprehensive data analytics.
- **Seaborn** - Seaborn is a Python visualization library based on Matplotlib that provides a high-level interface for illustrating appealing and statistical plots. It complements Matplotlib and is essential for depicting a variety of plots in data analytics.
- **Matplotlib** - Matplotlib is an extensive library to create static, animated, and interactive graphs in Python. It is a prerequisite to create and configure plots in data analytics. Again, it also serves as a foundation for Seaborn – working together to create comprehensive plots of all variety.
- **OS** - The OS package in Python provides a way to interact with our operating system. It is necessary to implement this package to read and write our datasets.

Now that all necessary packages are imported, we can proceed with writing the code to aggregate and integrate multiple desirable features into our main dataset. Upon analyzing all datasets, I have identified the ACCIDENT_NO feature as the consistent primary key across them all. This primary key will serve as the foundation for consolidating desired features from the other datasets into our main dataset. I will merge some features straightforwardly based on ACCIDENT_NO, while others will require more features to be based upon. This approach ensures that we effectively combine relevant data and maintain data integrity by accurately aligning data based on the primary key.

```
#Importing main dataset
main_df = gpd.read_file('C:/Users/Milan/VICTORIAN_ROAD_CRASH_DATA.geojson')
```

First, I need to import our primary dataset. The above code works by importing the Victorian Road Crash dataset which will serve as the main dataset for integrating additional datasets; specifically, only their certain desirable features. I use the read_file() method from GeoPandas to read the dataset and store it as the variable main_df.

Simple Merging:

ATMOSPHERIC CONDITION: ATMOSPH_COND_DESC:

```
#Load the atmosphere dataset containing the ATMOSPH_COND_DESC feature
at_df = pd.read_csv('C:/Users/Milan/ATMOSPHERIC_COND.csv')
```

```
#Merge the main & atmosphere datasets based on the ACCIDENT_NO column
main_df = pd.merge(main_df, at_df[['ACCIDENT_NO', 'ATMOSPH_COND_DESC']], on='ACCIDENT_NO', how='left')

#Reorder columns to place ATMOSPH_COND_DESC in the 7th position
columns = list(main_df.columns)
columns.insert(6, columns.pop(columns.index('ATMOSPH_COND_DESC')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

'_OF_WEEK	DCA_CODE	ATMOSPH_COND_DESC	LIGHT_CONDITION	POLICE_ATTEND	ROAD_GEOMETRY	SEVERITY	SPEED_ZONE	RUN_OFFROAD	NOD
Sunday	LEFT OFF CARRIAGEWAY INTO OBJECT/PARKED VEHICLE	Clear	Dark No street lights	Yes	Not at intersection	Other injury accident	100 km/hr	Yes	24

The above code does as follows:

1. Importing the ATMOSPHERIC CONDITION dataset, which contains the feature I want to merge: ATMOSPH_COND_DESC. I use the read_csv() method from Pandas to read the dataset and store it as the variable at_df.

2. Merging the main_df & at_df datasets based on the ACCIDENT_NO column to integrate ATMOSPH_COND_DESC into the main_df by employing the merge() method from Pandas. It works by only including ACCIDENT_NO and ATMOSPH_COND_DESC columns from the at_df dataset and then specifying the merge to be performed based on the ACCIDENT_NO column by setting the parameter (on = 'ACCIDENT_NO'), again, which serves as the primary key linking main_df and at_df. Finally, the parameter (how = 'left') ensures a left join, which means retaining all the rows from main_df and adding ATMOSPH_COND_DESC where ACCIDENT_NO values match from at_df into main_df.

3. I then reorder the ATMOSPH_COND_DESC feature to the 7th position within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the ATMOSPH_COND_DESC column is removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 6th position (which corresponds to the 7th position, as indexing in Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step wasn't necessary and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

4. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of ATMOSPH_COND_DESC into the main_df has been successfully executed.

I will also test if the aggregation has been correctly implemented by verifying if the results are consistent across my main dataset and the *Victora Road Crash Data* available on Discover Data Vic (Discover Data Vic, 2024). I will do this by verifying a specific ACCIDENT_NO value in both domains. The specific value in question is: T20230025526. This procedure will be done where applicable for all consolidations conducted – besides Kaggle.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df["ACCIDENT_NO"] == 'T20230025526']
```

Γ_TYPE_DESC	ATMOSPH_COND_DESC	SURFACE_COND_DESC
Collision	Clear	Dry

Atmospheric Condition result:

Showing 1 to 1 of 1 entries (filtered from 172,052 total entries)

Search: T20230025526

_id	ACCIDENT_NO	ATMOSPH_COND	ATMOSPH_COND_SEQ	ATMOSPH_COND_DESC
158424	T20230025526	1	1	Clear

ATMOSPHERIC CONDITION. Discover Data Vic. *(2024).*

We can clearly observe the results align and the merge is working as intended.

ROAD SURFACE CONDITION: SURFACE_COND_DESC:

```
#Load the road surface dataset containing the SURFACE_COND_DESC feature
sf_df = pd.read_csv('C:/Users/Milan/ROAD_SURFACE_COND.csv')
```

```
#Merge the main & surface datasets based on the ACCIDENT_NO column
main_df = pd.merge(main_df, sf_df[['ACCIDENT_NO', 'SURFACE_COND_DESC']], on='ACCIDENT_NO', how='left')

#Reorder columns to place SURFACE_COND_DESC in the 8th position
columns = list(main_df.columns)
columns.insert(7, columns.pop(columns.index('SURFACE_COND_DESC')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

DCA_CODE	ATMOSPH_COND_DESC	SURFACE_COND_DESC	LIGHT_CONDITION	POLICE_ATTEND	ROAD_GEOMETRY	SEVERITY	SPEED_ZONE	RUN_OFFR
LEFT OFF CARRIAGEWAY INTO OBJECT/PARKED VEHICLE	Clear	Dry	Dark No street lights	Yes	Not at intersection	Other injury accident	100 km/hr	

The above code does as follows:

1. Importing the ROAD SURFACE CONDITION dataset, which contains the feature I want to merge: SURFACE_COND_DESC. I use the read_csv() method from Pandas to read the dataset and store it as the variable sf_df.

2. Merging the main_df & sf_df datasets based on the ACCIDENT_NO column to integrate SURFACE_COND_DESC into the main_df by employing the merge() method from Pandas. It works by only including ACCIDENT_NO and SURFACE_COND_DESC columns from the sf_df dataset and then specifying the merge to be performed based on the ACCIDENT_NO column by setting the parameter (on = 'ACCIDENT_NO'), again, which serves as the primary key linking main_df and sf_df. Finally, the parameter (how = 'left') ensures a left join, which means retaining all the rows from main_df and adding SURFACE_COND_DESC where ACCIDENT_NO values match from sf_df into main_df.

3. I then reorder the SURFACE_COND_DESC feature to the 8th position within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the SURFACE_COND_DESC column is removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 7th position (which corresponds to the 8th position, as indexing in Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step wasn't necessary and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

4. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of SURFACE_COND_DESC into the main_df has been successfully executed.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df["ACCIDENT_NO"] == 'T20230025526']
```

TMOSPH_COND_DESC	SURFACE_COND_DESC	ROAD_SURFACE_TYPE_DESC
Clear	Dry	Paved

Road Surface Condition result:

Showing 1 to 1 of 1 entries (filtered from 170,770 total entries)

Search: T20230025526

_id	ACCIDENT_NO	SURFACE_COND	SURFACE_COND_DESC	SURFACE_COND_SEQ
138995	T20230025526	1	Dry	1

ROAD SURFACE CONDITION. Discover Data Vic. *(2024).*

We can clearly observe the results align and the merge is working as intended.

ACCIDENT LOCATION: ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT:

```
#Load the accident location dataset containing the ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT features
al_df = pd.read_csv('C:/Users/Milan/ACCIDENT_LOCATION.csv')
```

```
#Merge the main & accident location datasets based on the ACCIDENT_NO column
main_df = pd.merge(main_df, al_df[['ACCIDENT_NO', 'ROAD_NAME', 'ROAD_TYPE', 'ROAD_NAME_INT', 'ROAD_TYPE_INT']], on='ACCIDENT_NO',
                   how='left')

#Reorder columns to place ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, and ROAD_TYPE_INT in the 17th, 18th, 19th, and 20th positions
columns = list(main_df.columns)
columns.insert(16, columns.pop(columns.index('ROAD_NAME')))
columns.insert(17, columns.pop(columns.index('ROAD_TYPE')))
columns.insert(18, columns.pop(columns.index('ROAD_NAME_INT')))
columns.insert(19, columns.pop(columns.index('ROAD_TYPE_INT')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

NODE_ID	NODE_TYPE	ROAD_NAME	ROAD_TYPE	ROAD_NAME_INT	ROAD_TYPE_INT	LGA_NAME	LATITUDE	LONGITUDE	VICGRID_X	VICGRID_Y	TOT
249102	Non-Intersection	WESTERNPORT	ROAD	PHILLIPS	ROAD	BAW BAW	-38.234957	145.726709	2563628.962	2362700.434	

The above code does as follows:

1. Importing the ACCIDENT LOCATION dataset, which contains numerous features I want to merge: ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT. I use the read_csv() method from Pandas to read the dataset and store it as the variable al_df.

2. Merging the main_df & al_df datasets based on the ACCIDENT_NO column to integrate ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, and ROAD_TYPE_INT into the main_df by employing the merge() method from Pandas. It works by only including ACCIDENT_NO and ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT columns from the al_df dataset and then specifying the merge to be performed based on the ACCIDENT_NO column by setting the parameter (on = 'ACCIDENT_NO'), again, which serves as the primary key linking main_df and al_df. Finally, the parameter (how = 'left') ensures a left join, which means retaining all the rows from main_df and adding ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, and ROAD_TYPE_INT where ACCIDENT_NO values match from al_df into main_df.

3. I then reorder the ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT features to the 17th, 18th, 19th, and 20th positions within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT columns are removed and

returned from its current position using pop(), and then inserted at the specified index by using insert(): the 16th, 17th, 18th, and 19th positions (which corresponds to the 17th, 18th, 19th, and 20th positions, as indexing in Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step wasn't necessary and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

4. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, and ROAD_TYPE_INT into the main_df has been successfully executed.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df["ACCIDENT_NO"] == 'T20230025526']
```

ROAD_NAME	ROAD_TYPE	ROAD_NAME_INT	ROAD_TYPE_INT
JOSEPHINE	AVENUE	VICTORIA	ROAD

Accident Location result:

Showing 1 to 1 of 1 entries (filtered from 169,809 total entries)

Search: T20230025526

_id	ROAD_NAME	ROAD_TYPE	ROAD_NAME_INT	ROAD_TYPE_INT	DISTANCE_LOCATI(
135547	JOSEPHINE	AVENUE	VICTORIA	ROAD	92

ACCIDENT LOCATION. Discover Data Vic. *(2024).*

We can clearly observe the results align and the merge is working as intended.

Victoria State Accident DataSet: ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENCSED:

```
#Load the kaggle dataset containing the ALCOHOL_RELATED and HIT_RUN_FLAG, UNLICENCSED features
k_df= pd.read_csv('C:/Users/Milan/Crash Statistics Victoria.csv')
```

```
#Merge the main & kaggle datasets based on the ACCIDENT_NO column
main_df = pd.merge(main_df, k_df[['ACCIDENT_NO', 'ALCOHOL_RELATED', 'HIT_RUN_FLAG', 'UNLICENCSED']], on='ACCIDENT_NO', how='left'

#Reorder columns to place ALCOHOL_RELATED, HIT_RUN_FLAG, and UNLICENCSED in the 14th, 15th, and 17th positions
columns = list(main_df.columns)
columns.insert(13, columns.pop(columns.index('ALCOHOL_RELATED')))
columns.insert(14, columns.pop(columns.index('HIT_RUN_FLAG')))
columns.insert(16, columns.pop(columns.index('UNLICENCSED')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

SEVERITY	SPEED_ZONE	ALCOHOL_RELATED	HIT_RUN_FLAG	RUN_OFFROAD	UNLICENCSED	NODE_ID	NODE_TYPE	ROAD_NAME	ROAD_TYPE	ROAD_
Other injury accident	100 km/hr	NaN	NaN	Yes	NaN	249102	Non-Intersection	WESTERNPORT	ROAD	

The above code does as follows:

1. Importing the Victoria State Accident dataset from Kaggle, which contains a few features I want to merge: ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENCSED. I use the read_csv() method from Pandas to read the dataset and store it as the variable k_df.

2. Merging the main_df & al_df datasets based on the ACCIDENT_NO column to integrate ALCOHOL_RELATED, HIT_RUN_FLAG, and UNLICENCSED into the main_df by employing the merge() method from Pandas. It works by only including ACCIDENT_NO and ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENCSED columns from the k_df dataset and then specifying the merge to be performed based on the ACCIDENT_NO column by setting the parameter (on = 'ACCIDENT_NO'), again, which serves as the primary key linking main_df and k_df. Finally, the parameter (how = 'left') ensures a left join, which means retaining all the rows from main_df and adding ALCOHOL_RELATED, HIT_RUN_FLAG, and UNLICENCSED where ACCIDENT_NO values match from k_df into main_df.

3. I then reorder the ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENCSED features to the 14^{th}, 15^{th}, and 17^{th} positions within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the ALCOHOL_RELATED, HIT_RUN_FLAG, UNLICENCSED columns are removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 13^{th}, 14^{th}, and 16^{th} positions (which corresponds to the 14^{th}, 15^{th}, and 17^{th} positions, as indexing in

Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step wasn't necessary and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

4. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of ALCOHOL_RELATED, HIT_RUN_FLAG, and UNLICENCSED into the main_df has been successfully executed.

Since this dataset is from Kaggle – we cannot verify through the domain of *Victoria Road Crash Data* (Discover Data Vic, 2024). Also, this dataset was compiled from 2013-2020, so it unfortunately doesn't contain the ACCIDENT_NO value T20230025526 which occurred in 2023. Instead, I will verify another ACCIDENT_NO value: T20130013732. In this specific situation, I will be verifying through the dataset domain solely.

Verifying T20130013732:

Dataset result:

```
#Verifying T20130013732
main_df[main_df["ACCIDENT_NO"] == 'T20130013732']
```

ALCOHOL_RELATED	HIT_RUN_FLAG	RUN_OFFROAD	UNLICENCSED
No	No	No	0.0

Kaggle Dataset result:

```
#Verifying T20230025526
df[df["ACCIDENT_NO"] == 'T20130013732']
```

ALCOHOL_RELATED	UNLICENCSED	NO_OF_VEHICLES	HIT_RUN_FLAG
No	0	1	No

We can clearly observe the results align and the merge is working as intended. Although, for some reason UNLICENCSED was transformed to a float from the original int datatype; I will rectify this in the data cleaning phase.

Before we proceed with sophisticated merging, I want to explain the rationale behind this approach. Sophisticated merging will be used to aggregate desirable features from the remaining datasets into the main dataset. It is necessary to conduct the consolidation in this manner to achieve my desired outcome; the simple merging we were conducting on the previous datasets could not provide the outcome I was looking for when it comes to the remaining datasets to consolidate from. This is why I have to conduct a more sophisticated version of merging on the remaining datasets:

- **ACCIDENT EVENT**: EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC: This dataset contains a lot of duplicates because it lists every vehicle and other attributes involved in specific accidents, resulting in multiple duplicate ACCIDENT_NO and VEHICLE_1_ID entries. Besides the redundancy issue, this dataset includes information about every party involved in a particular traffic accident. However, I want to focus solely on the perpetrators of the traffic accidents. By doing so, we can analyse trends and patterns associated with the instigators of these road accidents during the Exploratory Data Analysis (EDA) and modelling phase, garnering significant insights into accident prevention. If I were to merge this dataset in the same manner as previously done with the other datasets, it would introduce redundant data and overall clutter, terribly skewing the dataset. This would negatively impact the data analysis and predictive modelling results, greatly obscuring our chances of uncovering critical insights. The solution is to correctly aggregate the perpetrators of traffic accidents: After analyzing the dataset, I noticed that the first data entries of ACCIDENT_NO belong to the perpetrator of the traffic accident. Therefore, I need to modify the original merge code we used previously to retain only the first sample of ACCIDENT_NO rows within this dataset.

- **VEHICLE**: VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC: This dataset presents similar challenges to the ACCIDENT_EVENT dataset described previously, with numerous duplicate rows listing every vehicle involved in specific traffic accidents. To streamline our analysis and avoid issues such as redundancy and noise, I aim to focus exclusively on the vehicles associated with the drivers at fault—the perpetrators of the traffic accidents. Upon thorough analysis of this dataset, I've observed that by matching VEHICLE_ID from the VEHICLE dataset with VEHICLE_1_ID's values in main_df based on the ACCIDENT_NO, I have identified the vehicles driven by the drivers at fault. Therefore, I will modify our previous merge code to merge main_df with the VEHICLE dataset. This merge will be based on the ACCIDENT_NO column, ensuring that only rows corresponding to VEHICLE_ID from the VEHICLE dataset, which matches VEHICLE_1_ID values from main_df are integrated. This approach

will help maintain data integrity and optimize our analysis for identifying key insights into accident prevention.

- **PERSON**: PERSON_ID, SEX, AGE_GROUP: Again, similar to other datasets, the PERSON dataset has issues with redundancy due to multiple entries for the same accident (ACCIDENT_NO), but different individuals (PERSON_ID). This redundancy arises because the dataset records all people involved in each particular traffic accident. However, we are solely focusing on aggregating data related to the drivers at fault. This focus is essential to avoid biased data, reduce noise, and prevent any adverse impacts on the overall data analytical process. By concentrating on the drivers at fault, We can maximize the insights gathered through data analysis, which can be instrumental in combating road accidents in Victoria. Through analysis, it has been determined that based on the ACCIDENT_NO, matching values from PERSON_ID and VEHICLE_ID directly link to the driver at fault. I need to modify the original merge code to merge the main_df with the PERSON dataset, ensuring that PERSON_ID from the PERSON dataset aligns with the values in VEHICLE_ID from main_df, based on the ACCIDENT_NO. This procedure facilitates the focus on data related to the drivers at fault, thus providing valuable insights for accident prevention.

Sophisticated merging:

ACCIDENT EVENT: EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC:

```
#Load the accident event dataset containing the EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC features
ae_df = pd.read_csv('C:/Users/Milan/ACCIDENT_EVENT.csv')
```

```
#Selecting the desired EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC columns from ae_df
ae_df_selected = ae_df[['ACCIDENT_NO', 'EVENT_TYPE_DESC', 'VEHICLE_1_ID', 'VEHICLE 1 COLL PT DESC']]

#Dropping duplicates based on ACCIDENT_NO, keeping the first occurrence only
ae_df_unique = ae_df_selected.drop_duplicates(subset=['ACCIDENT_NO'], keep='first')

#Merge the main_df & ae_df based on the ACCIDENT_NO column
main_df = pd.merge(main_df, ae_df_unique, on='ACCIDENT_NO', how='left')

#Reorder columns to place EVENT_TYPE_DESC, VEHICLE_1_ID, and VEHICLE 1 COLL PT DESC in the 7th, 19th, and 20th positions
columns = list(main_df.columns)
columns.insert(6, columns.pop(columns.index('EVENT_TYPE_DESC')))
columns.insert(18, columns.pop(columns.index('VEHICLE_1_ID')))
columns.insert(19, columns.pop(columns.index('VEHICLE 1 COLL PT DESC')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

)HOL_RELATED	HIT_RUN_FLAG	RUN_OFFROAD	UNLICENCSED	VEHICLE_1_ID	VEHICLE 1 COLL PT DESC	NODE_ID	NODE_TYPE	ROAD_NAME	ROAD_TYPE	ROAD_NAME_
NaN	NaN	Yes	NaN	A	Not known or Not Applicable	249102	Non-Intersection	WESTERNPORT	ROAD	PHILL

The above code does as follows:

1. Importing the ACCIDENT EVENT dataset, which contains a couple of features I want to merge: EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC. I use the read_csv() method from Pandas to read the dataset and store it as the variable ae_df.

2. I then store the columns I need for integration in the variable data frame ae_df_selected (ACCIDENT_NO, EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC).

3. Handling the duplicate values in ae_df_selected by removing duplicate rows and keeping only the first row based on the ACCIDENT_NO column. This is achieved by using the drop_duplicates() method from Pandas. The parameter keep='first' specifies that only duplicate rows after the first occurrence should be dropped. This ensures that we retain the first row for each ACCIDENT_NO, which corresponds to the drivers at fault in the traffic accidents that we want to merge into main_df. The resulting data frame, free of duplicates, is stored in the variable ae_df_unique

4. Now that I have dealt with the duplicates, we can return to our previous method of aggregating for this particular dataset. Merging the main_df & ae_df_unique datasets based on the ACCIDENT_NO column to integrate EVENT_TYPE_DESC, VEHICLE_1_ID, and VEHICLE 1 COLL PT DESC into the main_df by employing the merge() method from Pandas. It works by only including EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC columns from the ae_df_unique dataset and then specifying the merge to be performed based on the ACCIDENT_NO column by setting the parameter (on = 'ACCIDENT_NO'), again, which serves as the primary key linking main_df and ae_df_unique. Finally, the parameter (how = 'left') ensures a left join, which means retaining all the rows from main_df and adding EVENT_TYPE_DESC, VEHICLE_1_ID, and VEHICLE 1 COLL PT DESC where ACCIDENT_NO values match from ae_df_unique into main_df.

5. I then reorder the EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC features to the 7^{th}, 19^{th}, and 20^{th} positions within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the EVENT_TYPE_DESC, VEHICLE_1_ID, VEHICLE 1 COLL PT DESC columns are removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 6^{th}, 18^{th}, and 19^{th} positions (which corresponds to the 7^{th}, 19^{th}, and 20^{th} positions, as indexing in Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step wasn't necessary

and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

6. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of EVENT_TYPE_DESC, VEHICLE_1_ID, and VEHICLE 1 COLL PT DESC into the main_df has been successfully executed.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df["ACCIDENT_NO"] == 'T20230025526']
```

VEHICLE_1_ID	VEHICLE 1 COLL PT DESC	VEHICLE_ID	VEHICLE_YEAR_MANUF	EVENT_TYPE_DESC
B	Front	B	0.0	Collision

Accident Event result:

Showing 1 to 1 of 1 entries (filtered from 279,595 total entries)

Search: T20230025526

_id	EVENT_TYPE_DESC	VEHICLE_1_ID	VEHICLE_1_COLL_PT	VEHICLE 1 COLL PT DESC
236024	Collision	B	F	Front

ACCIDENT EVENT. Discover Data Vic. *(2024)*.

We can clearly observe the results align and the merge is working as intended.

VEHICLE: VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC:

```
#Load the VEHICLE dataset containing the VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE,VEHICLE_MAKE,
#VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC features
v_df = pd.read_csv('C:/Users/Danny/VEHICLE.csv')
```

```
#Select the desired columns besides VEHICLE_ID from v_df
v_df_selected = ['VEHICLE_YEAR_MANUF', 'ROAD_SURFACE_TYPE_DESC',
                 'VEHICLE_BODY_STYLE', 'VEHICLE_MAKE', 'VEHICLE_MODEL', 'VEHICLE_TYPE_DESC',
                 'FUEL_TYPE', 'NO_OF_CYLINDERS', 'CAUGHT_FIRE', 'TRAFFIC_CONTROL_DESC']

#Merge the main_df & v_df based on the ACCIDENT_NO column & ensure VEHICLE_ID from v_df matches VEHICLE_1_ID from main_df
main_df = pd.merge(main_df, v_df[['ACCIDENT_NO', 'VEHICLE_ID'] + v_df_selected],
                   left_on=['ACCIDENT_NO', 'VEHICLE_1_ID'],
                   right_on=['ACCIDENT_NO', 'VEHICLE_ID'],
                   how='left')

#Reorder columns to place ROAD_SURFACE_TYPE_DESC, TRAFFIC_CONTROL_DESC, VEHICLE_ID, VEHICLE_YEAR_MANUF, VEHICLE_BODY_STYLE,
#VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE in the 10th, 12th, 23rd,
#24th, 25th, 26th, 27th, 28th, 29th, 30th, and 31st positions
columns = list(main_df.columns)
columns.insert(9, columns.pop(columns.index('ROAD_SURFACE_TYPE_DESC')))
columns.insert(11, columns.pop(columns.index('TRAFFIC_CONTROL_DESC')))
columns.insert(22, columns.pop(columns.index('VEHICLE_ID')))
columns.insert(23, columns.pop(columns.index('VEHICLE_YEAR_MANUF')))
columns.insert(24, columns.pop(columns.index('VEHICLE_BODY_STYLE')))
columns.insert(25, columns.pop(columns.index('VEHICLE_MAKE')))
columns.insert(26, columns.pop(columns.index('VEHICLE_MODEL')))
columns.insert(27, columns.pop(columns.index('VEHICLE_TYPE_DESC')))
columns.insert(28, columns.pop(columns.index('FUEL_TYPE')))
columns.insert(29, columns.pop(columns.index('NO_OF_CYLINDERS')))
columns.insert(30, columns.pop(columns.index('CAUGHT_FIRE')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

VEHICLE_ID	VEHICLE_YEAR_MANUF	VEHICLE_BODY_STYLE	VEHICLE_MAKE	VEHICLE_MODEL	VEHICLE_TYPE_DESC	FUEL_TYPE	NO_OF_CYLINDERS	CAUC
A	1996.0	SEDAN	HOLDEN	ACCLAI	Car	P	6.0	

The above code does as follows:

1. Importing the VEHICLE dataset, which contains several features I want to merge: VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, and TRAFFIC_CONTROL_DESC. I use the read_csv() method from Pandas to read the dataset and store it as the variable v_df.

2. I then store the columns I want to integrate in the variable data frame v_df_selected (VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC) – mainly done for clarity reasons.

3. We merge main_df with v_df and v_df_selected datasets based on the ACCIDENT_NO and VEHICLE_1_ID columns to integrate the VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, and TRAFFIC_CONTROL_DESC features into main_df. Using the merge() method from Pandas, we include the columns VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, and TRAFFIC_CONTROL_DESC from v_df plus v_df_selected. This merge is performed by specifying left_on=['ACCIDENT_NO', 'VEHICLE_1_ID'] (using ACCIDENT_NO from both datasets and VEHICLE_1_ID from main_df as left keys for merging) and right_on=['ACCIDENT_NO', 'VEHICLE_ID'] (using ACCIDENT_NO from both datasets and VEHICLE_ID from v_df as right keys for merging). This ensures that VEHICLE_ID from v_df matches VEHICLE_1_ID from main_df based on the ACCIDENT_NO. Finally, we specify (how='left') to conduct a left join, which means retaining all rows from main_df and adding VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, and TRAFFIC_CONTROL_DESC where the keys (['ACCIDENT_NO', 'VEHICLE_1_ID'] and ['ACCIDENT_NO', 'VEHICLE_ID']) match. This approach allows for the integration of these desirable features into main_df.

4. I then reorder the VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC features to the 10th, 12th, 23rd, 24th, 25th, 26th, 27th, 28th, 29th, 30th, and 31st positions within main_df. This is done by creating a list of all the columns within main_df and utilizing the pop() and insert() methods from Python. Specifically, the VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, TRAFFIC_CONTROL_DESC columns are removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 9th, 11th, 22th, 23th, 24th, 25th, 26th, 27th, 28th, 29th, and 30th positions (which corresponds to the 10th, 12th, 23rd, 24th, 25th, 26th, 27th, 28th, 29th, 30th, and 31st positions, as indexing in Python is zero-based). Lastly, we reassign the columns of main_df to this newly ordered list. Overall, this step isn't necessary and won't have

any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

5. Finally, we display the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of VEHICLE_ID, VEHICLE_YEAR_MANUF, ROAD_SURFACE_TYPE_DESC, VEHICLE_BODY_STYLE, VEHICLE_MAKE, VEHICLE_MODEL, VEHICLE_TYPE_DESC, FUEL_TYPE, NO_OF_CYLINDERS, CAUGHT_FIRE, and TRAFFIC_CONTROL_DESC into the main_df has been successfully executed.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df['ACCIDENT_NO'] == 'T20230025526']
```

VEHICLE_ID	VEHICLE_YEAR_MANUF	VEHICLE_BODY_STYLE	VEHICLE_MAKE	VEHICLE_MODEL	VEHICLE_TYPE_DESC	FUEL_TYPE	NO_OF_CYLINDERS	CAU
B	0.0	BUS	UNKN	NaN	Bus/Coach	Z	NaN	

Vehicle result:

Showing 1 to 2 of 2 entries (filtered from 309,628 total entries)

Search: T20230025526

_id	ACCIDENT_NO	VEHICLE_ID	VEHICLE_YEAR_MANUF	VEHICLE_DCA_CODE	INITIAL
306694	T20230025526	A	2008	2	W
306695	T20230025526	B	0	1	W

VEHICLE. Discover Data Vic. *(2024).*

We can clearly observe the results align and the merge is working as intended. Only the vehicle from the driver at fault is depicted in our main dataset – which is what we want. We can further verify that this is in-fact the perpetrators vehicle of this specific traffic accident. By referring back to the Accident Event result and analysing the row containing the value of 'B' when it came to VEHICLE_1_ID; matching values, indicating it is indeed displaying the driver at fault's data.

PERSON: PERSON_ID, SEX, AGE_GROUP:

```
#Load the person dataset containing the PERSON_ID, SEX, AGE_GROUP features
p_df = pd.read_csv('C:/Users/Milan/PERSON.csv')
```

```
#Merge the main_df and p_df based on the ACCIDENT_NO column and ensure PERSON_ID from p_df matches VEHICLE_ID from main_df
main_df = pd.merge(main_df, p_df[['ACCIDENT_NO', 'PERSON_ID', 'SEX', 'AGE_GROUP']],
                   left_on=['ACCIDENT_NO', 'VEHICLE_ID'],
                   right_on=['ACCIDENT_NO', 'PERSON_ID'],
                   how='left')

#Reorder columns to place PERSON_ID, SEX, AGE_GROUP in the 17th, 18th, and 19th positions
columns = list(main_df.columns)
columns.insert(16, columns.pop(columns.index('PERSON_ID')))
columns.insert(17, columns.pop(columns.index('SEX')))
columns.insert(18, columns.pop(columns.index('AGE_GROUP')))
main_df = main_df[columns]

#Display the first row of the merged dataset to verify conversion
main_df.head(1)
```

SEVERITY	SPEED_ZONE	PERSON_ID	SEX	AGE_GROUP	ALCOHOL_RELATED	HIT_RUN_FLAG	RUN_OFFROAD	UNLICENCSED	VEHICLE_1_ID	VEHICLE 1 COLL PT DESC	VE
Other injury accident	100 km/hr	A	M	18-21	NaN	NaN	Yes	NaN	A	Not known or Not Applicable	

The above code does as follows:

1. Importing the PERSON dataset, which contains several features I want to merge: PERSON_ID, and SEX, AGE_GROUP. I use the read_csv() method from Pandas to read the dataset and store it as the variable p_df.

2. We merge main_df & p_df datasets based on the ACCIDENT_NO and VEHICLE_ID columns to integrate the PERSON_ID, SEX, and AGE_GROUP features into main_df. Using the merge() method from Pandas, we include the columns PERSON_ID, SEX, and AGE_GROUP from p_df. This merge is performed by specifying left_on=['ACCIDENT_NO', 'VEHICLE_ID'] (using ACCIDENT_NO from both datasets and VEHICLE_ID from main_df as left keys for merging) and right_on=['ACCIDENT_NO', 'PERSON_ID'] (using ACCIDENT_NO from both datasets and PERSON_ID from p_df as right keys for merging). This ensures that PERSON_ID from p_df matches VEHICLE_ID's values from main_df based on the ACCIDENT_NO. Lastly, we specify (how='left') to conduct a left join, which corresponds to retaining all the rows from main_df and adding PERSON_ID, SEX, and AGE_GROUP where the keys (['ACCIDENT_NO', 'VEHICLE_ID'] and ['ACCIDENT_NO', 'PERSON_ID']) match. This approach allows for the consolidation of these desirable features into main_df.

3. I then reorder the PERSON_ID, SEX, AGE_GROUP features to the 17th, 18th, and 19th positions within main_df. This is done by creating a list of all the columns

within main_df and utilizing the pop() and insert() methods from Python. Specifically, PERSON_ID, SEX, and AGE_GROUP columns are removed and returned from its current position using pop(), and then inserted at the specified index by using insert(): the 16th, 17th, and 18th positions (which corresponds to the 17th, 18th, and 19th positions, as indexing in Python is zero-based). Finally, we reassign the columns of main_df to this newly ordered list. Overall, this step isn't necessary and won't have any impact on the analysis at all, however I executed it solely for clarity reasons when viewing the dataset.

4. Displays the first row of the data frame by utilizing the head() method from Pandas. This is done to verify if the merge has been successful – we can clearly observe from the output that the integration of PERSON_ID, SEX, and AGE_GROUP into the main_df has been successfully executed.

Verifying T20230025526 across domains:

Dataset result:

```
#Verifying T20230025526
main_df[main_df["ACCIDENT_NO"] == 'T20230025526']
```

SPEED_ZONE	PERSON_ID	SEX	AGE_GROUP	ALCOHOL_RELATED	HIT_RUN_FLAG	RUN_OFFROAD	UNLICENCSED	VEHICLE_1_ID	VEHICLE 1 COLL PT DESC	VEHICLE_ID
40 km/hr	B	M	30-39	NaN	NaN	No	NaN	B	Front	B

Person result:

Showing 1 to 5 of 5 entries (filtered from 396,824 total entries)

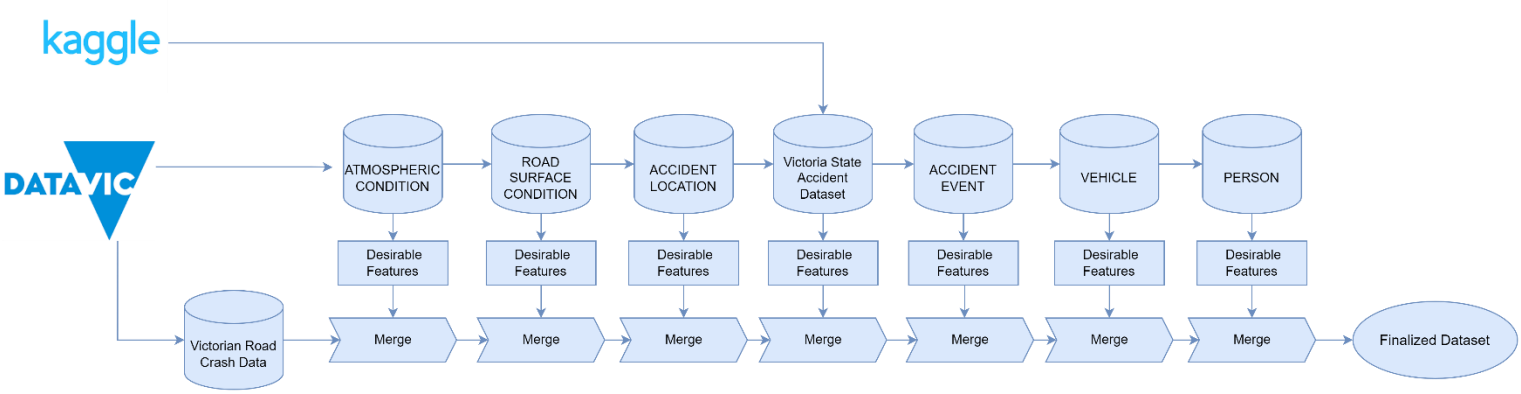
Search: T20230025526

_id	ACCIDENT_NO	PERSON_ID	VEHICLE_ID	SEX	AGE_GROUP	INJ_LEVEL	IN
393321	T20230025526	B	B	M	30-39	4	N
393322	T20230025526	01	A	F	40-49	3	O
393323	T20230025526	02	A	M	0-4	3	O
393324	T20230025526	03	A	F	5-12	3	O
394994	T20230025526	A	A	M	40-49	3	O

PERSON. Discover Data Vic. *(2024).*

We can clearly observe the results align and the merge is working as intended. Only the individual who caused the traffic accident is being displayed in our main dataset. We can further verify this by analysing past Vehicle and Accident Event results pertaining to T20230025526 – all values are consistent and align correctly. It is in-fact the driver at fault's personal data being depicted in this specific traffic accident.

Data Collection Flowchart:



Now that the data collection step has finally been completed, I will move on to thoroughly introduce the finalized dataset I will be conducting comprehensive data analysis on.

DATASET DESCRIPTION

Initial dataset before data cleaning:

Feature	Sample	Description
ACCIDENT_NO	T20230025526	Unique road accident identifier
ACCIDENT_DATE	2012/01/02	Date of the road accident
ACCIDENT_TIME	02:00:00	Time of the road accident
ACCIDENT_TYPE	Collision with vehicle	Type of road accident
DAY_OF_WEEK	Sunday	Day of the week accident occurred
DCA_CODE	LEFT OFF CARRIAGEWAY INTO OBJECT/PARKED VEHICLE	Description for the Accident Classification
EVENT_TYPE_DESC	Ran off carriageway	Event type description
ATMOSPH_COND_DESC	Clear	Atmosphere condition where accident occurred
SURFACE_COND_DESC	Wet	Surface condition of the road where accident occurred
ROAD_SURFACE_TYPE_DESC	Paved	Type of road surface where accident occurred
LIGHT_CONDITION	Dark no streetlights	Indicates the light condition or level of brightness at the time of the accident
TRAFFIC_CONTROL_DESC	No control	Indicates the traffic control that was facing the vehicle, prior to the accident
POLICE_ATTEND	Yes	Specifies if police attended or not
ROAD_GEOMETRY	Not at intersection	Layout of the road where accident occurred
SEVERITY	Fatal accident	Severity of the accident
SPEED_ZONE	100 km/hr	Speed zone at the location of the accident
PERSON_ID	A	Unique person identifier
SEX	M	Gender of the driver at fault
AGE_GROUP	18-21	Age group of the driver at fault
ALCOHOL_RELATED	Yes	Indicates whether driver at fault consumed any alcohol

HIT_RUN_FLAG	Yes	Indicates whether the accident was a hit & run
RUN_OFFROAD	No	Indicates whether driver at fault's vehicle ran off road
UNLICENESED	1	Whether or not the driver at fault holds a license
VEHICLE_1_ID	A	Unique identifier of perpetrators vehicle
VEHICLE 1 COLL PT DESC	Front	Collision point of the perpetrators vehicle
VEHICLE_ID	A	Unique identifier of all vehicles involved in the accident
VEHICLE_YEAR_MANUF	2001	The year in which the vehicle was manufactured
VEHICLE_BODY_STYLE	SEDAN	Body type of the vehicle
VEHICLE_MAKE	HOLDEN	Indicates the vehicle manufacturer
VEHICLE_MODEL	ACCLAI	Indicates the model of the vehicle
VEHICLE_TYPE_DESC	Car	Indicates the type of vehicle
FUEL_TYPE	P	Fuel type of the vehicle
NO_OF_CYLINDERS	6	Number of engine cylinders the vehicle contains
CAUGHT_FIRE	1	Whether or not the vehicle caught fire as a result of the accident
NODE_ID	249102	Unique node identifier of the accident
NODE_TYPE	Intersection	Location type identified by the RCIS spatial system
ROAD_NAME	WESTERNPORT	Indicates highest priority road at intersection or road where accident occurred
ROAD_TYPE	ROAD	Type of road where accident occurred
ROAD_NAME_INT	PHILLIPS	Indicates nearest intersecting road where accident occurred
ROAD_TYPE_INT	ROAD	Type of road where accident occurred
LGA_NAME	BAW BAW	Local Government Area (LGA) name for the location of the accident
LATITUDE	-38.234957	Geographical coordinates where accident occurred

LONGITUDE	145.726709	Geographical coordinates where accident occurred
VICGRID_X	2563628.962	VicGrid94 coordinates
VICGRID_Y	2362700.434	VicGrid94 coordinates
TOTAL_PERSONS	2	Total people involved in the accident
INJ_OR_FATAL	4	Total number of people involved in the accident killed or injured
FATALITY	1	Number of people who have died in the accident
SERIOUSINJURY	2	Number of people who have suffered a serious injury in the accident
OTHERINJURY	3	Number of people with an other injury because of the accident
NONINJURED	1	Number of people non-injured in the accident
MALES	2	Number of males involved in the accident
FEMALES	2	Number of females involved in the accident
BICYCLIST	1	Number of bicyclists involved in the accident
PASSENGER	5	Number of passengers involved in the accident
DRIVER	3	Number of drivers involved in the accident
PEDESTRIAN	1	Number of pedestrians involved in the accident
PILLION	1	Number of pillion passengers involved in the accident
MOTORCYCLIST	2	Number of motorcyclists involved in the accident
UNKNOWN	0	Number of unknown road users involved in the accident
PED_CYCLIST_5_12	1	Number of pedestrians and cyclists between the ages of 5-12 involved in the accident
PED_CYCLIST_13_18	2	Number of pedestrians and cyclists between the ages of 13-18 involved in the accident

OLD_PED_65_AND_OVER	1	Number of pedestrians aged 65 and over involved in the accident
OLD_DRIVER_75_AND_OVER	2	Number of drivers aged 75 and over involved in the accident
YOUNG_DRIVER_18_25	1	Number of drivers aged between 18-25 involved in the accident
NO_OF_VEHICLES	4	Number of vehicles involved in the accident
HEAVYVEHICLE	1	Number of heavy vehicles involved in the accident
PASSENGERVEHICLE	4	Number of passenger vehicles involved in the accident
MOTORCYCLE	2	Number of motorcycles involved in the accident
PT_VEHICLE	1	Number of public transport vehicles involved in the accident (tram, bus, train)
DEG_URBAN_NAME	RURAL_VICTORIA	Indicates the degree of the urban name for the location of the accident
SRNS	C	State road numbering system code
RMA	Arterial Other	RMA Classification/VicRoads road classification
DIVIDED	Undivided	Indicates whether or not the road is divided at the location of the accident
STAT_DIV_NAME	Metro	Indicates whether accident occurred in metro Victoria or Country Victoria
geometry	POINT (145.72671 -38.23496)	Geolocation coordinates where accident occurred

The dataset encompasses comprehensive records of traffic accidents in Victoria from 2012-2023, including detailed information on accident characteristics, environmental conditions, vehicle information, and driver details. This dataset contains every single possible feature I could implement that holds merit – when it comes to traffic accidents in Victoria. Currently, this dataset contains 76 features which can be analyzed and used to predict the severity of traffic accidents in Victoria by utilizing machine learning algorithms. The feature SEVERITY determines the severity of a particular road accident (fatal accident, serious injury accident, other injury accident, non-injury accident); this is the categorical label we are going to predict – classification. Supervised machine learning

algorithms will be employed to fulfill this task; by training the algorithms with this data, teaching them how to differentiate the values for severity. Once trained, the algorithms can be applied to new data that doesn't include a severity feature, simulating real-world scenarios on predicting our target feature severity in unseen traffic accidents, enabling the forecast of severity in Victoria's traffic accidents.

I choose the feature SEVERITY to be the target feature for classification, conducted by our supervised machine learning algorithms because it directly relates with the project's main goal of preventing severe accidents, minimizing death and serious injury on our roads – enhancing overall road safety in Victoria for Victorians. Again, the target feature indicates the severity of an accident, which has direct implications on public safety, healthcare costs, and overall societal impact. This is why it's crucial to understand and mitigate the most severe accidents. Reducing the number and severity of accidents is of the upmost importance to ultimately save lives and minimize injuries. By targeting accident severity, the analysis aims to leverage the dataset's rich information with data analytics, to provide actionable key insights that can lead to practical, data-driven solutions for improving road safety and mitigating the impact of traffic accidents in Victoria.

```
#Dimensions of the dataset
main_df.shape
```

```
(171647, 76)
```

Currently, the dataset dimensions before data cleaning: 171,647 rows and 76 columns. This is verified by the shape attribute from Pandas which returns the dimensions of the dataset.

DATA CLEANING

Data cleaning is a crucial step in the data analytics process and must be conducted thoroughly before proceeding to subsequent stages. This is because unclean data can result in misleading results and inaccurate conclusions.

I will start with identifying and removing duplicates if they are present:

```
#Removes duplicates
main_df.drop_duplicates()
#Verify if duplicate rows were dropped
main_df.shape
```

```
(171647, 76)
```

There are no duplicates present in the dataset.

```
#Rename multiple columns
main_df.rename(columns={'EVENT_TYPE_DESC': 'EVENT_TYPE', 'ATMOSPH_COND_DESC': 'ATMOSPH_COND', 'SURFACE_COND_DESC': 'SURFACE_COND'
#Verify name conversion
main_df.head(1)
```

EVENT_TYPE	ATMOSPH_COND	SURFACE_COND	ROAD_SURFACE_TYPE	LIGHT_CONDITION	TRAFFIC_CONTROL	POLICE_ATTEND	ROAD_GEOMETRY	SEVER
Ran off carriageway	Clear	Dry	Paved	Dark No street lights	No control	Yes	Not at intersection	Of in accid

Renaming multiple columns for clarity, errors, and naming convention reasons. This is done by utilizing the rename() method from Pandas, specifying the conversion to be true by setting the inplace parameter to be true: inplace=True applies the column name changes directly to main_df. Lastly, I verify the conversion with the head() method from Pandas.

Features Renamed:

- EVENT_TYPE_DESC is renamed to EVENT_TYPE (clarity)
- ATMOSPH_COND_DESC is renamed to ATMOSPH_COND (clarity)
- SURFACE_COND_DESC is renamed to SURFACE_COND (clarity)
- ROAD_SURFACE_TYPE_DESC is renamed to ROAD_SURFACE_TYPE (clarity)
- TRAFFIC_CONTROL_DESC is renamed to TRAFFIC_CONTROL (clarity)
- ALCOHOL_RELATED is renamed to ALCOHOL (clarity)
- HIT_RUN_FLAG is renamed to HIT_RUN (clarity)
- VEHICLE_TYPE_DESC is renamed to VEHICLE_TYPE (clarity)
- UNLICENCSED is renamed to UNLICENSED (data entry error)
- geometry is renamed to GEOMETRY (to fit the naming convention of the dataset, which is SCREAMING_SNAKE_CASE)

I am now going to investigate all the features corresponding data types and ascertain if they need amending.

```
#Summary of every columns data type
main_df.dtypes
```

```
ACCIDENT_NO                 object
ACCIDENT_DATE               object
ACCIDENT_TIME               object
ACCIDENT_TYPE               object
DAY_OF_WEEK                 object
DCA_CODE                    object
EVENT_TYPE                  object
ATMOSPH_COND                object
SURFACE_COND                object
ROAD_SURFACE_TYPE           object
LIGHT_CONDITION             object
TRAFFIC_CONTROL             object
POLICE_ATTEND               object
ROAD_GEOMETRY               object
SEVERITY                    object
SPEED_ZONE                  object
PERSON_ID                   object
SEX                         object
AGE_GROUP                   object
ALCOHOL                     object
HIT_RUN                     object
RUN_OFFROAD                 object
UNLICENSED                 float64
VEHICLE_1_ID                object
VEHICLE 1 COLL PT DESC      object
VEHICLE_ID                  object
VEHICLE_YEAR_MANUF         float64
VEHICLE_BODY_STYLE          object
VEHICLE_MAKE                object
VEHICLE_MODEL               object
VEHICLE_TYPE                object
FUEL_TYPE                   object
NO_OF_CYLINDERS            float64
CAUGHT_FIRE                float64
NODE_ID                      int64
NODE_TYPE                   object
ROAD_NAME                   object
ROAD_TYPE                   object
ROAD_NAME_INT               object
ROAD_TYPE_INT               object
LGA_NAME                    object
LATITUDE                   float64
LONGITUDE                  float64
VICGRID_X                  float64
VICGRID_Y                  float64
TOTAL_PERSONS                int64
INJ_OR_FATAL                 int64
FATALITY                     int64
SERIOUSINJURY                int64
OTHERINJURY                  int64
NONINJURED                   int64
MALES                        int64
FEMALES                      int64
BICYCLIST                    int64
PASSENGER                    int64
DRIVER                       int64
PEDESTRIAN                   int64
PILLION                      int64
MOTORCYCLIST                 int64
UNKNOWN                      int64
PED_CYCLIST_5_12             int64
PED_CYCLIST_13_18            int64
OLD_PED_65_AND_OVER          int64
OLD_DRIVER_75_AND_OVER       int64
YOUNG_DRIVER_18_25           int64
NO_OF_VEHICLES             float64
HEAVYVEHICLE               float64
PASSENGERVEHICLE           float64
MOTORCYCLE                 float64
PT_VEHICLE                 float64
DEG_URBAN_NAME              object
SRNS                        object
RMA                         object
DIVIDED                     object
STAT_DIV_NAME               object
GEOMETRY                  geometry
```

Majority of the features data types are fine besides: ACCIDENT_DATE, ACCIDENT_TIME, UNLICENSED, VEHICLE_YEAR_MANUF, NO_OF_CYLINDERS, CAUGHT_FIRE, NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, PT_VEHICLE. These certain features need correcting. I deal with them accordingly:

- **ACCIDENT_DATE, ACCIDENT_TIME:**

```
#Convert the features ACCIDENT_DATE & ACCIDENT_TIME to their appropriate formats
main_df['ACCIDENT_DATE'] = pd.to_datetime(main_df['ACCIDENT_DATE'])
main_df['ACCIDENT_TIME'] = pd.to_datetime(main_df['ACCIDENT_TIME'], format='%H%M%S').dt.time
#Verify conversion
main_df.head(1)
```

	ACCIDENT_NO	ACCIDENT_DATE	ACCIDENT_TIME	ACCIDENT_TYPE	DAY_OF_WEEK	DCA_CODE	EVENT_TYPE	ATMOSPH_COND	SURFACE_COND
0	T20120000009	2012-01-01	02:25:00	Collision with a fixed object	Sunday	LEFT OFF CARRIAGEWAY INTO OBJECT/PARKED VEHICLE	Ran off carriageway	Clear	Dry

- Transforming ACCIDENT_DATE from object to datetime64 data type; the appropriate format. This is achieved by using the pd.to_datetime() method from Pandas. This method converts string representations of dates and times into Pandas datetime objects. For ACCIDENT_DATE, each date string is parsed and converted into a datetime object, ensuring consistent formatting – greatly improving clarity. Similarly, for ACCIDENT_TIME, the pd.to_datetime() method is employed with the format='%H%M%S' parameter. This format specifically tells Pandas to interpret the time strings in a specific format: hours, minutes, and seconds. After conversion, the dt.time attribute is used to extract the time component (hours, minutes, seconds) from the datetime object, resulting in a time-only representation, which is appropriate for this feature, vastly boosting clarity. Overall, this is done so we possess the option to do time-based analysis, which was not possible with the previous object data type. Observing the changes in the row displayed above, it is much more concise.

- **UNLICENSED, VEHICLE_YEAR_MANUF, NO_OF_CYLINDERS, CAUGHT_FIRE, NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, PT_VEHICLE:**

```
#Convert the features datatype: UNLICENSED, VEHICLE_YEAR_MANUF, NO_OF_CYLINDERS, CAUGHT_FIRE, NO_OF_VEHICLES,
#HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, and PT_VEHICLE from float to their suitable format of int
main_df['UNLICENSED'] = main_df['UNLICENSED'].astype('Int64')
main_df['VEHICLE_YEAR_MANUF'] = main_df['VEHICLE_YEAR_MANUF'].astype('Int64')
main_df['NO_OF_CYLINDERS'] = main_df['NO_OF_CYLINDERS'].astype('Int64')
main_df['CAUGHT_FIRE'] = main_df['CAUGHT_FIRE'].astype('Int64')
main_df['NO_OF_VEHICLES'] = main_df['NO_OF_VEHICLES'].astype('Int64')
main_df['HEAVYVEHICLE'] = main_df['HEAVYVEHICLE'].astype('Int64')
main_df['PASSENGERVEHICLE'] = main_df['PASSENGERVEHICLE'].astype('Int64')
main_df['MOTORCYCLE'] = main_df['MOTORCYCLE'].astype('Int64')
main_df['PT_VEHICLE'] = main_df['PT_VEHICLE'].astype('Int64')

#Verify conversion
main_df.dtypes
```

```
ACCIDENT_NO                     object
ACCIDENT_DATE           datetime64[ns]
ACCIDENT_TIME                   object
ACCIDENT_TYPE                   object
DAY_OF_WEEK                     object
DCA_CODE                        object
EVENT_TYPE                      object
ATMOSPH_COND                    object
SURFACE_COND                    object
ROAD_SURFACE_TYPE               object
LIGHT_CONDITION                 object
TRAFFIC_CONTROL                 object
POLICE_ATTEND                   object
ROAD_GEOMETRY                   object
SEVERITY                        object
SPEED_ZONE                      object
PERSON_ID                       object
SEX                             object
AGE_GROUP                       object
ALCOHOL                         object
HIT_RUN                         object
RUN_OFFROAD                     object
UNLICENSED                       Int64
VEHICLE_1_ID                    object
VEHICLE 1 COLL PT DESC          object
VEHICLE_ID                      object
VEHICLE_YEAR_MANUF               Int64
VEHICLE_BODY_STYLE              object
VEHICLE_MAKE                    object
VEHICLE_MODEL                   object
VEHICLE_TYPE                    object
FUEL_TYPE                       object
NO_OF_CYLINDERS                  Int64
CAUGHT_FIRE                      Int64
NODE_ID                          int64
NODE_TYPE                       object
ROAD_NAME                       object
ROAD_TYPE                       object
ROAD_NAME_INT                   object
ROAD_TYPE_INT                   object
LGA_NAME                        object
LATITUDE                       float64
LONGITUDE                      float64
VICGRID_X                      float64
VICGRID_Y                      float64
TOTAL_PERSONS                    int64
INJ_OR_FATAL                     int64
FATALITY                         int64
SERIOUSINJURY                    int64
OTHERINJURY                      int64
NONINJURED                       int64
MALES                            int64
FEMALES                          int64
BICYCLIST                        int64
PASSENGER                        int64
DRIVER                           int64
PEDESTRIAN                       int64
PILLION                          int64
MOTORCYCLIST                     int64
UNKNOWN                          int64
```

- Transforming UNLICENSED, VEHICLE_YEAR_MANUF, NO_OF_CYLINDERS, CAUGHT_FIRE, NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, and PT_VEHICLE from their current float data type to the appropriate integer data type. This conversion is facilitated using the astype() method from Pandas. It works by inputting a column to the specified data type (Int64 in this case). This method ensures that each value in the specified column is

converted to an integer. I do this for the specified features as they were originally integer data types (e.g., UNLICENSED, CAUGHT_FIRE) or logically, they just don't make sense to pertain a float datatype; for example, VEHICLE_YEAR_MANUF represents years, but years are whole numbers and should not be represented as floating-point numbers. Nor can you have a fraction of a vehicle, which majority of these features represent – thus I apply the appropriate integer data type to these specific features. Increasing conciseness. Overall, dealing with these data types ensures consistency and enhances data integrity.

Now that the data types are sorted, I will move onto removing irrelevant features:

```
#Dropping irrelevant columns
main_df.drop('PERSON_ID',axis=1,inplace=True)
main_df.drop('VEHICLE_1_ID',axis=1,inplace=True)
main_df.drop('VEHICLE_ID',axis=1,inplace=True)
main_df.drop('NODE_ID',axis=1,inplace=True)
main_df.drop('UNKNOWN',axis=1,inplace=True)
main_df.drop('SRNS',axis=1,inplace=True)

#Rename column
main_df.rename(columns={'VEHICLE 1 COLL PT DESC': 'VEHICLE_COLL_PT'}, inplace=True)
#Verify removal + rename
main_df.head(1)
```

SEX	AGE_GROUP	ALCOHOL	HIT_RUN	RUN_OFFROAD	UNLICENSED	VEHICLE_COLL_PT	VEHICLE_YEAR_MANUF	VEHICLE_BODY_STYLE	VEHICLE_MAKE
M	18-21	NaN	NaN	Yes	<NA>	Not known or Not Applicable	1996	SEDAN	HOLDEN

Irrelevant features removed:

- **PERSON_ID, VEHICLE_1_ID, VEHICLE_ID**: These particular ID features have served their purpose during the data collection phase; moving forward with these features retained would negatively impact the analysis and modelling phase due to their irrelevancy. Removing these features will improve analyzation and modelling performance.
- **NODE_ID, UNKNOWN, SRNS**: These specific features retain no value – does not provide any valuable information for analysis nor is it good for the modelling phase; in fact, removing it will reduce noise to our model, subsequently enhancing model performance.

I deal with each irrelevant feature in the same way, utilizing the drop() method from Pandas. it works by removing the specified column – in our case the columns above. Overall, this is done to improve data quality, whilst simultaneously avoiding noise, and optimizing modelling performance. I also add in some code to rename VEHICLE 1 COLL PT DESC to VEHICLE_COLL_PT for clarity reasons, I then verify the removal of the above columns plus the rename, by displaying the first row of the dataset.

```
#Identifies NULLS/missing values
main_df.isnull().sum()
```

ACCIDENT_NO	0
ACCIDENT_DATE	0
ACCIDENT_TIME	0
ACCIDENT_TYPE	0
DAY_OF_WEEK	0
DCA_CODE	0
EVENT_TYPE	4
ATMOSPH_COND	0
SURFACE_COND	0
ROAD_SURFACE_TYPE	52
LIGHT_CONDITION	0
TRAFFIC_CONTROL	52
POLICE_ATTEND	0
ROAD_GEOMETRY	0
SEVERITY	0
SPEED_ZONE	0
SEX	3627
AGE_GROUP	3605
ALCOHOL	95174
HIT_RUN	95174
RUN_OFFROAD	0
UNLICENSED	95174
VEHICLE_COLL_PT	4
VEHICLE_YEAR_MANUF	3449
VEHICLE_BODY_STYLE	11064
VEHICLE_MAKE	7264
VEHICLE_MODEL	14038
VEHICLE_TYPE	52
FUEL_TYPE	7267
NO_OF_CYLINDERS	16098
CAUGHT_FIRE	52
NODE_TYPE	21
ROAD_NAME	426
ROAD_TYPE	2528
ROAD_NAME_INT	1457
ROAD_TYPE_INT	2886
LGA_NAME	0
LATITUDE	0
LONGITUDE	0
VICGRID_X	0
VICGRID_Y	0
TOTAL_PERSONS	0
INJ_OR_FATAL	0
FATALITY	0
SERIOUSINJURY	0
OTHERINJURY	0
NONINJURED	0
MALES	0
FEMALES	0
BICYCLIST	0
PASSENGER	0
DRIVER	0
PEDESTRIAN	0
PILLION	0
MOTORCYCLIST	0
PED_CYCLIST_5_12	0
PED_CYCLIST_13_18	0
OLD_PED_65_AND_OVER	0
OLD_DRIVER_75_AND_OVER	0
YOUNG_DRIVER_18_25	0
NO_OF_VEHICLES	1
HEAVYVEHICLE	1
PASSENGERVEHICLE	1
MOTORCYCLE	1
PT_VEHICLE	1
DEG_URBAN_NAME	1081
RMA	20742
DIVIDED	20742
STAT_DIV_NAME	1088
GEOMETRY	0

Now it's time to analyse the NULLS/missing values within the dataset and subsequently deal with them:

1 null value in NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGER VEHICLE, MOTORCYCLE, and PT_VEHICLE, 4 null values in EVENT_TYPE and VEHICLE_COLL_PT, 21 null values in NODE_TYPE, 52 null values in ROAD_SURFACE_TYPE, TRAFFIC_CONTROL, VEHICLE_TYPE, and CAUGHT_FIRE, 426 null values in ROAD_NAME, 1081 null values in DEG_URBAN_NAME, 1088 null values in STAT_DIV_NAME, 1457 null values in ROAD_NAME_INT, 2528 null values in ROAD_TYPE, 2886 null values in ROAD_TYPE_INT, 3449 null values in VEHICLE_YEAR_MANUF, 3605 null values in AGE_GROUP, 3627 null values in SEX, 7264 null values in VEHICLE_MAKE, 7267 null values in FUEL_TYPE, 11,064 null values in VEHICLE_BODY_STYLE, 14,038 null values in VEHICLE_MODEL, 16,098 null values in NO_OF_CYLINDERS, 20,742 null values in RMA and DIVIDED, 95,174 null values in ALCOHOL, HIT_RUN, and UNLICENSED. There is an extreme amount of missing values present across numerous features; 31 features in total.

- **Significant null values in**: VEHICLE_YEAR_MANUF, AGE_GROUP, SEX, VEHICLE_MAKE, FUEL_TYPE, VEHICLE_BODY_STYLE, VEHICLE_MODEL, NO_OF_CYLINDERS, RMA, DIVIDED, ALCOHOL, HIT_RUN, and UNLICENSED.

- **Insignificant null values in**: NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, PT_VEHICLE, EVENT_TYPE, VEHICLE_COLL_PT, NODE_TYPE, ROAD_SURFACE_TYPE, TRAFFIC_CONTROL, VEHICLE_TYPE, CAUGHT_FIRE, ROAD_NAME, DEG_URBAN_NAME, STAT_DIV_NAME, ROAD_NAME_INT, ROAD_TYPE, ROAD_TYPE_INT.

I deal with the insignificant and significant null values accordingly:

```
#List of insignificant null features
insignificant_null_columns = [
    'NO_OF_VEHICLES', 'HEAVYVEHICLE', 'PASSENGERVEHICLE', 'MOTORCYCLE', 'PT_VEHICLE',
    'EVENT_TYPE', 'VEHICLE_COLL_PT', 'NODE_TYPE', 'ROAD_SURFACE_TYPE', 'TRAFFIC_CONTROL',
    'VEHICLE_TYPE', 'CAUGHT_FIRE', 'ROAD_NAME', 'DEG_URBAN_NAME', 'STAT_DIV_NAME',
    'ROAD_NAME_INT', 'ROAD_TYPE', 'ROAD_TYPE_INT'
]

#Store dataset dimensions before removing null values
before_shape = main_df.shape

#Remove all insignificant null rows in the specified columns
main_df.dropna(subset=insignificant_null_columns, inplace=True)

#Store dataset dimensions after removing null values
after_shape = main_df.shape

#Output the dimensions of the dataset before and after removing null values
print("Dimensions before removing insignificant null values:", before_shape)
print("Dimensions after removing insignificant null values:", after_shape)
```

```
Dimensions before removing insignificant null values: (171647, 70)
Dimensions after removing insignificant null values: (165923, 70)
```

- **Insignificant null values**: I deal with the insignificant null values in NO_OF_VEHICLES, HEAVYVEHICLE, PASSENGERVEHICLE, MOTORCYCLE, PT_VEHICLE, EVENT_TYPE, VEHICLE_COLL_PT, NODE_TYPE, ROAD_SURFACE_TYPE, TRAFFIC_CONTROL, VEHICLE_TYPE, CAUGHT_FIRE, ROAD_NAME, DEG_URBAN_NAME, STAT_DIV_NAME, ROAD_NAME_INT, ROAD_TYPE, and ROAD_TYPE_INT by removing all of the nulls in these specific features. This is achieved above by storing all the insignificant columns we identified into the variable insignificant_null_columns (clear readability). Then, utilizing the dropna() method from Pandas; the dropna() method is operated on main_df to remove rows where any of the features specified in insignificant_null_columns have null values. The inplace=True parameter ensures that the operation modifies main_df directly. I then store the dimensions of the dataset before and after removing the nulls into two variables: before_shape and after_shape to determine the precise number of rows removed during this process – by utilizing the shape attribute from Pandas. Exactly 5724 null containing rows have been dropped; this approach is the most efficient as it was only 5724 rows removed in total, which equates to less than 3.4% of the entire dataset: insignificant, maintaining data integrity and quality – removing nulls.

```
#Replace significant numerical features with median:
main_df['VEHICLE_YEAR_MANUF'].fillna(main_df['VEHICLE_YEAR_MANUF'].median(), inplace=True)
main_df['NO_OF_CYLINDERS'].fillna(main_df['NO_OF_CYLINDERS'].median(), inplace=True)

#Replace significant categorical features with mode:
main_df['AGE_GROUP'].fillna(main_df['AGE_GROUP'].mode()[0], inplace=True)
main_df['UNLICENSED'].fillna(main_df['UNLICENSED'].mode()[0], inplace=True)
main_df['SEX'].fillna(main_df['SEX'].mode()[0], inplace=True)
main_df['VEHICLE_MAKE'].fillna(main_df['VEHICLE_MAKE'].mode()[0], inplace=True)
main_df['FUEL_TYPE'].fillna(main_df['FUEL_TYPE'].mode()[0], inplace=True)
main_df['VEHICLE_BODY_STYLE'].fillna(main_df['VEHICLE_BODY_STYLE'].mode()[0], inplace=True)
main_df['VEHICLE_MODEL'].fillna(main_df['VEHICLE_MODEL'].mode()[0], inplace=True)
main_df['RMA'].fillna(main_df['RMA'].mode()[0], inplace=True)
main_df['DIVIDED'].fillna(main_df['DIVIDED'].mode()[0], inplace=True)
main_df['ALCOHOL'].fillna(main_df['ALCOHOL'].mode()[0], inplace=True)
main_df['HIT_RUN'].fillna(main_df['HIT_RUN'].mode()[0], inplace=True)

#Verify all null values are rectified
main_df.isnull().sum()
```

```
ACCIDENT_NO              0
ACCIDENT_DATE            0
ACCIDENT_TIME            0
ACCIDENT_TYPE            0
DAY_OF_WEEK              0
DCA_CODE                 0
EVENT_TYPE               0
ATMOSPH_COND             0
SURFACE_COND             0
ROAD_SURFACE_TYPE        0
LIGHT_CONDITION          0
TRAFFIC_CONTROL          0
POLICE_ATTEND            0
ROAD_GEOMETRY            0
SEVERITY                 0
SPEED_ZONE               0
SEX                      0
AGE_GROUP                0
ALCOHOL                  0
HIT_RUN                  0
RUN_OFFROAD              0
UNLICENSED               0
VEHICLE_COLL_PT          0
VEHICLE_YEAR_MANUF       0
VEHICLE_BODY_STYLE       0
VEHICLE_MAKE             0
VEHICLE_MODEL            0
VEHICLE_TYPE             0
FUEL_TYPE                0
NO_OF_CYLINDERS          0
CAUGHT_FIRE              0
NODE_TYPE                0
ROAD_NAME                0
ROAD_TYPE                0
ROAD_NAME_INT            0
ROAD_TYPE_INT            0
LGA_NAME                 0
LATITUDE                 0
LONGITUDE                0
VICGRID_X                0
VICGRID_Y                0
TOTAL_PERSONS            0
INJ_OR_FATAL             0
FATALITY                 0
SERIOUSINJURY            0
OTHERINJURY              0
NONINJURED               0
MALES                    0
FEMALES                  0
BICYCLIST                0
PASSENGER                0
DRIVER                   0
PEDESTRIAN               0
PILLION                  0
MOTORCYCLIST             0
PED_CYCLIST_5_12         0
PED_CYCLIST_13_18        0
OLD_PED_65_AND_OVER      0
OLD_DRIVER_75_AND_OVER   0
YOUNG_DRIVER_18_25       0
NO_OF_VEHICLES           0
HEAVYVEHICLE             0
PASSENGERVEHICLE         0
MOTORCYCLE               0
PT_VEHICLE               0
DEG_URBAN_NAME           0
RMA                      0
DIVIDED                  0
STAT_DIV_NAME            0
GEOMETRY                 0
```

- **Significant null values:** I deal with the significant null values in VEHICLE_YEAR_MANUF, AGE_GROUP, SEX, VEHICLE_MAKE, FUEL_TYPE, VEHICLE_BODY_STYLE, VEHICLE_MODEL, NO_OF_CYLINDERS, RMA, DIVIDED, ALCOHOL, HIT_RUN, and UNLICENSED by replacing them with their respective median or mode. This is achieved by employing the fillna() method from Pandas, which works by replacing the null values in a feature with specified statistical values (mean, median, mode) of the specific feature – in our case the median and mode values of certain features. The median values are implemented specifically for the numerical features here as they contain outliers, and median is robust against outliers. For the categorical features, all nulls are replaced in each feature by their respective mode – mode is the most appropriate measure of replacement for null values when it comes to categorical features as mean or median is not applicable to categorical features. Overall, this is done to preserve 95,174 rows, which equates to approximately 57% of the dataset – extremely significant.

This approach eliminates null values, subsequently enhancing data integrity and quality whilst preserving the dataset. Addressing null values was necessary because they would have otherwise distorted the data, negatively impacting both exploratory data analysis (EDA) and modelling performance.

Now that I've addressed the nulls in the dataset, it's time to investigate the outliers in all numerical features.

```
#Simple statistical summary of numerical features
main_df.describe()
```

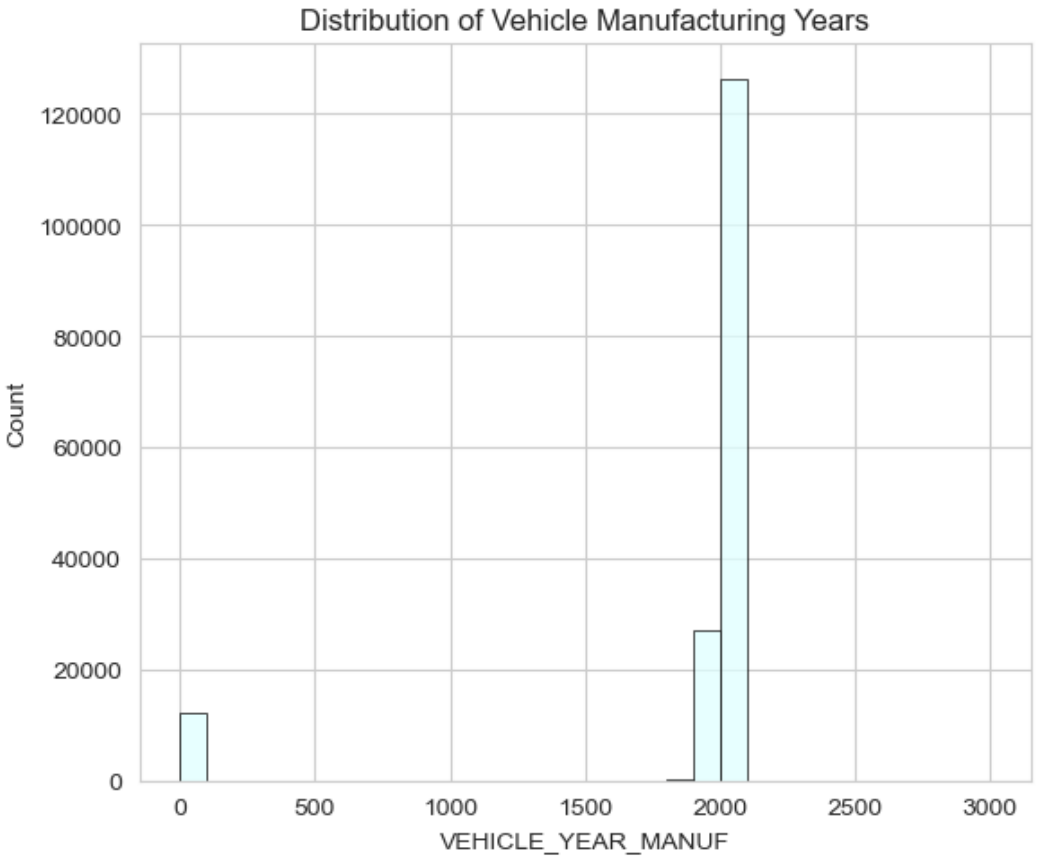
	UNLICENSED	VEHICLE_YEAR_MANUF	NO_OF_CYLINDERS	CAUGHT_FIRE	LATITUDE	LONGITUDE	VICGRID_X	VICGRID_Y	TOTAL_PERSONS
count	165923.0	165923.0	165923.0	165923.0	165923.000000	165923.000000	1.659230e+05	1.659230e+05	165923.000000
mean	0.014923	1857.900598	4.429898	2.055465	-37.713370	144.970225	2.497282e+06	2.420523e+06	2.366664
std	0.122135	526.262649	1.397989	1.100238	0.563430	0.815524	7.239941e+04	6.223188e+04	1.449925
min	0.0	0.0	1.0	0.0	-39.030830	140.966483	2.129485e+06	2.273772e+06	1.000000
25%	0.0	2001.0	4.0	2.0	-37.960525	144.831707	2.485169e+06	2.393273e+06	2.000000
50%	0.0	2007.0	4.0	2.0	-37.816682	145.012487	2.501099e+06	2.409330e+06	2.000000
75%	0.0	2012.0	6.0	2.0	-37.694765	145.207641	2.518262e+06	2.422839e+06	3.000000
max	2.0	3001.0	93.0	9.0	-34.115694	149.757468	2.920148e+06	2.815696e+06	97.000000

The above table depicts a simple statistical summary of every numerical feature within the dataset: highlighting the count, mean, standard deviation, minimum value, 25%, 50% (median), 75% percentile values, and the maximum value of each and every numerical feature.

- **Count**: The number of non-null values in each column.
- **Mean**: The average (mean) of each column.
- **Standard Deviation (std)**: The measure of the amount of variation from their mean values in each column.
- **Minimum (min)**: The smallest value in the column.
- **25th Percentile (25%)**: The value below which 25% of the data fall.
- **50th Percentile (50%) or Median**: The middle value of the dataset.
- **75th Percentile (75%)**: The value below which 75% of the data fall.
- **Maximum (max)**: The largest value in the column.

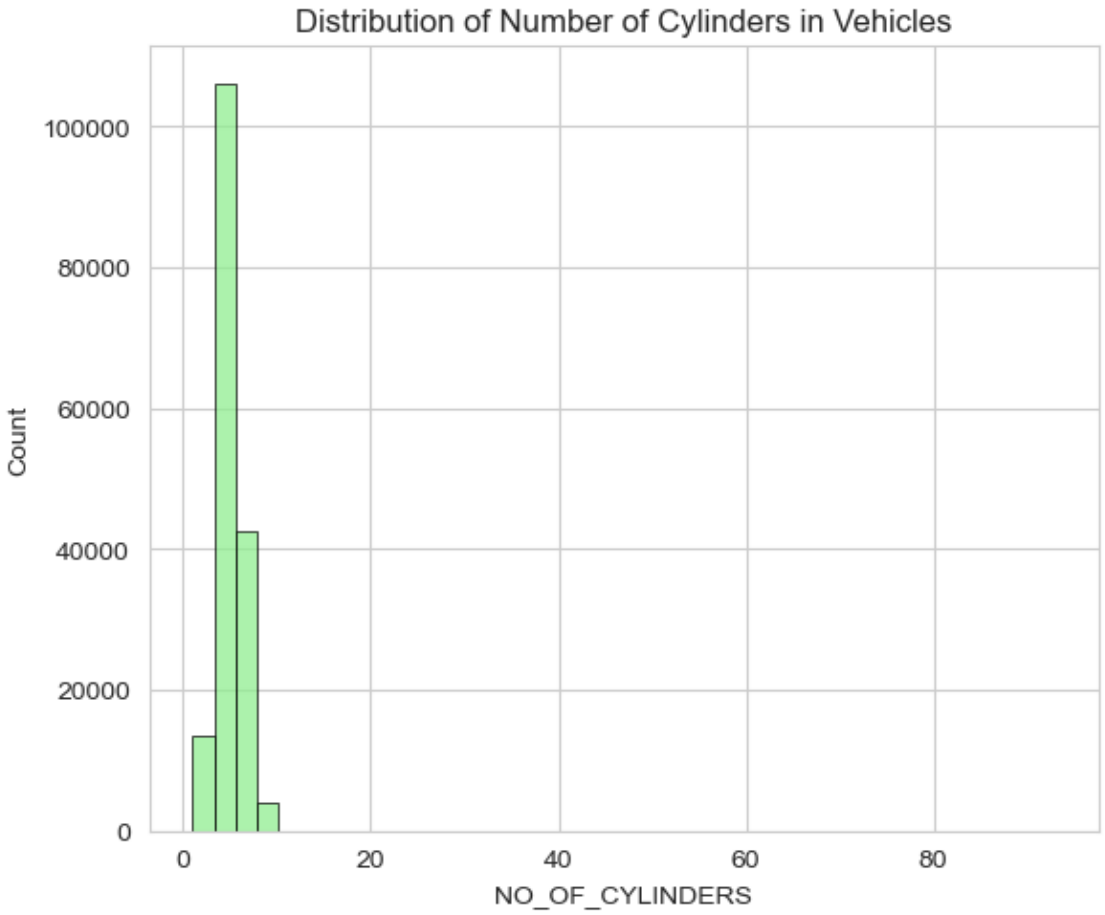
I will only be focusing on the minimum and maximum values, as these values are the outliers present. Upon thorough observation, only the features: VEHICLE_YEAR_MANUF, and NO_OF_CYLINDERS stand out – particularly their minimum and maximum values. I will investigate these features further visually, as it will paint a clearer picture. This will be achieved by data visualization techniques — specifically histograms. Histograms illustrate the distribution of a specified numerical feature; excels in spotting outliers visually. Histograms not only display the distribution of data in a concise and easy-to-understand manner, but they also highlight key descriptive statistics such as the mode. However, I will only be focusing on outliers currently, as this is a crucial step of the data cleaning process.

```
#Histogram which reflects the VEHICLE_YEAR_MANUF distribution
plt.figure(figsize=(6,5))
sns.set_style("whitegrid")
sns.histplot(data=main_df, x='VEHICLE_YEAR_MANUF', bins = 30, color='lightcyan', edgecolor = 'black', linewidth = 0.5)
plt.title('Distribution of Vehicle Manufacturing Years')
plt.tight_layout()
plt.show()
```



By analyzing this histogram representing the distribution of VEHICLE_YEAR_MANUF, it is evident that there are significant outliers present. The upper outlier value of 3001 is clearly impossible, as these values correspond to years. Similarly, the extreme lower outlier of 0 is also implausible as a manufacturing year. Notably, there are approximately 12,321 entries with a year value of 0, which is substantial. Additionally, there are other lower outliers ranging from 1900 to 1960. Given that this dataset holds Victorian traffic accident records from 2012 to 2023, it seems highly implausible to have vehicles from these years involved. Such old vehicles would be considered antiques and are rarely driven today, making it extremely unlikely for them to be involved in road accidents within the last decade. There are 240 entries in total with manufacturing years between 1900 and 1960. These outliers in VEHICLE_YEAR_MANUF are data entry errors that need to be corrected, as they can introduce biases and negatively impact the analysis and modelling phases.

```
#Histogram which reflects the NO_OF_CYLINDERS distribution
plt.figure(figsize=(6,5))
sns.set_style("whitegrid")
sns.histplot(data=main_df, x='NO_OF_CYLINDERS', bins=40, color='lightgreen', edgecolor='black', linewidth=0.5)
plt.title('Distribution of Number of Cylinders in Vehicles')
plt.tight_layout()
plt.show()
```



Unlike VEHICLE_YEAR_MANUF, the lower outlier value of 1 appears to be valid in the context of cylinders, as motorcycles are included in the dataset and many motorcycles only have 1 cylinder. However, the same cannot be said for the upper outliers. There are 21 upper outliers in total, consisting of non-valid values, specifically 7 and 11 cylinders, or any number greater than 12 cylinders. A 7 or 11-cylinder engine configuration is implausible for any vehicle, as such configurations do not exist. While train engines can have up to 20 cylinders, all the upper outliers in this dataset are associated with cars or motorcycles. Additionally, these upper outliers span from 21 to 93 cylinders, which is impossible for any vehicle. These values are unfeasible and clearly indicate data entry errors that need to be rectified to ensure the accuracy of the analysis and subsequent modelling phase.

1. **VEHICLE_YEAR_MANUF** outliers/errors:

```
#VEHICLE_YEAR_MANUF upper outlier
main_df[main_df['VEHICLE_YEAR_MANUF'] > 2023]
```

VEHICLE_YEAR_MANUF	VEHICLE_BODY_STYLE	VEHICLE_MAKE	VEHICLE_MODEL	VEHICLE_TYPE	FUEL_TYPE	NO_OF_CYLINDERS	CAUGHT_FIRE	NODE_T
3001	UTIL	HOLDEN	COMMOD	Utility	P	8	2	Intersec

- 1 invalid upper outlier (3001) – insignificant.

```
#VEHICLE_YEAR_MANUF lower outliers
filtered_year = ((main_df['VEHICLE_YEAR_MANUF'] >= 1900) & (main_df['VEHICLE_YEAR_MANUF'] <= 1960)).sum()
print(filtered_year)
```

```
240
```

- 240 invalid lower outlier values between 1900-1960 – insignificant.

```
#Returns the 0-values in VEHICLE_YEAR_MANUF
print('Number of Zero values in VEHICLE_YEAR_MANUF:  ', main_df[main_df['VEHICLE_YEAR_MANUF']==0].shape[0])
```

```
Number of Zero values in VEHICLE_YEAR_MANUF:   12321
```

- 12,321 invalid outlier zero values – significant.

2. **NO_OF_CYLINDERS** outliers/errors:

```
#NO_OF_CYLINDERS outlier count
count_7 = (main_df['NO_OF_CYLINDERS'] == 7).sum()
print(count_7)
count_greater_than_8 = (main_df['NO_OF_CYLINDERS'] == 11).sum()
print(count_greater_than_8)
count_greater_than_12 = (main_df['NO_OF_CYLINDERS'] > 12).sum()
print(count_greater_than_12)
```

```
5
4
12
```

- 21 outliers in total across 7, 11 and over 12 cylinders – insignificant.

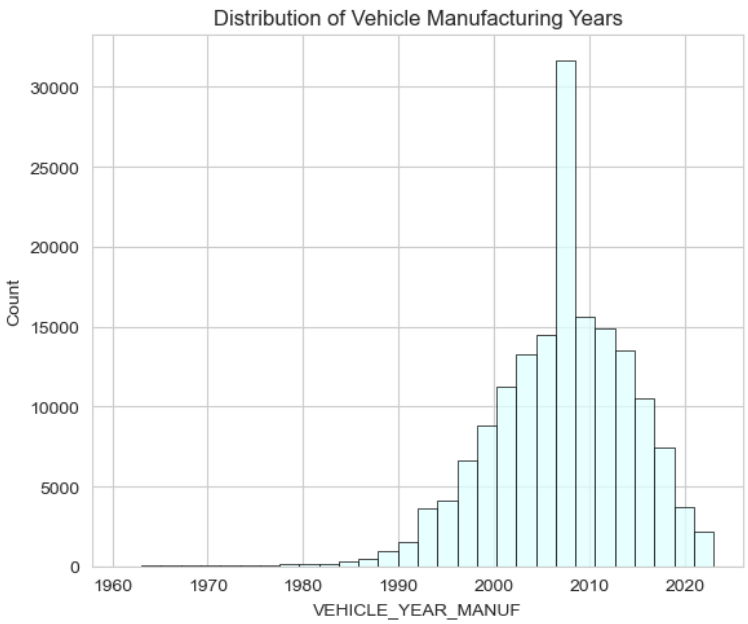
I have identified insignificant and significant outliers in VEHICLE_YEAR_MANUF and NO_OF_CYLINDERS. These outliers need to be handled as they are actually data entry errors that need to be rectified; junk values which would skew and distort the data.

```
#Remove insignificant outliers from VEHICLE_YEAR_MANUF & NO_OF_CYLINDERS

#Drop == 7 rows from NO_OF_CYLINDERS
main_df.drop(index=main_df[main_df['NO_OF_CYLINDERS']==7].index,inplace=True)
#Drop == 11 rows from NO_OF_CYLINDERS
main_df.drop(index=main_df[main_df['NO_OF_CYLINDERS']==11].index,inplace=True)
#Drop >12 rows from NO_OF_CYLINDERS
main_df.drop(index=main_df[main_df['NO_OF_CYLINDERS']>12].index,inplace=True)
#Drop rows between 1900-1960 from VEHICLE_YEAR_MANUF
main_df.drop(index=main_df[(main_df['VEHICLE_YEAR_MANUF'] >= 1900) & (main_df['VEHICLE_YEAR_MANUF'] <= 1960)].index, inplace=True
#Drop 3001 row from VEHICLE_YEAR_MANUF
main_df.drop(index=main_df[main_df['VEHICLE_YEAR_MANUF']==3001].index,inplace=True)


#Replace significant zero outlier values in VEHICLE_YEAR_MANUF with the median
VEHICLE_YEAR_MANUF_median = main_df['VEHICLE_YEAR_MANUF'].median()
main_df['VEHICLE_YEAR_MANUF'].replace(0, VEHICLE_YEAR_MANUF_median, inplace=True)

#Validating the replacement of 0-values in VEHICLE_YEAR_MANUF
print('Number of Zero values in VEHICLE_YEAR_MANUF:  ', main_df[main_df['VEHICLE_YEAR_MANUF']==0].shape[0])
```

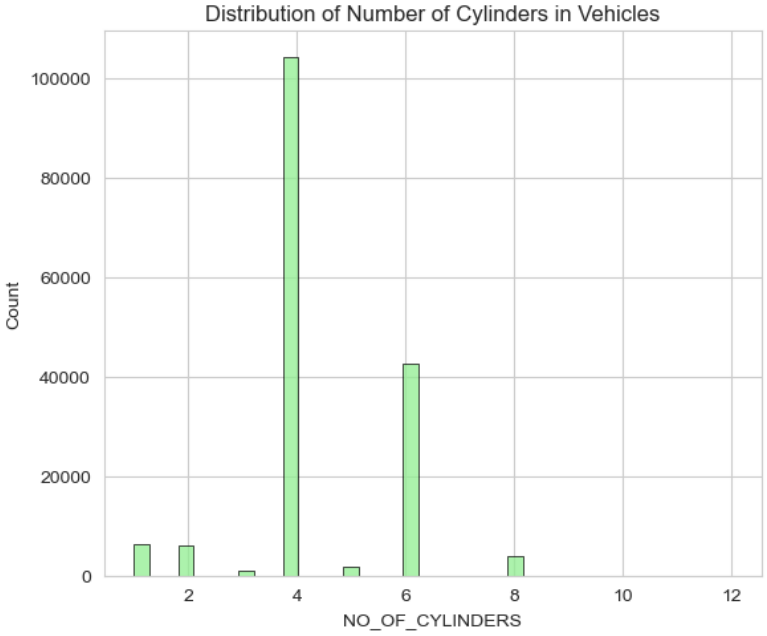
- **Insignificant outlier values:** We begin by removing all the insignificant outliers: specifically, 7, 11, and any values greater than 12 cylinders in the NO_OF_CYLINDERS feature. This was followed by eliminating the outliers in the VEHICLE_YEAR_MANUF feature, specifically the years ranging from 1900 to 1960, and the year 3001. This was achieved by utilizing the drop() method from Pandas, all these outliers were identified as data entry errors. Removing them was essential to prevent biases in the data. The removed rows constitute less than 0.2% of the total dataset, with 262 rows dropped in total – insignificant.

- **Significant outlier values:** I deal with the significant outliers in VEHICLE_YEAR_MANUF by replacing them with its own median. This is mainly done to preserve the dataset: 12,321 rows in total – approximately 7.2% of the total dataset. This is enabled by retrieving the median and storing it in the variable VEHICLE_YEAR_MANF_median and replacing the 0-values with the median stored in said variable by using the replace() method from Pandas. We also deal with the junk zero values at the same time, which would have distorted the data and negatively affected the analysis.

```
#Histogram which reflects the VEHICLE_YEAR_MANUF distribution
plt.figure(figsize=(6,5))
sns.set_style("whitegrid")
sns.histplot(data=main_df, x='VEHICLE_YEAR_MANUF', bins = 30, color='lightcyan', edgecolor = 'black', linewidth = 0.5)
plt.title('Distribution of Vehicle Manufacturing Years')
plt.tight_layout()
plt.show()
```




```
#Histogram which reflects the NO_OF_CYLINDERS distribution
plt.figure(figsize=(6,5))
sns.set_style("whitegrid")
sns.histplot(data=main_df, x='NO_OF_CYLINDERS', bins=40, color='lightgreen', edgecolor='black', linewidth=0.5)
plt.title('Distribution of Number of Cylinders in Vehicles')
plt.tight_layout()
plt.show()
```



We can clearly observe the noisy outliers have been dealt with by analyzing the updated histograms. Overall, by dealing with these outliers, we improve the data quality and integrity of the dataset, in addition we rectify the data entry errors (noise) which would have otherwise skewed the data, adversely affecting the modelling performance and the quality of the dataset.

Now that our dataset is free of nulls and non-valid outliers, we can proceed to the last stages of data cleaning. This phase includes minor feature engineering/thorough investigation of feature values.

```
#Concatenate ROAD_NAME and ROAD_TYPE to make ROAD_NAME_TYPE
main_df['ROAD_NAME_TYPE'] = main_df['ROAD_NAME'] + ' ' + main_df['ROAD_TYPE']
#Concatenate ROAD_NAME_INT and ROAD_TYPE_INT to make INT_ROAD_NAME
main_df['INT_ROAD_NAME'] = main_df['ROAD_NAME_INT'] + ' ' + main_df['ROAD_TYPE_INT']

#Drop the original columns
main_df.drop(['ROAD_NAME', 'ROAD_TYPE', 'ROAD_NAME_INT', 'ROAD_TYPE_INT'], axis=1, inplace=True)
#Rename ROAD_NAME_TYPE to ROAD_NAME
main_df.rename(columns={'ROAD_NAME_TYPE': 'ROAD_NAME'}, inplace=True)

#Reorder the columns to place ROAD_NAME & INT_ROAD_NAME in the 33th and 34th positions
columns = list(main_df.columns)
columns.insert(32, columns.pop(columns.index('ROAD_NAME')))
columns.insert(33, columns.pop(columns.index('INT_ROAD_NAME')))
main_df = main_df[columns]

#Verify conversion
main_df.head(1)
```

	ROAD_NAME	INT_ROAD_NAME	LGA_NAME	LATITUDE	LONGITUDE	VICGRID_X	VICGRID_Y	TOTAL_PERSONS	INJ_OR_FATAL	FATALITY	SERIOUSINJUF
	WESTERNPORT ROAD	PHILLIPS ROAD	BAW BAW	-38.234957	145.726709	2563628.962	2362700.434	2	2	0	

I conducted minor feature engineering by creating two new features: ROAD_NAME and INT_ROAD_NAME. This was achieved by concatenating the existing ROAD_NAME and ROAD_TYPE columns to form ROAD_NAME_TYPE, and similarly, concatenating ROAD_NAME_INT and ROAD_TYPE_INT to form INT_ROAD_NAME. The original columns (ROAD_NAME, ROAD_TYPE, ROAD_NAME_INT, ROAD_TYPE_INT) were dropped to prevent redundancy. The ROAD_NAME_TYPE column was then renamed to ROAD_NAME for simplicity and consistency. I reordered the new features, placing ROAD_NAME and INT_ROAD_NAME in the 33rd and 34th positions within the data frame to enhance clarity when viewing the dataset. Finally, I verified the conversion to ensure the newly engineered features were accurately represented. Traditionally, feature engineering typically aims to improve modelling performance, but in this case, the purpose was to improve clarity and facilitate enhanced exploratory data analysis (EDA) for these two specific features.

To finalize the data cleaning phase, I will be finishing off by thoroughly analyzing every categorical feature value and ascertain if they need to be modified. This is done to see if there are any values that shouldn't be there – data entry errors.

```
#UNLICENSED values
main_df.UNLICENSED.value_counts()
```

```
0    163204
1      2439
2        18
Name: UNLICENSED, dtype: Int64
```

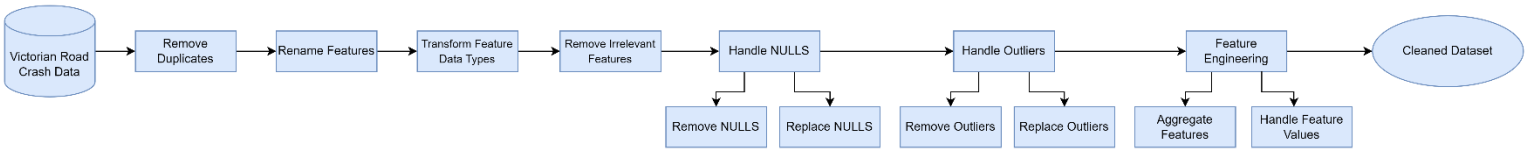
```
#Drop == 2 rows from UNLICENSED
main_df.drop(index=main_df[main_df['UNLICENSED']==2].index,inplace=True)
#Verify removal
main_df.UNLICENSED.value_counts()
```

```
0    163204
1      2439
Name: UNLICENSED, dtype: Int64
```

Upon thorough observation, only the UNLICENSED feature in the dataset raised some suspicion due to its values: 0, 1, and 2. There is no data dictionary available for this feature, but typically, binary values in such features represent 'No' (0) and 'Yes' (1). The presence of the value '2' with only 18 entries suggests it is a data entry error. To address this issue, I decided to drop the rows where the UNLICENSED value was 2. To identify these suspicious values, I used the value_counts() method from Pandas, which provides a count of all unique values within a specified feature. I then utilized the drop() method from Pandas to remove the 2 values from UNLICENSED, ensuring the dataset only contained valid binary data in the UNLICENSED feature. The removed 18 rows equate to less than 0.1% of the dataset – insignificant.

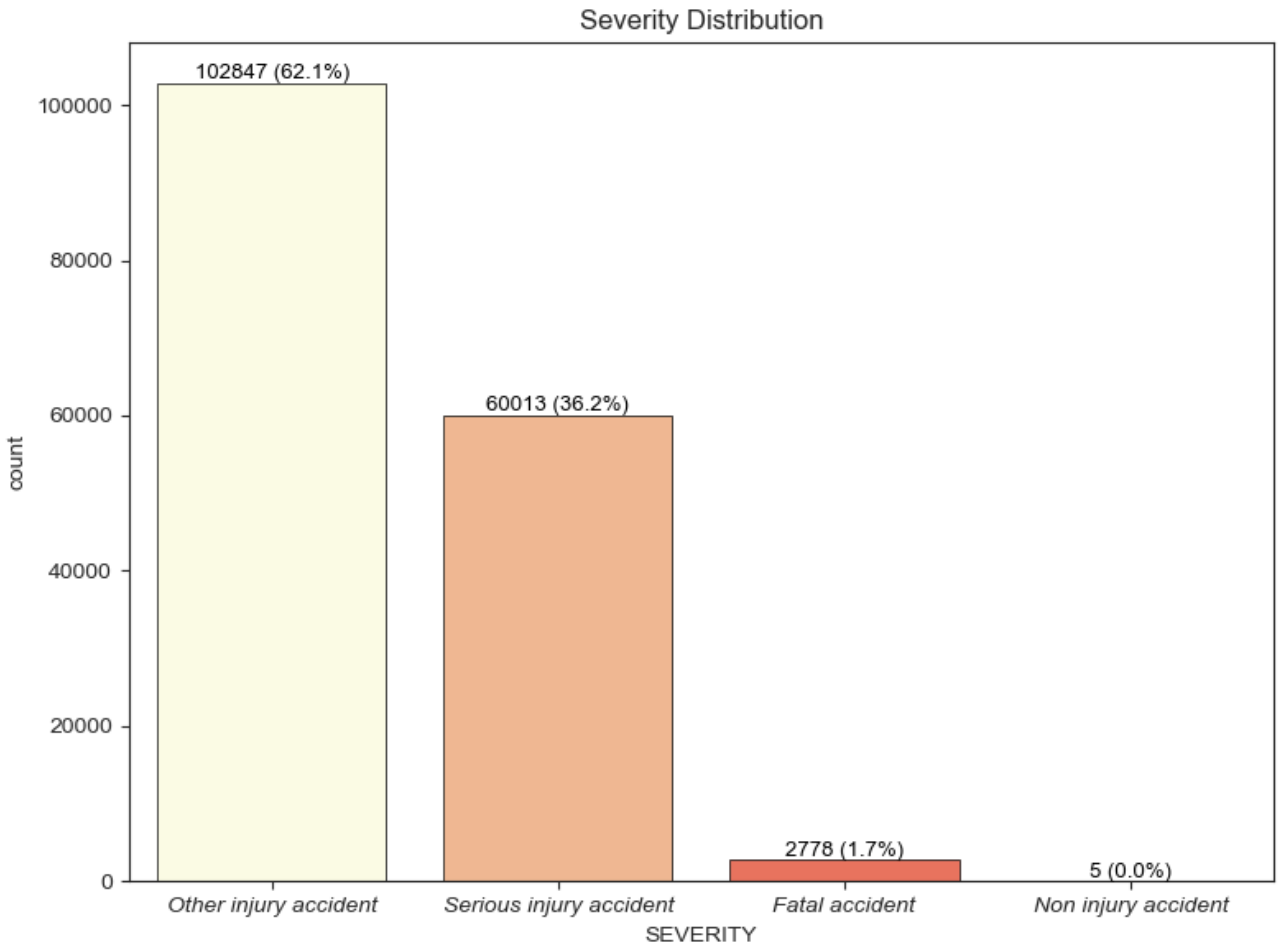
Overall, in the data cleaning phase, we successfully rectified all instances of null values, non-valid outliers, and data entry errors – noise. We also checked for and confirmed the absence of duplicate entries, removed irrelevant features, corrected data types, and ensured clarity and consistency across the dataset. These actions significantly enhanced the quality and integrity of our data, setting a solid foundation for extracting key insights in the subsequent steps of our data analysis. With the data cleaning phase complete, we are now ready to proceed to the next stage: exploratory data analysis (EDA).

Data Cleaning Flowchart:

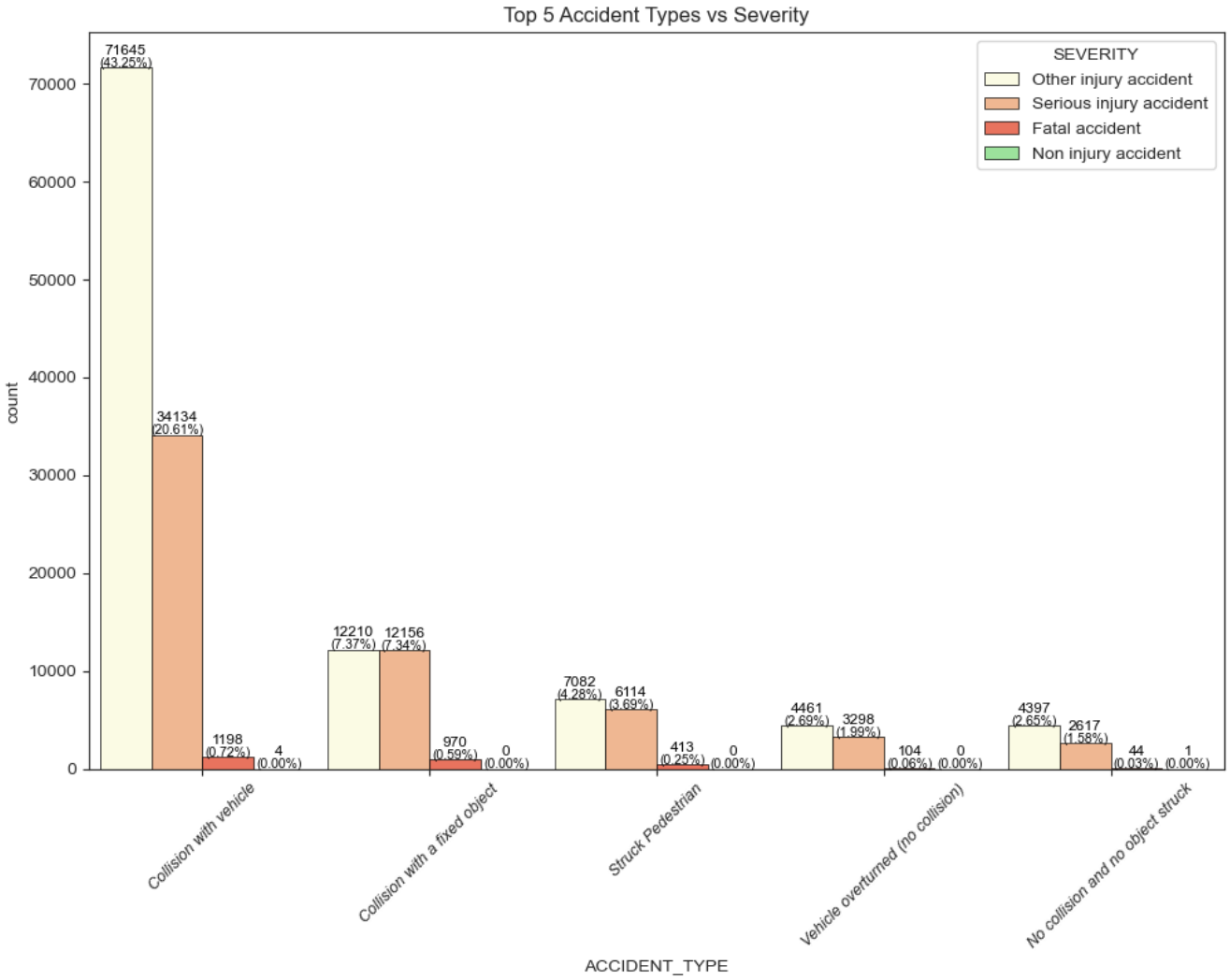


EXPLORATORY DATA ANALYSIS

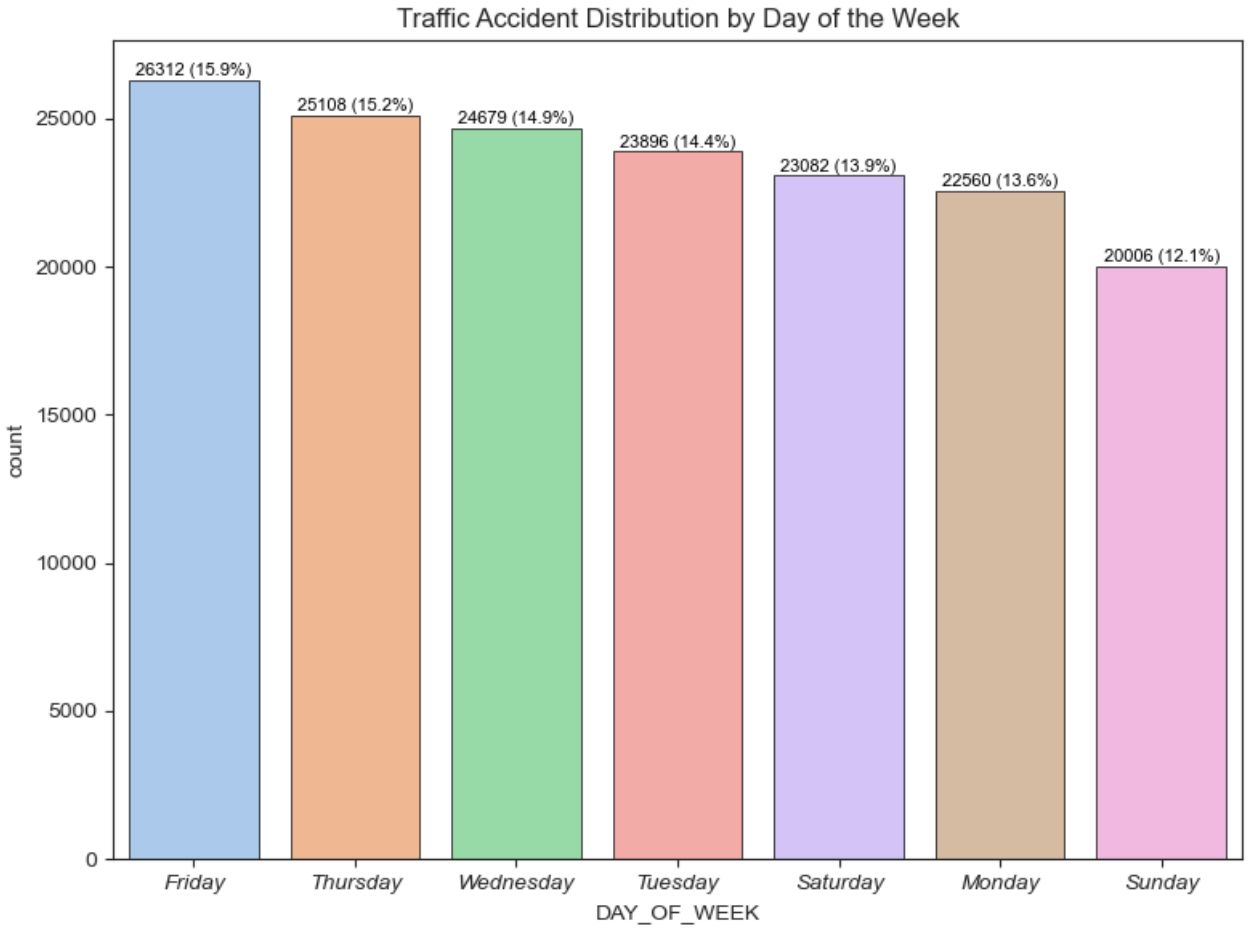
Exploratory Data Analysis (EDA): the process of analyzation and visualization to summarize the features and their corresponding relationships within the data, providing valuable insights into the factors contributing to traffic accidents in Victoria.



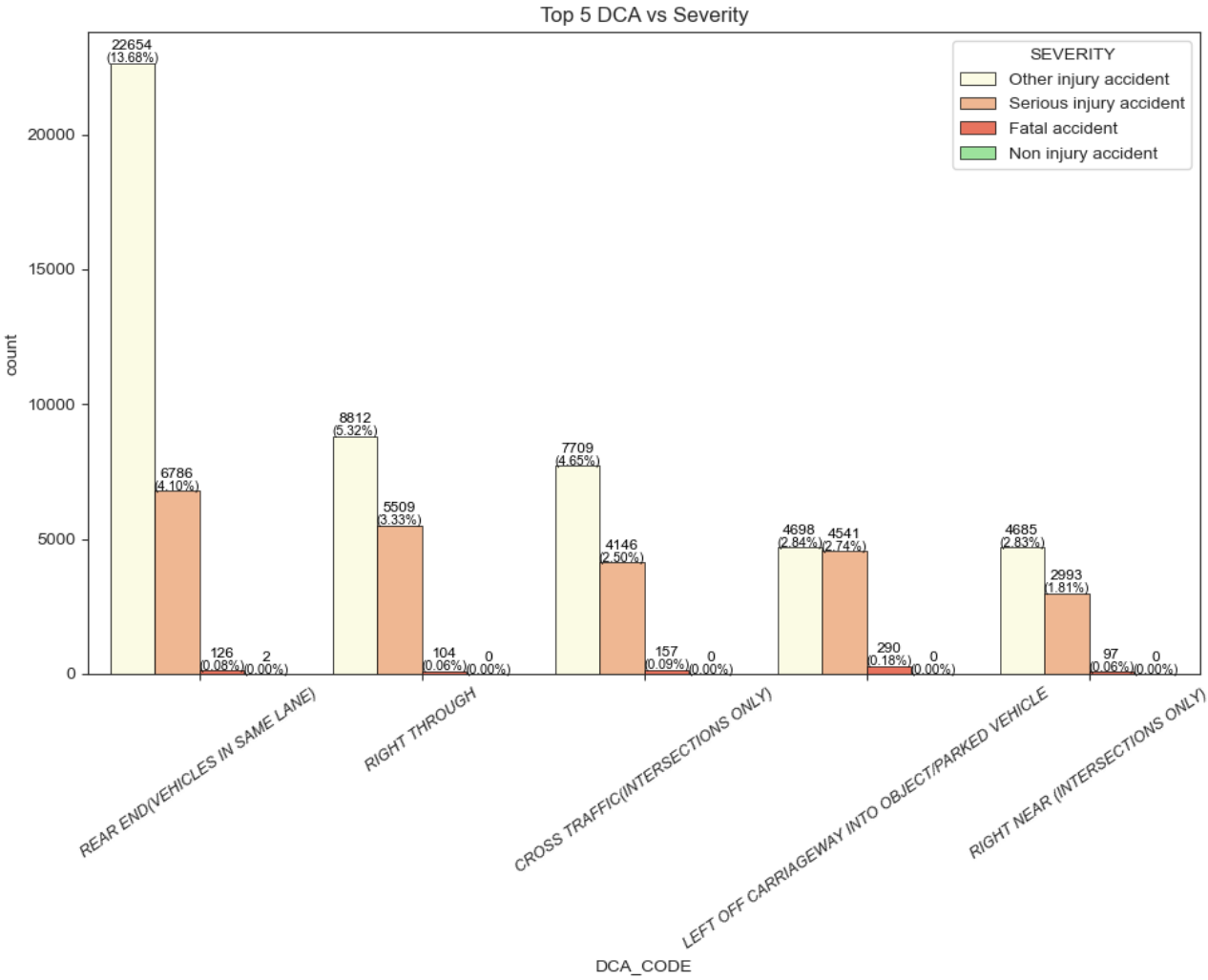
This count plot represents the count of the target feature (SEVERITY), which highlights the individuals who have sustained injuries or death due to traffic accidents in Victoria. Clearly there is a vast difference between the severities: 102,847 people have experienced an other injury; representing the vast majority of the data at 62.1%. Following up, 60,013 or 36.2% of individuals within the data have suffered from serious injury. 2778 individuals have passed away, whereas only 5 people have walked scot-free from an accident.



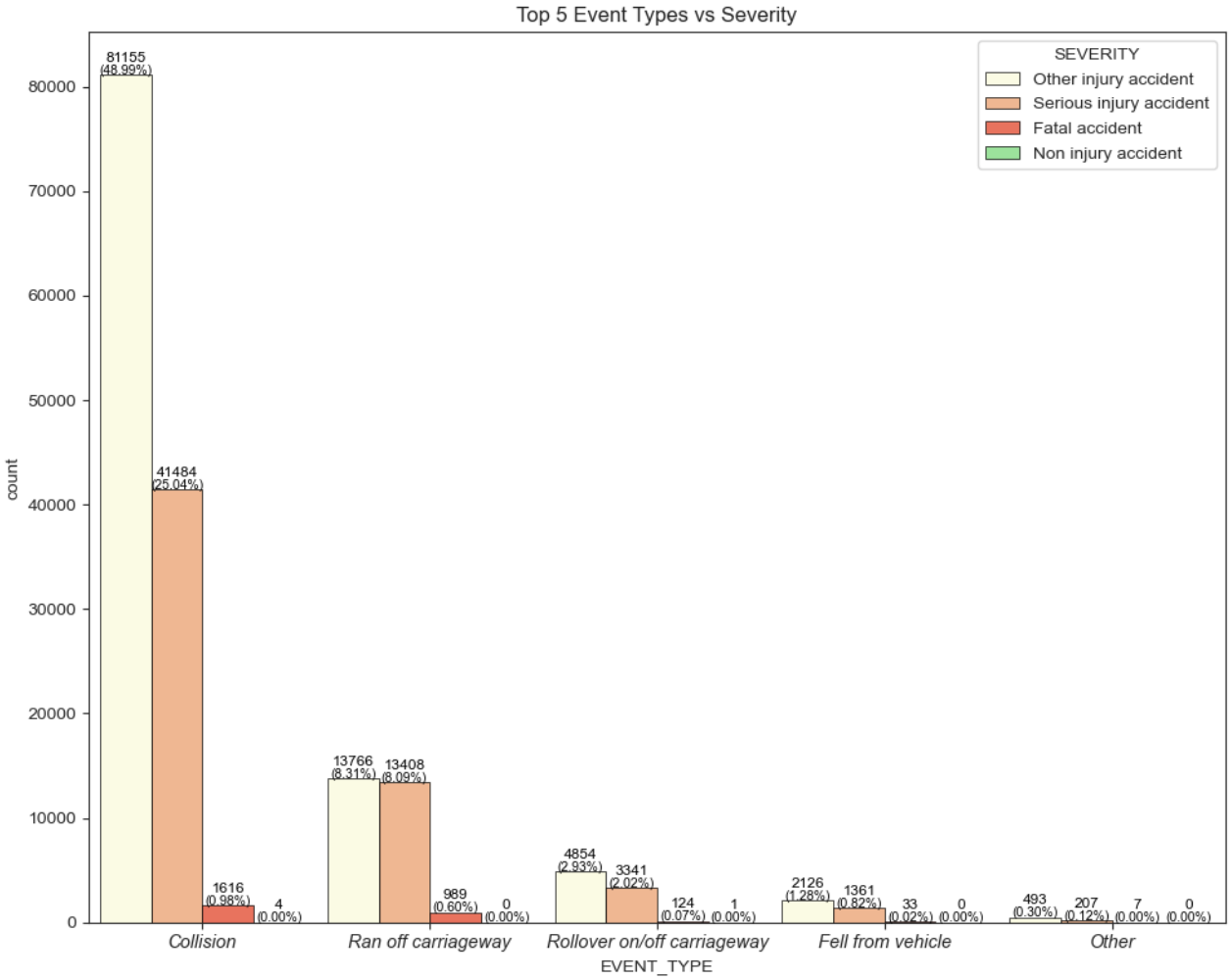
The count plot illustrates the distribution of the top 5 accident types in relation to their severity in descending order within the dataset. From the visualization, it is evident that the majority of accident types fall under the Collision with vehicle category, accounting for 106,981 incidents, constituting 64.58% of the total accidents. Other injury accidents are the most relevant in this regard, with a count of 71,645 (43.25%), followed by serious injury accidents at 34,134 (20.61%), then fatal accidents at 1,198 (0.72%), and lastly, non-injury accidents with a count of 4. Proportionally, the Collision with a fixed object category exhibits the highest ratios of both fatal and serious injury accidents, with approximately 3.83% of incidents resulting in fatalities and 48% resulting in serious injuries. This indicates that accidents of this type are particularly dangerous. In contrast, the No collision and no object struck category shows the lowest frequency and represents minimal severity within the dataset.



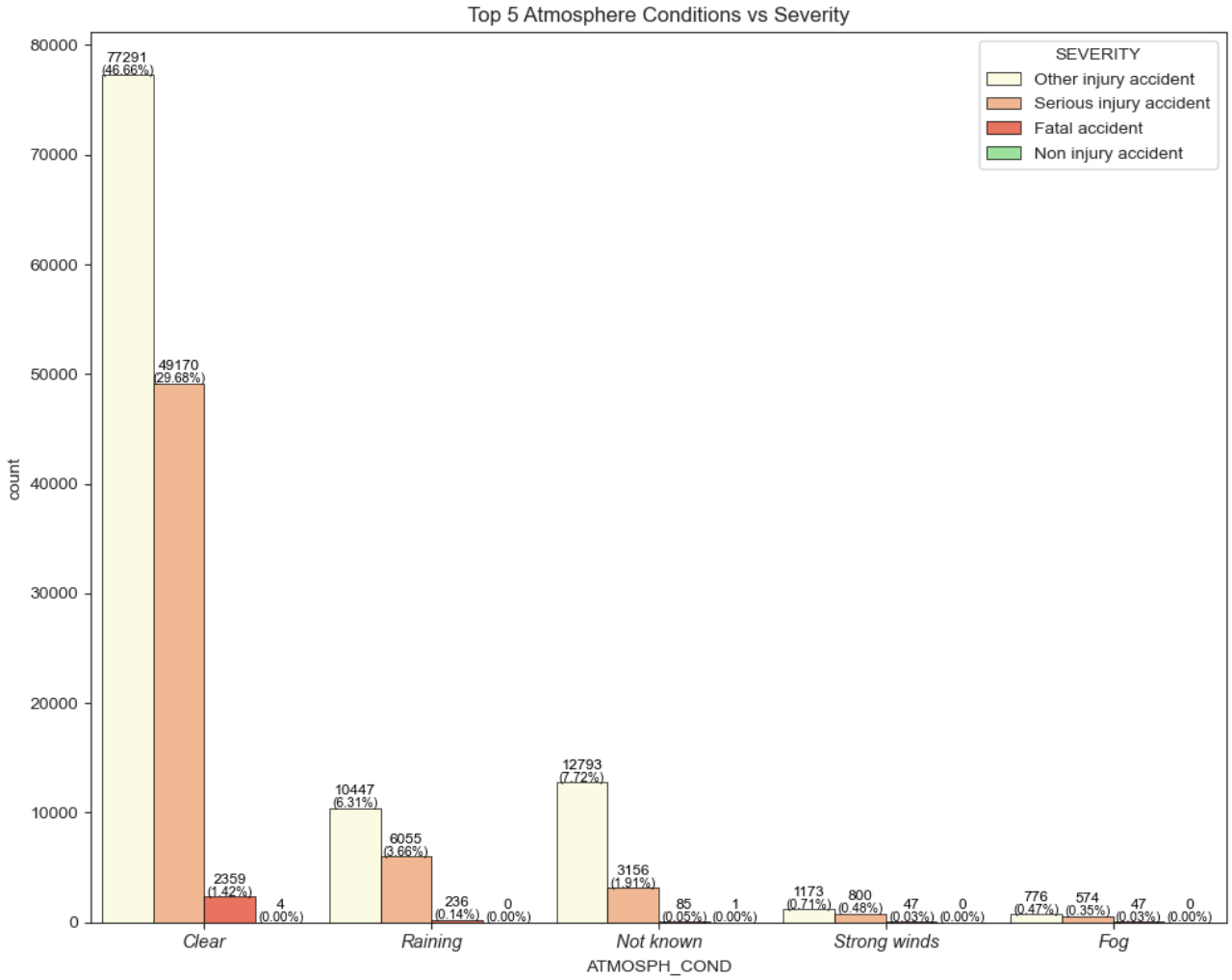
This count plot displays the distribution of traffic accidents across each day of the week in Victoria, highlighting the variation in accident frequency by day. Friday has the highest count of accidents, totalling 26,312 incidents, which represents 15.9% of all recorded accidents. Thursday and Wednesday follow closely with 25,108 (15.2%) and 24,679 (14.9%) accidents, respectively. Tuesday and Saturday also show substantial numbers, with 23,896 (14.4%) and 23,082 (13.9%) accidents. In contrast, Monday and Sunday record the lowest accident counts, with 22,560 (13.6%) on Monday and 20,006 (12.1%) on Sunday. This distribution suggests that the latter part of the workweek, particularly Friday, experiences higher traffic accident rates, possibly due to increased travel associated with work, social activities, and the beginning of the weekend. Sunday, on the other hand, has the fewest accidents, possibly reflecting reduced traffic volume on this day.



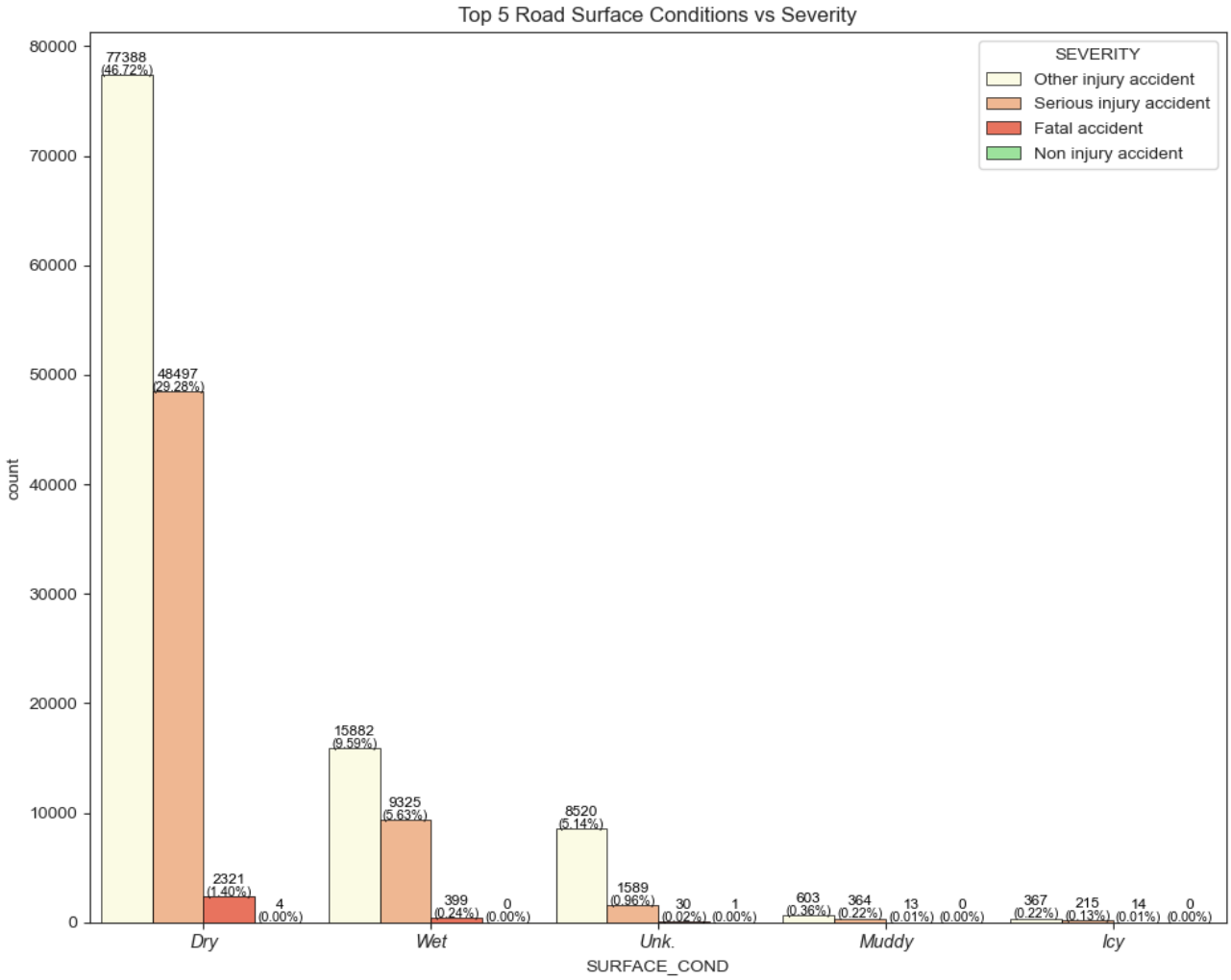
This count plot depicts the distribution of top 5 DCA codes (type of road accident) in relation to their severity in descending order, highlighting the frequency of traffic accidents across different DCA categories in Victoria. Clearly, the Rear End (vehicles in same lane) category is the most prominent, with a total of 29,568 incidents. This total comprises 22,654 other injury accidents (13.68%), 6,786 serious injury accidents (4.10%), 126 fatal accidents (0.08%), and 2 non-injury accidents. This indicates that rear-end collisions are by far the most frequent type of accident in the dataset. In terms of severity, the Left off carriageway into object/parked vehicle category exhibits the highest ratio of both fatal and serious injury accidents, with 47.65% serious injury accidents and 3.04% fatal accidents. This makes it the most dangerous accident type among the top 5, as a higher proportion of incidents result in more severe outcomes. On the other hand, the Right near (intersections only) category shows the lowest frequency among the top accident types, with a total of 7,775 incidents. This includes 4,685 other injury accidents (2.83%), 2,993 serious injury accidents (1.81%), 97 fatal accidents (0.06%), and 0 non-injury accidents. This category has the lowest counts across all severity types, suggesting it is less frequent and less severe than other accident types in the dataset.



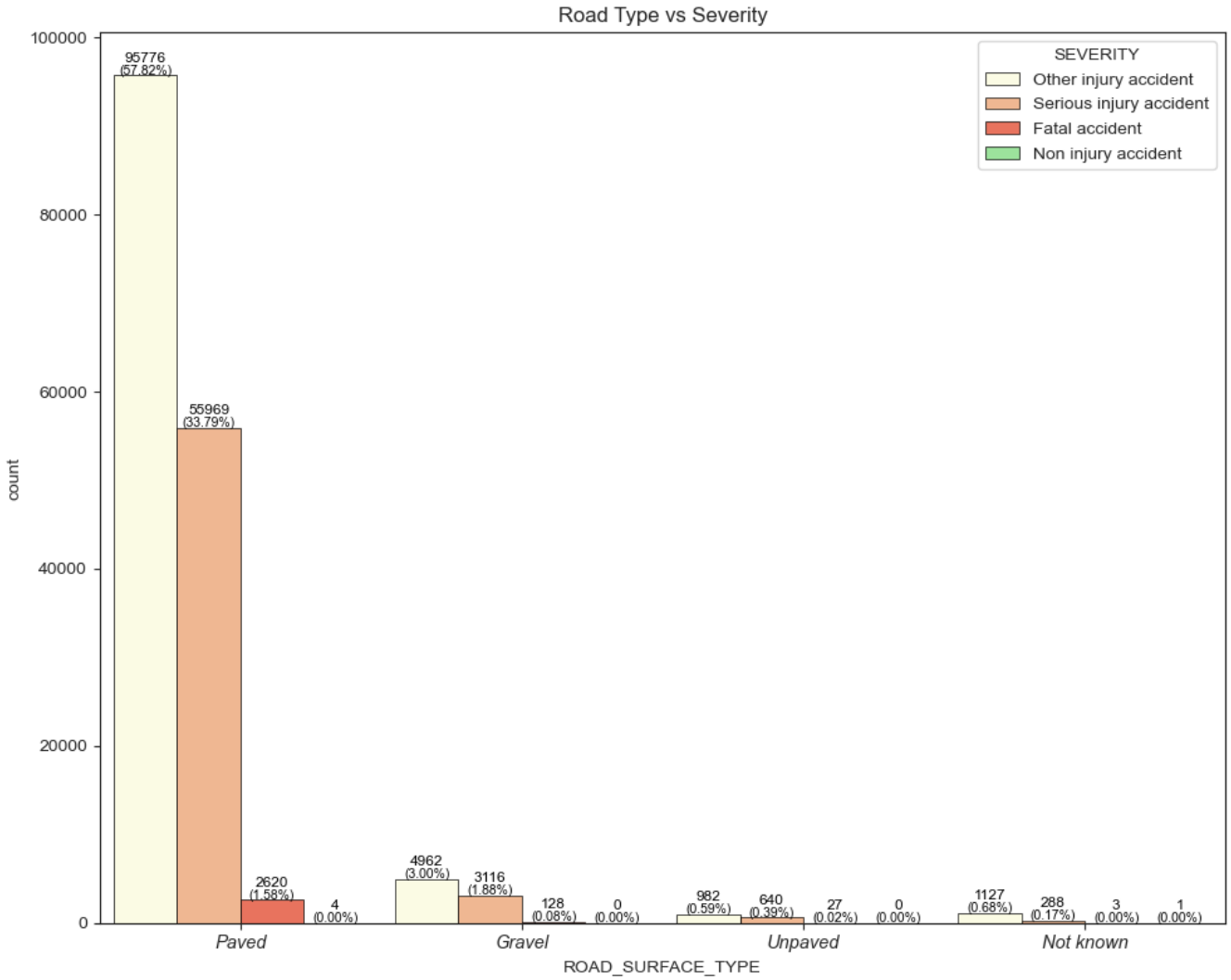
The count plot illustrates the distribution of the top 5 event types by severity, showcasing the frequency of accidents across various event types in Victoria. The Collision category stands out as the most prevalent, with a total of 124,259 incidents. This includes 81,155 other injury accidents (48.95%), 41,484 serious injury accidents (25.04%), 1,616 fatal accidents (0.98%), and 4 non-injury accidents. This shows that collisions are by far the most common event type and significantly contribute to injury and fatal accidents. The Ran off carriageway category exhibits the highest ratio of both serious injury accidents (47.60%) and fatal accidents (3.64%). This indicates that running off the road is particularly dangerous in terms of accident severity. In contrast, the Other category shows the lowest frequency, with a total of 707 incidents. This includes 493 other injury accidents (0.30%), 207 serious injury accidents (0.12%), 7 fatal accidents, and no non-injury accidents. This event type contributes minimally to the total number of accidents and exhibits lower severity compared to other event types.



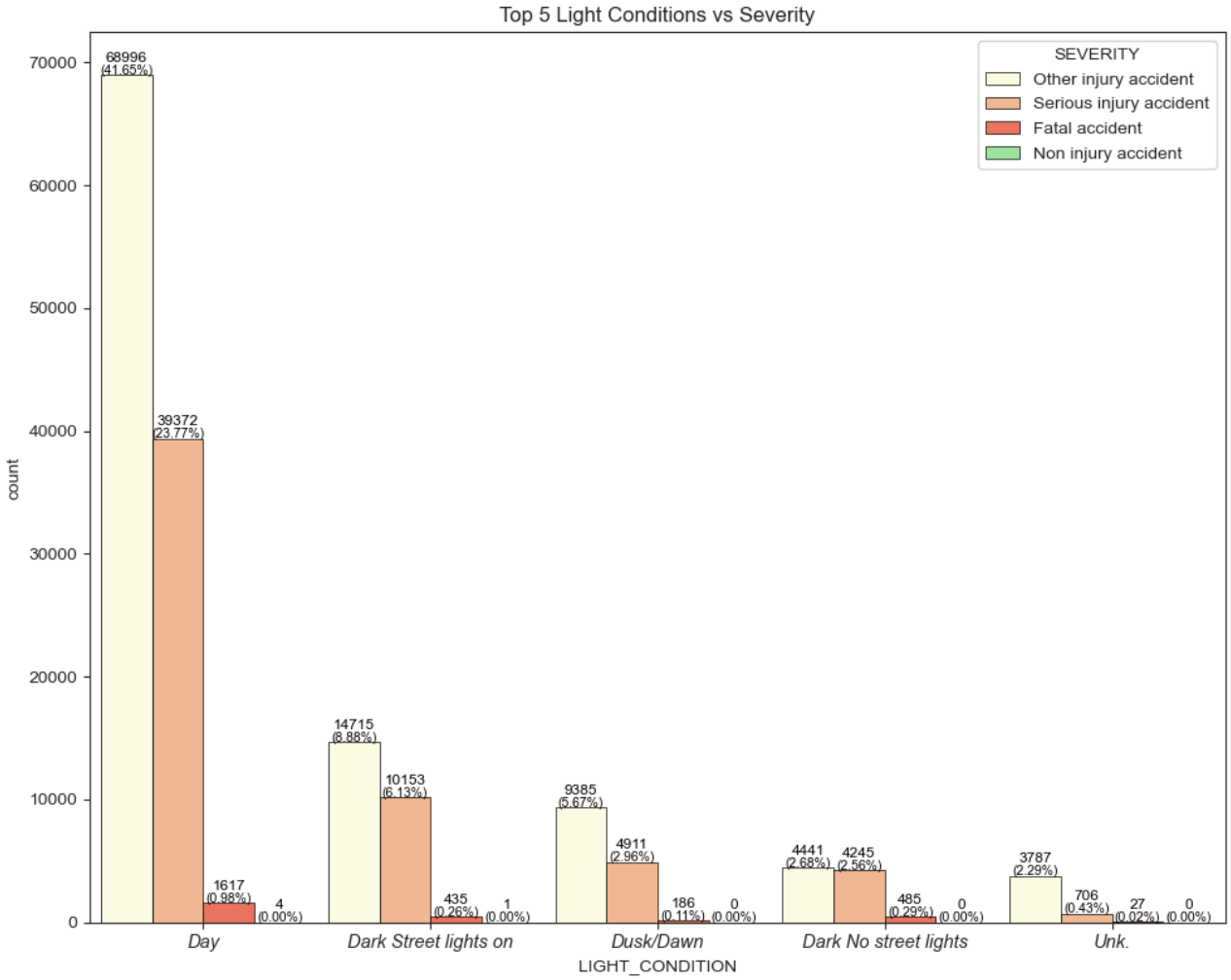
This count plot depicts the distribution of the top 5 atmosphere conditions vs severity, displaying the count of accidents across multiple atmospheric conditions in Victoria. The Clear atmospheric condition is the most prevalent, with a total of 128,824 incidents. This comprises 77,291 other injury accidents (46.66%), 49,170 serious injury accidents (29.65%), 2,359 fatal accidents (1.42%), and 4 non-injury accidents. This suggests that the majority of accidents happen during clear weather conditions. However, a foggy atmosphere has the highest ratio of serious injury accidents at 41.09% and fatal accidents at 3.36%. Therefore, despite having a lower total count, accidents in foggy conditions present the most significant risk of serious and fatal outcomes. The Fog category also has the lowest frequency, with a total of 1,397 incidents. This includes 776 other injury accidents (0.47%), 574 serious injury accidents (0.35%), and 47 fatal accidents (0.03%). While it has the lowest count, it still presents the highest serious/fatal accident ratios compared to the rest of the atmosphere conditions.



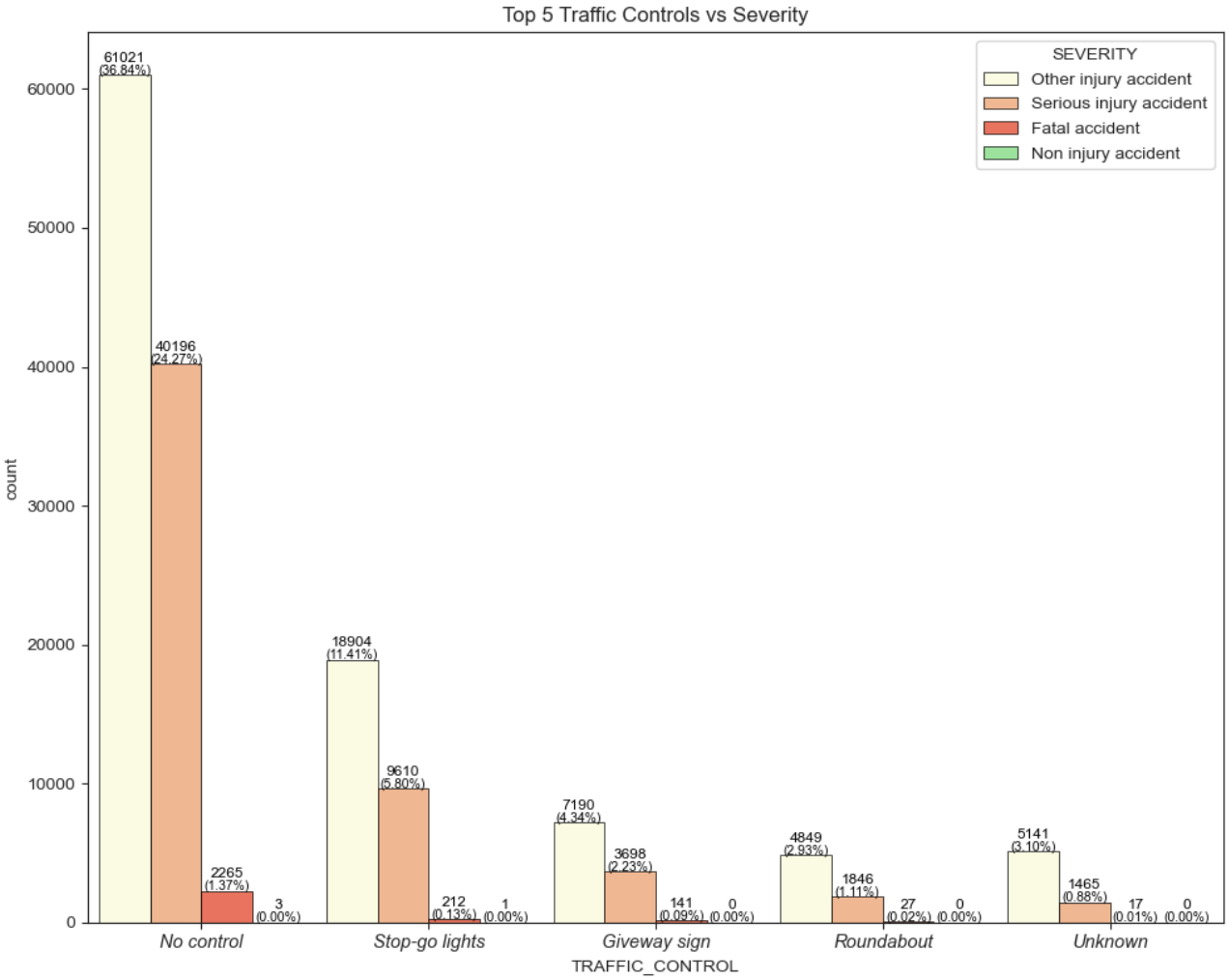
This count plot visualizes the distribution of the top 5 surface conditions of roads vs severity, displaying the count of accidents across a multitude of road surface conditions in Victoria. The Dry surface condition is by far the most prominent, with a total of 128,210 incidents. These incidents constitute of 77,388 other injury accidents (46.72%), 48,497 serious injury accidents (29.28%), 2,321 fatal accidents (1.40%), and 4 non-injury accidents; the majority of accidents occur on dry road surfaces. Although, Dry surfaces exhibit the highest ratio of serious injury accidents at 37.83%, Icy surfaces have the highest proportion of fatal accidents at 2.35%. Also, the Icy surface condition ultimately has the lowest frequency, with a total of 596 incidents. This includes 367 other injury accidents (0.22%), 215 serious injury accidents (0.13%), and 14 fatal accidents (0.01%). While Dry surfaces account for the most accidents and exhibit the highest proportion of serious injury accidents, Icy surfaces have the highest proportion of fatal accidents, making these conditions particularly hazardous despite their lower frequency.



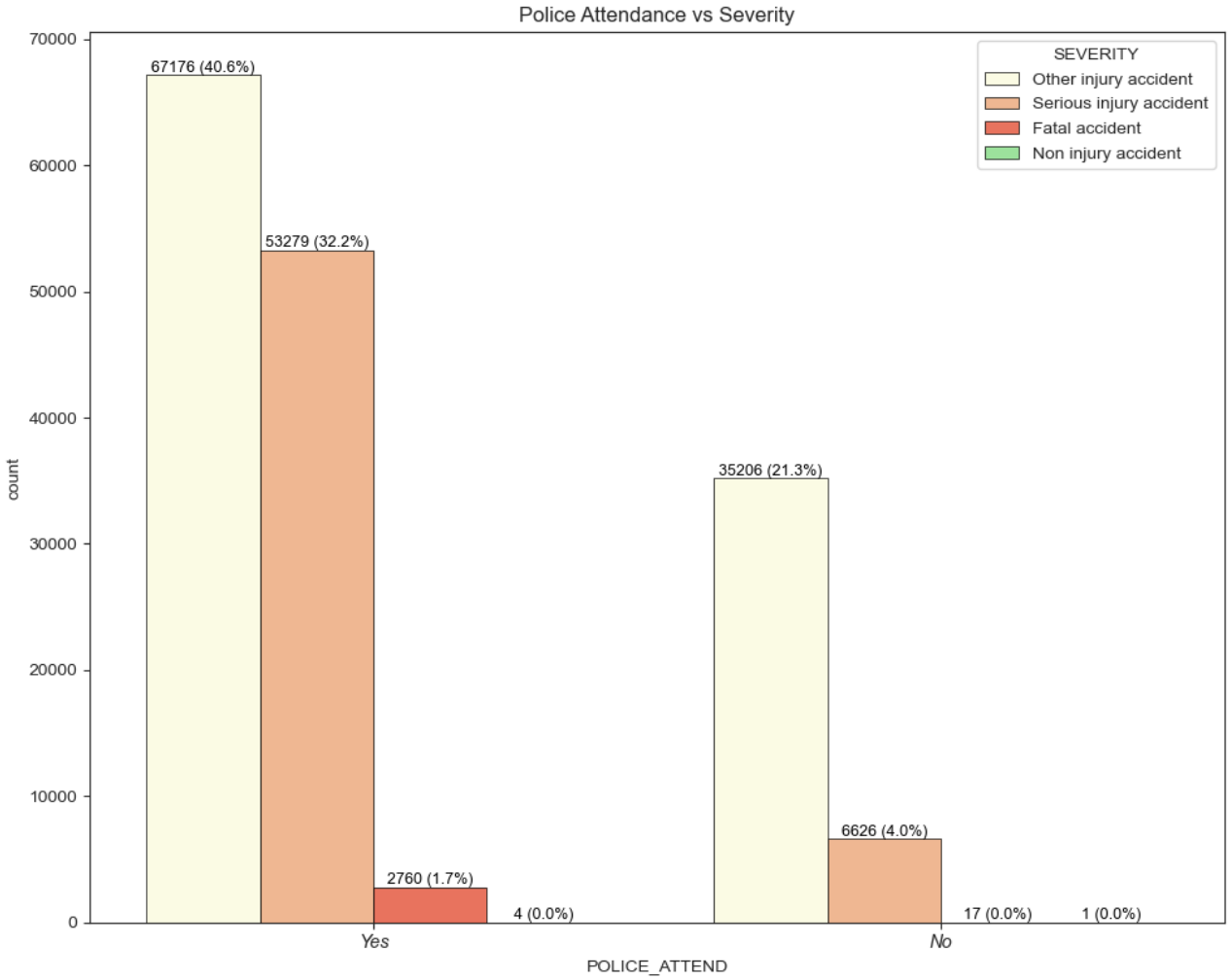
This count plot illustrates the distribution of the road surface types versus severity, highlighting the number of accidents across various surface conditions in descending order within Victoria. Clearly, Paved roads dominate, with a total of 151,631 incidents, consisting of 95,776 other injury accidents (57.82%), 55,969 serious injury accidents (33.79%), 2,620 fatal accidents (1.58%), and 4 non-injury accidents. However, Unpaved roads exhibit the highest proportion of serious injury accidents at 38.80%. Despite this, Paved surfaces still account for the highest ratio of fatal accidents at 1.73%. In contrast, the Not Known road surface type has the fewest incidents, with 1,419 total accidents, including 1,127 other injury accidents (0.68%), 288 serious injury accidents (0.17%), and 3 fatal accidents. While most accidents occur on Paved roads due to their prevalence, Unpaved roads have the highest rate of serious injury accidents, whereas Paved roads leads in fatal accident proportions.



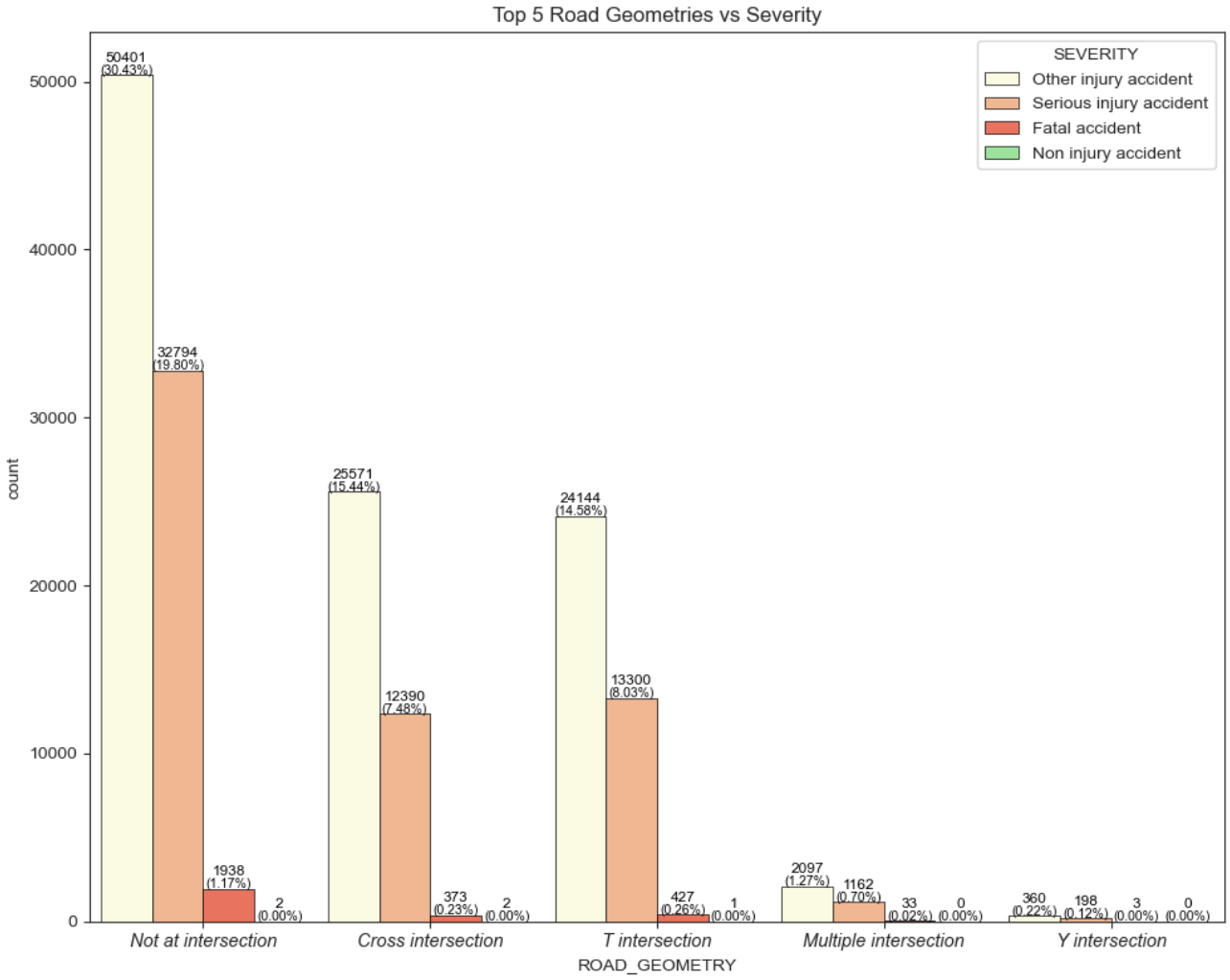
This count plot visualizes the distribution of the top 5 light conditions by severity, illustrating the number of accidents under different lighting environments in Victoria. Daylight is the most dominant condition, with a total of 109,989 accidents, including 68,996 other injury accidents (41.65%), 39,372 serious injury accidents (23.77%), 1,617 fatal accidents (0.98%), and 4 non-injury accidents. This indicates that most accidents occur during the day, likely due to higher traffic volumes. However, Dark No Street Lights conditions stand out with the highest proportion of serious injury accidents at 46.29% and the highest proportion of fatal accidents at 5.29%; indicating that poor lighting conditions without streetlights significantly increase the severity of accidents. On the other hand, the Unknown light condition records the fewest incidents, with 4,520 total accidents, comprising 3,787 other injury accidents (2.59%), 706 serious injury accidents (0.43%), and 27 fatal accidents (0.02%). Overall, Day conditions dominate the total number of accidents but are not the most dangerous in terms of severity. Dark No Street Lights conditions present the highest risk for both serious injuries and fatalities.



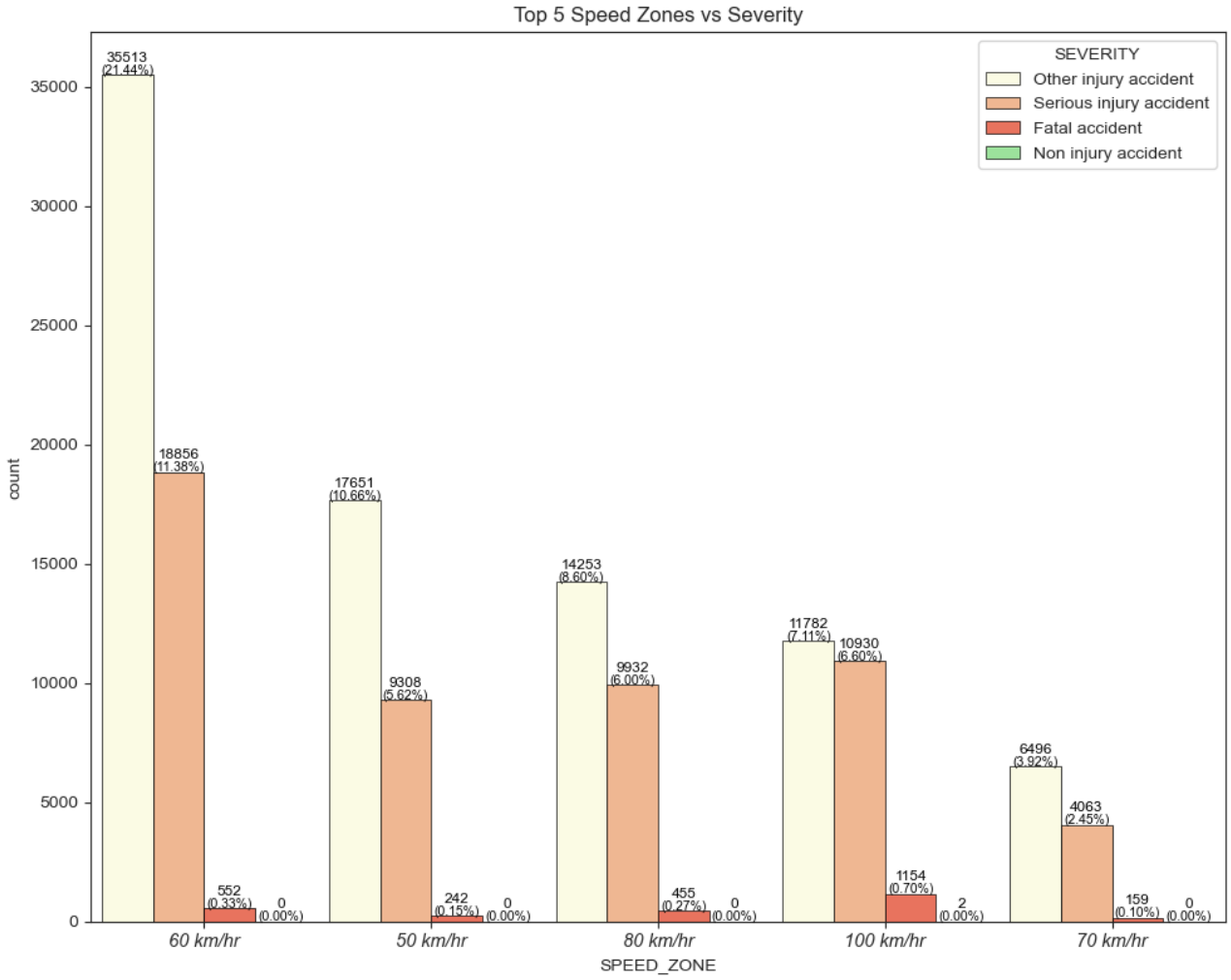
The count plot illustrates the distribution of the top 5 traffic control types in relation to accident severity, showing the number of accidents across different traffic control conditions in Victoria. The No Control category is the most prominent, with a total of 103,485 incidents. This includes: 61,021 other injury accidents (36.84%), 40,196 serious injury accidents (24.27%), 2,265 fatal accidents (1.37%), and 3 non-injury accidents. This indicates that areas without traffic control measures are more prone to accidents due to unregulated traffic. Whilst No Control has the highest total number of accidents, it also has the highest ratio of serious injury accidents at 38.84% and the highest ratio of fatal accidents at 2.19%. This shows the significant risk posed by intersections or roads with no traffic control measures. Conversely, the Unknown category has the lowest total number of incidents, with 6,623 accidents. This constitutes of 5,141 other injury accidents (3.10%), 1,465 serious injury accidents (0.88%), and 17 fatal accidents (0.01%).



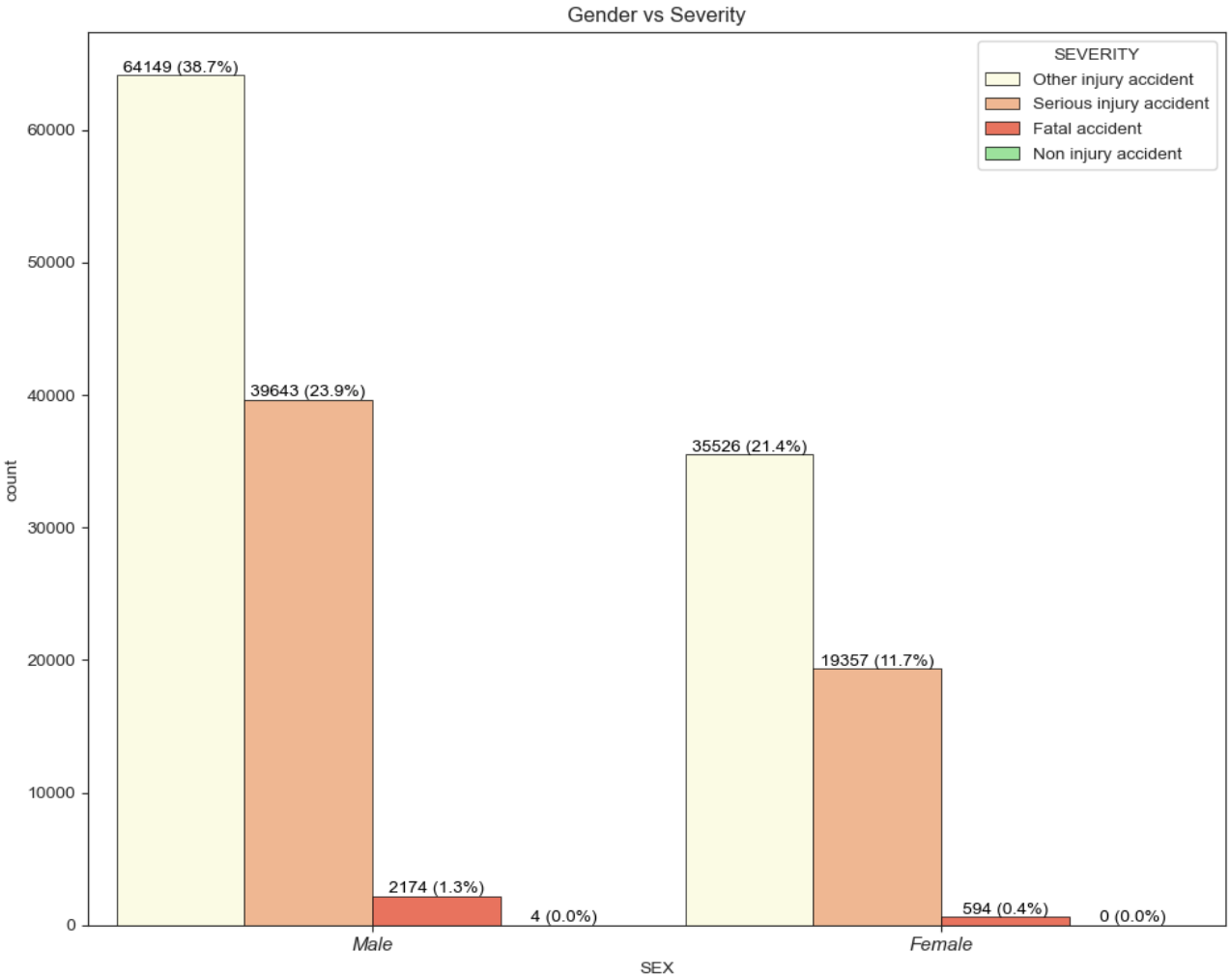
The count plot displays the distribution of accident severity based on police attendance at the accident scene, categorizing cases where police were present or absent. Yes (police attended) is the most prevalent category, with 123,219 total incidents, comprising 67,176 other injury accidents (40.55%), 53,279 serious injury accidents (32.16%), 2,760 fatal accidents (1.67%), and 4 non-injury accidents. This suggests that the police are generally more likely to be present at accidents across all severity levels. The Yes category also shows the highest proportions of both serious injury accidents (43.23%) and fatal accidents (2.24%), indicating that police are more frequently called to accidents of greater severity. In contrast, the No category has the fewest incidents, with 41850 total accidents; this includes 35,206 other injury accidents (21.3%), 6626 serious injury accidents (4.0%), 17 fatal accidents, and 1 non-injury accident.



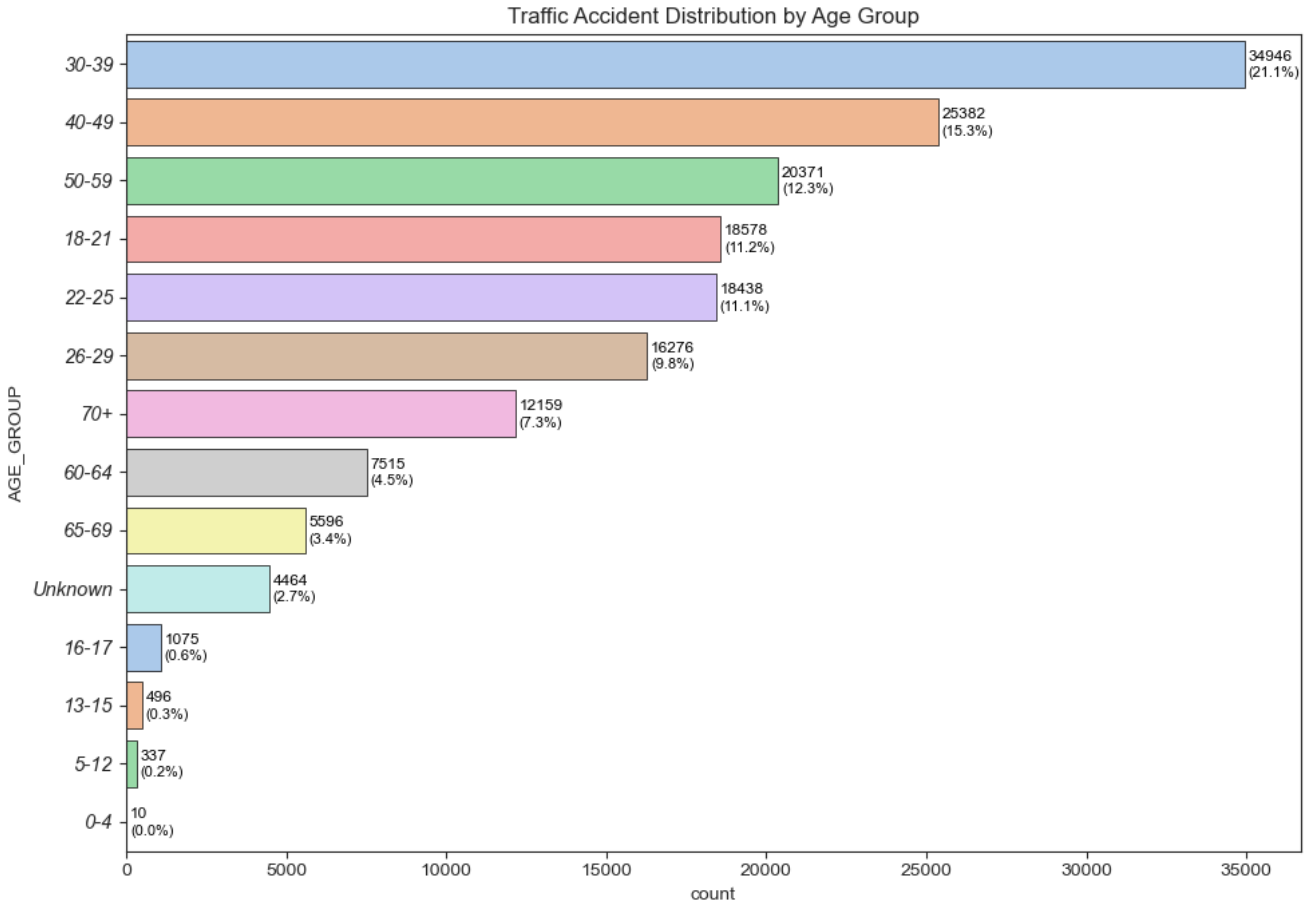
This count plot highlights the distribution of accident severity across the top 5 road geometries in Victoria, distinguishing between incidents that occur at intersections (e.g., Cross, T, Y) and those that happen away from intersections. The Not at Intersection category has the highest number of accidents, with a total of 85,135 incidents, comprising 50,401 other injury accidents (30.43%), 32,794 serious injury accidents (19.80%), 1,938 fatal accidents (1.17%), and 2 non-injury accidents. This suggests the majority of accidents occur away from intersections. In terms of severity, Not at Intersection also has the highest ratio of serious injuries, with 38.52% of accidents resulting in serious injuries, and it records the highest fatal accident proportion at 2.28%, indicating a heightened risk level in these areas. Conversely, the Y Intersection category has the lowest number of incidents, totalling 561 accidents. This includes 360 other injury accidents (0.22%), 198 serious injury accidents (0.12%), and 3 fatal accidents.



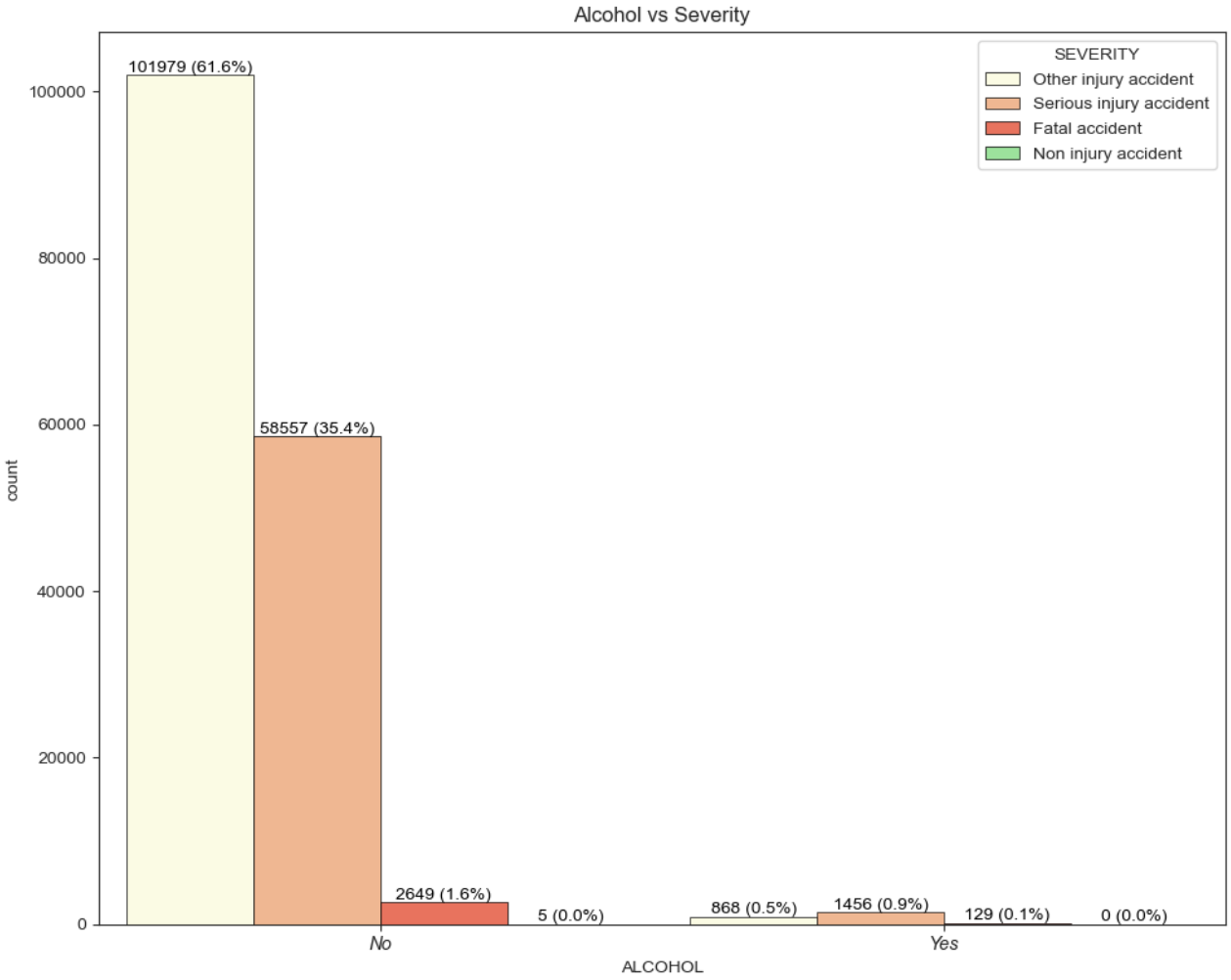
This count plot visualizes the distribution of accident severity across the top 5 speed zones in Victoria, ranked by the total number of accidents in each speed limit category. These categories represent the speed limits where accidents have most frequently occurred, providing insight into how accident severity varies with speed. The 60 km/hr zone ranks as the highest, with a total of 54,921 incidents. This includes 35,513 other injury accidents (21.44%), 18,856 serious injury accidents (11.35%), 552 fatal accidents (0.33%), and 0 non-injury accidents, indicating a significant concentration of accidents in this speed range. When considering the severity of accidents, the 100 km/hr zone shows the highest risk, with a serious injury proportion of 45.80% and a fatal accident proportion of 4.83%, underlining the elevated risk associated with higher speeds. Conversely, the 70 km/hr zone records the lowest total number of incidents among the top five, with 10,718 accidents in total, including 6,496 other injury accidents (3.92%), 4,063 serious injury accidents (2.45%), and 159 fatal accidents (0.10%). These statistics reveal that while the 60 km/hr zone is more accident-prone overall, higher speed zones like 100 km/hr have a greater likelihood of resulting in severe outcomes.



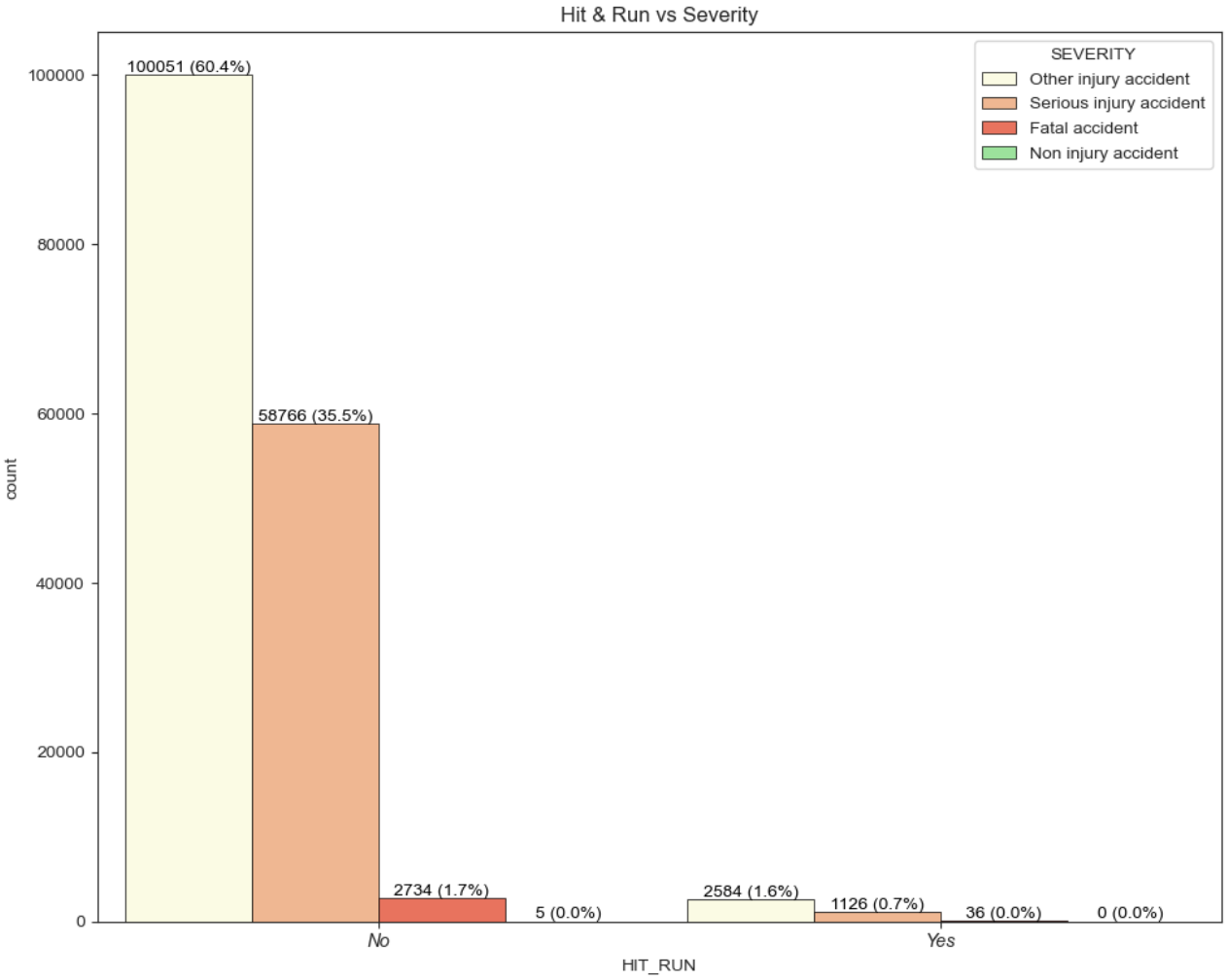
This count plot shows the distribution of accident severity based on gender in Victoria. The plot categorizes accidents involving Male and Female drivers who initiated the incidents (perpetrator), highlighting the number of accidents across different severities. Males have a higher total number of accidents, with 105,970 incidents. This includes 64,149 other injury accidents (38.7%), 39,643 serious injury accidents (23.9%), 2,174 fatal accidents (1.3%), and 4 non-injury accidents. This suggests that males are involved in the majority of accidents across all severity types in Victoria. When it comes to accident severity, males exhibit a higher ratio of serious injury accidents (37.4%) and fatal accidents (2.05%); which suggests that accidents involving male drivers have a slightly higher likelihood of resulting in severe or fatal outcomes. In comparison, the Female category has a lower total of 55,477 incidents. This comprises 35,526 other injury accidents (21.4%), 19,357 serious injury accidents (11.7%), 594 fatal accidents (0.4%), and 0 non-injury accidents; indicating that females are involved in fewer accidents overall, the accidents also tend to be less severe on average. Ultimately, this reveals a gender disparity in both the frequency and severity of accidents in Victoria. Specifically, in terms of ratios, males are approximately 1.91 times more likely to be involved in accidents compared to females.



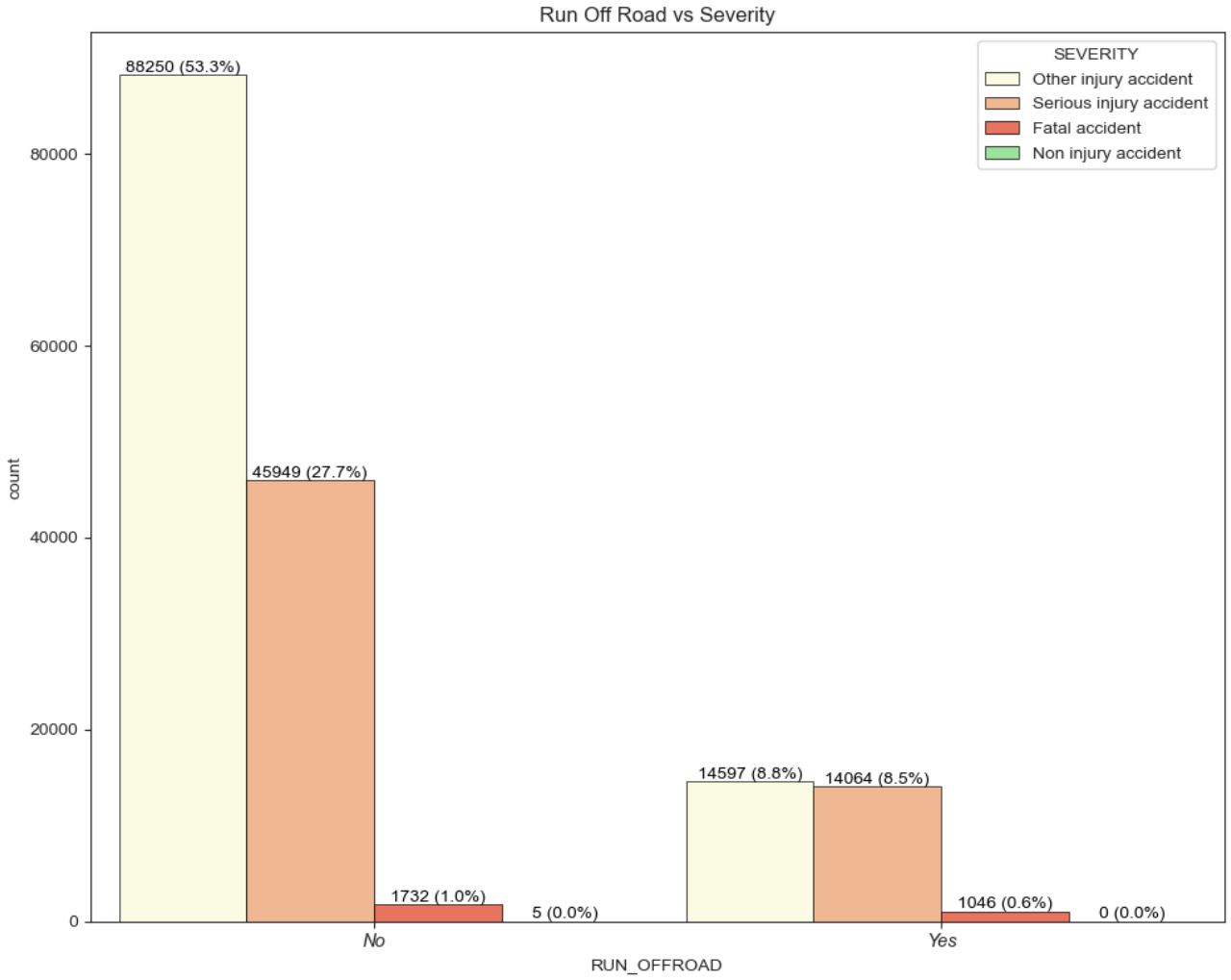
The count plot illustrates the distribution of traffic accidents in Victoria across different age groups, highlighting the demographics most frequently involved in accidents. The age group 30-39 stands out as the most prevalent, accounting for 34,946 incidents (21.1% of total accidents). This is followed by the age groups 40-49 with 25,382 accidents (15.3%) and 50-59 with 20,371 incidents (12.3%). Younger age groups, such as 18-21 and 22-25, also represent substantial portions, with 18,578 (11.2%) and 18,438 (11.1%) accidents, respectively. Interestingly, older age groups such as 65-69 and 70+ contribute less to the overall accident count, with 5,596 (3.4%) and 12,159 (7.3%) incidents. Additionally, the very young age groups, including 5-12 and 0-4, have negligible accident counts, reflecting limited road exposure. This distribution emphasizes that while all age groups are involved in traffic accidents, middle-aged individuals (particularly those aged 30-59) represent the majority of cases.



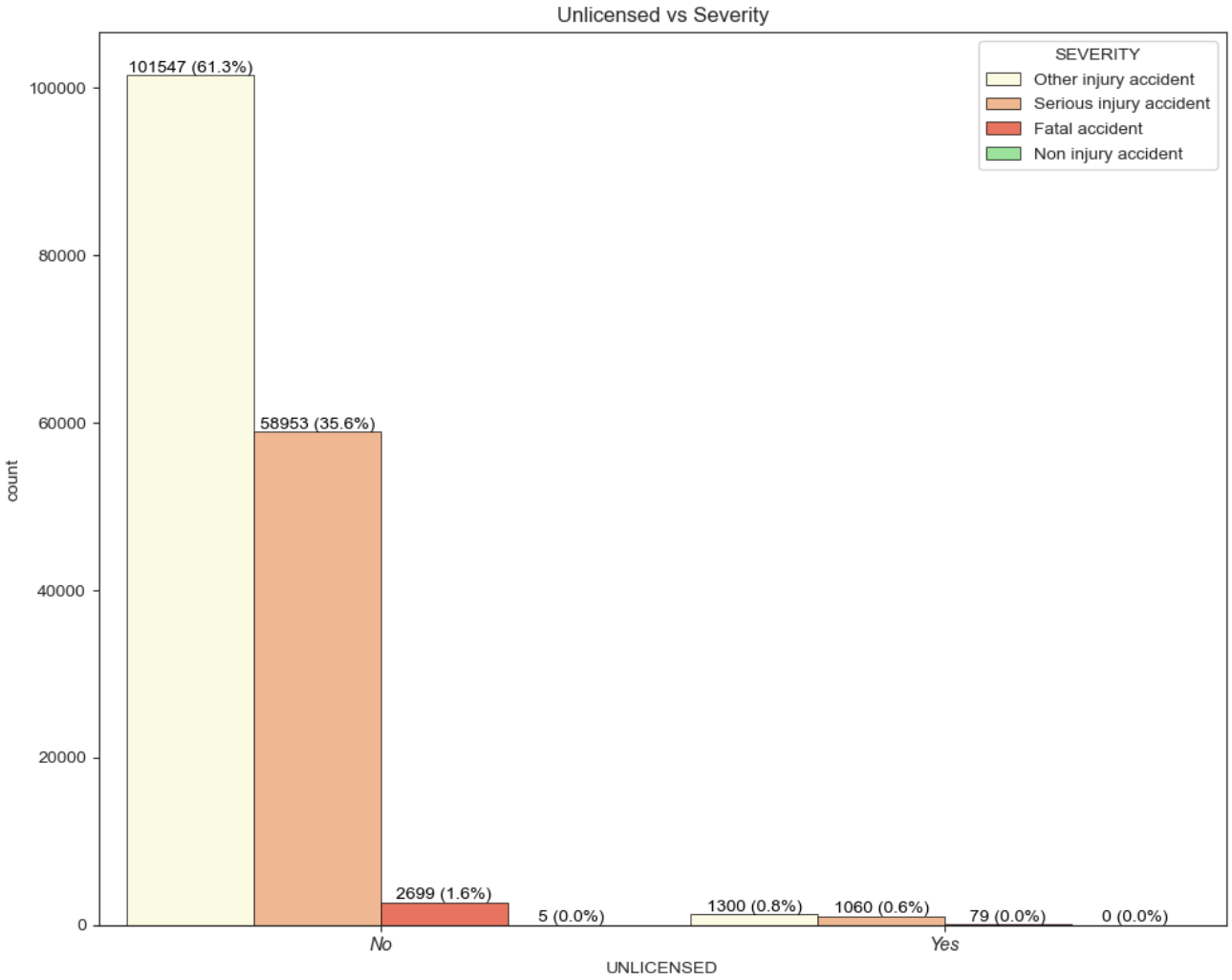
This count plot depicts the relationship between alcohol involvement and accident severity in Victoria, categorizing accidents involving alcohol consumption by the driver (Yes/No), highlighting the number of accidents across different severities. The vast majority of accidents occur without alcohol involvement, totaling 163,190 incidents with 101,979 other injury accidents (61.6%), 58,557 serious injury accidents (35.4%), 2,649 fatal accidents (1.6%) and 5 non-injury accidents recorded where alcohol was not a factor. This distribution indicates that most accidents occur without alcohol involvement, yet they span all severity levels. In contrast, alcohol-involved accidents are vastly less frequent at 2,453 total incidents, which constitutes of 868 other injury accidents (0.5%), 1,456 serious injury accidents (0.9%), and 129 fatal accidents (0.1%). However, alcohol-involved accidents shows a higher proportion of serious and fatal injuries: Among alcohol-involved accidents, 59.3% resulted in serious injuries, significantly higher than the 35.9% in non-alcohol related accidents. Also, alcohol-involved accidents have a higher fatal accident ratio at 5.3%, compared to 1.6% in accidents without alcohol involvement. These findings highlight that, while alcohol-related accidents are less frequent, they are significantly more likely to result in serious or fatal injuries.



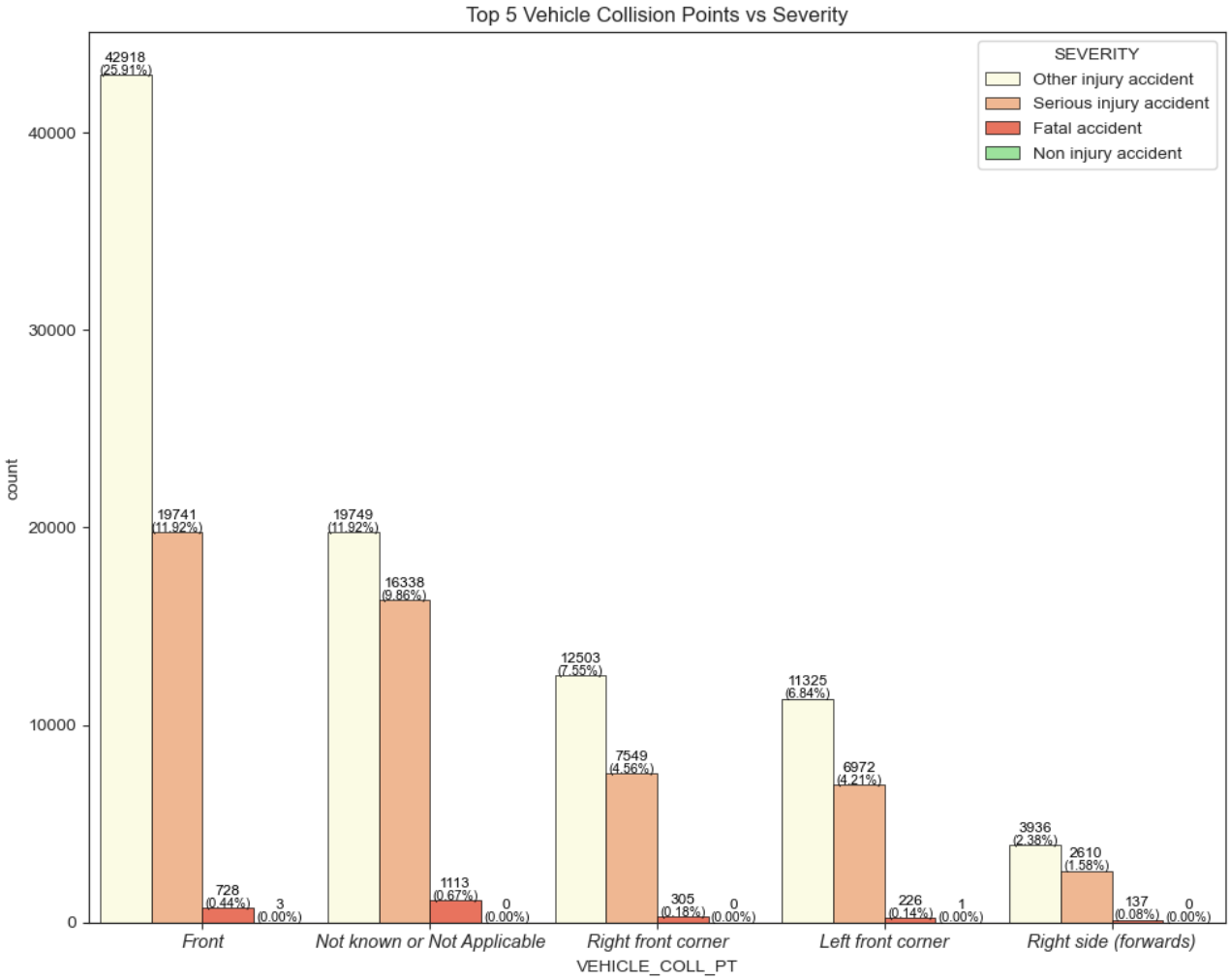
The count plot highlights the distribution of accident severity based on hit-and-run involvement in Victoria. The plot distinguishes between accidents where the incident was classified as a hit-and-run (Yes) and those that were not (No), highlighting the number of accidents across various severities. The No category accounts for the vast majority of incidents, with a total of 161,556 accidents. This includes 100,051 other injury accidents (60.4%), 58,766 serious injury accidents (35.5%), 2,734 fatal accidents (1.7%), and 5 non-injury accidents. This distribution suggests the vast majority of accidents in Victoria do not involve hit-and-run scenarios. In comparison, the Yes category (hit-and-run incidents) has a significantly lower count, totaling 3,746 accidents. Among these, 2,584 are other injury accidents (1.6%), 1,126 are serious injury accidents (0.7%), and 36 are fatal accidents. In terms of ratios, for hit-and-run incidents, 30.1% result in serious injuries, while non-hit-and-run incidents show a higher ratio at 35.5%, indicating that non-hit-and-run incidents are slightly more likely to involve serious injuries. For fatalities, non-hit-and-run incidents have a fatal accident ratio of 1.65%, compared to a lower fatal accident ratio of 0.96% in hit-and-run incidents. This suggests that hit-and-run accidents are less likely to result in fatalities compared to non-hit-and-run incidents.



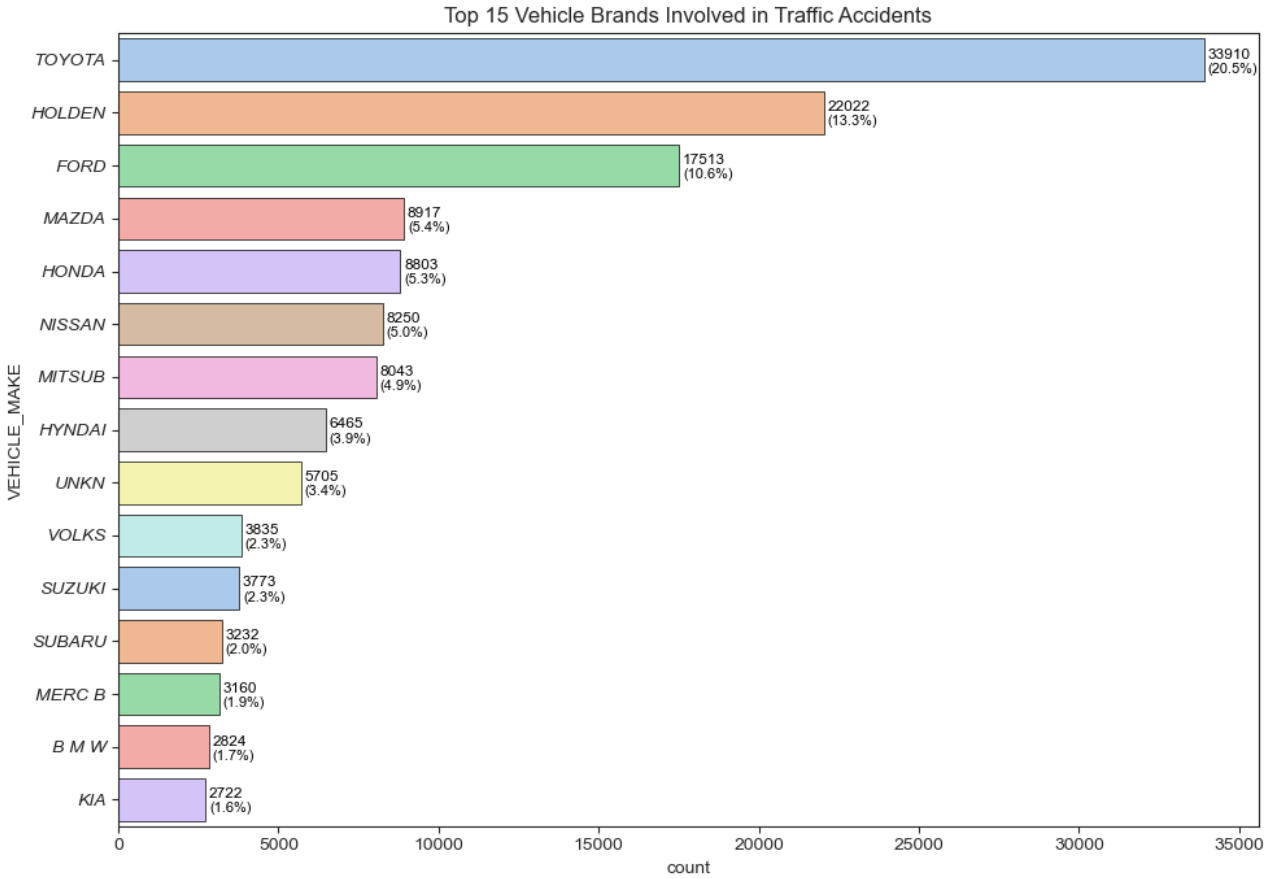
This count plot displays the distribution of accident severity based on whether the vehicle ran off the road in Victoria. The plot categorizes accidents as either involving vehicles that stayed on the road ("No") or vehicles that ran off the road ("Yes") and breaks down the severity of these accidents. The No category, where vehicles remained on the road, has the highest total number of accidents, with 135,936 incidents. This constitutes of 88,250 other injury accidents (53.3%), 45,949 serious injury accidents (27.7%), 1,732 fatal accidents (1.0%), and 5 non-injury accidents. This suggests that most accidents occur without vehicles leaving the roadway. In comparison, the Yes category, where vehicles ran off the road, shows a lower total of 29,707 incidents. This includes 14,597 other injury accidents (8.8%), 14,064 serious injury accidents (8.5%), and 1,046 fatal accidents (0.6%). Despite the lower overall frequency, the Yes category exhibits a higher ratio of both serious injury (47.3%), and fatal accidents (3.5%) compared to those that remain on the road; highlighting that running off the road is associated with increased accident severity. Essentially, these ratios underline the notably higher likelihood of severe or fatal outcomes in such cases.



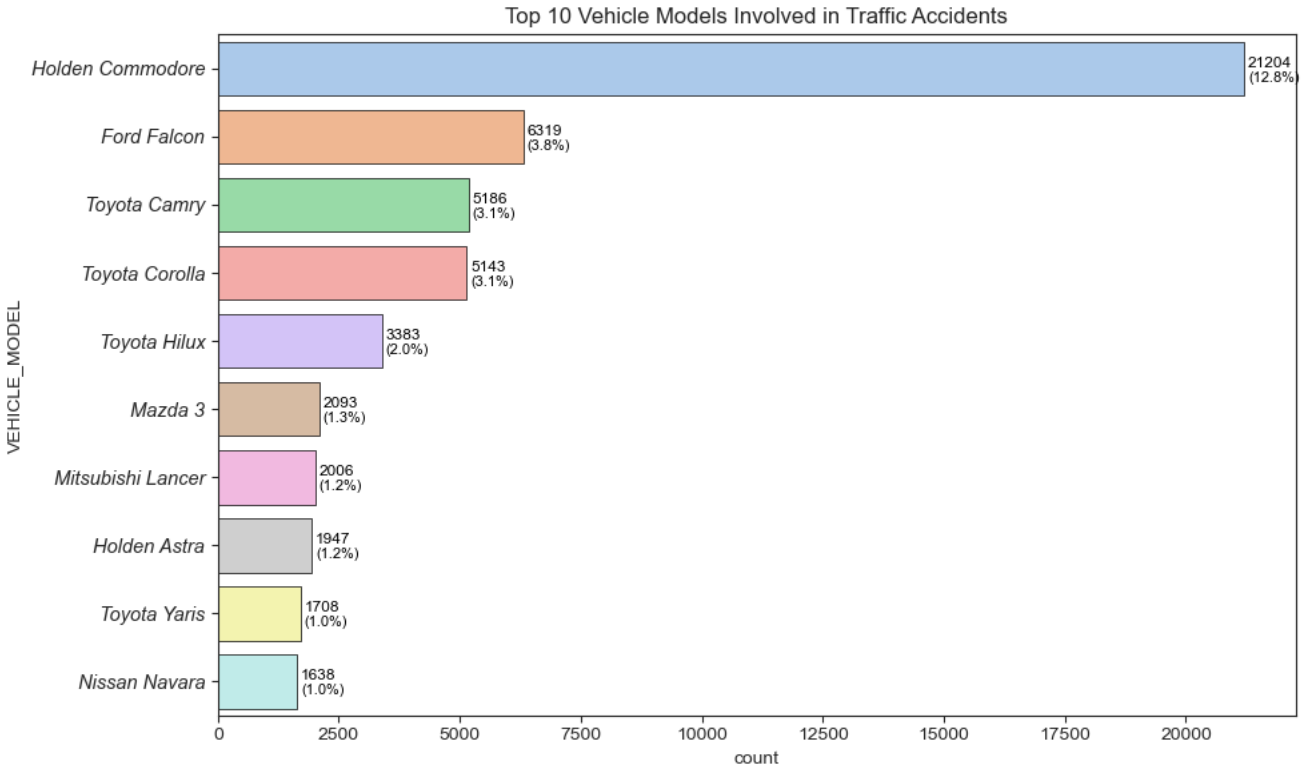
This count plot illustrates the distribution of accident severity based on the licensing status of the driver (perpetrator) involved in incidents in Victoria. The plot differentiates between drivers who were licensed and unlicensed at the time of the accident, with severity categories indicated for each group. The No category (licensed drivers) has the highest number of accidents, totaling 163,204 incidents. This includes 101,547 other injury accidents (61.3%), 58,953 serious injury accidents (35.6%), 2,699 fatal accidents (1.6%), and 5 non-injury accidents; indicating that the majority of accidents in Victoria involve licensed drivers, spanning all severities. In contrast, the Yes category (unlicensed drivers) has a significantly lower total of 2,439 incidents. This comprises 1,300 other injury accidents (0.8%), 1,060 serious injury accidents (0.6%), and 79 fatal accidents (0.05%). However, regardless of the lower overall count, unlicensed drivers display higher ratios of severe outcomes; the unlicensed group exhibits a notably higher proportion of both serious injury and fatal accidents compared to licensed drivers, with a serious injury ratio of 43.5% and a fatal accident ratio of 3.2%. This indicates that accidents involving unlicensed drivers are more likely to result in severe or fatal consequences, highlighting the elevated risk associated with unlicensed driving.



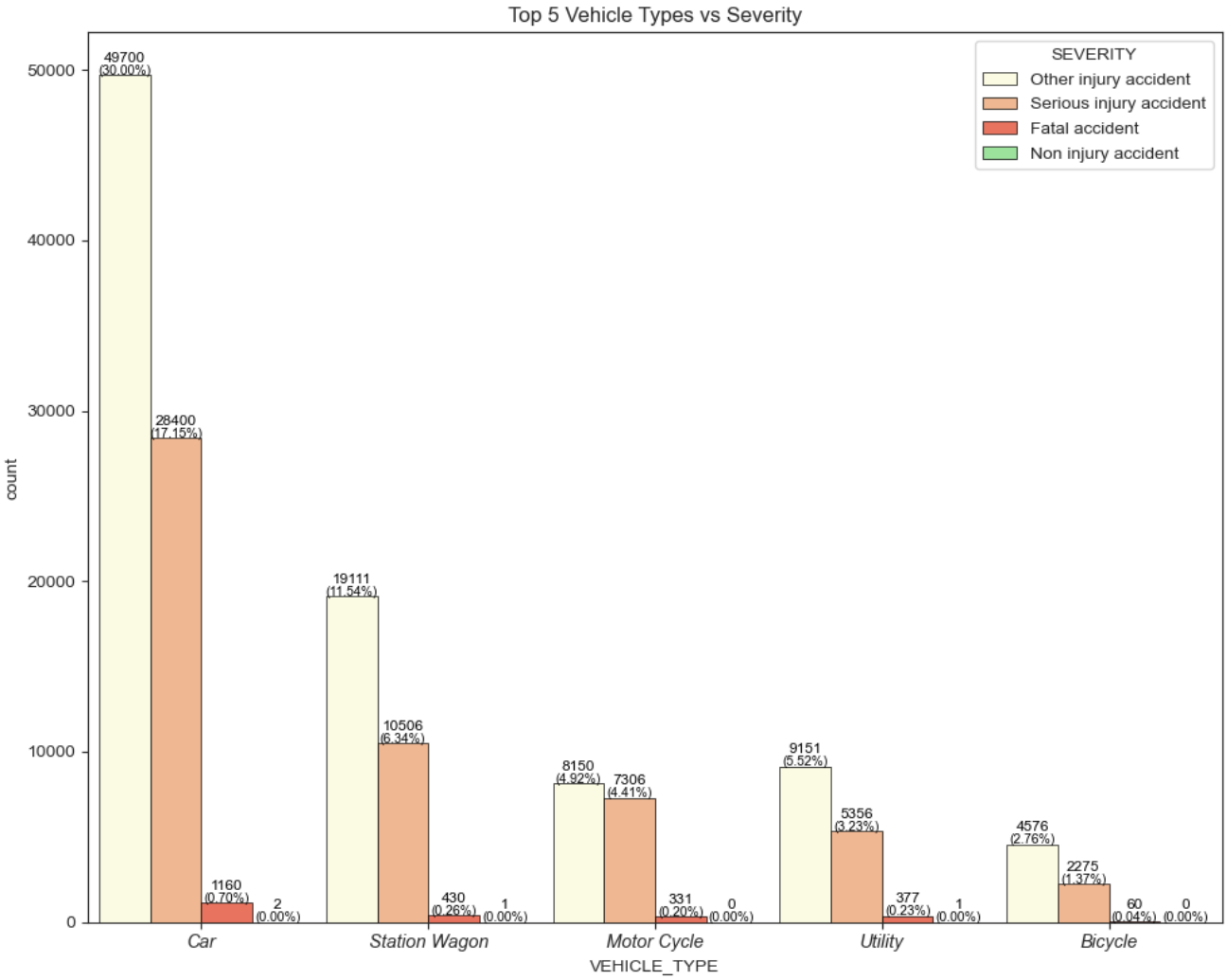
This count plot visualizes the distribution of accident severity based on the top five collision points of the perpetrator's vehicle in Victoria. The collision points are categorized by where the vehicle was impacted, the severity of each accident is further broken down within these collision points. The Front collision point has the highest number of accidents, with a total of 63,390 incidents. This includes 42,918 other injury accidents (25.91%), 19,741 serious injury accidents (11.92%), 728 fatal accidents (0.44%), and 3 non-injury accidents. This suggests that frontal collisions are the most common in traffic accidents, with a relatively high count across all severities. When considering accident severity ratios, the Not Known or Not Applicable category shows the highest ratios of serious injury (44%) and fatal accidents (3%), highlighting a concerning association with severe outcomes in cases where the collision point is unclear. Conversely, the Right Side (forwards) collision point has the lowest total number of incidents, with 6,683 accidents, comprising 3,936 other injury accidents (2.4%), 2,610 serious injury accidents (1.6%), and 137 fatal accidents (0.1%), indicating that side impacts may lead to less frequent but still serious outcomes.



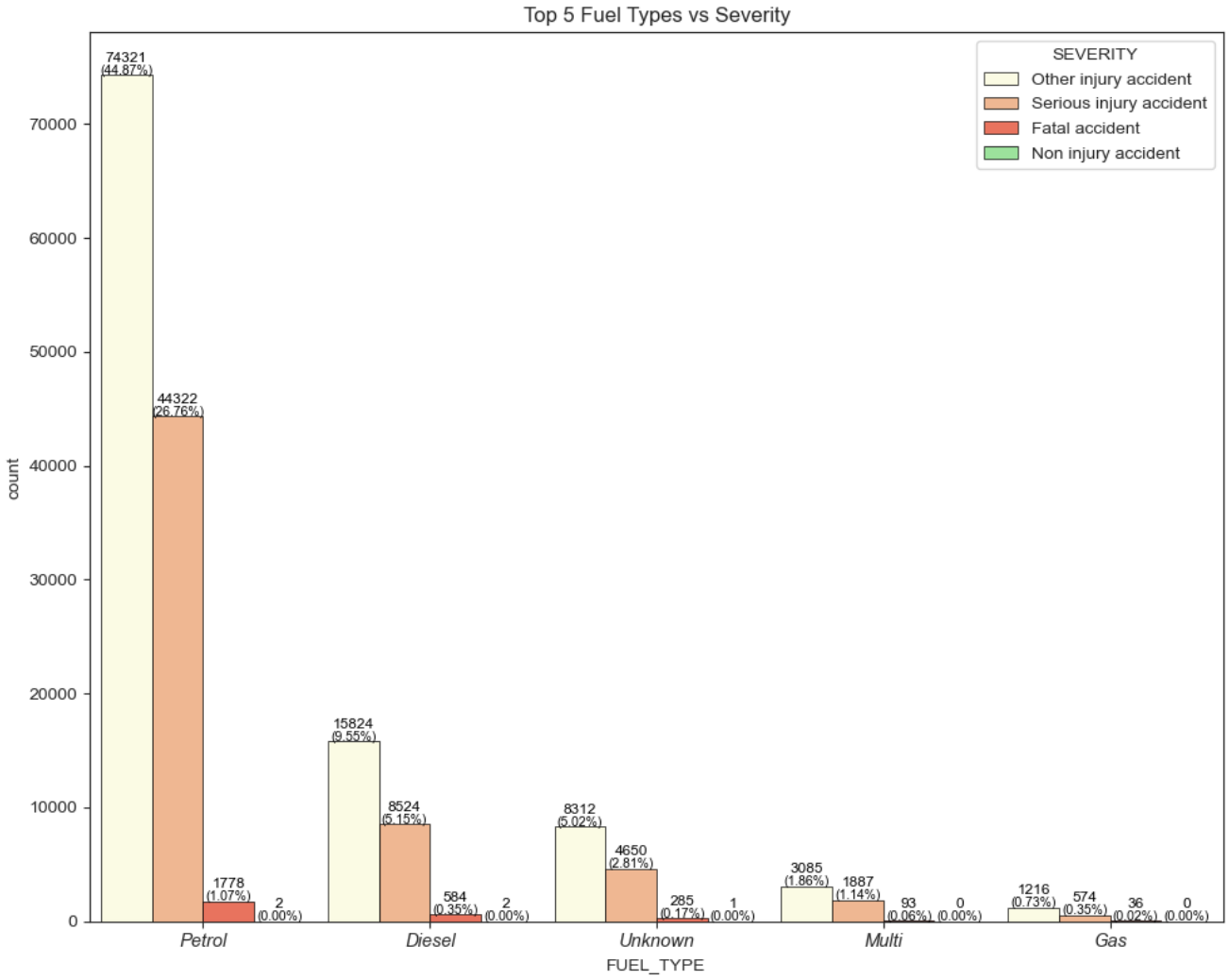
The count plot shows the distribution of traffic accidents among the top 15 vehicle brands involved in accidents in Victoria. The plot ranks vehicle brands by accident frequency, providing insight into which brands are most commonly associated with traffic incidents. Toyota holds the highest count of accidents, with 33,910 incidents, making up 20.5% of the accidents within the dataset. Holden follows as the second most common, with 22,022 accidents (13.3%). Ford ranks third, with 17,513 accidents, representing 10.6% of the total. Other brands, including Mazda (8,917 incidents, 5.4%), Honda (8,803 incidents, 5.3%), and Nissan (8,250 incidents, 5.0%), show a moderate representation. Lesser represented brands such as Kia and BMW have accident counts of 2,722 (1.6%) and 2,824 (1.7%), respectively. Overall, this distribution indicates that Toyota, Holden, and Ford vehicles are most frequently involved in accidents compared to other brands.



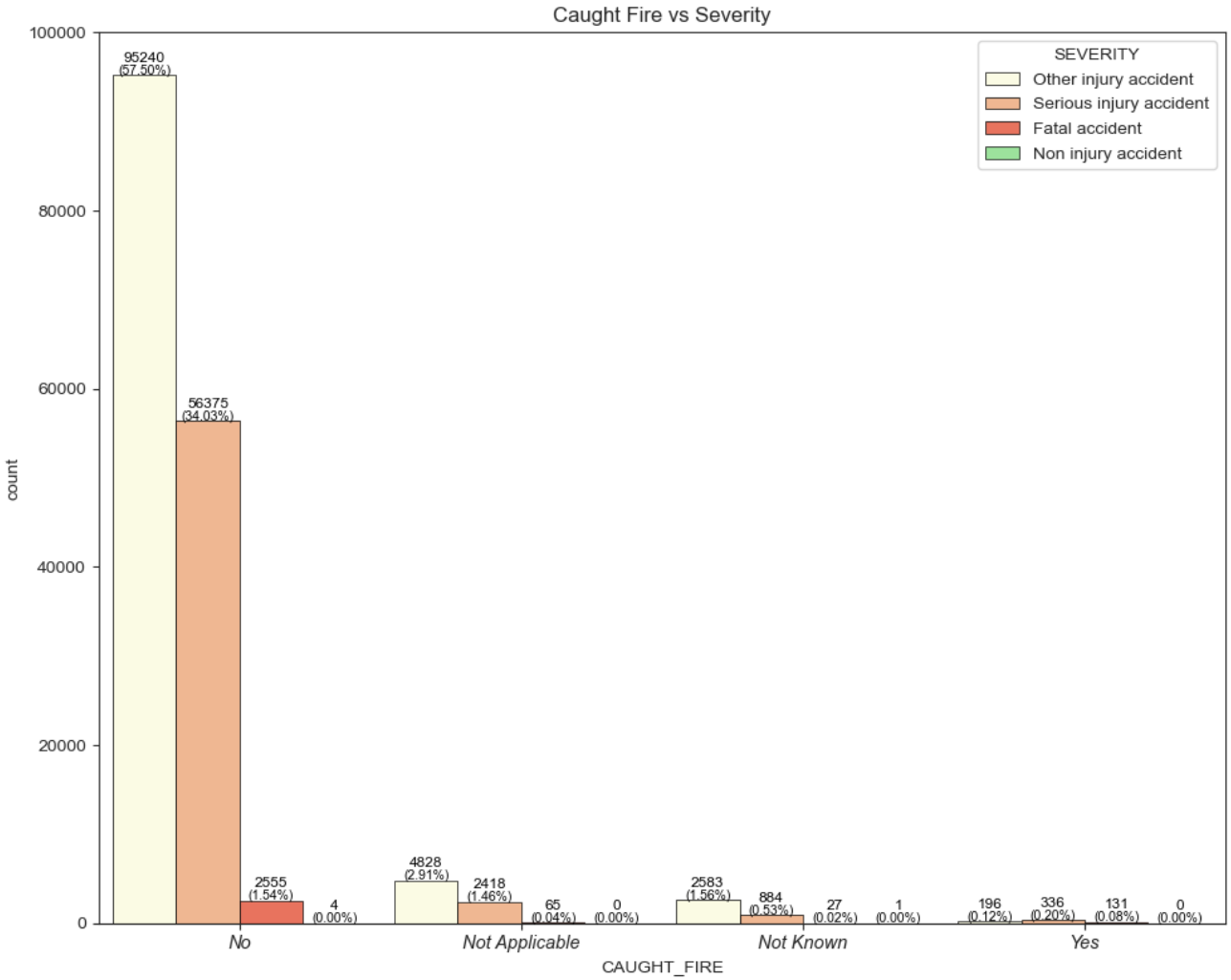
This count plot displays the top 10 vehicle models involved in traffic accidents in Victoria. The most frequently involved model is the Holden Commodore, accounting for 12.8% of all incidents within the dataset, with a count of 21,204. The Ford Falcon follows with 6,319 accidents (3.8%), and Toyota Camry comes in third with 5,186 accidents (3.1%). Toyota models are notably prevalent in this list, with four models represented: Camry, Corolla (3.1%, 5,186 & 5143 accidents), Hilux (2.0%, 3,383 accidents), and Yaris (1.0%, 1,708 accidents). This indicates Toyota's significant presence among accident-involved vehicles, suggesting that Toyota models might be widely used in Victoria. Other vehicle models in the top 10 include the Mazda 3 (1.3%, 2,093 accidents), Mitsubishi Lancer (1.2%, 2,006 accidents), Holden Astra (1.2%, 1,947 accidents), and Nissan Navara (1.0%, 1,638 accidents); the lowest count among all models.



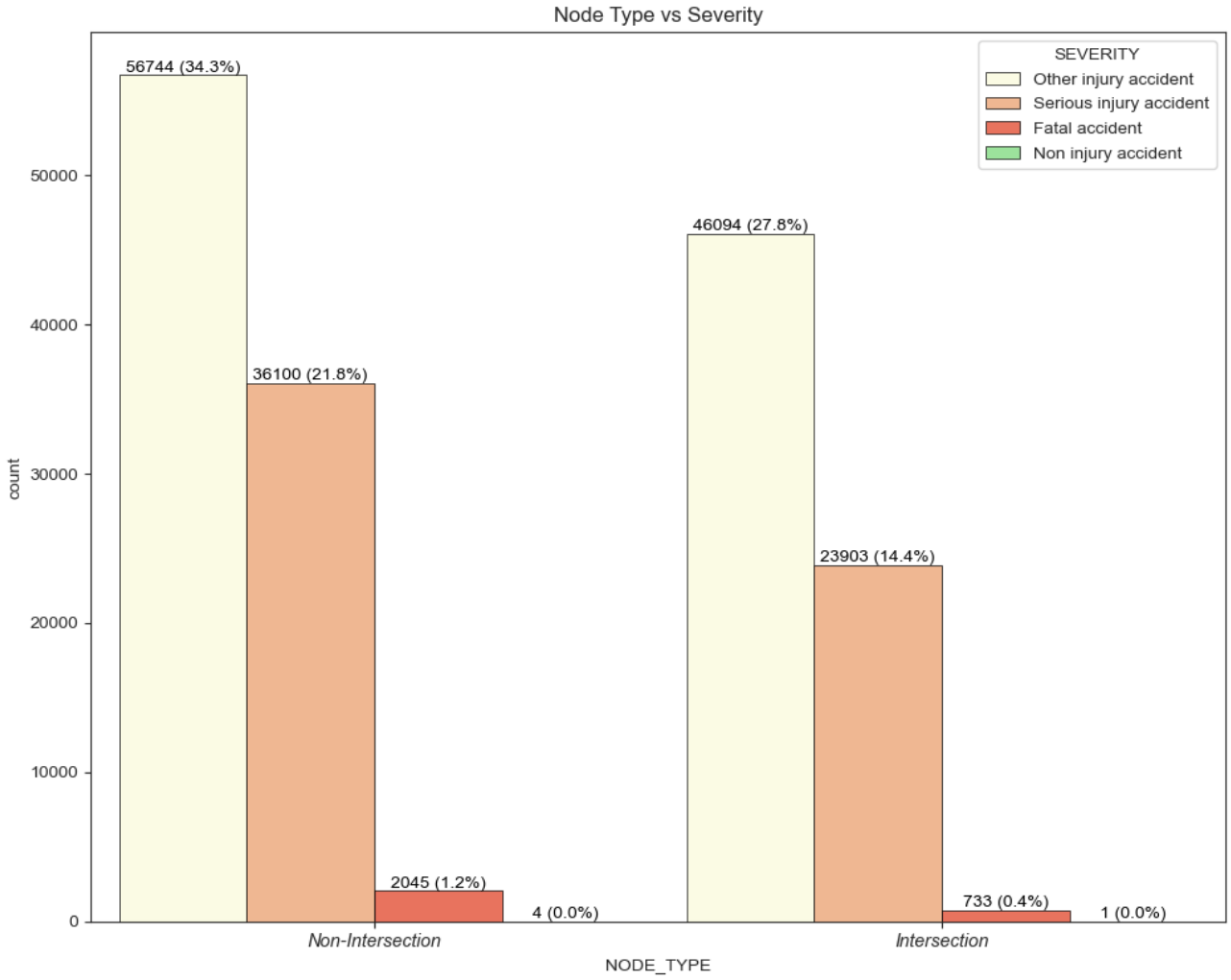
This count plot illustrates the distribution of accident severity based on the top five vehicle types involved in traffic accidents in Victoria. The vehicle types are categorized by type, and the severity of each accident is within these categories. Cars account for the highest number of accidents, with a total of 79,262 incidents. This includes 49,700 other injury accidents (30%), 28,400 serious injury accidents (17.15%), 1,160 fatal accidents (0.70%), and 2 non-injury accidents, making cars the most frequently involved vehicle type across all severities in traffic accidents. In terms of severity ratios, Motorcycles have the highest proportion of serious injury accidents at 46.3%, indicating a notably higher risk of severe outcomes for this type. Additionally, Utility vehicles show the highest fatal accident ratio at 2.7%, suggesting an increased likelihood of fatal outcomes in accidents involving this vehicle type. On the other hand, Bicycles are involved in the fewest total accidents, with 6,911 incidents. This includes 4,576 other injury accidents (2.76%), 2,275 serious injury accidents (1.37%), and 60 fatal accidents (0.04%). Although bicycles are less frequently involved in accidents overall, they still carry a considerable risk of serious injuries.



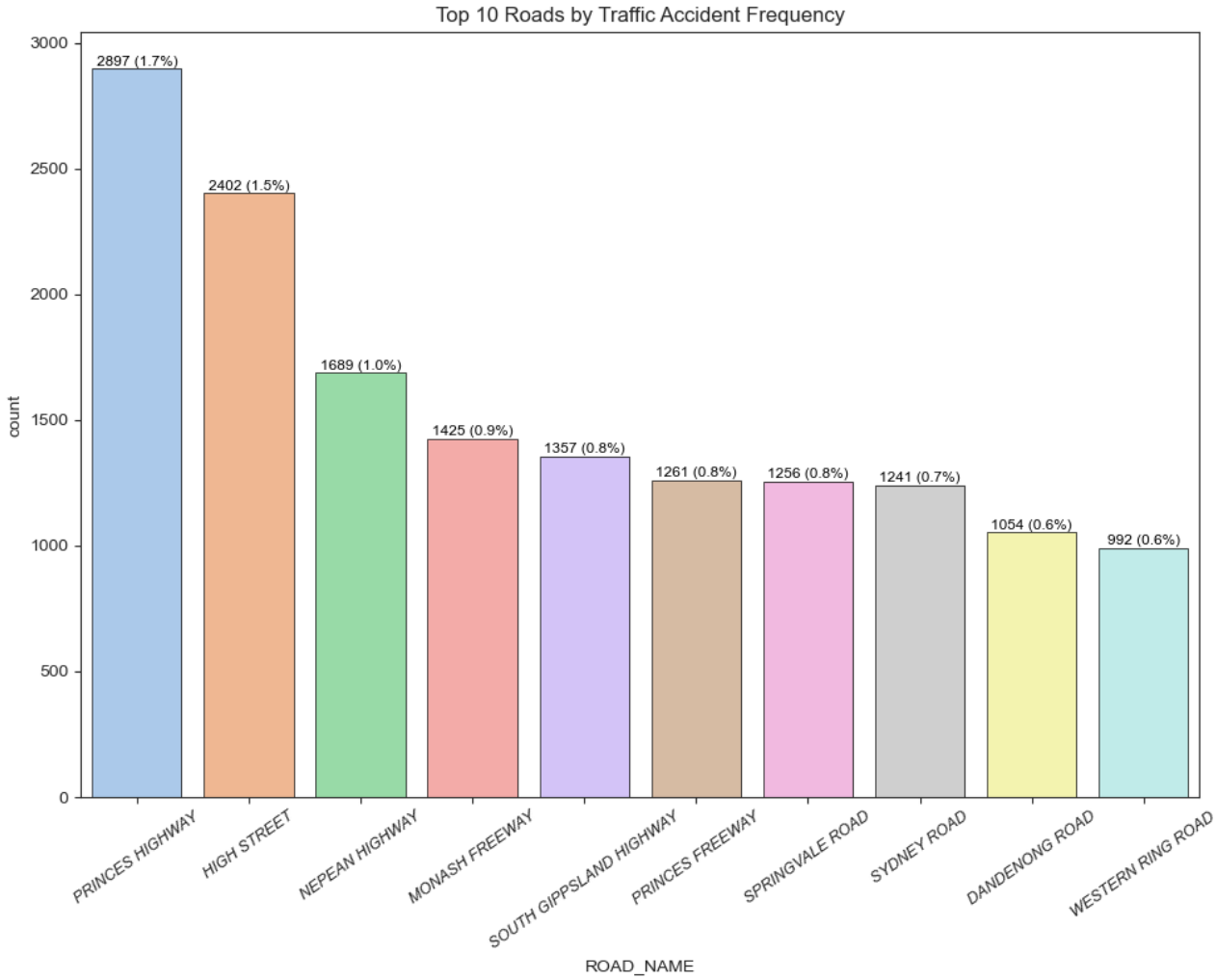
This count plot highlights the distribution of accident severity across the top five fuel types used by vehicles involved in accidents in Victoria. Each bar represents a different fuel type, with segments indicating the severity of accidents. Petrol-powered vehicles are involved in the highest number of accidents, with a total of 120,423 incidents. This includes 74,321 other injury accidents (44.87%), 44,322 serious injury accidents (26.76%), 1,778 fatal accidents (1.07%), and 2 non-injury accidents, indicating that petrol-powered vehicles are by far the most frequently involved in traffic accidents, with a substantial count across all severities. Multi-fuel vehicles have the highest ratio of serious injury accidents at 37.2%, indicating a notably increased risk for this fuel type in terms of severe outcomes. Diesel vehicles exhibit the highest proportion of fatal accidents at 2.34%, implying a greater chance of fatal outcomes in accidents involving diesel-powered vehicles. In contrast, gas-powered vehicles have the lowest overall accident count, with 1,826 incidents. This includes 1,216 other injury accidents (0.73%), 574 serious injury accidents (0.35%), and 36 fatal accidents (0.02%). While gas vehicles are involved in fewer accidents overall, they still present a higher fatality risk relative to other fuel types.



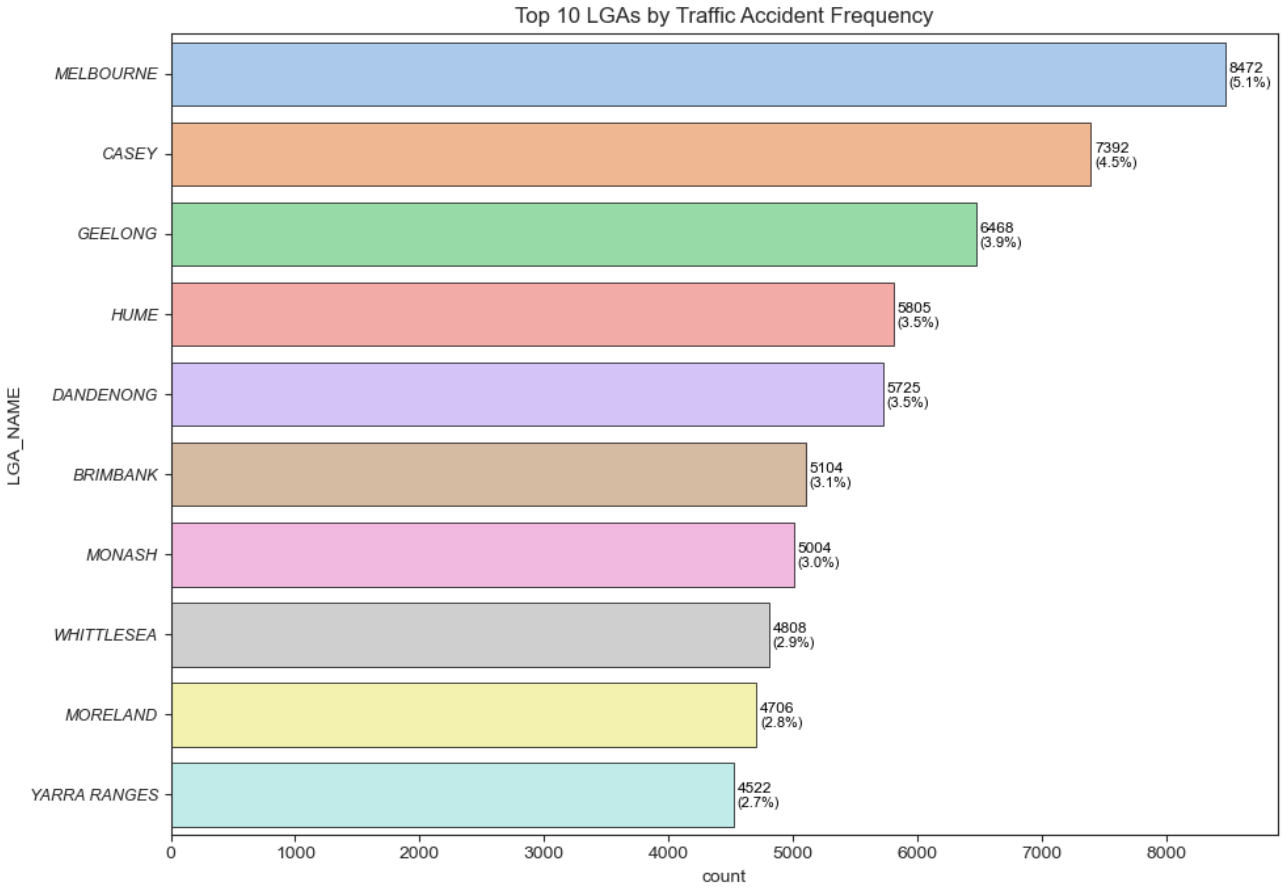
This count plot visualizes the distribution of accident severity based on whether the vehicle involved caught fire during the incident. The No category has the highest number of incidents, totaling 154,174 accidents. This constitutes of 95,240 other injury accidents (57.50%), 56,375 serious injury accidents (34.03%), 2,555 fatal accidents (1.54%), and 4 non-injury accidents. This suggests that the majority of accidents did not involve vehicles catching fire, yet they encompass a substantial portion across all severity types. When considering accident severity ratios, the Yes category, where vehicles catch fire, stands out with the highest ratios for both serious injury and fatal accidents. Specifically, this category exhibits a serious injury accident ratio of 51% and a fatal accident ratio of 19.8%, highlighting a significantly elevated risk of severe outcomes when a vehicle catches fire. The Yes category also has the lowest number of incidents, totaling only 663 accidents. This includes 196 other injury accidents (0.12%), 336 serious injury accidents (0.20%), and 131 fatal accidents (0.08%). Ultimately, while infrequent, accidents where vehicles caught fire display notable severity, particularly with respect to serious injury and fatal accidents, highlighting the severe impact of fire in traffic incidents.



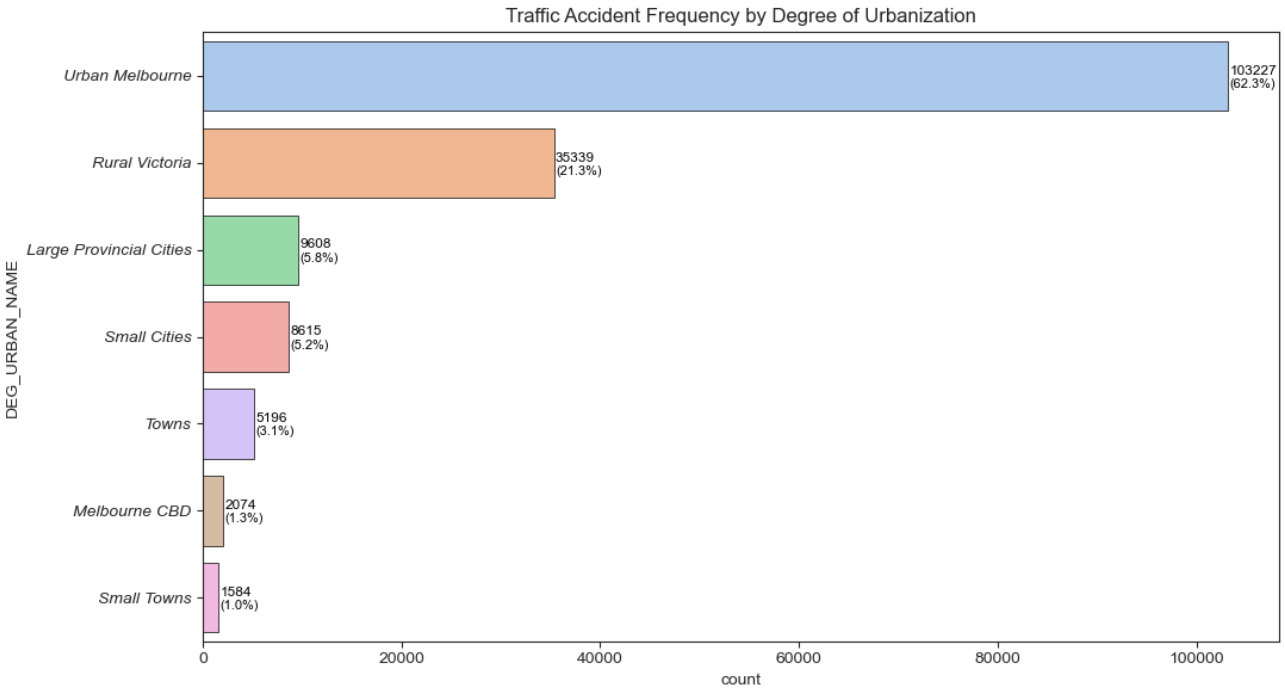
This count plot illustrates the distribution of accident severity by location type, as identified by the RCIS spatial system, with two main categories: Non-Intersection and Intersection. Non-Intersection locations have the highest number of accidents, totaling 94,893 incidents. This includes 56,744 other injury accidents (34.3%), 36,100 serious injury accidents (21.8%), 2,045 fatal accidents (1.2%), and 4 non-injury accidents; indicating that most accidents occur away from intersections, spanning all severities. Within these location types, Non-Intersection sites exhibit the highest ratios for both serious injury and fatal accidents, with a serious injury ratio of 38% and a fatal accident ratio of 2.15%. This indicates a significantly elevated risk of severe outcomes for accidents occurring at non-intersections. In comparison, Intersection locations have a lower overall count of accidents, with 70,731 incidents, including 46,094 other injury accidents (27.8%), 23,903 serious injury accidents (14.4%), 733 fatal accidents (0.4%), and 1 non-injury accident. This lower count may reflect a relatively safer outcome profile in terms of severe injuries and fatalities when accidents occur at intersections.



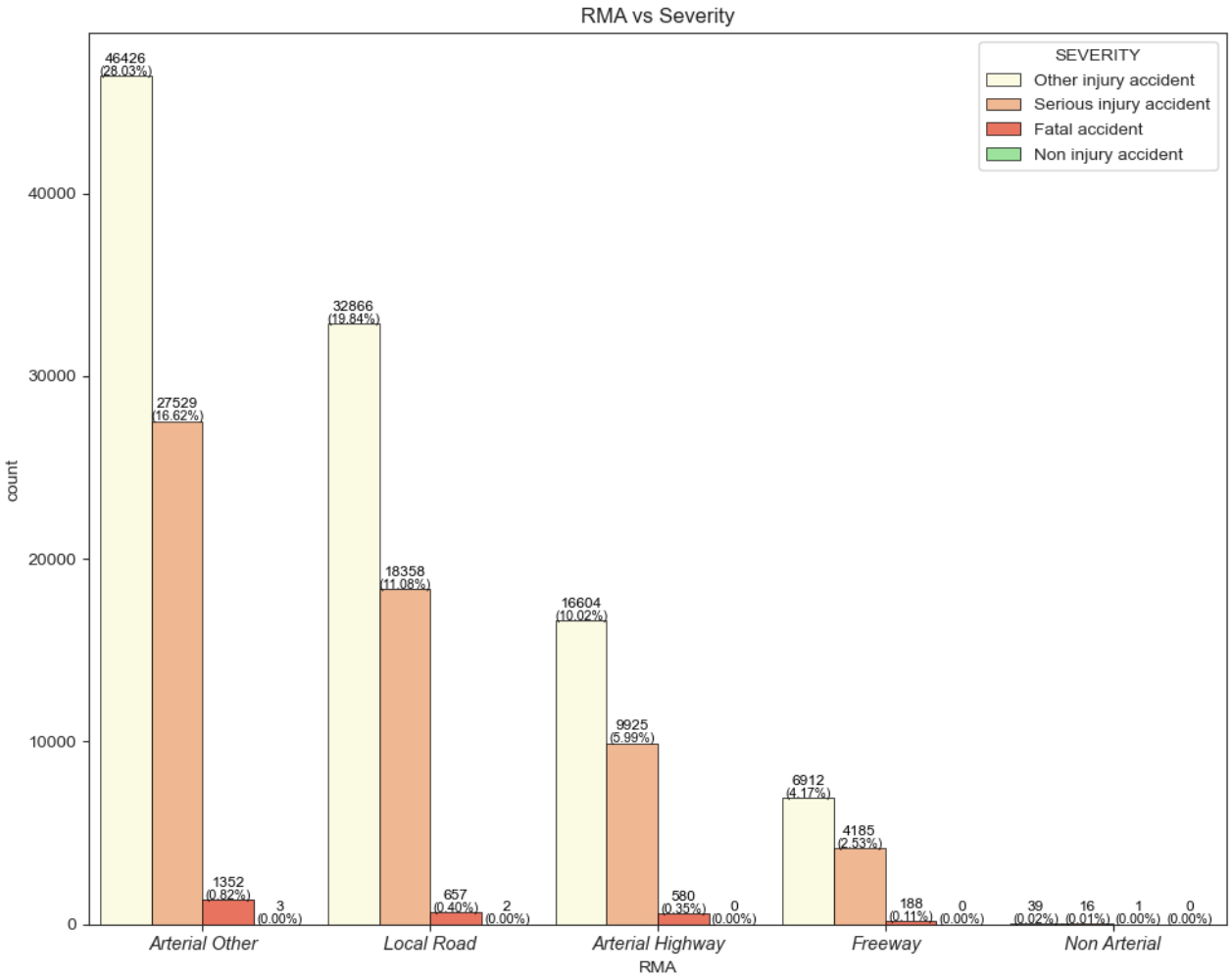
This count plot depicts the top 10 roads in Victoria most frequently involved in traffic accidents. The plot ranks these roads by their accident counts, with percentages indicating each road's share of total incidents in the dataset. The Princes Highway has the highest number of accidents, totaling 2,897 incidents, which accounts for 1.7% of all recorded accidents. Following it are High Street with 2,402 accidents (1.5%) and Nepean Highway with 1,689 accidents (1.0%), marking them as high-risk roads as well. Other notable roads include Monash Freeway with 1,425 accidents (0.9%) and South Gippsland Highway with 1,357 accidents (0.8%), indicating they also experience a considerable number of traffic incidents. Rounding out the list, Dandenong Road has 1,054 accidents (0.6%), and Western Ring Road has 992 accidents (0.6%). Although they are the lowest in rank among the top 10, these roads still represent significant accident hotspots. The data suggests that major highways and high-traffic roads are frequently associated with traffic incidents.



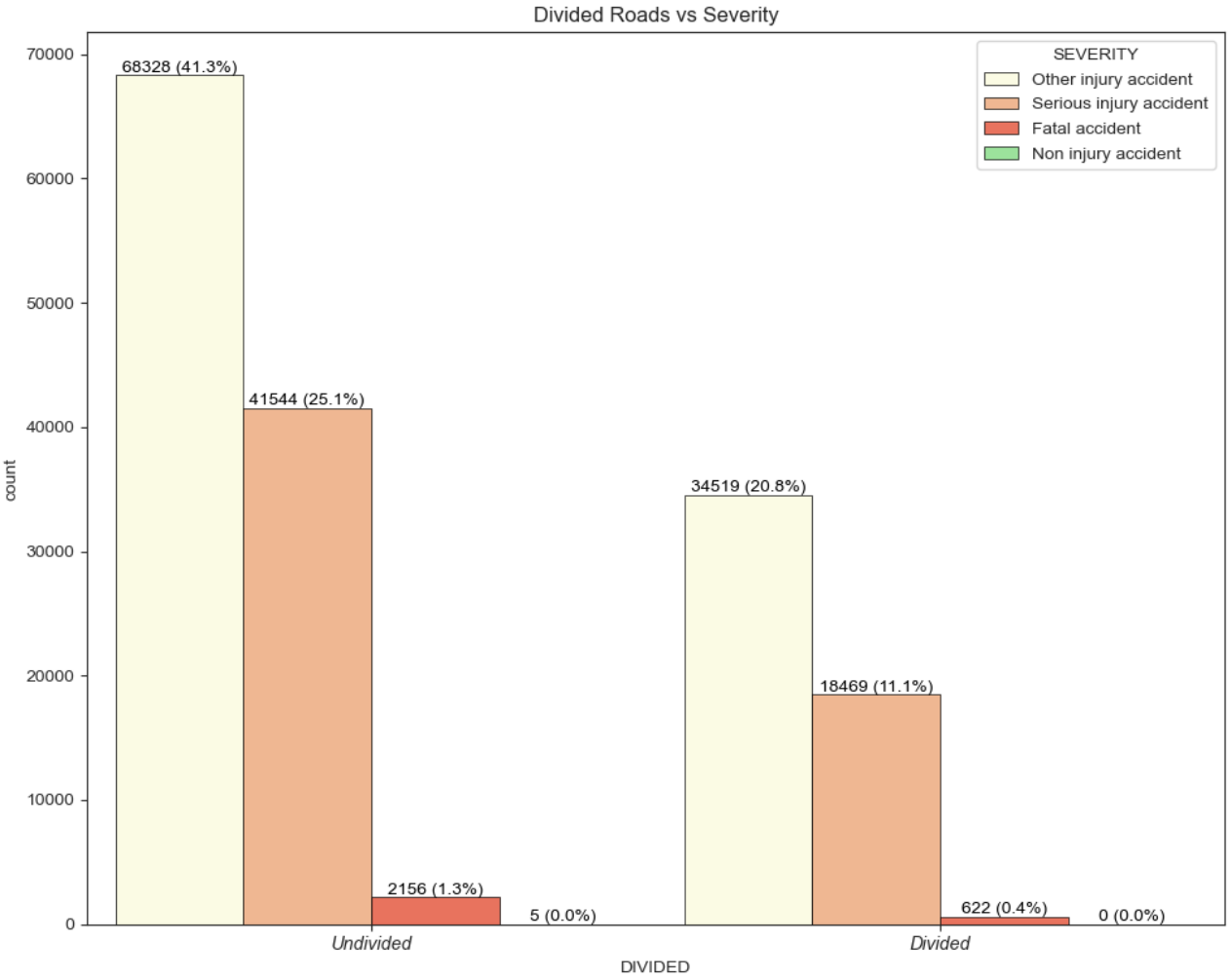
This count plot highlights the top 10 local government areas (LGAs) in Victoria with the highest frequency of traffic accidents. Each LGA is shown alongside the count and percentage of total accidents within the dataset. Melbourne leads with the highest number of traffic accidents, totalling 8,472 incidents, representing 5.1% of all recorded accidents. Casey follows with 7,392 accidents (4.5%), and Geelong ranks third with 6,468 accidents (3.9%). LGAs like Hume (3.5%), Dandenong (3.5%), and Brimbank (3.1%) also show substantial accident counts, highlighting these areas as other notable hotspots for traffic incidents. Yarra Ranges closes out the top 10 with 4,522 accidents, accounting for 2.7% of all recorded accidents, indicating that while still significant, it has a relatively lower count compared to Melbourne or Casey. This distribution underlines that certain metropolitan and suburban areas, such as Melbourne, Casey, and Geelong, experience a notably higher frequency of traffic accidents, likely due to factors like higher population density, traffic volume, and infrastructure layout.



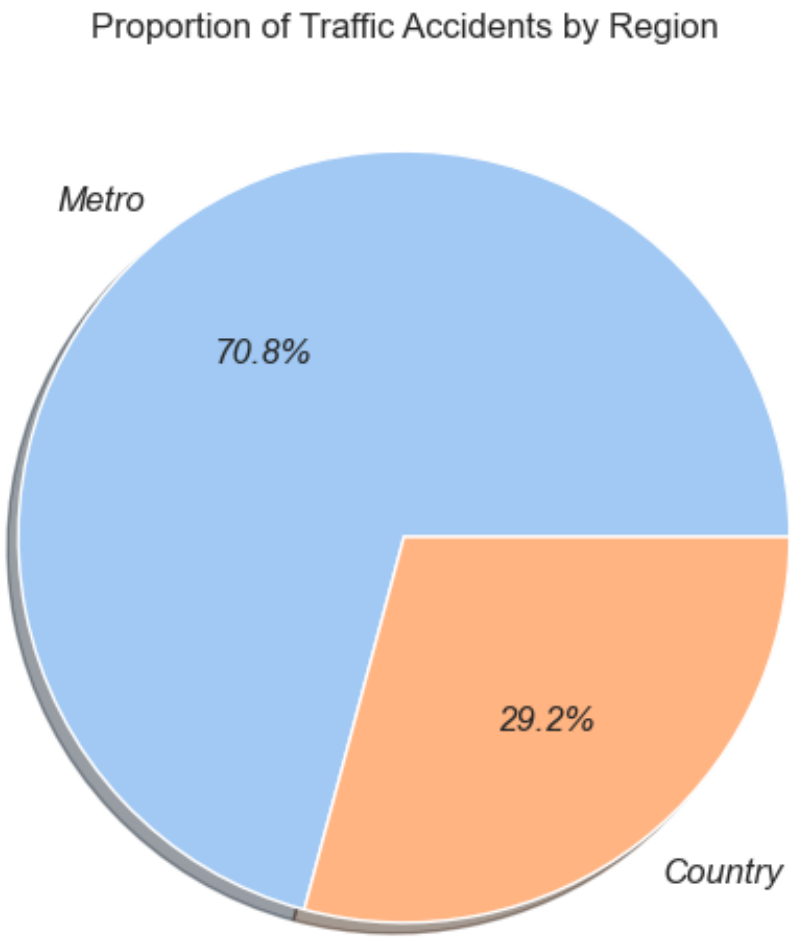
This count plot illustrates the distribution of traffic accident frequency across different degrees of urbanization in Victoria, categorized by urban areas, rural areas, and towns. Urban Melbourne is by far the highest in accident frequency, accounting for 103,227 incidents (62.3% of the total). This indicates a high concentration of accidents within highly urbanized areas, likely due to higher traffic volumes and increased road density. Rural Victoria follows as the second most frequent accident location, with 35,339 incidents (21.3%). Large Provincial Cities and Small Cities also show notable counts, with 9,608 (5.8%) and 8,615 (5.2%) incidents, respectively. These areas, while less densely populated than Urban Melbourne, still experience a substantial number of accidents. Melbourne CBD, Towns, and Small Towns report lower accident frequencies, with Small Towns having the fewest incidents at 1,584 (1.0%). These regions generally have lower traffic density, which may contribute to their lower accident frequency. This distribution provides insights into the varying impact of urbanization on traffic accident occurrences, highlighting that while urban areas see the highest accident frequency, rural and less densely populated regions are not immune to significant accident numbers.



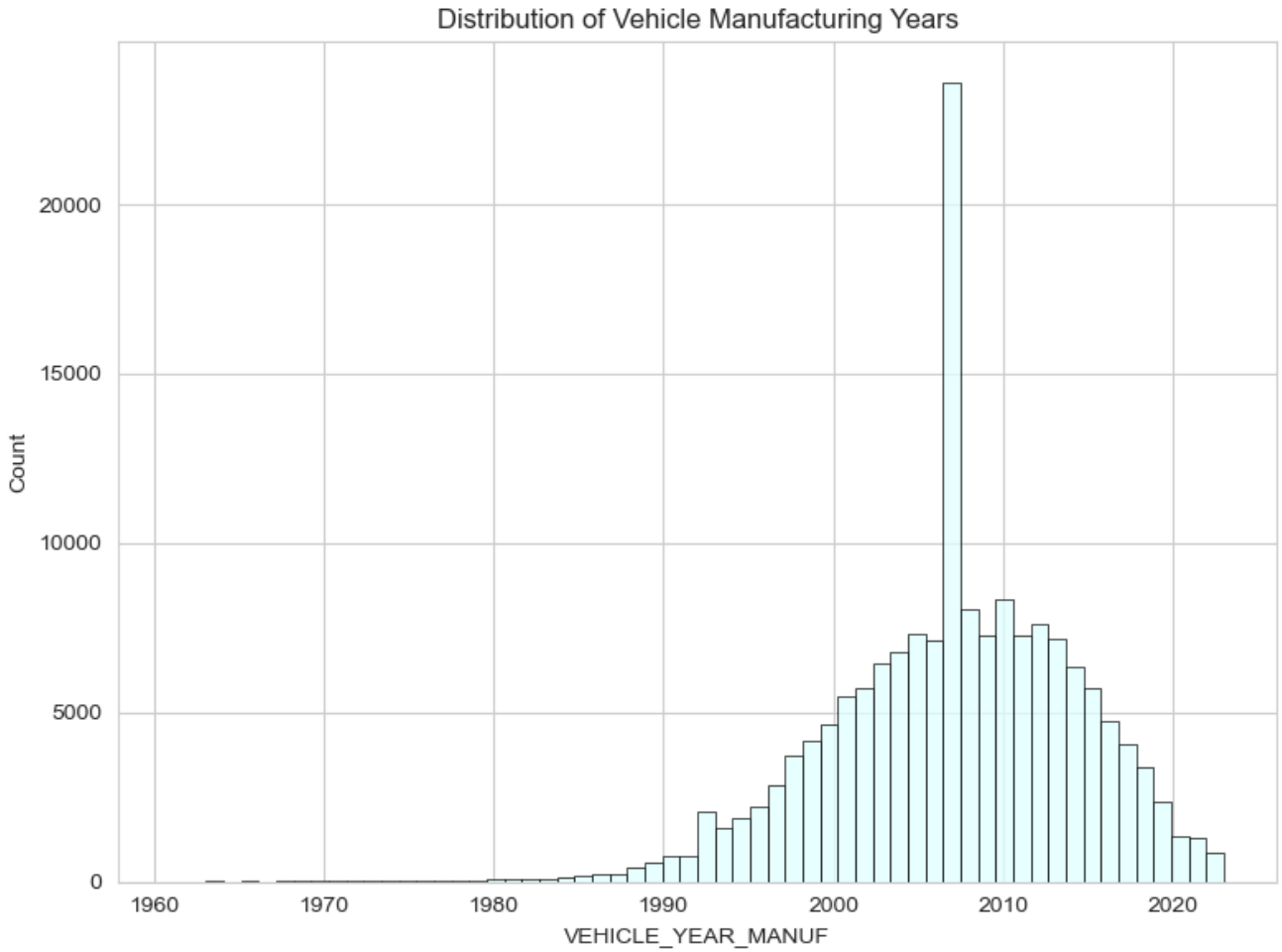
This count plot shows the distribution of accident severity across different road classifications (Road Management Act/RMA) as per VicRoads' classification system. Each RMA category reflects the type of road within the network: Arterial Other roads have the highest number of accidents, with a total of 75,310 incidents. This includes 46,426 other injury accidents (28.03%), 27,529 serious injury accidents (16.62%), 1,352 fatal accidents (0.82%), and 3 non-injury accidents. This significant volume of accidents indicate that arterial roads are the major contributor to overall accidents. In terms of severity ratios, Freeways show the highest ratio of serious injury accidents, with a serious injury rate of 37%. This suggests that accidents on Freeways tend to result in serious injuries more often, compared to other road types. In contrast, Arterial Highways exhibit the highest fatal accident ratio at 2.14%, indicating a relatively elevated risk of fatal outcomes in accidents occurring on these highways. Conversely, Non-Arterial roads have the lowest accident count, with only 56 incidents. This includes 39 other injury accidents, 16 serious injury accidents, and 1 fatal accident. This low count might be due to lesser usage or lower traffic volumes on these roads.



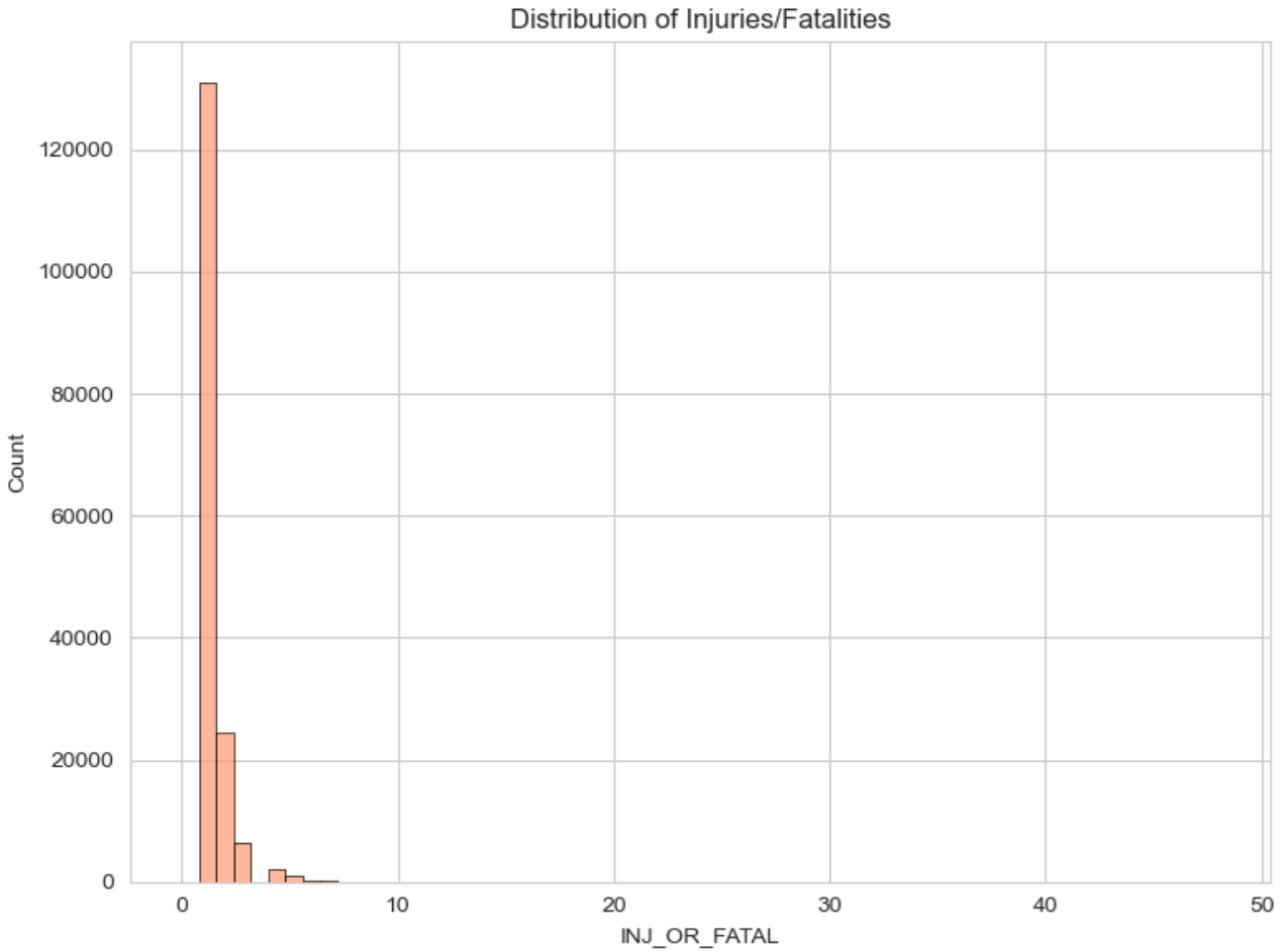
This count plot shows the distribution of accident severity based on whether the road is divided or undivided. Undivided roads have the highest number of incidents, with a total of 112,033 accidents. This includes 68,328 other injury accidents (41.3%), 41,544 serious injury accidents (25.1%), 2,156 fatal accidents (1.3%), and 5 non-injury accidents. The substantial accident frequency on undivided roads suggests that these roads may be more susceptible to accidents, potentially due to the lack of a median barrier separating opposing traffic flows. In comparison, Divided roads have a lower total number of incidents, with 53,610 accidents. This includes 34,519 other injury accidents (20.8%), 18,469 serious injury accidents (11.1%), and 622 fatal accidents (0.4%). While divided roads show a reduced frequency of accidents compared to undivided roads, they still account for a notable number of incidents across all severity levels. However, when analyzing severity ratios, undivided roads present a heightened risk profile, with serious injury accidents accounting for 37% and fatal accidents making up 1.9%. This elevated ratio underscores the increased danger on roads lacking a physical divider, where the absence of a median may contribute to more severe outcomes – emphasizing the safety concerns associated with undivided road types.



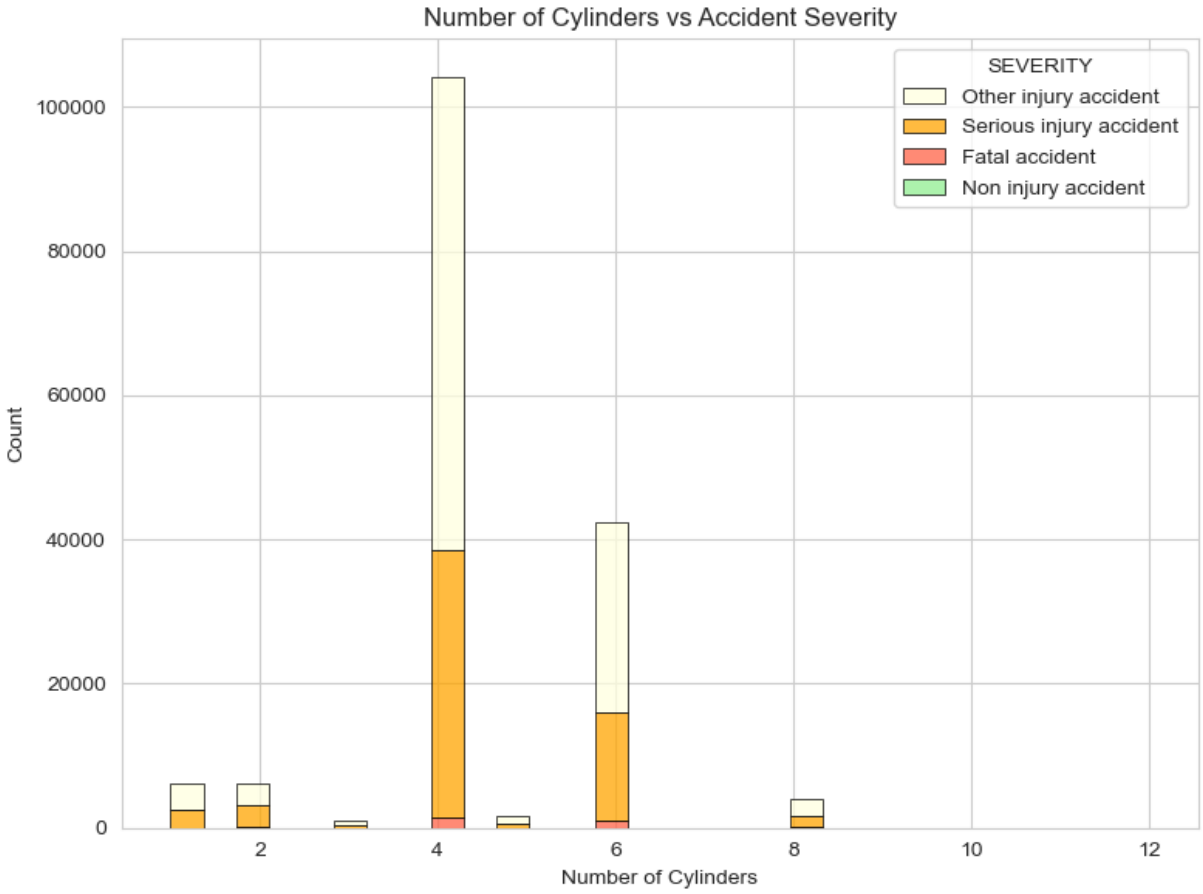
This pie chart illustrates the distribution of traffic accidents in Victoria by region, comparing metropolitan (Metro) and country areas. The Metro region accounts for the majority of traffic accidents, making up 70.8% of the total, while the Country region represents the remaining 29.2%. This distribution highlights the vast majority of accidents occur in metropolitan areas compared to country regions, which may reflect differences in traffic volume or population density between these areas.



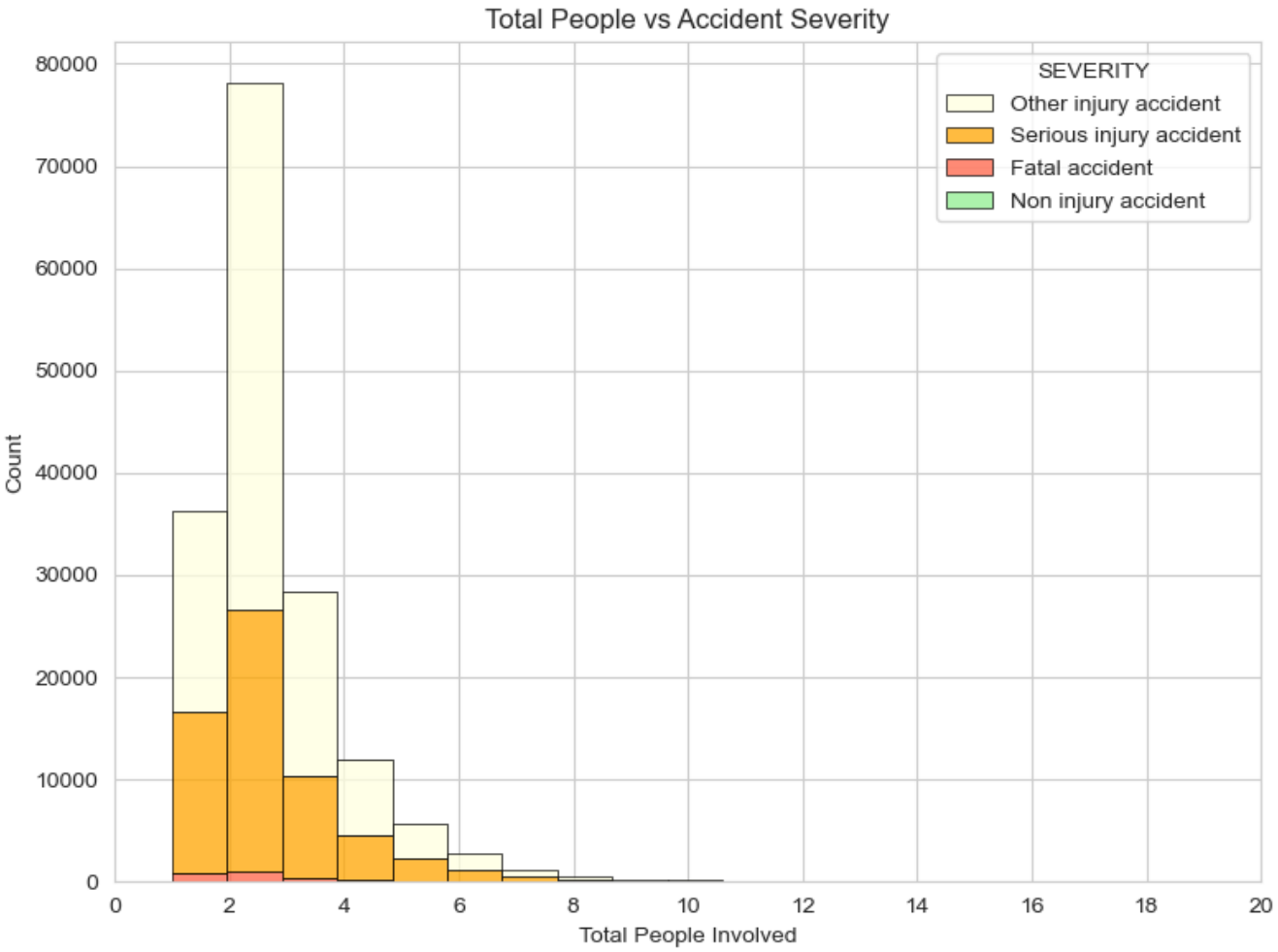
This histogram depicts the distribution of vehicle manufacturing years for vehicles involved in accidents, spanning from 1961-2023. The data reveals a concentration of vehicles manufactured between the mid-1990s and the early 2010s, with a pronounced peak around 2007-2008. Approximately 23,000 vehicles from this manufacturing year were involved in accidents, indicating that vehicles from this period are most frequently involved in accidents (mode). There is a noticeable decline in accidents involving vehicles manufactured before the 1990s, as well as for more recent vehicles produced after 2015. In contrast, the minor contingent; vehicles manufactured before the 1980s (valid lower outliers) may be due to the reduced presence of very old vehicles in traffic. Older vehicles, potentially considered antiques, are less likely to be driven regularly, leading to fewer accident records. Overall, this pattern suggests that the vast majority of vehicles involved in accidents on the road during the timeframe analyzed were manufactured around 2007-2008, potentially reflecting vehicle age demographics or ownership trends in the region.



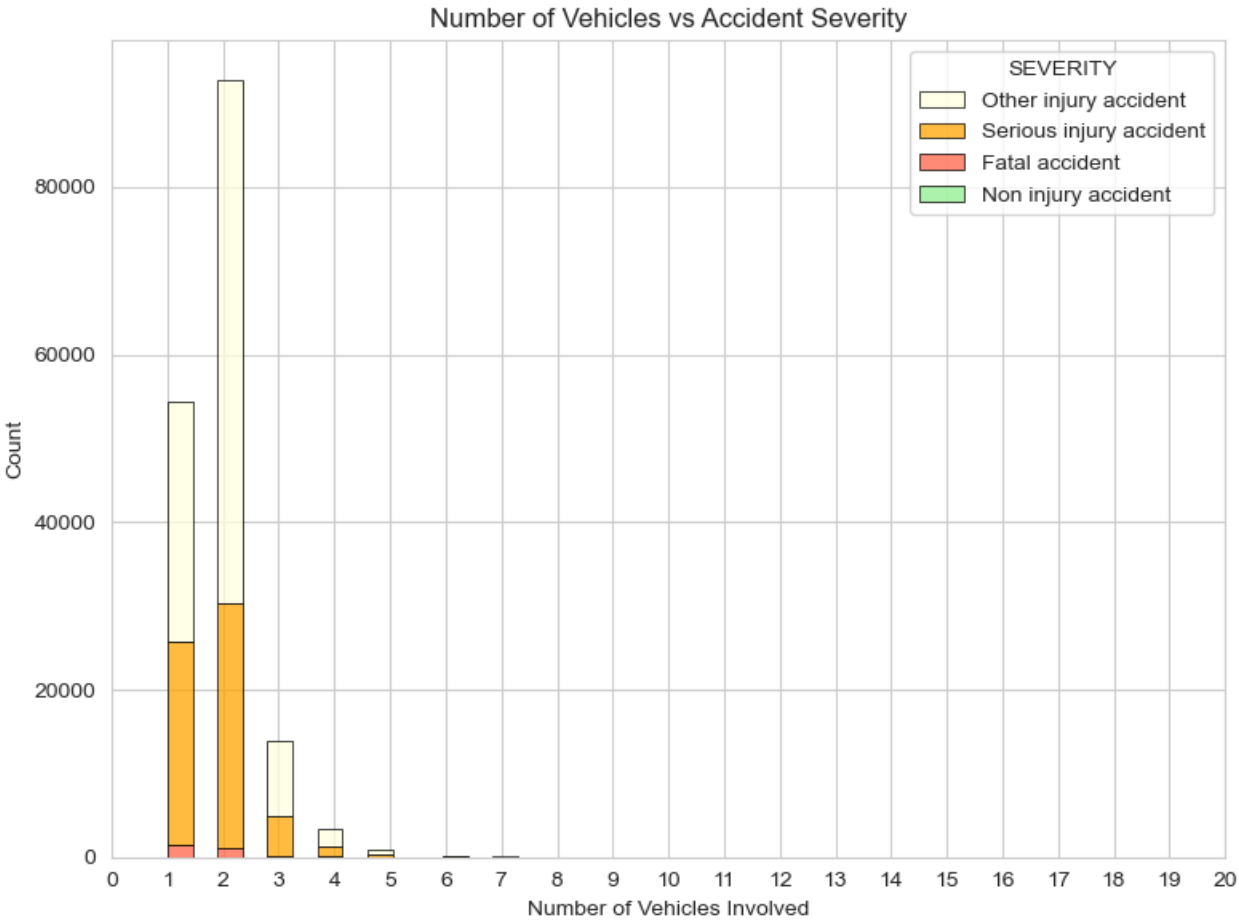
This histogram illustrates the distribution of injury or fatality counts across traffic accidents in Victoria, scaling from 0-48 injuries/fatalities. The majority of incidents involve one or two injuries or fatalities, with a sharp decline in frequency as the count increases. The distribution is heavily skewed toward lower counts, emphasizing that most accidents result in a small number of injuries or fatalities. The mode, or most frequently observed count, is approximately 1 injury/fatality per accident (in approximately 130,000 incidents). This distribution indicates that severe accidents involving multiple injuries or fatalities are rare, while single fatalities or injury incidents are far more common in the dataset.



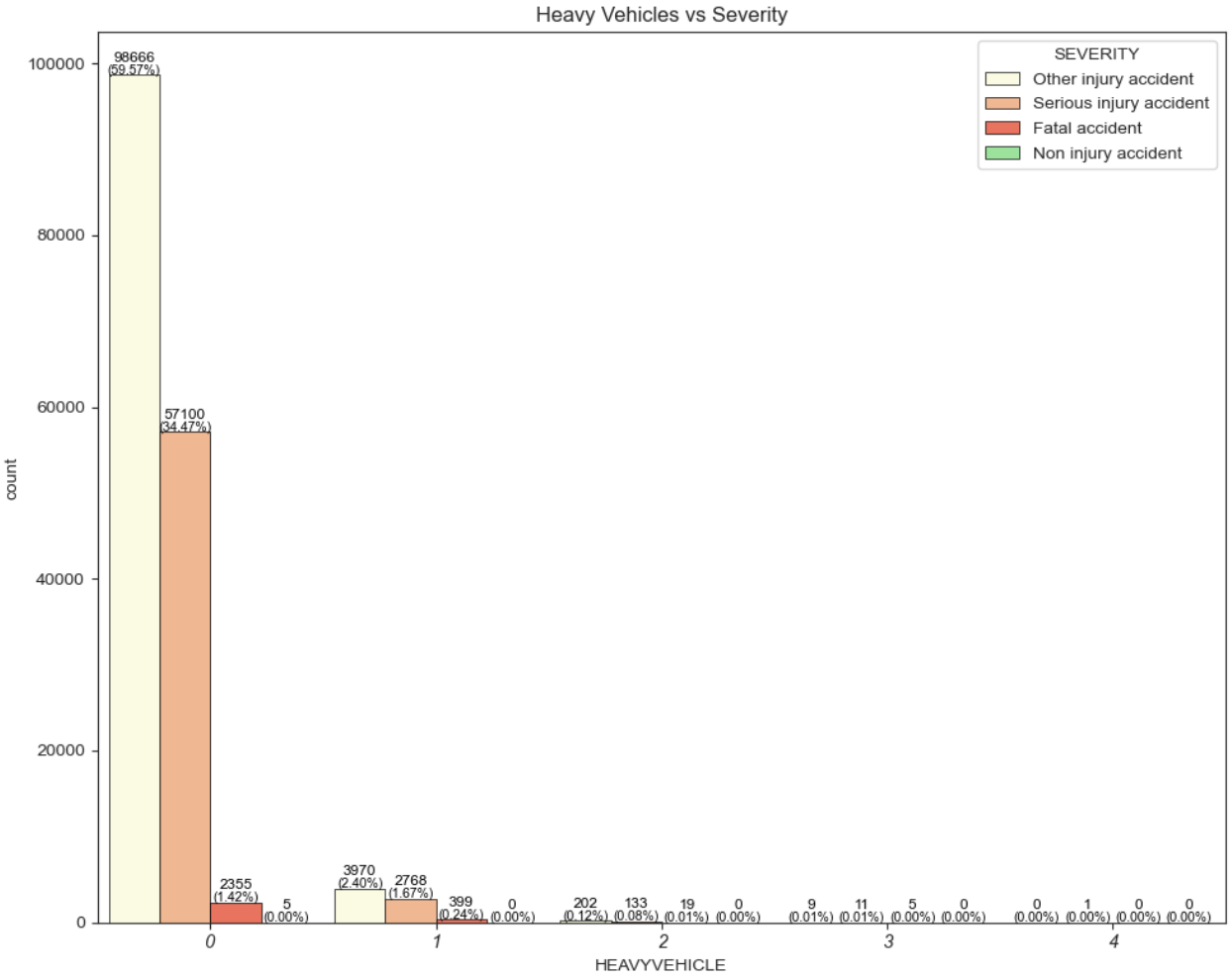
This histogram displays the distribution of accident severity across different numbers of vehicle cylinders, ranging from 1-12 cylinders. The data reveals a substantial concentration of accidents involving vehicles with 4 and 6 cylinders. Vehicles with 4 cylinders have the highest accident count (mode), reaching over 100,000 incidents, with other injury accidents being the most prevalent severity type within this group, followed by serious injury accidents and a small proportion of fatal accidents. Vehicles with 6 cylinders also show a significant number of accidents, though lower than those with 4 cylinders. Vehicles with less common cylinder counts (such as 8, 10, and 12 cylinders) show minimal representation, reflecting fewer accidents involving these vehicles. This pattern suggests that vehicles with 4 and 6 cylinders are more frequently involved in accidents, likely due to their prevalence on the road. Additionally, other injury accidents dominate the severity distribution across all cylinder categories, with serious injury accidents occurring at a lower rate, and fatal accidents being relatively rare in each category. Ultimately, vehicles with 4 cylinders have the highest overall count for both serious injury accidents and fatal accidents. This category shows a greater number of these severe outcomes compared to other cylinder counts, reflecting both a higher absolute count and a higher ratio of serious outcomes within this group.



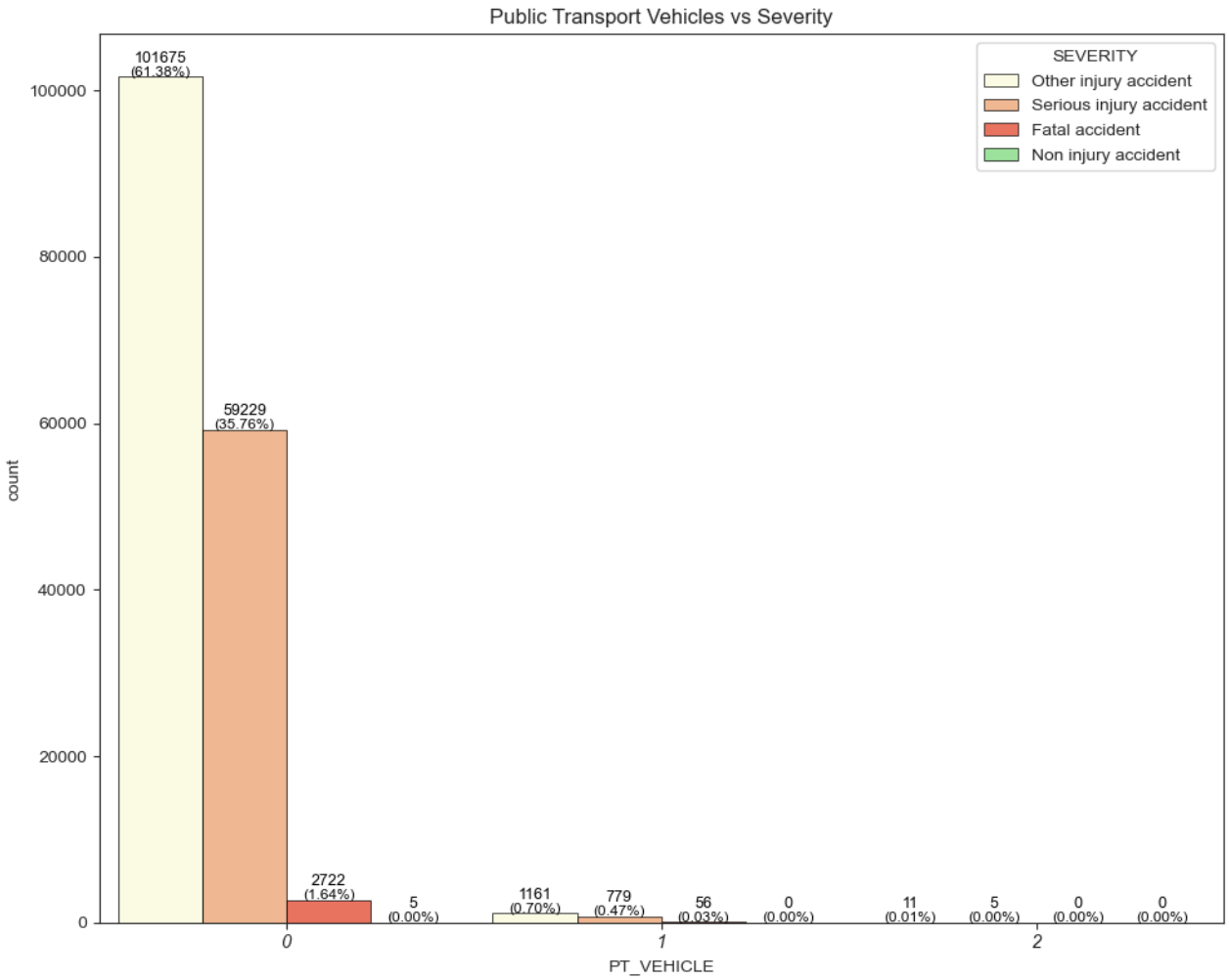
This histogram illustrates the distribution of the total number of people involved in accidents, categorized by accident severity. The original range spans from 1-97 total people, however due to clarity reasons I limited the range to 1-20 – from 8 onwards these values are minimal/negligible (valid outliers). The data is heavily skewed towards lower counts, with most accidents involving a small number of people. Specifically, incidents with 2 people involved make up the majority of cases (mode), with approximately 78,000 incidents. Other injury accidents are the most common severity type within this group, followed by serious injury accidents and a smaller proportion of fatal accidents. As the number of people involved increases beyond 2-3, the frequency of accidents sharply decreases. The dominance of other injury accidents persists across all groups, with serious injury accidents following at a lower frequency. Fatal accidents are rare across the distribution but are present in greater numbers for incidents involving 1-3 people than for higher group sizes. This pattern reflects that multi-person accidents are relatively rare, and accidents involving higher numbers of individuals are even less frequent. The data suggests that accidents with only a few people involved are much more common, while those with higher numbers of people are infrequent.



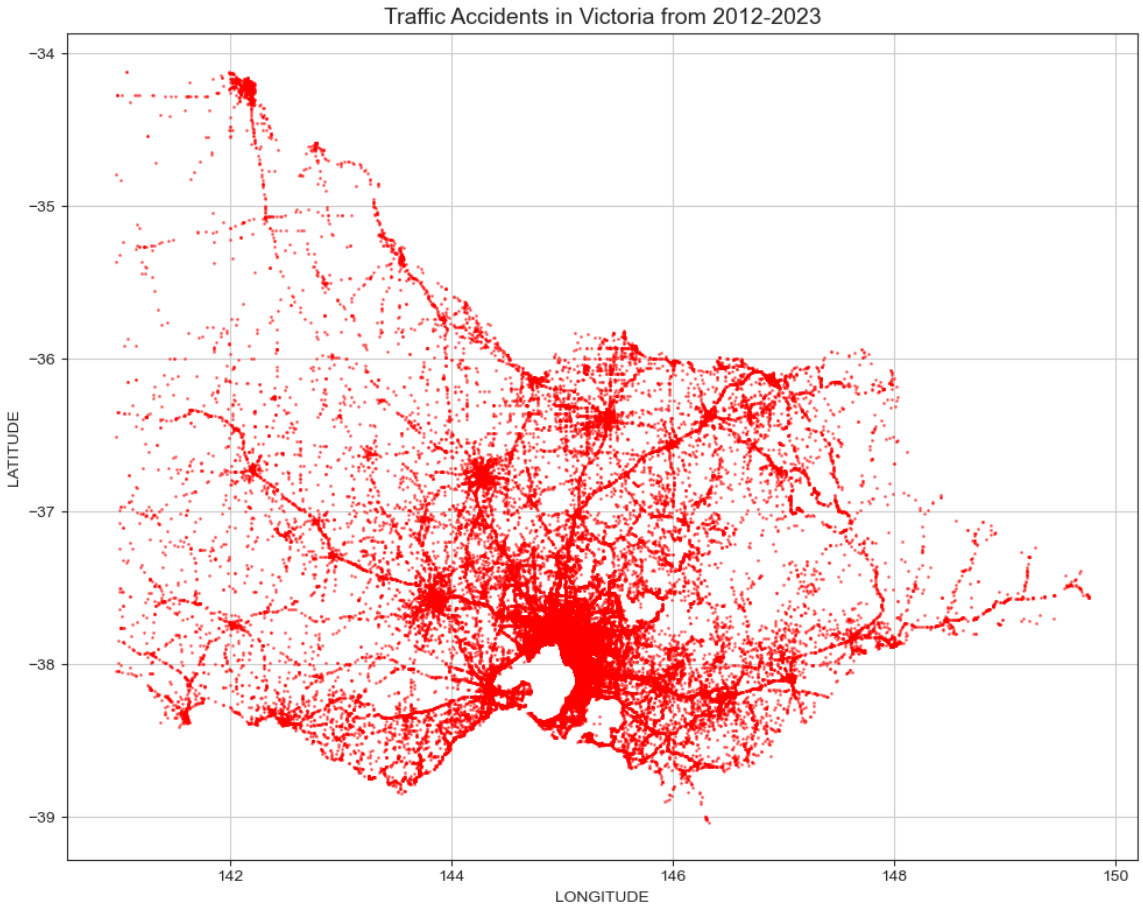
This histogram highlights the distribution of accidents based on the number of vehicles involved, broken down by accident severity, ranging from 1-20. The data is heavily skewed toward accidents involving one or two vehicles. Accidents with two vehicles account for the largest proportion, followed closely by single-vehicle incidents. Two-vehicle accidents, the most frequent, represent the mode with approximately 93,000 occurrences. In both single and two vehicle accidents, other injury accidents are the most common severity type, followed by serious injury accidents and a smaller proportion of fatal accidents. As the number of vehicles involved increases beyond two, the frequency of accidents drops sharply. Accidents involving three or more vehicles are relatively uncommon, with incidents involving five or more vehicles being particularly rare. Despite the overall decline in frequency, accidents involving three vehicles show a relatively marginally higher proportion of serious injury accidents compared to those involving one or two vehicles, suggesting a slightly elevated risk of serious injuries in multi-vehicle accidents. Overall, the majority of accidents involve a small number of vehicles, with single and two-vehicle accidents comprising the vast majority of recorded incidents. Serious injury accidents occur less frequently than other injury accidents but still represent a significant portion of the total. Fatal accidents, on the other hand, remain rare throughout the distribution, with single-vehicle accidents accounting for the highest number of fatalities.



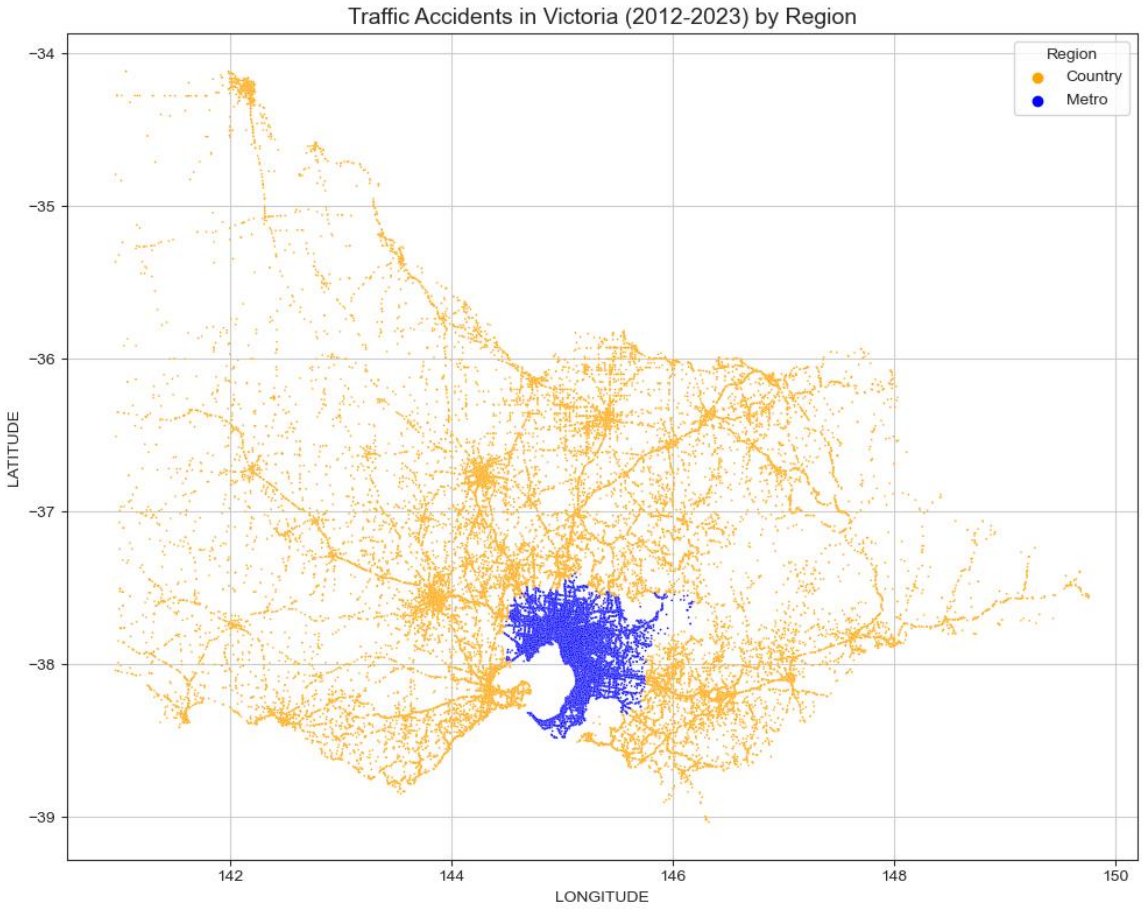
This count plot shows the distribution of accident severity based on the number of heavy vehicles involved in accidents across Victoria. Accidents without any heavy vehicles involved account for a total of 158,126 incidents. This constitutes of other injury accidents at 98,666 accidents (59.57%), followed by serious injury at 57,100 accidents (34.47%), 2,355 fatal accidents (1.42%), and 5 non-injury accidents. This indicates that the vast majority of accidents occur without the involvement of heavy vehicles. In comparison, accidents involving a single heavy vehicle total 7,137 incidents. This includes 3,970 other injury accidents (2.40%), 2,768 serious injury accidents (11.1%), and 399 fatal accidents (0.24%). While accidents involving heavy vehicles are significantly fewer in number, they present a higher relative risk of resulting in serious or fatal injuries. When examining severity ratios, accidents involving one heavy vehicle have a serious injury rate of 38.8% and a fatal accident rate of 5.59%. This is notably higher compared to accidents with no heavy vehicles, where the serious injury rate is 36.1% and the fatal accident rate is 1.48%. This comparison highlights that the presence of even a single heavy vehicle significantly increases the likelihood of serious injuries and fatalities. Overall, the involvement of heavy vehicles correlates with more severe outcomes, even though such accidents are less frequent.



The count plot depicts the distribution of accident severity based on the involvement of public transport vehicles in accidents across Victoria. Accidents involving no public transport vehicles account for the overwhelming majority of accidents, with 163,631 total incidents. Of these, 101,675 accidents (61.38%) are other injury accidents, followed by 59,229 serious injury accidents (35.76%), 2,722 fatal accidents (1.64%), and 5 non-injury accidents – suggesting that most accidents do not involve public transport vehicles. In contrast, accidents involving one public transport vehicle total 1,996 incidents, constituting of 1,161 other injury accidents (0.70%), 779 serious injury accidents (0.47%), and 56 fatal accidents (0.03%). Accidents involving two public transport vehicles are exceedingly rare, with only 16 incidents recorded. These include 11 other injury accidents and 5 serious injury accidents. In terms of severity ratios, accidents involving one public transport vehicle have a serious injury rate of 39.02% and a fatal accident rate of 2.8%. This is slightly higher compared to accidents with no public transport vehicles, where the serious injury rate is 36.2% and the fatal accident rate is 1.6%. This comparison highlights that the involvement of even a single public transport vehicle increases the likelihood of serious injuries and fatalities.



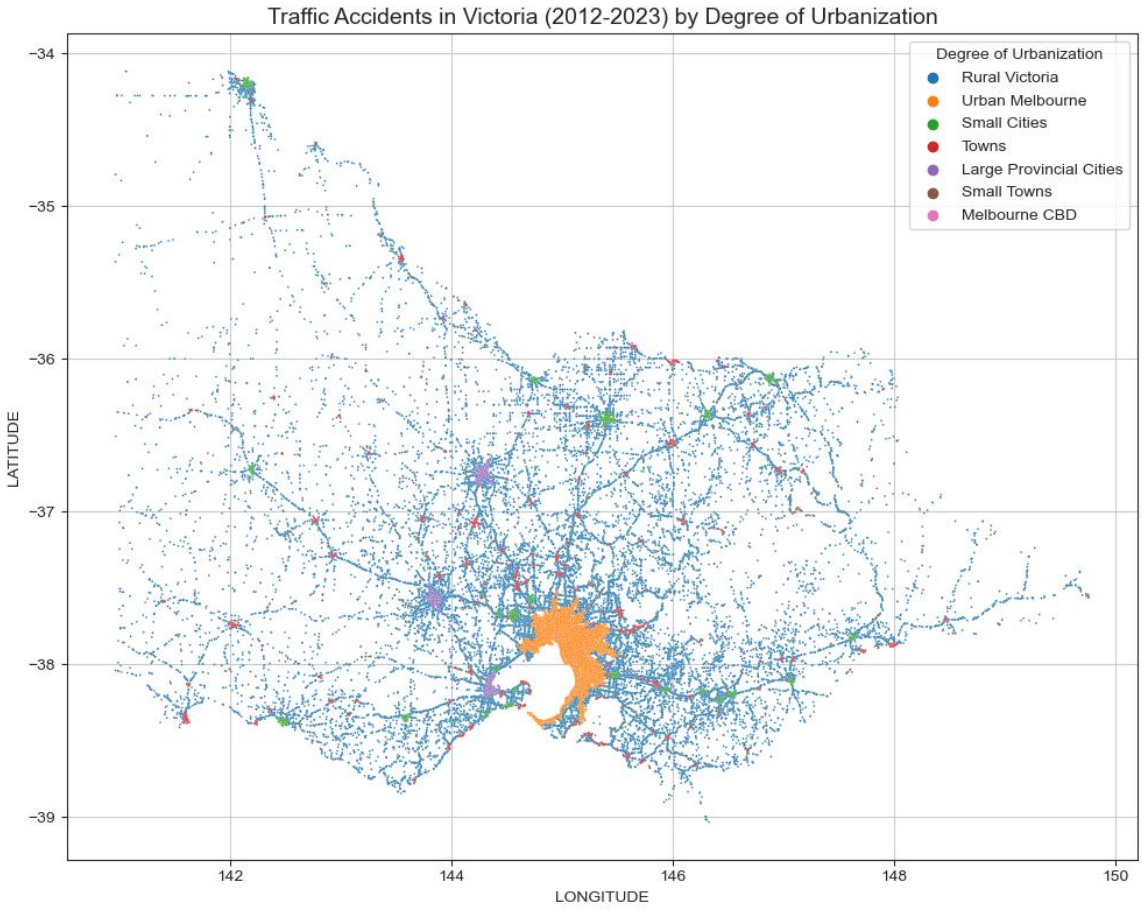
This geospatial plot visualizes the distribution of traffic accidents across Victoria from 2012-2023, using latitude and longitude coordinates to mark each accident's location. The plot clearly highlights the high concentration of accidents around major urban areas, particularly Melbourne, which is visible as a dense cluster in the southeastern part of the map. The spread of accidents across regional roads and highways is also evident, with notable clusters along the state's major transport routes. The red dots represent individual accidents, and the density of these points provides a visual representation of accident hotspots across the region. Rural and less densely populated areas display significantly fewer accidents, while arterial roads connecting different regions show a higher frequency of incidents. This map provides valuable insights into the geographical distribution of traffic accidents, helping to identify areas that may require more focused traffic management or safety interventions.



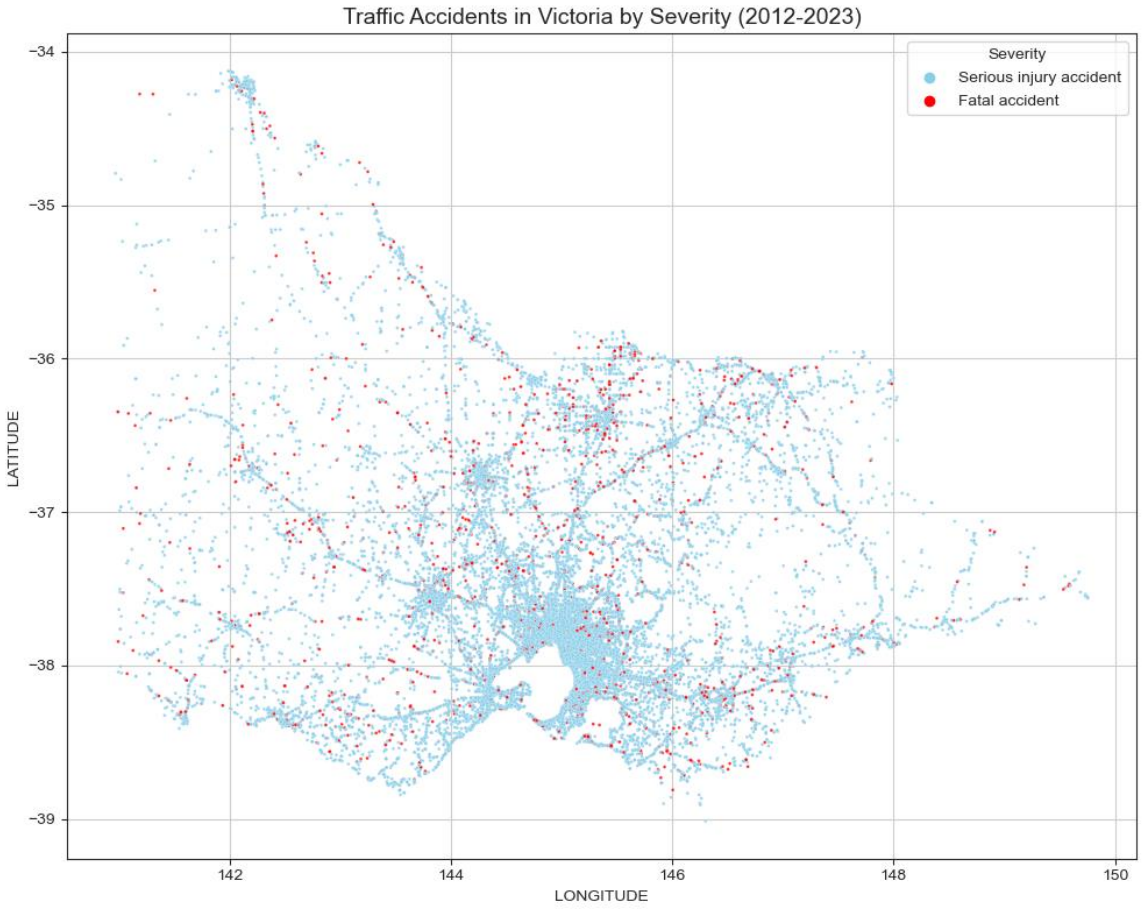
This scatter plot shows the geospatial distribution of traffic accidents in Victoria between 2012 and 2023, categorized by region. The regions are represented by two distinct colors: blue for accidents occurring in the Metropolitan (Metro) area and orange for accidents occurring in the Country (rural) areas.

- The Metropolitan region, concentrated around Melbourne and its surroundings, has a dense cluster of accidents, indicating the higher traffic density and urban nature of this area.
- The Country region shows a more dispersed distribution of accidents across the rural parts of Victoria, with notable concentrations along major highways and regional centres.

The plot effectively illustrates the significant geographical divide in accident frequency and distribution between Metro and Country regions, with Metro areas displaying a denser clustering of accidents. It highlights the importance of region-specific safety measures in traffic accident prevention, considering the different patterns observed in urban and rural settings.



This scatterplot displays the geospatial distribution of traffic accidents across Victoria from 2012 to 2023, categorized by the degree of urbanization. The data points are represented by their geographical coordinates (longitude and latitude), with different colors indicating the type of region where each accident occurred. The regions are classified as Rural Victoria (blue), covering expansive areas outside major urban centers and representing the majority of the state's landmass; Urban Melbourne (orange), marking the densely populated metropolitan area, with a notable cluster of accidents particularly around the city center; Small Cities (green), indicating smaller urban centers dispersed across the state; Towns (red), representing smaller population centers within Victoria; Large Provincial Cities (purple), such as Geelong and Ballarat, which are key regional hubs with larger populations; Small Towns (brown), showing smaller rural communities across the state; and Melbourne CBD (pink), which highlights the central business district, where a relatively tiny number of accidents occur, reflected by minimal pink markers. Ultimately, the plot shows a high concentration of accidents in Melbourne and its surrounding urban areas, with more sparsely distributed accidents in rural regions. It highlights the contrast between urban and rural accident patterns, with dense clusters in metropolitan areas and more dispersed accidents in rural Victoria. This visualization provides insight into how accident frequency and location vary by degree of urbanization.



This scatter plot illustrates the geographic distribution of traffic accidents in Victoria from 2012 to 2023, classified by severity – specifically serious injury and fatal accidents. The data points are plotted based on their geographical coordinates (longitude and latitude), with each severity type represented by a different color.

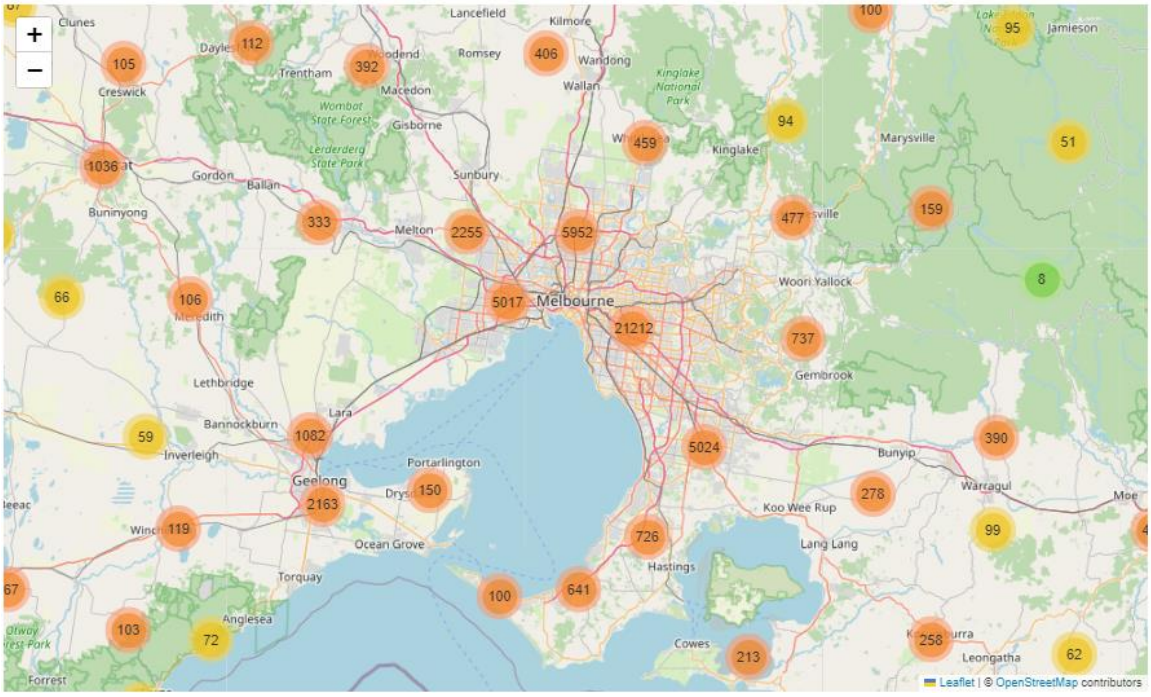
- **Serious Injury Accident** (blue): These accidents are widely distributed across both rural and urban areas, with denser clusters in and around metropolitan Melbourne. Noticeable concentrations appear along major roadways and densely populated regions.
- **Fatal Accident** (red): Fatal accidents, although less frequent, are spread throughout the state, with clusters visible in both urban and rural areas. Some areas show a higher density of fatal accidents, particularly along major highways.

Overall, serious injury and fatal accidents are not limited to specific areas but are dispersed across regions. Highlighting key accident locations and indicating a widespread road safety issue. These key areas may require targeted interventions to improve road safety. The focus on these two severity types helps identify accident hotspots that pose the most significant risks to public health and safety.

- This interactive map visually represents the distribution of traffic accidents across Victoria from 2012 to 2023. The accidents are plotted using their latitude and longitude coordinates from the dataset, with a clustering technique applied to manage dense areas of accidents. Each orange cluster shows the total number of accidents in a specific region, breaking down into smaller clusters and individual red markers as users zoom in, representing single accident events.

- The map is a useful tool for identifying accident "hotspots," especially in high-traffic areas such as Melbourne and its suburbs. It highlights regions with high accident densities, which may be due to factors like traffic volume, road infrastructure, or hazardous conditions. It also reveals clusters along rural highways, indicating potential risks in less urbanized areas, likely related to road conditions, speed limits, or the availability of safety measures.

- The interactive features of the map, such as dynamic clustering and zooming, allow for detailed exploration of accident distribution across the state. This makes it a valuable tool for visualizing patterns in accident occurrence, enabling users to focus on areas with higher accident frequencies and investigate potential contributing factors.



- This interactive map visualizes the distribution of serious injury and fatal traffic accidents across Victoria from 2012 to 2023. Using latitude and longitude coordinates from the dataset for each accident, the data is filtered to display only serious injury and fatal accidents. A clustering technique is applied to group accident markers, which dynamically break into individual markers as users zoom in. The markers are color-coded: red for fatal accidents and blue for serious injury accidents, allowing users to quickly differentiate between the two severity levels.

- This map is especially useful for highlighting high-risk areas in terms of accident severity. Major clusters around Melbourne and its suburbs indicate regions where serious and fatal accidents are most prevalent, likely due to high traffic volumes and the complexity of urban infrastructure. Additionally, clusters in rural areas and highways point to potential danger zones where road conditions, higher speed limits, and limited safety measures may contribute to the severity of accidents.

- The map enables an in-depth exploration of important accident severity patterns. By zooming in, users can analyze specific roads or intersections prone to severe accidents, which can inform future safety interventions or traffic policy adjustments. This visualization serves as a crucial tool for identifying high-priority areas for road safety improvements, focusing specifically on accidents that result in the most severe public health outcomes.

Exploratory Data Analysis Insights Summary

165,643 Traffic Accidents in Victoria (2012-2023):

Severity:

- 60,013 people suffered from serious injury accidents.
- 2,778 individuals passed away as a result of fatal accidents.

Accident Types:

- The majority of accidents are collisions with vehicles, accounting for 106,981 incidents (64.58% of total accidents).
- Collision with a fixed object shows the highest ratio of serious injuries (48%) and fatalities (3.83%).

DCA Codes:

- Rear End (vehicles in the same lane) is the most frequent type of accident with 29,568 incidents.
- Left off carriageway into object/parked vehicle has the highest serious injury (47.65%) and fatal accident ratios (3.04%).

Event Types:

- Collision is the most common event type, with 124,259 incidents.
- Ran off carriageway events result in the highest serious injury (47.60%) and fatal accident ratios (3.64%).

Atmospheric Conditions:

- Most accidents occur under clear conditions, with 128,824 incidents.
- Fog has the highest ratio of serious injuries (41.09%) and fatalities (3.36%).

Road Surface Conditions:

- Dry road surfaces account for 128,210 accidents.
- Icy surfaces have the highest fatal accident ratio (2.35%), while dry surfaces have the highest serious injury ratio (37.83%).

Road Surface Types:

- Most accidents occur on paved roads (151,631 incidents).

- Unpaved roads show the highest ratio of serious injury accidents (38.80%), while paved roads have the highest fatal accident ratio (1.73%).

Light Conditions:

- Most accidents occur in daylight, with 109,989 incidents.
- Dark conditions with no streetlights has the highest serious injury (46.29%) and fatal accident ratios (5.29%).

Traffic Control Types:

- Accidents most frequently occur where there is no traffic control, with 103,485 incidents.
- No traffic control also has the highest serious injury (38.84%) and fatal accident ratios (2.19%).

Police Attendance:

- 123,219 accidents had police attendance.
- Accidents with police attendance show the highest serious injury (43.23%) and fatal accident ratios (2.24%).

Road Geometries:

- Most accidents occur away from intersections (85,135 incidents).
- Accidents at non-intersections show the highest serious injury (38.52%) and fatal accident ratios (2.28%).

Speed Zones:

- The 60 km/h speed zone records the highest number of accidents, with 54,921 incidents.
- The 100 km/h zone has the highest ratio of serious injuries (45.80%) and fatalities (4.83%).

Alcohol Involvement:

- Most accidents (163,190 incidents) had no alcohol involvement.
- Accidents involving alcohol have a significantly higher ratio of serious injuries (59.3%) and fatalities (5.3%).

Hit-and-Run Involvement:

- Non-hit-and-run accidents account for 161,556 incidents.
- Non-hit-and-run accidents have higher serious injury (35.5%) and fatal accident ratios (1.65%).

Run Off Road:

- 135,936 incidents involved vehicles staying on the road.
- Accidents where vehicles ran off the road show higher serious injury (47.3%) and fatal accident ratios (3.5%).

Licensing Status:

- Licensed drivers were involved in 163,204 accidents.
- Accidents involving unlicensed drivers have higher serious injury (43.5%) and fatal accident ratios (3.2%).

Collision Points:

- The front of the vehicle is the most common collision point, with 63,390 incidents.
- The "Not Known/Not Applicable" collision point category has the highest serious injury (44%) and fatal accident ratios (3%).

Vehicle Types:

- Cars are the most frequently involved vehicle type, with 79,262 incidents.
- Motorcycles have the highest serious injury ratio (46.3%), while utility vehicles have the highest fatal accident ratio (2.7%).

Fuel Types:

- Petrol-powered vehicles are involved in 120,423 accidents.
- Multi-fuel vehicles show the highest serious injury ratio (37.2%), and diesel vehicles have the highest fatal accident ratio (2.34%).

Vehicle Fire:

- 154,174 vehicles did not catch fire during accidents.
- Vehicles that caught fire have the highest serious injury (51%) and fatal accident ratios (19.8%).

Location Types:

- Non-intersection accidents account for 94,893 incidents.
- Accidents at non-intersections have the highest serious injury (38%) and fatal accident ratios (2.15%).

Road Classifications (RMA):

- Arterial Other roads recorded 75,310 accidents.
- Freeways have the highest ratio of serious injury accidents (37%), while arterial highways have the highest fatal accident ratio (2.14%).

Divided vs. Undivided Roads:

- Undivided roads accounted for 112,033 accidents.
- Undivided roads show the highest serious injury (37%) and fatal accident ratios (1.9%).

Heavy Vehicle Involvement:

- Most accidents (158,126 incidents) did not involve heavy vehicles.
- Accidents involving one heavy vehicle show a higher serious injury (38.8%) and fatal accident ratio (5.59%).

Public Transport Vehicle Involvement:

- 163,631 accidents did not involve public transport vehicles.
- Accidents involving one public transport vehicle have a higher serious injury (39.02%) and fatal accident ratio (2.8%).

Gender:

- Male drivers were involved in 105,970 accidents.
- Males have higher serious injury (37.4%) and fatal accident ratios (2.05%) and are 1.91 times more likely to be involved in accidents compared to females.

Day of the Week:

- Friday has the highest number of accidents, with 26,312 incidents (15.9%).

Age Groups:

- The age group 30-39 has the highest involvement, with 34,946 incidents (21.1%).

Vehicle Brands:

- Toyota vehicles are most frequently involved, with 33,910 incidents (20.5%).

Vehicle Models:

- The Holden Commodore is the most frequently involved vehicle model, with 21,204 incidents (12.8%).

Roads:

- Princes Highway has the highest number of accidents, with 2,897 incidents (1.7%).

Local Government Areas (LGAs):

- Melbourne leads with 8,472 incidents (5.1%).

Degrees of Urbanization:

- Urban Melbourne has the highest number of accidents, with 103,227 incidents (62.3%).

Region:

- The Metro region accounts for 70.8% of accidents, while the Country region accounts for 29.2%.

Vehicle Manufacturing Years:

- Most accidents involve vehicles manufactured around 2007-2008 (approximately 23,000 vehicles).

Injury or Fatality Counts:

- The mode is approximately 1 injury/fatality per accident (in about 130,000 incidents).

Number of Vehicle Cylinders:

- Vehicles with 4 cylinders are involved in over 100,000 incidents.
- They also have the highest count of serious injury and fatal accidents.

Total Number of People Involved:

- Most accidents involve 2 people (approximately 78,000 incidents).
- Incidents involving 1-3 people have the highest count of serious injury and fatal accidents.

Number of Vehicles Involved:

- Most accidents involve 2 vehicles (approximately 93,000 incidents).
- 2-vehicle accidents have the highest count of serious injury accidents, while single-vehicle accidents have the highest count of fatal accidents.

Traffic Accidents in Victoria:

- The highest concentration of accidents occurs in Melbourne, forming a dense cluster in the southeastern part of the map.
- Major urban areas and arterial roads show higher frequencies of accidents, particularly along the state's main transport routes.
- Rural and less densely populated areas exhibit significantly fewer accidents.

Traffic Accidents in Victoria by Degree of Urbanization:

- Urban Melbourne shows the highest concentration of accidents, particularly around the metropolitan area.
- Major urban areas such as Melbourne, Geelong, and Ballarat display notable accident clusters.
- Rural Victoria has more sparsely distributed accidents, reflecting lower traffic density.

Traffic Accidents in Victoria by Severity:

- Serious injury accidents are the most prevalent, with higher concentrations in urban areas, especially around Melbourne and major roadways.
- Fatal accidents, though less frequent, are spread across both urban and rural areas, with notable clusters near major highways.

Through comprehensive analysis of Victoria's traffic accident data from 2012 to 2023, our Exploratory Data Analysis (EDA) insights have highlighted key patterns and trends that can directly support Victoria's Road Safety Strategy 2021-2030. These findings provide essential data-driven insights that can be leveraged to implement targeted safety interventions, optimize resource allocation, and inform policy decisions aimed at reducing traffic accidents and enhancing road safety across the state. The EDA results show that urban areas, particularly Melbourne, experience the highest concentration of accidents, emphasizing the need for urban-focused traffic management strategies. At the same time, rural areas, while having fewer accidents, still show significant risks in high-speed zones such as 100 km/h zones, which exhibit a higher proportion of fatalities and serious

injuries. Interventions like improved road infrastructure, enhanced police patrols in high-risk zones, and better speed management could reduce these accidents.

Key insights into factors like road conditions, atmospheric conditions, and traffic control highlight the types of roads and conditions where accidents are most likely to occur. For example, uncontrolled intersections and poor lighting conditions in non-urban areas contribute to higher accident severity. These findings suggest that improved lighting, the installation of traffic controls at key intersections, and adjustments to road geometries could significantly reduce accident severity, especially in areas with high-speed limits or limited visibility. Also, the involvement of heavy vehicles and motorcycles in accidents has a higher ratio of serious injuries and fatalities, which indicates that safety campaigns and regulations targeting vulnerable road users could help prevent severe accidents. Insights into the time of day and day of the week when most accidents occur provide opportunities for targeted safety initiatives such as heightened law enforcement presence during peak accident times, especially on Fridays and in heavy traffic zones.

Our findings regarding driver behavior, such as accidents involving unlicensed drivers, alcohol, or hit-and-run incidents, call for more stringent enforcement policies and public awareness campaigns that address risky behaviors on the road. Enhancing community engagement through educational programs on safe driving practices and promoting the dangers of driving under the influence could lead to safer roads.

In conclusion, these EDA insights provide a robust foundation for predictive modelling and the development of data-driven recommendations. By identifying accident hotspots, common causes, and factors contributing to accident severity, authorities can deploy proactive measures such as infrastructure improvements, focused law enforcement, and targeted public awareness campaigns to mitigate severe accidents. As we continue to harness the potential of data analytics, we will not only enhance road safety but also contribute to achieving the ambitious goals set out by Victoria's Road Safety Strategy, aiming to halve fatalities by 2030 and eliminate road deaths by 2050.

Importing necessary packages for the subsequent steps (feature selection/engineering, modelling):

```
import folium
from folium.plugins import MarkerCluster
from scipy.stats import chi2_contingency
from pandas import get_dummies
from sklearn.preprocessing import LabelEncoder, label_binarize
from sklearn.model_selection import train_test_split, KFold, cross_val_score, cross_validate, StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, classification_report, confusion_matrix,
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier, plot_importance
from itertools import combinations
import warnings
from sklearn.exceptions import ConvergenceWarning
```

FEATURE SELECTION/ENGINEERING

For feature selection, we will begin by immediately removing features that would adversely affect the model's performance in classifying SEVERITY:

Irrelevant Features (No Predictive Value for Severity):

- **ACCIDENT_NO:** Unique identifier of each accident (high cardinality); which means it has as many unique values as there are rows in the dataset. High cardinality features offer no generalizable pattern and add unnecessary noise, confusing the model. Essentially, the feature is irrelevant as it does not provide any valuable information for severity classification – not beneficial for the modelling process.
- **ACCIDENT_DATE, ACCIDENT_TIME:** These two features represent specific timestamps but don't inherently influence the severity of an accident; they don't provide enough relevant predictive information for the severity of an accident. The date and times of an accident can introduce noise if not properly engineered, skewing results of the model - no correlation between these time points and severity.
- **DAY_OF_WEEK:** Day of the week has no direct impact on the severity of accidents (no correlation). Hence, it doesn't provide predictive value for the severity classification task.
- **LGA_NAME, ROAD_NAME, INT_ROAD_NAME, LATITUDE, LONGITUDE, VICGRID_X, VICGRID_Y, GEOMETRY:** These location-specific features are unique to each accident location and lead to high cardinality. Again, high cardinality makes it difficult for models to generalize. While location may determine accident hotspots, it doesn't directly influence the classification of severity. These features are more relevant for spatial analysis (as seen in EDA) rather than for predicting severity.
- **NO_OF_CYLINDERS, VEHICLE_YEAR_MANUF:** These features describe specific attributes of vehicles involved in accidents but show little to no correlation with accident severity. The number of cylinders or manufacturing years don't inherently determine the severity of an accident. For example, a car's engine configuration has negligible influence at best on whether an accident results in a fatal or serious injury outcome. Including these low-value predictors would increase the risk of model overfitting, as the model tries to find patterns in noise.

Redundant/Irrelevant Features:

- **MALES, FEMALES, BICYCLIST, DRIVER, PED_CYCLIST_5_12, PED_CYCLIST_13_18, YOUNG_DRIVER_18_25:** These features provide a specific breakdown of the demographics of everyone involved in the accident. However, they are redundant as the number of people involved (TOTAL_PERSONS) is already represented, and knowing their gender or role in the accident (e.g., driver,

cyclist) doesn't directly enhance the model's understanding of SEVERITY. Ultimately, these features were removed to reduce dimensionality within the dataset as including these specific demographic breakdowns could confuse the model by introducing unnecessary or redundant variables – improving computational efficiency and model interpretability.

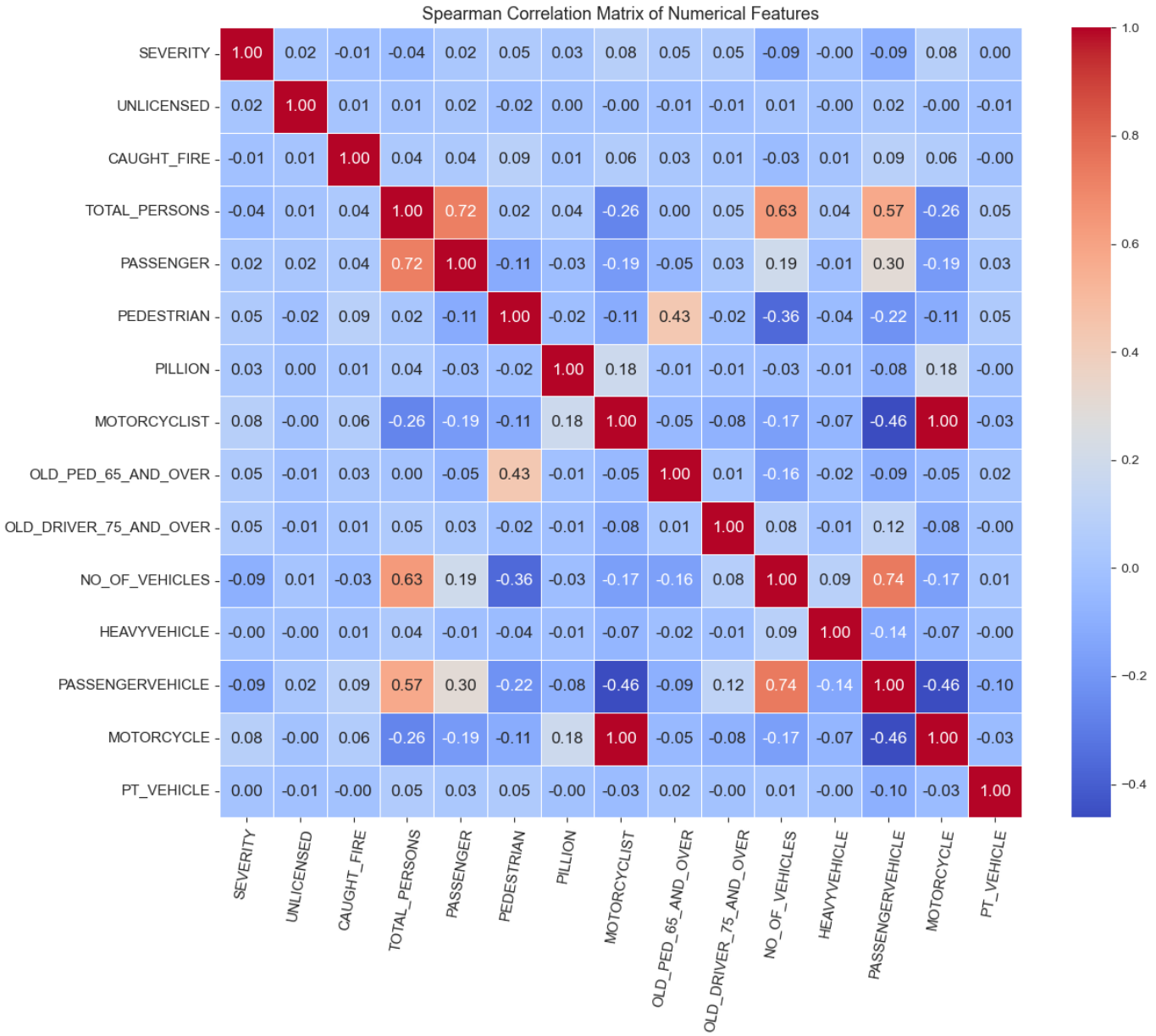
Data-leaking Features (Severity outcome-related):

- **INJ_OR_FATAL, FATALITY, SERIOUSINJURY, OTHERINJURY, NONINJURED:** These features describe the severity outcomes directly – highly correlated with the target feature SEVERITY. Including them would mean the model essentially has prior knowledge of the answer, leading to overly optimistic performance during training but poor generalization to testing/new data. Also, the inclusion of these features leads to predictive bias as they would undermine the model's ability to truly learn patterns from other meaningful features. Basically, these features provide direct predictive information on severity, leading to unrealistic model performance.

```
#Create a copy of the main df
df = main_df.copy()

#Dropping irrelevant/redundant/data-leaking columns
df.drop('ACCIDENT_NO',axis=1,inplace=True)
df.drop('ACCIDENT_DATE',axis=1,inplace=True)
df.drop('ACCIDENT_TIME',axis=1,inplace=True)
df.drop('DAY_OF_WEEK',axis=1,inplace=True)
df.drop('VEHICLE_YEAR_MANUF',axis=1,inplace=True)
df.drop('LGA_NAME',axis=1,inplace=True)
df.drop('ROAD_NAME',axis=1,inplace=True)
df.drop('INT_ROAD_NAME',axis=1,inplace=True)
df.drop('LATITUDE',axis=1,inplace=True)
df.drop('LONGITUDE',axis=1,inplace=True)
df.drop('VICGRID_X',axis=1,inplace=True)
df.drop('VICGRID_Y',axis=1,inplace=True)
df.drop('GEOMETRY',axis=1,inplace=True)
df.drop('NO_OF_CYLINDERS',axis=1,inplace=True)
df.drop('INJ_OR_FATAL',axis=1,inplace=True)
df.drop('FATALITY',axis=1,inplace=True)
df.drop('SERIOUSINJURY',axis=1,inplace=True)
df.drop('OTHERINJURY',axis=1,inplace=True)
df.drop('NONINJURED',axis=1,inplace=True)
df.drop('MALES',axis=1,inplace=True)
df.drop('FEMALES',axis=1,inplace=True)
df.drop('BICYCLIST',axis=1,inplace=True)
df.drop('DRIVER',axis=1,inplace=True)
df.drop('PED_CYCLIST_5_12',axis=1,inplace=True)
df.drop('PED_CYCLIST_13_18',axis=1,inplace=True)
df.drop('YOUNG_DRIVER_18_25',axis=1,inplace=True)
```

I first create a copy of my main data frame by utilizing the copy() method from Pandas (the new data frame will be used for the last phases of the data analysis). I then deal with each irrelevant/ redundant/data-leaking feature in the same way; using the drop() method from Pandas to remove all the specified features from the data frame.

Now that I have significantly reduced the dimensionality of the dataset (26 features dropped), we can proceed with clearly plotting a correlation matrix between all numerical features to further refine feature selection.



This is a correlation matrix between all numerical features within the data frame. In every row, you can observe each numerical feature's correlation against one another. The closer the value is to 1 (or -1), the stronger the positive (or negative) correlation. For this correlation matrix, we used Spearman's correlation instead of Pearson's by default. Spearman's correlation measures the monotonic relationship between two variables, making it better suited for our dataset as it captures non-linear relationships. Additionally, Spearman's method is particularly advantageous when dealing with unevenly distributed data, which is the case with our dataset. Essentially, Spearman's method is ideal for identifying meaningful correlations that may not follow a linear trend. I won't delve into every feature here, as I'll be focusing on the most important feature – SEVERITY (target variable). The matrix allows us to see how well each numerical feature correlates with

SEVERITY, aiding in feature selection and understanding which numerical features may hold predictive value for the classification task.

Positive Correlation with SEVERITY:

- UNLICENSED, PASSENGER, PILLION, PEDESTRIAN, OLD_PED_75_AND_OVER, OLD_DRIVER_75_AND_OVER, MOTORCYCLIST, and MOTORCYCLE have a positive correlation with SEVERITY – with MOTORCYCLIST and MOTORCYCLE having the highest rate of positive correlation at 0.08.

Negative Correlation with SEVERITY:

- CAUGHT_FIRE, TOTAL_PERSONS, NO_OF_VEHICLES, AND PASSENGERVEHICLE have a negative correlation with SEVERITY — with PASSENGERVEHICLE and NO_OF_VEHICLES having the highest rate of negative correlation at -0.09 each.

No Correlation with SEVERITY:

- HEAVYVEHICLE and PT_VEHICLE show no significant correlation with SEVERITY, with correlation scores at 0.

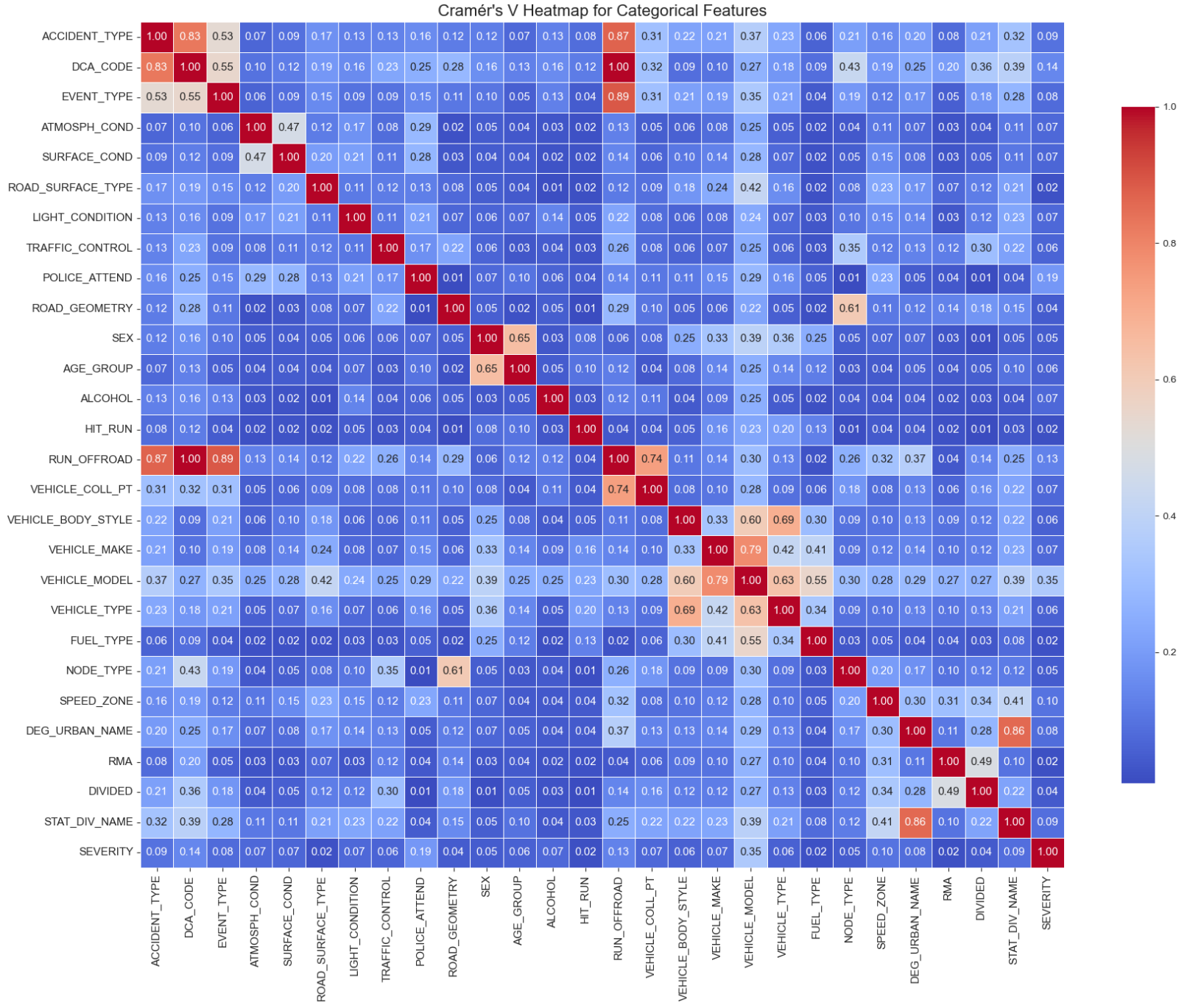
By combining domain knowledge with insights from the correlation matrix, I've decided to remove another feature:

- **PASSENGERVEHICLE:** This feature represents the number of passenger vehicles involved in an accident; however, this information overlaps with NO_OF_VEHICLES, which already captures the total number of vehicles involved – redundant. Moreover, the correlation score of -0.09 indicates little to no predictive value for the target feature. Removing PASSENGERVEHICLE aids in further reducing dimensionality without sacrificing meaningful information for predictive capabilities; enhancing model efficiency and interpretability by focusing on the more relevant features.

```
#Removing irrelevant column
df.drop('PASSENGERVEHICLE',axis=1,inplace=True)
```

- Deleting PASSENGERVEHICLE from the dataset by utilizing the drop() method from Pandas once again.

Lastly, to finalize the refinement of feature selection, I will be plotting a heatmap depicting the association of all categorical features against each other to conclude feature selection.



This Cramér's V Heatmap visualizes the association between all categorical features in the dataset. Each row represents the strength of association between categorical features, measured by Cramér's V. The closer the value is to 1, the stronger the association. This heatmap aids in identifying association relationships between all categorical features and determines importance. Cramér's V is a robust metric for measuring the strength of association between categorical variables. Cramér's V is advantageous for multi-class categorical features, making it highly suitable for our dataset. Cramér's V captures

associations between categorical features without assuming any specific relationship type. The primary focus here is the association between each categorical feature and SEVERITY (our target variable). By observing this heatmap, we can identify which categorical features show stronger associations with SEVERITY, aiding in the feature selection process. Features with low association scores may hold limited predictive value and could be candidates for removal to reduce dimensionality, while those with higher scores may provide valuable insights for classifying accident severity. This heatmap helps ensure a robust approach in selecting categorical features, optimizing modelling performance.

Strong Association with SEVERITY (>=0.05):

- SEX, NODE_TYPE, AGE_GROUP, VEHICLE_BODY_STYLE, VEHICLE_TYPE, TRAFFIC_CONTROL, VEHICLE_MAKE, ALCOHOL, SURFACE_COND, ATMOSPH_COND, LIGHT_CONDITION, VEHICLE_COLL_PT, EVENT_TYPE, DEG_URBAN_NAME, STAT_DIV_NAME, ACCIDENT_TYPE, SPEED_ZONE, RUN_OFFROAD, DCA_CODE, POLICE_ATTEND, and VEHICLE_MODEL have a strong association with SEVERITY – with POLICE_ATTEND and VEHICLE_MODEL having the highest association scores at 0.19 and 0.35, respectively.

Weak Association with SEVERITY (<0.05):

- FUEL_TYPE, ROAD_SURFACE_TYPE, HIT_RUN, RMA, DIVIDED, and ROAD_GEOMETRY have a weak association with SEVERITY – with FUEL_TYPE. ROAD_SURFACE_TYPE. HIT_RUN, and RMA having the lowest association scores at 0.02.

To finalize feature selection, I have decided to remove additional features based on domain knowledge and the insights gained from the Cramér's V Heatmap:

- **HIT_RUN (Cramér's V Association with SEVERITY: 0.02):** This feature provides minimal predictive value for SEVERITY with one of the lowest association scores. Essentially, HIT_RUN possesses negligible correlation towards predicting accident severity.
- **FUEL_TYPE (Cramér's V Association with SEVERITY: 0.02):** This feature indicates the type of fuel used by vehicles involved in accidents. However, fuel type is unlikely to have a meaningful impact on the severity of traffic accidents. The low association score further confirms its limited utility in predicting SEVERITY.
- **RMA (Cramér's V Association with SEVERITY: 0.02):** Captures VicRoads classification on the road where accident occurred. Ultimately, this feature has a very low correlation with SEVERITY, unlikely to impact severity outcomes positively. This is further highlighted by the feature's low association score with SEVERITY.

- **ROAD_SURFACE_TYPE (Cramér's V Association with SEVERITY: 0.02):** Describes the type of road surface where crash occurred. While road surface types might intuitively affect accident severity, the low association score suggests it provides minimal predictive value in this context.
- **VEHICLE_BODY_STYLE (Cramér's V Association with SEVERITY: 0.06):** Represents the body style of vehicles involved (e.g., sedan, SUV). This feature adds minimal predictive value for SEVERITY and is largely redundant when VEHICLE_TYPE is retained, which provides broader classification of vehicles.
- **DEG_URBAN_NAME (Cramér's V Association with SEVERITY: 0.08):** Expands on urban/rural classifications, but its value is captured more sufficiently by STAT_DIV_NAME. STAT_DIV_NAME provides a simpler categorization (Metro/Country), which aligns well with accident severity trends, making DEG_URBAN_NAME redundant.
- **SEX (Cramér's V Association with SEVERITY: 0.05):** Indicates the gender of individuals involved in accidents. While males were observed to have slightly higher serious injury and fatality ratios (1-2%) during EDA, this is likely due to their higher overall frequency of involvement in accidents. Therefore, this feature doesn't add any significant predictive power when it comes to classifying SEVERITY.
- **ROAD_GEOMETRY (Cramér's V Association with SEVERITY: 0.04):** Captures specific intersection types, but NODE_TYPE provides a more simplified and effective classification (intersection vs. non-intersection). Ultimately, ROAD_GEOMETRY has higher cardinality and overlaps with NODE_TYPE, adding unnecessary complexity – redundant.
- **VEHICLE_MAKE (Cramér's V Association with SEVERITY: 0.07):** Represents the brand of the vehicle. While VEHICLE_MAKE could provide some predictive value, its utility is largely overshadowed by VEHICLE_MODEL, which offers more detail and has a much higher association with SEVERITY; making VEHICLE_MAKE redundant.

Removing these features reduces irrelevancy, redundancy, simplifies the dataset, and focuses on features with higher predictive potential, improving model efficiency and interpretability; thereby improving modelling performance.

```
#Removing irrelevant columns
df.drop('HIT_RUN',axis=1,inplace=True)
df.drop('FUEL_TYPE',axis=1,inplace=True)
df.drop('RMA',axis=1,inplace=True)
df.drop('ROAD_SURFACE_TYPE',axis=1,inplace=True)
df.drop('VEHICLE_BODY_STYLE',axis=1,inplace=True)
df.drop('DEG_URBAN_NAME',axis=1,inplace=True)
df.drop('SEX',axis=1,inplace=True)
df.drop('ROAD_GEOMETRY',axis=1,inplace=True)
df.drop('VEHICLE_MAKE',axis=1,inplace=True)
```

- Dropping all specified features mentioned above from the data frame by employing the drop() method from Pandas.

Overall, the feature selection process involved removing 36 irrelevant, redundant, or data-leaking features to ensure the model's integrity and predictive accuracy. By eliminating features with minimal or no correlation/association to the target feature SEVERITY, we reduced noise and avoided overfitting, enabling the model to generalize better to unseen data. Additionally, redundant features that provided overlapping or unnecessary information were excluded to reduce dimensionality, improving modelling efficiency and interpretability. By refining our dataset in this way, we are ensuring that only the most relevant and useful predictive information is used to build our classification models. Essentially, this refined feature set optimizes modelling performance, enhancing both the accuracy and reliability of classifying accident severity, ultimately maximizing the model's overall performance.

```
#Drop Non injury accident rows
df.drop(index=df[df['SEVERITY']=='Non injury accident'].index,inplace=True)
df.SEVERITY.value_counts()
```

```
Other injury accident      102847
Serious injury accident     60013
Fatal accident               2778
```

- Starting off feature engineering by removing 'Non injury accident' from SEVERITY (target feature). This is done for a few reasons, mainly because this project focuses on mitigating serious injury and fatal accidents. Non-injury accidents aren't important in general and are completely irrelevant to our goal. It also detracts from the models focus on predicting higher-severity outcomes. Non injury accidents only account for 5 values in the dataset, making it statistically insignificant compared to other severity classes. This imbalance could skew model training and evaluation, especially when aiming for key insights into the more severe accident outcomes. Including this class could mislead the evaluation metrics by introducing noise, especially when calculating accuracy or other metrics like F1-score. Therefore, I remove non injury accidents by utilizing the drop() method from Pandas yet again, equating to less than 0.1% of the data being removed – insignificant.

```
#Combine Unknown (9) and Not Applicable (0) in CAUGHT_FIRE
df['CAUGHT_FIRE'] = df['CAUGHT_FIRE'].replace({9: 0})
#Verify
df.CAUGHT_FIRE.value_counts()
```

```
2    154170
0     10805
1       663
```

- Merge Unknown (9) and Not Applicable (0) records from CAUGHT_FIRE to make a single category (0) by using the replace() method from Pandas; reducing redundant information to prevent the model from overfitting to irrelevant categories and aiding the model to focus on more meaningful classes.

```
#Combine Not known and Not Applicable in EVENT_TYPE
df['EVENT_TYPE'] = df['EVENT_TYPE'].replace({'Not known': 'Unknown', 'Not applicable': 'Unknown'})
#Verify
df.EVENT_TYPE.value_counts()
```

```
Collision                       124255
Ran off carriageway              28163
Rollover on/off carriageway       8319
Fell from vehicle                 3520
Other                              707
Struck by stone/projectile/load    234
Mechanical failure                 204
Fell in vehicle                    184
Unknown                             52
```

- Combining the values Not known and Not applicable under the new single category Unknown, in EVENT_TYPE. This reduces redundancy by consolidating similar categories. Again, the replace() method is applied for value substitution. This reduces noise and improves modelling generalization by enabling the model to focus on more important event types, preventing the model from being biased towards rare/irrelevant values.

```
#Combine rare <18 age groups into Under 18 for AGE_GROUP
df['AGE_GROUP'] = df['AGE_GROUP'].replace({'16-17': 'Under 18', '13-15': 'Under 18', '5-12': 'Under 18', '0-4': 'Under 18'})
#Verify
df.AGE_GROUP.value_counts()
```

```
30-39       34946
40-49       25382
50-59       20370
18-21       18577
22-25       18437
26-29       16275
70+         12159
60-64        7515
65-69        5596
Unknown      4463
Under 18     1918
```

- Grouping rare age categories (16-17, 13-15, 5-12, 0-4) into a single category Under 18 within AGE_GROUP by using the replace() method. This ensures the model focuses on more statistically significant age categories, improving its ability to generalize better.

```
#Combine Camping grounds of off road and Other speed limit in SPEED_ZONE
df['SPEED_ZONE'] = df['SPEED_ZONE'].replace({'Camping grounds or off road': 'Other speed limit'})
#Verify
df.SPEED_ZONE.value_counts()
```

```
60 km/hr             54921
50 km/hr             27201
80 km/hr             24640
100 km/hr            23866
70 km/hr             10718
Not known            10290
40 km/hr             10134
110 km/hr             1826
Other speed limit     1238
90 km/hr               490
30km/hr                296
75 km/hr                18
```

- Consolidating Camping grounds or off road with the Other speed limit value in SPEED_ZONE by conducting the replace() method from Pandas. This avoids overfitting and improves model interpretability by simplifying SPEED_ZONE, reducing the number of speed zone categories, making the feature more manageable for the model.

```
#Combine Not Applicable and Not Known in VEHICLE_TYPE
df['VEHICLE_TYPE'] = df['VEHICLE_TYPE'].replace({'Not Applicable': 'Not Known'})
#Verify
df.VEHICLE_TYPE.value_counts()
```

```
Car                                                79260
Station Wagon                                      30047
Motor Cycle                                        15787
Utility                                            14884
Bicycle                                             6911
Panel Van                                           3764
Not Known                                           3194
Light Commercial Vehicle (Rigid) <= 4.5 Tonnes GVM  2622
Heavy Vehicle (Rigid) > 4.5 Tonnes                  2283
Taxi                                                1486
Prime Mover - Single Trailer                        1471
Motor Scooter                                        844
Bus/Coach                                            750
Other Vehicle                                        575
Prime Mover B-Double                                 460
Prime Mover Only                                     428
Tram                                                 252
Mini Bus(9-13 seats)                                 169
Plant machinery and Agricultural equipment           156
Quad Bike                                            127
Moped                                                 68
Prime Mover B-Triple                                  48
Parked trailers                                       17
Rigid Truck(Weight Unknown)                           12
Horse (ridden or drawn)                               11
Prime Mover (No of Trailers Unknown)                   9
Train                                                  3
```

- Aggregating Not Applicable and Not Known values into a single category (Not Known) in VEHICLE_TYPE. Consolidating these categories safeguards the model from disproportionately focusing on rare, ambiguous cases. This improves modelling prediction stability as the models will not waste capacity differentiating between categories that do not add predictive value.

```
#Frequency encoding VEHICLE_MODEL
df['VEHICLE_MODEL'] = df['VEHICLE_MODEL'].map(df['VEHICLE_MODEL'].value_counts(normalize=True))
#Verify
df.VEHICLE_MODEL.value_counts()
```

```
0.128008    21203
0.038149     6319
0.031309     5186
0.031050     5143
```

- The VEHICLE_MODEL feature initially had 9,237 unique values, making it a high-cardinality categorical feature. Despite its high cardinality, it showed a strong Cramér's V association score of 0.35 with SEVERITY, indicating significant predictive potential. To address the challenges of sparsity, overfitting, and computational inefficiency associated with high cardinality, frequency encoding was applied. This method replaces each unique category with its relative frequency, preserving the feature's predictive value while reducing dimensionality. Frequency encoding helps the model generalize better by focusing on common patterns, improving training efficiency, and maintaining valuable insights without introducing noise from rare categories. Ultimately, this transformation optimizes modelling performance by enhancing interpretability and reducing overfitting risk.

```
#Manually mapping SEVERITY
df['SEVERITY'] = df['SEVERITY'].map({'Other injury accident': 0, 'Serious injury accident': 1, 'Fatal accident': 2})
#Verify
df.SEVERITY.value_counts()
```

```
0    102847
1     60013
2      2778
```

- The SEVERITY feature (target feature), representing accident severity levels ("Other injury accident," "Serious injury accident," and "Fatal accident"), is mapped to numerical values (0, 1, 2) to ensure compatibility with machine learning algorithms. This transformation preserves the ordinal nature of the data, allowing models to recognize the progression of severity. It enhances model performance by enabling algorithms to identify patterns effectively, particularly for serious and fatal accidents, which are the focus of the project. Additionally, the numerical encoding simplifies interpretation and prioritizes key safety outcomes, optimizing the data for predictive modelling.

```
#One-Hot encoding categorical to numerical data
df = pd.get_dummies(df, columns =  ['ACCIDENT_TYPE', 'DCA_CODE', 'EVENT_TYPE', 'ATMOSPH_COND',
                                    'SURFACE_COND', 'LIGHT_CONDITION', 'TRAFFIC_CONTROL',
                                    'POLICE_ATTEND', 'SPEED_ZONE', 'AGE_GROUP', 'ALCOHOL',
                                    'RUN_OFFROAD', 'UNLICENSED', 'VEHICLE_COLL_PT',
                                    'VEHICLE_TYPE', 'CAUGHT_FIRE', 'NODE_TYPE',
                                    'DIVIDED', 'STAT_DIV_NAME'])
```

To prepare the data for machine learning, it is crucial to convert categorical features into numerical format, as machine learning algorithms can only operate on numerical data. Here, the get_dummies() method from Pandas is employed to perform one-hot encoding. This process creates binary (0/1) indicator columns (represents the presence or absence of that category) for each unique value in every categorical feature listed. This encoding approach is beneficial as it ensures that no ordinal relationships are implied between categorical values, which could otherwise mislead the model. By expanding categorical features into multiple columns, one for each unique value, it allows the model to better differentiate between categories without introducing unintended bias. This process enhances the performance and interpretability of various machine learning algorithms by providing a clear and precise numerical representation of categorical data. Ultimately, by encoding categorical variables into a numerical format, we improve the dataset's usability for predictive modelling while preserving the integrity of the categorical information.

```
#Feature-target splitting
X = df.drop('SEVERITY', axis = 1)
y = df['SEVERITY']
```

- Now we split the features into two components (X, y): X, containing all the independent features (predictors), and y, the dependent/target feature (SEVERITY) that the model aims to predict. This separation is crucial for supervised machine learning algorithms, as it ensures the models learn patterns from the predictors to make accurate predictions on the target. By isolating the target, it prevents data leakage during preprocessing, ensuring that transformations like scaling are applied only to the predictors.

```
#Splitting data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

- Splitting the dataset into training and testing sets using the train_test_split() method from the sklearn library. The independent variables (X) and the target variable (y) are divided into X_train, X_test, y_train, and y_test, with 80% of the data allocated for training and 20% for testing (test_size=0.2). The random_state=42 parameter ensures reproducibility and consistency by producing the same random split each time. The training set is used to train the machine learning algorithms; during training the model acquires insights into the patterns and relationships in the training data, facilitating the models ability to classify based on the insights gained from training. Following training, to assess the model's performance and ensure it can generalize well to new, unseen data, it is crucial to evaluate it on data it has not encountered before. This is where the testing set comes in. The testing set serves as an independent dataset, providing unseen data that allows us to evaluate the model's ability to accurately predict the

dependent variable (SEVERITY) – simulating real-world scenarios on predicting accident severity in unseen traffic accidents in Victoria.

```
#Feature Scaling
sc = StandardScaler()
#Fit on the training data and transform
X_train_sc = sc.fit_transform(X_train)
#Transform the test data
X_test_sc = sc.transform(X_test)
```

Feature scaling using StandardScaler from sklearn, which standardizes features by removing the mean and scaling to unit variance. This ensures that all features contribute equally to models that are sensitive to feature magnitudes, such as Logistic Regression and K-Nearest Neighbors (KNN). These algorithms rely on distance metrics or gradient-based optimization and are particularly susceptible to unscaled data because features with larger magnitudes can dominate the distance calculations or optimization process, leading to biased or inefficient learning. The StandardScaler method addresses this issue by standardizing the data so that each feature has a mean of 0 and a standard deviation of 1. This ensures that all features contribute equally to the model, preventing any single feature from dominating due to its magnitude. The scaler is first initiated then fitted on the training data using fit_transform(), which calculates the mean and standard deviation, then applies the scaling transformation. The test data is subsequently transformed using the same scaling parameters via transform() to maintain consistency and prevent data leakage (ensuring no information from the test set influences the training process). This process improves model convergence, performance, and fairness by preventing features with larger magnitudes from disproportionately influencing the learning process. Consequently, it helps the model learn more effectively and generalize better to unseen data.

Ultimately, the feature engineering process focused on refining the dataset further to set a robust foundation for modelling and optimizing performance. Key steps included removing irrelevant records like Non-injury accidents to focus on serious and fatal outcomes, aligning with the project's goal of mitigating severe accidents. Redundant or rare categorical values were consolidated to reduce noise and enhance model generalization. High-cardinality features, such as VEHICLE_MODEL, were frequency encoded to retain predictive power while avoiding sparsity and overfitting. The target variable, SEVERITY, was mapped to numerical values to preserve its ordinal nature, improving the model's ability to detect severity progression. Categorical features were one-hot encoded to ensure clear, unbiased numerical representation. The dataset was then split into training and testing sets to ensure dependable evaluation of model generalization. Additionally, feature scaling using StandardScaler was applied to algorithms sensitive to feature magnitudes, improving convergence and performance. This comprehensive feature engineering approach laid a strong groundwork for modelling moving forward, enhancing interpretability, efficiency, and overall model performance.

METHODOLOGY

We'll evaluate five distinct supervised machine learning algorithms to determine the most effective one for classifying severity (multi-class classification), which simulates real-world scenarios on predicting our target feature severity in unseen traffic accidents:

1. **Logistic Regression** - Logistic Regression is a supervised machine learning algorithm used for classification tasks. It predicts the probability that an instance belongs to a particular class. In this case, the dependent variable is Severity (e.g., fatal accident, serious injury accident, other injury accident, non-injury accident), and the independent variables are the other features (e.g., road conditions, vehicle type, etc.). Logistic regression analyzes the relationship between the independent variables (which can be categorical or numeric) and the dependent variable (which is categorical) by estimating probabilities. It computes the probability of the dependent variable Y (Severity) given the independent variables X (all other features) using the logistic function (also called the sigmoid function). The logistic function outputs a probability between 0 and 1, which can then be mapped to a class label. In this context, Logistic Regression would predict the severity of an accident by calculating the probability of each severity class (fatal accident, serious injury accident, other injury accident, non-injury accident) given the values of the independent variables. Based on this probability, the accident would be classified into one of the four severity categories.

2. **K-Nearest Neighbor** (KNN) – K-Nearest Neighbor (KNN) is a supervised machine learning algorithm that makes classifications based on proximity to the data point being analyzed. It classifies a new data point by identifying its k-nearest neighbors among the training examples. In classification tasks, KNN assigns the data point to the category of its closest neighbors. For instance, if K = 1, the data point is classified based on its single nearest neighbor. When K > 1, the classification is determined by a majority vote among the K nearest neighbors. The value of K can significantly affect the performance of the algorithm, and it is often tuned during model optimization (hyperparameter tuning). A common heuristic to determine K is to use the square root of the total number of samples (N), but this may not always be optimal and often requires experimentation to find the best value for a given dataset. KNN operates under the assumption that similar data points exist near each other, and it uses distance metrics such as Euclidean, Manhattan, and Minkowski distances to calculate the distance between data points. For instance, in this case, KNN would classify accidents by severity (other injury, serious injury, fatal, non-injury) by comparing each new accident data point to its K-nearest neighbors and assigning it the most common severity label among those neighbors.

3. **Decision Tree Classifier** – A Decision Tree Classifier is a supervised machine learning algorithm used for classification tasks. It works by splitting the dataset into smaller subsets based on specific features to create a tree-like structure of decisions. At each internal node of the tree, the algorithm selects a feature and a threshold that best separates the data into distinct classes (e.g., accident severity: fatal, serious injury, other injury). This selection is usually based on metrics like Gini Impurity or Entropy (used in Information Gain), which measure the purity of the data after each split. The process continues recursively until the stopping criteria are met, such as reaching a maximum tree depth or having a minimum number of samples in each leaf node. Each leaf node of the tree represents a class label (e.g., accident severity), and the path from the root to the leaf represents the sequence of decisions that lead to that classification. For example, in the context of accident severity prediction, a decision tree might first split the data based on weather conditions (e.g., clear, raining), then on vehicle type (e.g., car, truck), and finally on road surface conditions to predict whether an accident will result in a serious injury, fatality, or other outcome. Decision trees are easy to interpret, as the flow of decisions is straightforward. However, they are prone to overfitting, especially on noisy or complex datasets. To mitigate this, techniques like pruning or setting limits on tree depth and leaf size are often applied. Decision trees serve as the foundation for more advanced ensemble methods like Random Forest and Gradient Boosting, which build multiple trees to improve accuracy and robustness.

4. **Random Forest Classifier** – A Random Forest Classifier is a supervised machine learning algorithm that builds upon the concept of decision trees, which operate like a flowchart to split data points into progressively more similar groups. In a decision tree, data points are split based on features, and the tree grows until it reaches a predefined limit, such as the maximum depth or minimum number of samples per leaf. The Random Forest Classifier expands on this idea by creating an ensemble of decision trees. Each tree in the forest is trained on a random subset of the data (using bootstrap sampling) and a random subset of features at each split, which introduces diversity among the trees. Once all the trees are built, the model makes a classification based on the majority vote across all the trees. This ensemble approach helps reduce overfitting, which can occur in individual decision trees, and improves the model's overall accuracy and stability. In this context, where the target feature is severity (other injury, serious injury, fatal, non-injury accidents) each decision tree would attempt to classify accident data points (based on features such as atmospheric conditions, road type, or vehicle characteristics) by predicting the severity of the accident. The individual trees may classify each accident as either serious injury, fatal, non-injury, or other injury. After all trees in the forest make their predictions, the final classification for

severity would be determined by a majority vote – the most frequent severity classification across all trees.

5. **XGBoost** – XGBoost (Extreme Gradient Boosting) is a powerful and efficient supervised machine learning algorithm used for classification tasks. It is an implementation of the gradient boosting framework, which builds a model in a stage-wise fashion by combining the predictions of many weak learners (usually decision trees) to create a strong model. Each tree is built sequentially, with each one correcting the errors of its predecessor, and XGBoost enhances this process by introducing regularization techniques, tree pruning, and optimized computational methods to prevent overfitting and improve performance. XGBoost operates by minimizing a loss function (the difference between the predicted and actual values) and applies a gradient descent optimization to iteratively improve the model. Its strength lies in its ability to handle large datasets efficiently, work well with both linear and non-linear data, and its robustness to outliers and noisy data. In our context, XGBoost will be used to predict the severity of an accident (fatal accident, serious injury accident, other injury accident, non-injury accident) by learning from the relationships between all features (e.g., road conditions, vehicle types, atmospheric conditions). Each decision tree in the model contributes to predicting the accident severity, and the combined predictions from multiple trees provide the final classification. XGBoost can automatically account for complex interactions between variables, making it particularly effective for large, complex datasets – which is our scenario.

We will measure the performance of our models by using these evaluation metrics:

- **Accuracy** – Accuracy measures the proportion of correctly predicted observations (true positives and true negatives) out of the total number of observations. It is calculated as:

  $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

  Essentially, the total correct answers are divided by the total number of entries. It's an efficient way to measure the predictive success of the model, although in some cases it can be misleading – particularly in cases of class imbalance.

- **Precision** – Precision represents the proportion of true positive predictions (correctly predicted severity class) out of all positive predictions made by the model (both true positives and false positives). It is calculated as:

$$Precision = \frac{TP}{TP+FP}$$

In this context, precision tells us how accurate the model is when it predicts a specific accident severity class. For instance, when the model predicts fatal accidents, precision indicates how many of those predictions were correct. Precision focuses on the model's ability to avoid false positives; ensures that identified severe cases are indeed severe.

- **Recall** – Recall (also known as Sensitivity or True Positive Rate) measures the proportion of true positives that the model correctly identified. Basically, It measures the accuracy of identifying actual positive classes. It is calculated as:

  $$Recall = \frac{TP}{TP+FN}$$

  Recall is important when the goal is to capture as many positive instances as possible, especially in imbalanced datasets. In this project, recall is critical as it shows how well the model captures the actual serious and fatal accidents. High recall ensures the model identifies most severe accidents, which aligns with our goal of mitigating high-severity accidents.

- **F1 Score** – F1 Score is the harmonic mean between precision and recall. It balances the trade-off between precision and recall, particularly when there is an uneven class distribution. It is calculated as:

  $$F1 = \frac{2xPrecisionxRecall}{Precision+Recall}$$

  Harmonic mean is used instead of regular mean because it punishes false predictions more. Essentially, it provides a single measure of model performance by balancing how well the model avoids false positives and false negatives. Ultimately, in this context, where identifying serious injury and fatal accidents is crucial, F1-score is a critical metric. A high F1-score ensures that the model not only captures the severe cases (high recall) but also minimizes false alarms (high precision).

- **Confusion Matrix** – A confusion matrix is an N X N matrix, where N represents the number of classes being predicted. It's a tool for summarizing the performance of a classification algorithm; it gives us a clear picture of the specific classification models performance and the types of errors produced by the model. The summary provides correct and incorrect predictions broken down by each category,

represented by a matrix. All performance metrics are based on the confusion matrix and the numbers inside it.

Confusion Matrix Elements:

- **True Positives (TP):** The number of observations that are correctly classified as belonging to their actual severity class. In other words, these are cases where the model accurately predicts the correct severity level (e.g., predicting Serious Injury for an actual Serious Injury accident). Essentially, these are the correctly predicted observations for each severity class.
- **False Positives (FP)** - The number of observations that are actually from a different severity class but are incorrectly classified as belonging to another particular severity class by the model. This represents cases where the model overestimates the severity (e.g., predicting Fatal Accident when the actual class is Serious Injury). Also referred to as Type I error, these are observations predicted as a severity class they do not belong to.
- **False Negatives (FN)** – The number of observations that are actually from a particular severity class but are incorrectly classified as belonging to a different (usually less severe) class by the model. This indicates cases where the model underestimates severity (e.g., predicting Other Injury for an actual Serious Injury accident). Also known as Type II error, this type of error is particularly critical, as it involves accidents that should be classified as more severe but are predicted otherwise, potentially downplaying the severity of road accidents.

In the context of this project, the most critical elements in the confusion matrix are False Negatives (FN) and True Positives (TP), particularly for the Serious Injury and Fatal Accident classes. False Negatives are the highest priority, as they represent severe accidents that were incorrectly classified as lower severity. This is crucial to minimize, as underestimating the severity of accidents could lead to inadequate resource allocation and undermine safety measures. True Positives, on the other hand, ensure that severe accidents are accurately identified, supporting proactive interventions and aligning with the project's goal of mitigating high-severity outcomes. False Positives (FP), while less critical, will also be monitored, as overestimating severity could lead to unnecessary resource use. To optimize the model's performance, a balance between precision (ensuring that predicted severe accidents truly belong to those classes) and recall (capturing as many actual severe accidents as possible) is essential, with recall being slightly more critical to avoid missing high-severity cases.

MODELLING

Before conducting our models, I have defined two functions to facilitate cross-validation, record and display comprehensive modeling performance metrics, and present a confusion matrix for a clear visual assessment of classification results.

```
def evaluation(model, X_train, y_train, X_test, y_test, train=True, cv=5):
    if train:
        #Perform stratified k-fold cross-validation on training data
        skf = StratifiedKFold(n_splits=cv, shuffle=True, random_state=42)
        scoring = ['accuracy', 'precision_macro', 'recall_macro', 'f1_macro']
        cv_results_train = cross_validate(model, X_train, y_train, cv=skf, scoring=scoring)

        #Print cross-validation results for training data
        print("\nStratified K-Fold Cross-Validation Results for Training Data (k={}):".format(cv))
        print("====================================================")
        print("Mean Accuracy: {:.2f}%".format(cv_results_train['test_accuracy'].mean() * 100))
        print("Mean Precision: {:.2f}".format(cv_results_train['test_precision_macro'].mean()))
        print("Mean Recall: {:.2f}".format(cv_results_train['test_recall_macro'].mean()))
        print("Mean F1-score: {:.2f}".format(cv_results_train['test_f1_macro'].mean()))
        print("____________________________________________________")
        print()

        #Train the model on the full training data
        model.fit(X_train, y_train)

        #Evaluate the model on training data
        pred_train = model.predict(X_train)
        print("Train Result:\n====================================================")
        print("Accuracy Score: {:.2f}%".format(accuracy_score(y_train, pred_train) * 100))
        print("Precision: {:.2f}".format(precision_score(y_train, pred_train, average='weighted')))
        print("Recall: {:.2f}".format(recall_score(y_train, pred_train, average='weighted')))
        print("F1 Score: {:.2f}".format(f1_score(y_train, pred_train, average='weighted')))
        print("____________________________________________________")
        print("CLASSIFICATION REPORT:\n{}".format(classification_report(y_train, pred_train, zero_division=0)))
        print("____________________________________________________")
        #Plot confusion matrix for training data
        cm_train = confusion_matrix(y_train, pred_train)
        plot_confusion_matrix(cm_train, labels=['Other Injury', 'Serious Injury', 'Fatal Accident'])
        print("\n\n\n")

    else:
        #Evaluate the model on test data
        pred_test = model.predict(X_test)
        print("Test Result:\n====================================================")
        print("Accuracy Score: {:.2f}%".format(accuracy_score(y_test, pred_test) * 100))
        print("Precision: {:.2f}".format(precision_score(y_test, pred_test, average='weighted')))
        print("Recall: {:.2f}".format(recall_score(y_test, pred_test, average='weighted')))
        print("F1 Score: {:.2f}".format(f1_score(y_test, pred_test, average='weighted')))
        print("____________________________________________________")
        print("CLASSIFICATION REPORT:\n{}".format(classification_report(y_test, pred_test, zero_division=0)))
        print("____________________________________________________")
        #Plot confusion matrix for test data
        cm_test = confusion_matrix(y_test, pred_test)
        plot_confusion_matrix(cm_test, labels=['Other Injury', 'Serious Injury', 'Fatal Accident'])
```

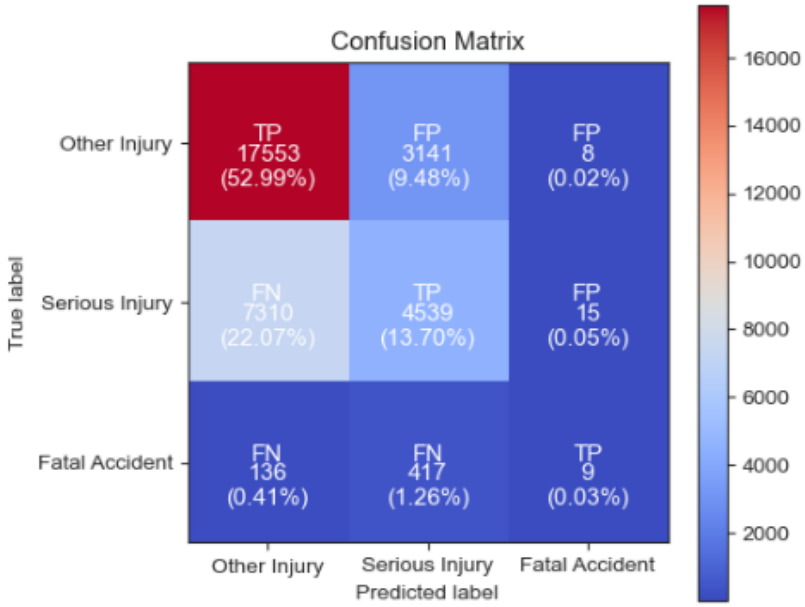
```
def plot_confusion_matrix(cm, labels, fontsize=11):
    plt.figure(figsize=(5, 5))
    ax = plt.gca()
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
    disp.plot(ax=ax, cmap='coolwarm')

    #Remove default annotations
    for text in ax.texts:
        text.set_visible(False)

    #Annotate the cells with counts, percentages, and TP/FP/FN
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            text_label = ""
            if i == j:
                text_label = "TP"  #True Positive
            elif i != j and i < j:
                text_label = "FP"  #False Positive
            elif i != j and i > j:
                text_label = "FN"  #False Negative

            #Adjust label and count placement
            plt.text(j, i - 0.05, f'{text_label}', ha='center', va='center', color='white', fontsize=fontsize)
            plt.text(j, i + 0.15, f'{cm[i, j]}\n({cm[i, j] / cm.sum():.2%})',
                     ha='center', va='center', color='white', fontsize=fontsize)

    plt.title('Confusion Matrix')
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
    plt.grid(False)
    plt.show()
```

This code defines two functions: evaluation and plot_confusion_matrix. The evaluation function is a comprehensive tool designed to assess the performance of machine learning models during both training and testing phases. It incorporates cross-validation, model training, and performance evaluation through metrics like accuracy, precision, recall, and F1-score. During the training phase, Stratified K-Fold Cross-Validation ensures that each fold maintains the class distribution of the entire dataset, which is particularly useful for imbalanced datasets. This provides a robust estimate of the model's generalization performance. The function also trains the model on the entire training set and evaluates it by calculating performance metrics and generating a classification report. For both training and test datasets, the function calculates and prints accuracy, precision, recall, and F1-score. Additionally, a confusion matrix is generated and visualized, giving a detailed breakdown of the model's predictions for each class. The matrix highlights true positives, false positives, and false negatives, allowing for a clear understanding of the model's performance. The plot_confusion_matrix function provides a detailed visualization of the model's classification results. It visually emphasizes the distribution of predictions and includes annotations for counts, percentages, and classification labels like True Positives (TP), False Positives (FP), and False Negatives (FN). This visualization enhances interpretability, helping identify specific areas where the model performs well or struggles. Together, these functions establish a robust evaluation framework for machine learning models. They ensure comprehensive assessment, interpretability, and focus on model generalization. Additionally, the framework accounts for class imbalances, which is crucial for the project's focus on predicting severe and fatal accidents. This approach allows for informed decision-making and refinement of models to optimize performance.

Lastly, before we start modeling, it is crucial to distinguish between the roles and significance of the training and testing set scores. The testing set metrics hold greater importance as they evaluate the model's performance on unseen data, simulating real-world scenarios where the model predicts accident severity for unseen traffic incidents in Victoria. This directly aligns with the project's goal of forecasting accident severity, providing actionable insights to enhance road safety across the region. In contrast, the training set metrics measure how well the model fits the data it was trained on, essentially evaluating the model's performance on the original dataset. While these metrics can indicate how well the model has learned from the data, they are of limited value in the context of this project. Training set performance does not reflect the model's ability to generalize to new, unseen data, which is crucial for real-world applications. As a result, relying on training set metrics would provide a misleading evaluation of the model's practical utility. Therefore, the testing set metrics will be prioritized in this project, as they provide a more accurate representation of the model's real-world predictive capabilities, supporting data-driven recommendations to facilitate safer roads in Victoria.

```
#Supervised Machine Learning Algorithm: Logistic Regression
lr = LogisticRegression(max_iter=500)
#Fitting the model with training data
lr.fit(X_train_sc, y_train)
#Evaluate the model on the testing data
evaluation(lr, X_train_sc, y_train, X_test_sc, y_test, train=False)
```

```
Test Result:
================================================
Accuracy Score: 66.71%
Precision: 0.64
Recall: 0.67
F1 Score: 0.64
________________________________________________
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.70      0.85      0.77     20702
           1       0.56      0.38      0.45     11864
           2       0.28      0.02      0.03       562

    accuracy                           0.67     33128
   macro avg       0.51      0.42      0.42     33128
weighted avg       0.64      0.67      0.64     33128

________________________________________________
```



Logistic Regression Model

Overall Performance Metrics:

- **Accuracy**: **66.71%**

This indicates that the model correctly classified approximately 66.71% of all instances. In other words, 66.71% of accident severity levels in unseen Victorian traffic accident data were correctly predicted by the model – a decent performance.

- **Precision: 0.64**

In this context, precision measures how well the model avoids false alarms when predicting accident severity. A precision of 0.64 suggests that 64% of all predictions made by the model across severity classes in unseen Victorian traffic accident data were correct and not false positives.

- **Recall: 0.67**

Recall reflects the model's ability to capture all actual positive cases (true positives). For this project, a recall of 0.67 means the model successfully classified 67% of all actual accident severity levels in unseen Victorian traffic accident data.

- **F1-Score: 0.64**

A F1- score of 0.64 indicates the model maintains a fair balance between avoiding false positives and correctly classifying actual accident severities. Specifically, it reflects the model's effectiveness in managing the trade-off between precision (avoiding false alarms) and recall (capturing actual cases) for unseen Victorian traffic accidents.

Class Performance Metrics:

- **Other Injury (Class 0) – Precision: 0.70, Recall: 0.85, F1-Score: 0.77:**
  - The model excels in predicting Other Injury accidents, which is expected due to the class's prevalence in the dataset. High recall (85%) indicates that the

model captures the majority of actual Other Injury accidents, and with a precision of 70%, it correctly identifies Other Injury cases 70% of the time when making such predictions.

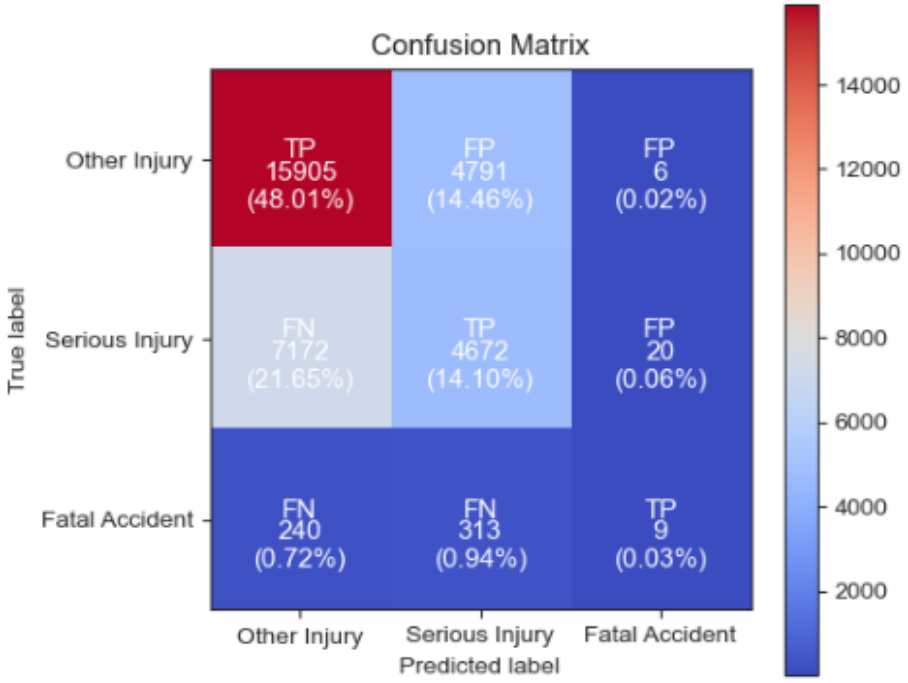
- **Serious Injury (Class 1) – Precision: 0.56, Recall: 0.38, F1-Score: 0.45:**
  - The model struggles with this class, as indicated by the low recall of 38%, meaning it identifies only 38% of actual Serious Injury accidents. Additionally, the precision of 0.56 shows that when the model predicts a Serious Injury accident, it is correct 56% of the time. Many Serious Injury accidents are misclassified as either Other Injury or Fatal Accident, limiting its effectiveness in identifying this critical category.
- **Fatal Accident (Class 2) – Precision: 0.28, Recall: 0.02, F1-Score: 0.03:**
  - Fatal accidents are the hardest for the model to predict, as evidenced by the very low recall and F1-score. The model identifies very few actual fatal accidents, highlighting a significant challenge in predicting rare, severe events – only 2% of actual fatal accidents are correctly identified (recall). Additionally, when the model predicts a fatal accident, it is correct only 28% of the time (precision).

Confusion Matrix Analysis:

- **Other Injury (Class 0):**
  - True Positives (TP): 17,553 (53% of the test dataset) – the model correctly classified 17,553 accidents as Other Injury, which constitutes the majority of true positives.
  - False Positives (FP): 3,141 – these are cases misclassified as Other Injury but belong to Serious Injury or Fatal Accident.
  - False Negatives (FN): 3149 – these are actual Other Injury cases that were misclassified as more severe accidents.
- **Serious Injury (Class 1):**
  - True Positives (TP): 4,539 (13.70% of the test dataset) – the model correctly identified 4,539 serious injuries.
  - False Positives (FP): 3,558 – these cases were incorrectly classified as Serious Injury but belonged to other categories.
  - False Negatives (FN): 7,325 (around 22% of the test dataset) – a large number of actual serious injuries were misclassified, indicating poor recall for this class.
- **Fatal Accident (Class 2):**
  - True Positives (TP): 9 (0.03% of the test dataset) – Only 9 fatal accidents were correctly identified, highlighting the model's significant struggle with this critical class.
  - False Positives (FP): 23 – these are non-fatal accidents wrongly classified as fatal
  - False Negatives (FN): 553 – A considerable number of fatal accidents were missed, which is a critical weakness for predicting severe outcomes.

```
#Supervised Machine Learning Algorithm: K-Nearest Neighbour(KNN)
knn = KNeighborsClassifier()
#Fitting the model with training data
knn.fit(X_train_sc, y_train)
#Evaluate the model on the testing data
evaluation(knn, X_train_sc, y_train, X_test_sc, y_test, train=False)
```

```
Test Result:
================================================
Accuracy Score: 62.14%
Precision: 0.60
Recall: 0.62
F1 Score: 0.61
________________________________________________
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.68      0.77      0.72     20702
           1       0.48      0.39      0.43     11864
           2       0.26      0.02      0.03       562

    accuracy                           0.62     33128
   macro avg       0.47      0.39      0.39     33128
weighted avg       0.60      0.62      0.61     33128

________________________________________________
```



KNN Model

Overall Performance Metrics:

- **Accuracy: 62.14%**

This suggest that 62.14% of accident severity levels in unseen Victorian traffic accident data were correctly predicted by the KNN model, suggesting moderate performance.

- **Precision: 0.60**

Precision of 0.60 indicates that 60% of all predictions made by the KNN model across severity classes in unseen Victorian traffic accident data were correct and not false positives.

- **Recall: 0.62**

The model identified 62% of all actual accident severity levels in unseen Victorian traffic accident data, showcasing fair recall performance.

- **F1-Score: 0.61**

An F1-score of 0.61 entails the model maintains a decent balance between precision and recall, reflecting its ability to manage the trade-off between avoiding false alarms and correctly identifying accident severities in unseen Victorian traffic accident data.

Class Performance Metrics:

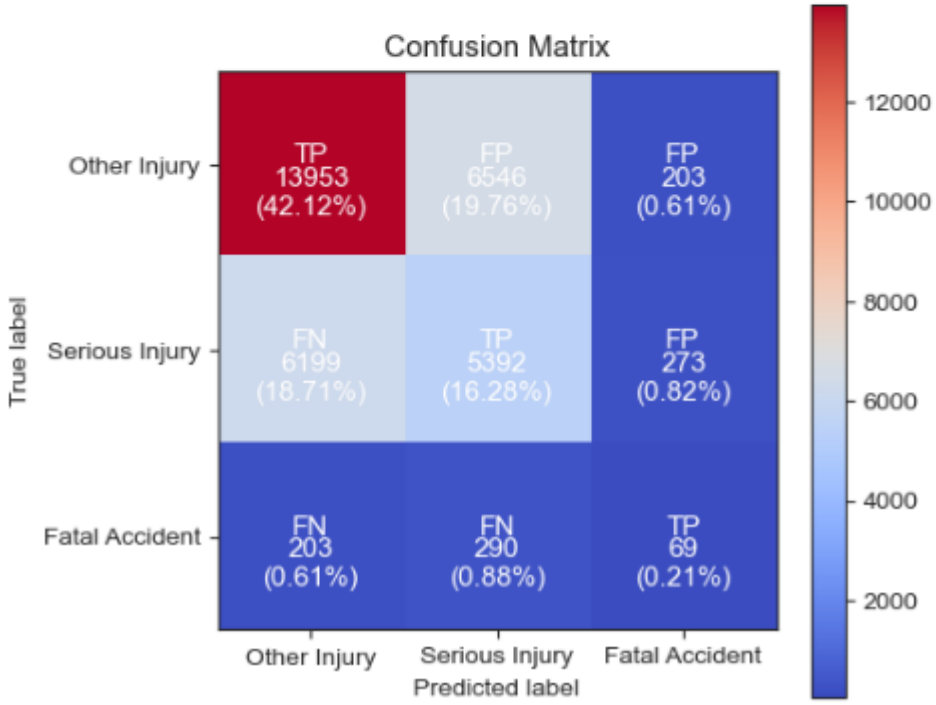
- **Other Injury (Class 0) – Precision: 0.68, Recall: 0.77, F1-Score: 0.72:**
  - The model performs relatively well in predicting Other Injury accidents, apprehending 77% of actual cases (recall) and correctly identifying Other Injury accidents 68% of the time when making such classifications (precision).
- **Serious Injury (Class 1) – Precision: 0.48, Recall: 0.39, F1-Score: 0.43:**
  - KNN has difficulties with this class, identifying only 39% of actual Serious Injury accidents (recall). When predicting Serious Injury accidents, it was correct 48% of the time (precision), reflecting challenges in effectively distinguishing this class from others.
- **Fatal Accident (Class 2) – Precision: 0.26, Recall: 0.02, F1-Score: 0.03:**
  - Fatal accidents remain the most challenging for the model, with only 2% of actual fatal accidents being identified (recall). Additionally, when predicting fatal accidents, the model was correct only 26% of the time (precision), highlighting significant difficulties in classifying these rare events.

Confusion Matrix Analysis:

- **Other Injury (Class 0):**
  - True Positives (TP): 15,905 (48.01% of the test dataset) – the model correctly classified 15,905 accidents as Other Injury.
  - False Positives (FP): 4,791 – these are cases misclassified as Other Injury but belong to Serious Injury or Fatal Accident.
  - False Negatives (FN): 4,797 – actual Other Injury cases misclassified as more severe accidents.
- **Serious Injury (Class 1):**
  - True Positives (TP): 4,672 (14.10% of the test dataset) – the model correctly identified 4,672 serious injuries.
  - False Positives (FP): 4,791 – these cases were incorrectly classified as Serious Injury but belonged to other categories.
  - False Negatives (FN): 7,192 (21.65% of the test dataset) – many actual serious injuries were misclassified, indicating poor recall for this class.
- **Fatal Accident (Class 2):**
  - True Positives (TP): 9 (0.03% of the test dataset) – only 9 fatal accidents were correctly identified.
  - False Positives (FP): 26 – these are non-fatal accidents wrongly classified as fatal.
  - False Negatives (FN): 553 – a substantial number of fatal accidents were missed, further demonstrating the model's struggles with predicting severe outcomes.

```
#Supervised Machine Learning Algorithm: Decision Tree Classifier
dt = DecisionTreeClassifier()
#Fitting the model with training data
dt.fit(X_train, y_train)
#Evaluate the model on the testing data
evaluation(dt, X_train, y_train, X_test, y_test, train=False)
```

```
Test Result:
======================================================
Accuracy Score: 58.60%
Precision: 0.59
Recall: 0.59
F1 Score: 0.59
______________________________________________________
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.69      0.67      0.68     20702
           1       0.44      0.45      0.45     11864
           2       0.13      0.12      0.12       562

    accuracy                           0.59     33128
   macro avg       0.42      0.42      0.42     33128
weighted avg       0.59      0.59      0.59     33128

______________________________________________________
```



Decision Tree Model

Overall Performance Metrics:

- **Accuracy: 58.60%**
Approximately 58.60% of accident severity levels in unseen Victorian traffic accident data were correctly predicted by the Decision Tree model, indicating average performance.

- **Precision: 0.59**
Precision of 0.59 suggests that 59% of all predictions made by the model across severity classes in unseen Victorian traffic accident data were correct and not false positives.

- **Recall: 0.59**
The model identified 59% of all actual accident severity levels in unseen Victorian traffic accident data, showcasing moderate recall performance.

- **F1-Score: 0.59**
An F1-score of 0.59 indicates the model struggles to balance avoiding false positives and correctly classifying actual accident severities, reflecting limited effectiveness for unseen Victorian traffic accidents.

Class Performance Metrics:

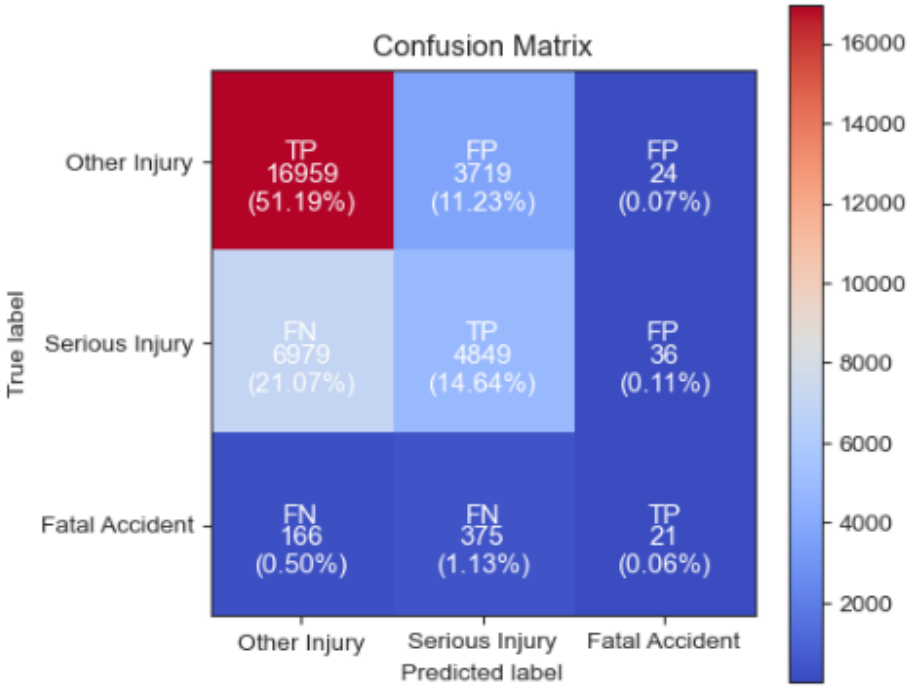
- **Other Injury (Class 0) – Precision: 0.69, Recall: 0.67, F1-Score: 0.68:**
  - The model performs adequately in predicting Other Injury accidents. It captures 67% of actual Other Injury cases (recall) and correctly identifies Other Injury accidents 69% of the time when making such predictions (precision).
- **Serious Injury (Class 1) – Precision: 0.44, Recall: 0.45, F1-Score: 0.45:**
  - The model struggles with this class, correctly identifying only 45% of Serious Injury accidents (recall). Additionally, when predicting Serious Injury, it is correct 44% of the time (precision), indicating significant misclassification within this category.
- **Fatal Accident (Class 2) – Precision: 0.13, Recall: 0.12, F1-Score: 0.12:**
  - Fatal accidents remain the most challenging to predict. Only 12% of actual fatal accidents were identified (recall), and when predicting fatal accidents, the model was correct only 13% of the time (precision), highlighting considerable difficulty in classifying these rare but critical cases.

Confusion Matrix Analysis:

- **Other Injury (Class 0):**
  - True Positives (TP): 13,953 (42.12% of the test dataset) – the model correctly classified 13,953 accidents as Other Injury.
  - False Positives (FP): 6,546 – these are cases misclassified as Other Injury but belong to Serious Injury or Fatal Accident.
  - False Negatives (FN): 6,749 – actual Other Injury cases misclassified as more severe accidents.
- **Serious Injury (Class 1):**
  - True Positives (TP): 5,392 (16.28% of the test dataset) – the model correctly identified 5,392 serious injuries.
  - False Positives (FP): 6,546 – these cases were incorrectly classified as Serious Injury but belonged to other categories.
  - False Negatives (FN): 6,472 – a large number of actual serious injuries were misclassified, indicating poor recall for this class.
- **Fatal Accident (Class 2):**
  - True Positives (TP): 69 (0.21% of the test dataset) – only 69 fatal accidents were correctly identified.
  - False Positives (FP): 476 – non-fatal accidents wrongly classified as fatal.
  - False Negatives (FN): 493 – a significant number of fatal accidents were missed, emphasizing the model's limitations in predicting severe outcomes.

```
#Supervised Machine Learning Algorithm: Random Forest Classifier
rfc = RandomForestClassifier()
#Fitting the model with training data
rfc.fit(X_train, y_train)
#Evaluate the model on the testing data
evaluation(rfc, X_train, y_train, X_test, y_test, train=False)
```

```
Test Result:
================================================
Accuracy Score: 65.89%
Precision: 0.64
Recall: 0.66
F1 Score: 0.64
________________________________________________
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.70      0.82      0.76     20702
           1       0.54      0.41      0.47     11864
           2       0.26      0.04      0.07       562

    accuracy                           0.66     33128
   macro avg       0.50      0.42      0.43     33128
weighted avg       0.64      0.66      0.64     33128

________________________________________________
```



Random Forest Model

Overall Performance Metrics:

- **Accuracy: 65.89%**

The model correctly predicted the severity level of approximately 65.89% of accidents in unseen Victorian traffic accident data. This is a reasonable level of performance, aligning closely with the Logistic Regression model.

- **Precision: 0.64**

A precision score of 0.64 highlights that 64% of all classifications made in unseen Victorian traffic accident data by the model across all severity classes were correct and not false positives, indicating a fair ability to distinguish between classes.

- **Recall: 0.66**

The model caught 66% of all actual accident severity levels in unseen Victorian traffic accident data, demonstrating decent recall performance.

- **F1-Score: 0.64**

The F1-score of 0.64 highlights the model's ability to balance avoiding false positives and correctly identifying actual accident severities, maintaining a fair trade-off for unseen Victorian traffic accidents.

Class Performance Metrics:

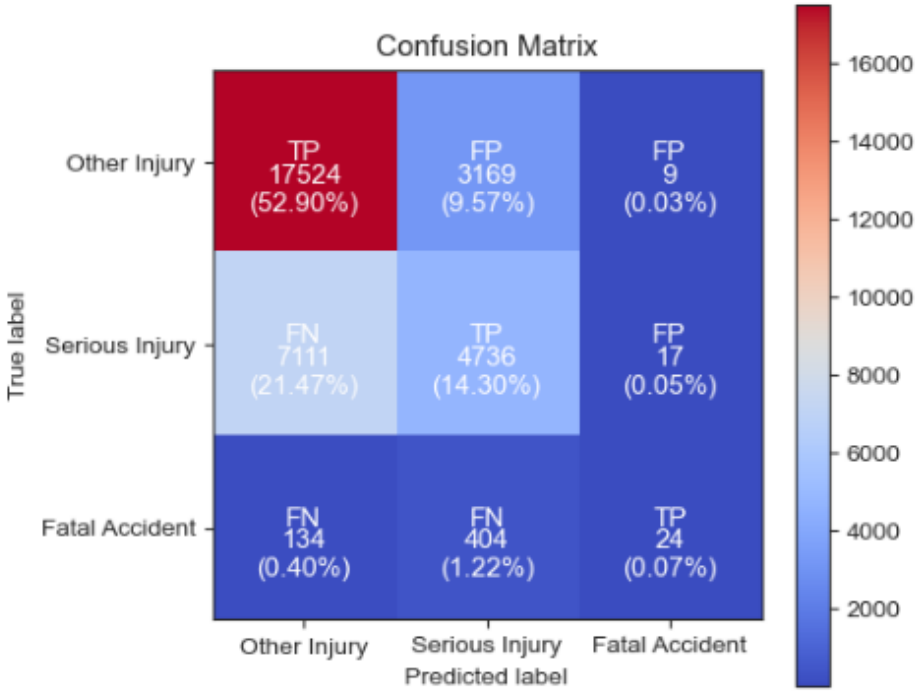
- **Other Injury (Class 0) – Precision: 0.70, Recall: 0.82, F1-Score: 0.76:**
  - The model shows strong performance in identifying Other Injury accidents. With a recall of 82%, the majority of actual Other Injury cases are correctly detected, and a precision of 70% indicates that when Other Injury is predicted, it is correct 70% of the time.
- **Serious Injury (Class 1) – Precision: 0.54, Recall: 0.41, F1-Score: 0.47:**
  - Predictions for Serious Injury reveal some difficulty. The model captures only 41% of actual Serious Injury cases (recall), and when it predicts this class, it is correct in 54% of instances (precision). This highlights a limitation in distinguishing Serious Injury from other classes.
- **Fatal Accident (Class 2) – Precision: 0.26, Recall: 0.04, F1-Score: 0.07:**
  - Fatal accidents remain challenging to predict. Only 4% of actual fatal accidents were identified, and when predicting fatal accidents, the model was correct 26% of the time.

Confusion Matrix Analysis:

- **Other Injury (Class 0):**
  - True Positives (TP): 16,959 (51.19%) – correctly classified as Other Injury.
  - False Positives (FP): 3,719 – misclassified as Other Injury but actually belongs to Serious Injury or Fatal Accident.
  - False Negatives (FN): 3,743 – actual Other Injury cases misclassified as more severe accidents.
- **Serious Injury (Class 1):**
  - True Positives (TP): 4,849 (14.64%) – correctly identified as Serious Injury.
  - False Positives (FP): 3,755 – misclassified as Serious Injury but belongs to other classes.
  - False Negatives (FN): 6,979 – misclassified as less severe accidents.
- **Fatal Accident (Class 2):**
  - True Positives (TP): 21 (0.06%) – correctly classified as Fatal Accident.
  - False Positives (FP): 60 – non-fatal accidents classified as Fatal Accident.
  - False Negatives (FN): 541 – a substantial number of fatal accidents missed.

```
#Supervised Machine Learning Algorithm: XGBoost Classifier
xgb = XGBClassifier(eval_metric='logloss', random_state=42)
#Fitting the model with training data
xgb.fit(X_train, y_train)
#Evaluate the model on the testing data
evaluation(xgb, X_train, y_train, X_test, y_test, train=False)
```

```
Test Result:
============================================================
Accuracy Score: 67.27%
Precision: 0.65
Recall: 0.67
F1 Score: 0.65
____________________________________________________________
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.71      0.85      0.77     20702
           1       0.57      0.40      0.47     11864
           2       0.48      0.04      0.08       562

    accuracy                           0.67     33128
   macro avg       0.59      0.43      0.44     33128
weighted avg       0.65      0.67      0.65     33128

____________________________________________________________
```



XGBoost Model

Overall Performance Metrics:

- **Accuracy: 67.27%**

The model achieved an accuracy of 67.27%, meaning it correctly classified nearly two-thirds of accident severity levels in unseen Victorian traffic accident data, showing the best performance among the models tested.

- **Precision: 0.65**

Precision of 0.65 indicates that 65% of all severity predictions made were correct and not false positives, showing the model moderately limits false alarms.

- **Recall: 0.67**

The model encapsulated 67% of actual accident severity levels in unseen Victorian traffic accident data, highlighting its ability to identify a considerable portion of actual cases.

- **F1-Score: 0.65**

An F1-score of 0.65 reflects a solid balance between precision and recall, meaning the model is effectively managing the trade-off between avoiding false positives and correctly classifying actual accident severities for unseen Victorian traffic accident data.

Class Performance Metrics:

- **Other Injury (Class 0) – Precision: 0.71, Recall: 0.85, F1-Score: 0.77:**
  - This class is well-predicted, with a recall of 85%, meaning the model identifies most Other Injury cases, and precision of 71%, correctly classifying them in 71% of cases.
- **Serious Injury (Class 1) – Precision: 0.57, Recall: 0.40, F1-Score: 0.47:**
  - Serious Injury predictions were less effective, with the model identifying only 40% of actual cases (recall). Additionally, 57% of Serious Injury predictions were correct (precision), with many misclassified into other categories.
- **Fatal Accident (Class 2) – Precision: 0.48, Recall: 0.04, F1-Score: 0.08:**
  - Fatal Accidents remain difficult, with only 4% of actual cases identified. Precision of 48% shows improvement in avoiding false alarms but highlights severe struggles in reliably predicting this rare class.

Confusion Matrix Analysis:

- **Other Injury (Class 0):**
  - **True Positives (TP):** 17,524 (52.90%) – correctly identified as Other Injury.
  - **False Positives (FP):** 3,169 – misclassified as Other Injury but belongs to Serious Injury or Fatal Accident.
  - **False Negatives (FN):** 3,178 – actual Other Injury cases misclassified.
- **Serious Injury (Class 1):**
  - **True Positives (TP):** 4,736 (14.30%) – correctly identified as Serious Injury.
  - **False Positives (FP):** 3,186 – misclassified as Serious Injury.
  - **False Negatives (FN):** 7,128 – many Serious Injury cases misclassified as Other Injury or Fatal Accident.
- **Fatal Accident (Class 2):**
  - **True Positives (TP):** 24 (0.07%) – correctly classified as Fatal Accident.
  - **False Positives (FP):** 50 – non-fatal accidents misclassified as Fatal Accident.
  - **False Negatives (FN):** 538 – many fatal accidents were misclassified as less severe.

	Test Accuracy	Test Precision	Test Recall	Test F1 Score
Logistic Regression	66.71	64.43	66.71	64.34
K-Nearest Neighbors	62.14	60.18	62.14	60.67
Decision Tree	58.60	58.84	58.60	58.72
Random Forest	65.89	63.82	65.89	64.11
XGBoost	67.27	65.44	67.27	65.12

The table above summarizes the performance metrics for five supervised machine learning algorithms applied to predict traffic accident severity in Victoria. Each model was evaluated on Test Accuracy, Precision, Recall, and F1 Score using weighted averages to account for the class imbalance in the target feature, SEVERITY. Currently, before hyperparameter tuning, XGBoost is the best performing model; achieving the highest test scores across all metrics, with 67.27% accuracy, 65.44% precision, 67.27% recall, and an F1 score of 65.12%. These scores indicate that XGBoost maintains a better balance between correctly predicting severity classes and avoiding false alarms compared to the other models. Its ability to handle complex, non-linear relationships and manage imbalanced datasets through gradient boosting makes it the most suitable algorithm for this task currently.

Weighted averages were used for precision, recall, and F1 score instead of macro averages due to the highly imbalanced target class: Other Injury (Class 0) significantly dominates with 20,702 instances. Serious Injury (Class 1) and Fatal Accident (Class 2) are minority classes, with much lower support counts of 11,864 and 562, respectively. Macro averages treat all classes equally, resulting in low overall scores due to poor model performance on minority classes (Serious Injury and Fatal Accident). This skews the evaluation; Serious Injury and Fatal Accident classes have poor recall and precision, pulling macro scores down vastly. In contrast, weighted averages account for class prevalence, yielding a more realistic and fair representation of model performance in this imbalanced scenario.

Despite decent scores, these results highlight the challenges of predicting accident severity:

Low Feature Association with SEVERITY:

- Numerical features show minimal correlation with the target variable.
- Categorical features also have weak associations (relatively low Cramér's V values), limiting their predictive utility.

Class Imbalance:

- Other Injury constitutes a large majority of the dataset, while minority classes, especially Fatal Accident, are hard to predict accurately due to their rarity.

High Dimensionality and Complexity:

- The dataset contains numerous features, some with complex interdependencies.
- Accident severity prediction is inherently non-linear and difficult, as it depends on a multitude of interacting variables.

These results serve as a strong baseline. Next, we will focus on hyperparameter tuning to optimize each model's performance. This process will involve adjusting parameters to better handle the dataset's complexity and imbalances, potentially improving precision, recall, and F1 scores—especially for minority classes like Fatal Accident.

Hyperparameter Tuning

Hyperparameter tuning is a crucial step in optimizing machine learning models, involving the adjustment of parameters that govern the learning process to achieve the best performance. Initially, I attempted to use RandomizedSearchCV from sklearn for automated hyperparameter tuning. However, even with reduced parameters and minimal iterations to speed up the process, the execution times were extremely long. For instance, after 30 minutes of execution on Logistic Regression, the verbose output hadn't even updated, let alone completed. This delay is largely attributed to the sheer size and complexity of the dataset, which significantly increases the computational burden during cross-validation. Given the time constraints and the need for efficiency, manual hyperparameter tuning emerged as the most viable alternative. This approach involves systematically testing different hyperparameter values based on domain knowledge, observed performance trends, and model requirements. For instance, in Logistic Regression, we tweaked the C parameter for regularization strength and switched solvers (saga). In KNN, we optimized the number of neighbors (n_neighbors) and the distance metric (p). For Decision Tree, we adjusted the max_depth to control the complexity of the tree and prevent overfitting. In Random Forest, we modified the number of trees (n_estimators) to enhance model stability and generalization. Similarly, for XGBoost, parameters like n_estimators, max_depth, and learning_rate were fine-tuned to improve learning efficiency and generalization. By directly controlling these parameters, we ensured the models were refined efficiently without excessive computational overhead, allowing for quicker iterations and better performance outcomes.

To streamline the presentation of hyperparameter tuning results, I opted for a concise summary format rather than detailing each tuned model individually, as done earlier for pre-tuned models. Given the time constraints and the redundancy of repeating the process for all five models, I provided a summarized, color-coded table displaying the performance metrics (Test Accuracy, Test Precision, Test Recall, and Test F1 Score) after manual hyperparameter tuning. This approach ensures clarity and conciseness, while still highlighting the improvements achieved through tuning. The table allows for an efficient comparison across tuned models, offering a comprehensive yet simplified view of their performance post-optimization.

	Test Accuracy	Test Precision	Test Recall	Test F1 Score
Tuned Logistic Regression	66.71	64.43	66.71	64.34
Tuned K-Nearest Neighbors	64.14	61.21	64.14	61.45
Tuned Decision Tree	65.74	63.24	65.74	62.62
Tuned Random Forest	66.06	63.98	66.06	64.28
Tuned XGBoost	67.29	65.37	67.29	65.23

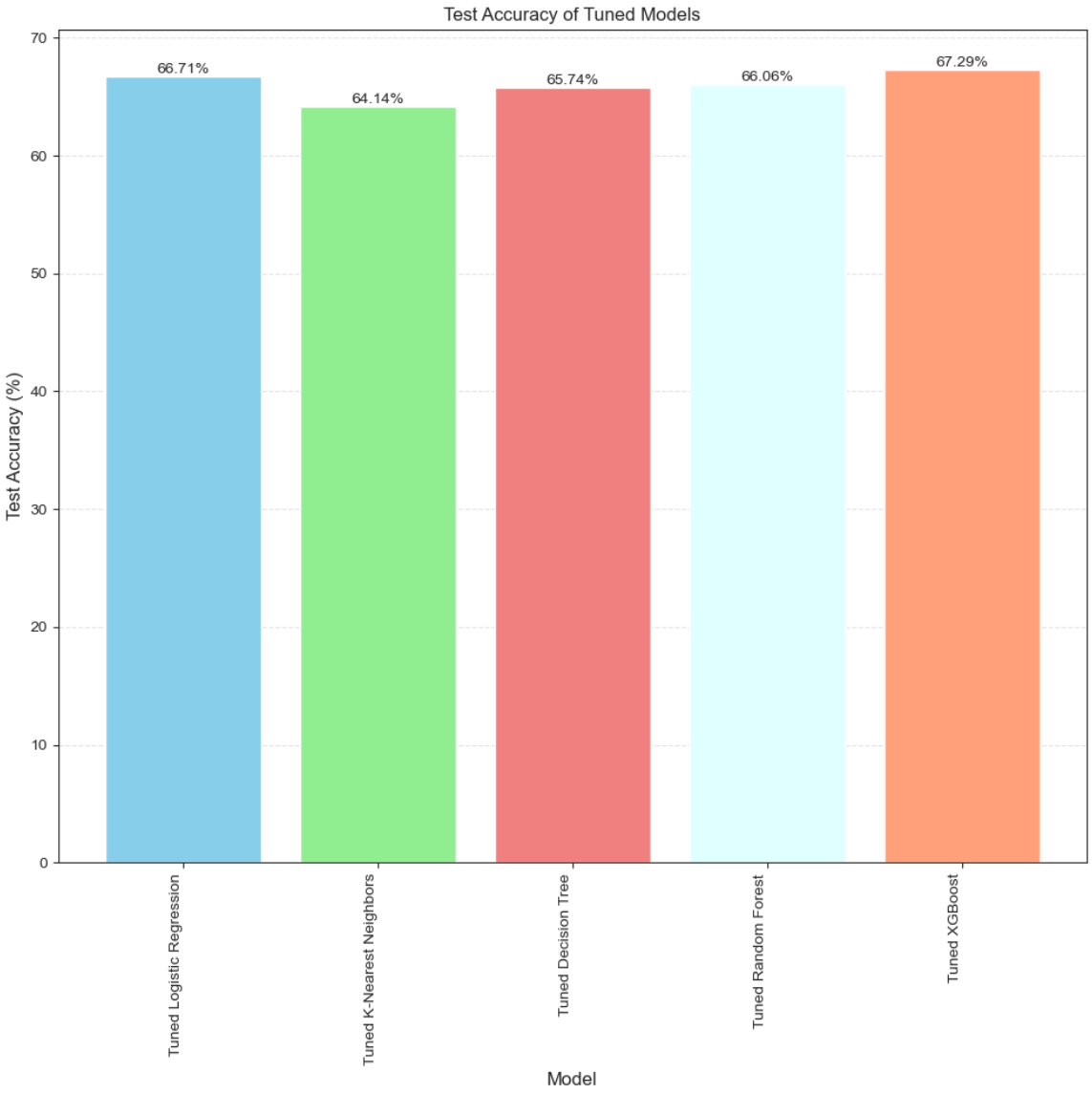
The hyperparameter tuning process significantly improved the performance of multiple models, as evidenced by the comparison between pre-tuned and tuned test summary tables. The model that benefited the most from tuning was the Decision Tree model, which saw noticeable increases across all metrics, particularly in Test Accuracy (from 58.60% to 65.74%) and Test F1 Score (from 58.72 to 62.62%). This demonstrates that manual hyperparameter adjustments have effectively reduced overfitting and enhanced the model's ability to generalize on unseen Victorian traffic accident data.

Post-tuning, the XGBoost model remained the best-performing model overall, achieving the highest scores in all evaluation metrics: Test Accuracy (67.29%), Test Precision (65.37%), Test Recall (67.29%), and Test F1 Score (65.23). These improvements further solidify XGBoost as the most optimal model for forecasting road accident SEVERITY in Victoria.

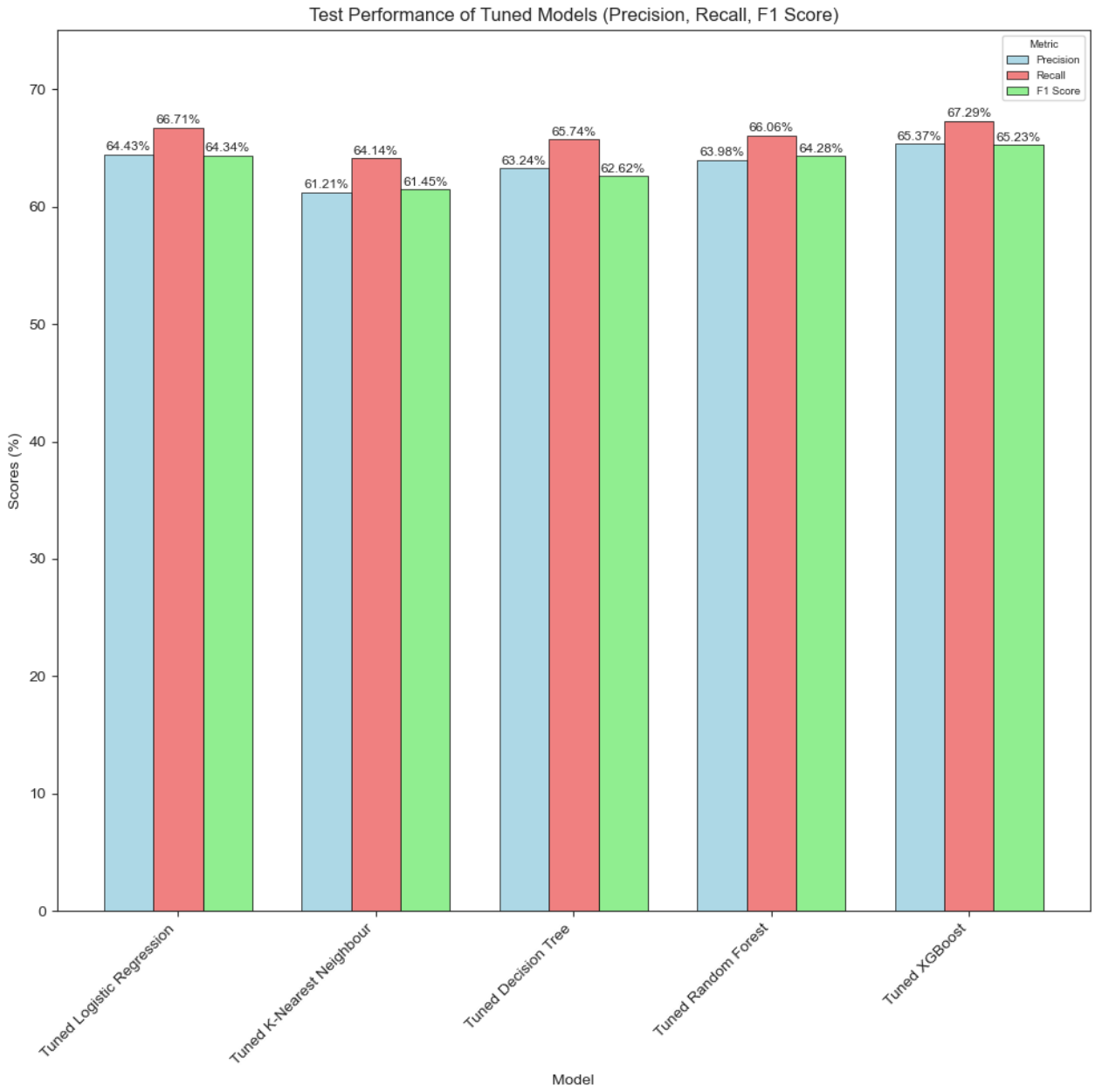
In the context of this project, Recall is the most critical metric, as it reflects the model's ability to correctly identify actual accident severities, especially serious and fatal accidents. Missing these cases could lead to significant underestimation of risks in high-severity areas, hindering preventative measures. Precision is the second most important metric, as it helps minimize false alarms, ensuring that when the model predicts a severe accident, it is likely correct. XGBoost excels in both these metrics, boasting the highest recall (67.29%) and precision (65.37%) among all tuned models, making it a reliable tool for real-world deployment.

Given XGBoost's superior performance across key metrics, it is recommended for deployment in predicting accident SEVERITY in Victoria. This model not only excels in overall accuracy but also demonstrates a robust ability to minimize false negatives (crucial for serious and fatal accident detection) while keeping false positives relatively low. Its advanced ensemble-based approach ensures resilience against data imbalance and complex feature interactions, aligning well with the project's objectives of improving road safety and mitigating severe accidents. Ultimately, hyperparameter tuning highlighted the importance of model refinement in improving performance, especially when working with real-world data challenges such as imbalanced classes, high-dimensionality, and non-linear relationships. XGBoost stands out as the most reliable tool to support data-driven decision-making in Victoria's road safety strategy.

RESULTS ANALYSIS

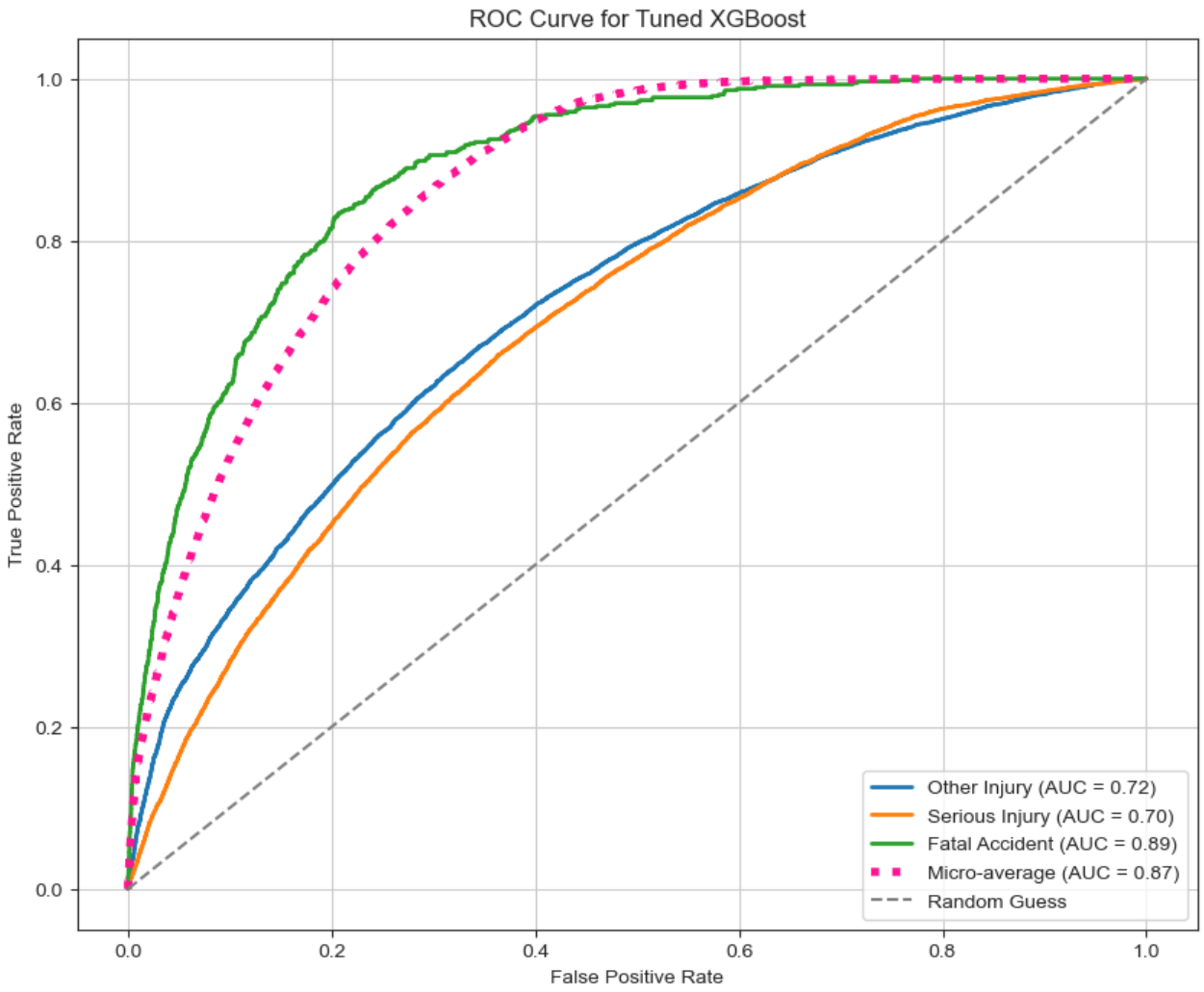


The bar plot illustrates the test accuracy of five manually tuned models, with XGBoost achieving the highest accuracy at 67.29%, making it the best-performing model for predicting accident severity in unseen Victorian traffic accident data. Logistic Regression and Random Forest followed closely with accuracies of 66.71% and 66.06%, respectively, showcasing their effectiveness despite the dataset's complexity. Decision Tree and K-Nearest Neighbors (KNN) improved after tuning, reaching 65.74% and 64.14% but lagged behind due to limitations in handling high-dimensional and imbalanced data. XGBoost's strong performance, especially in capturing both linear and non-linear patterns, makes it the most suitable model for deployment in forecasting accident severity, supporting data-driven road safety measures in Victoria.



This grouped bar plot highlights the test performance of manually tuned models across Precision, Recall, and F1 Score, key metrics for evaluating accident severity prediction in Victoria. Among the models, Tuned XGBoost emerges as the best performer, achieving the highest scores in Precision (65.37%), Recall (67.29%), and F1 Score (65.23%). This makes it the most reliable model for accurately predicting severe accidents while minimizing false predictions. Logistic Regression and Random Forest follow closely, with strong Recall and balanced Precision-F1 scores, making them viable alternatives. Decision Tree shows significant improvement after tuning but lacks the stability of ensemble models, while K-Nearest Neighbors underperforms due to its sensitivity to high-dimensional data and imbalanced classes. Overall, again the tuned XGBoost model is recommended for

deployment, given its superior ability to capture and forecast severe accidents, a critical requirement for improving road safety in Victoria.



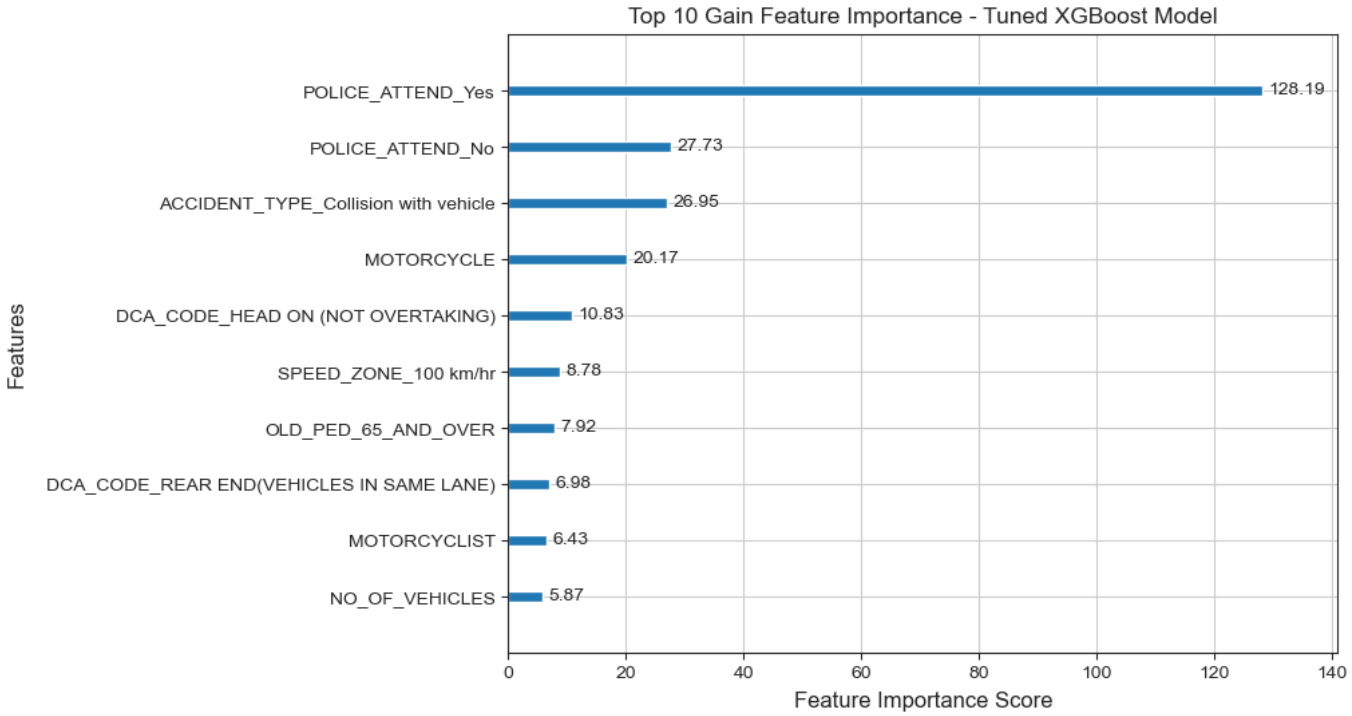
The ROC Curve (Receiver Operating Characteristic) is a graphical representation of the True Positive Rate (TPR or Recall) against the False Positive Rate (FPR) at various classification thresholds. TPR measures the proportion of actual positive cases correctly identified by the model, indicating its ability to capture positive outcomes (e.g., serious or fatal accidents). In contrast, FPR measures the proportion of actual negative cases incorrectly classified as positive, reflecting how often the model falsely signals severe accidents. The AUC (Area Under the Curve) assesses the overall performance of the classifier. A perfect classifier would have an AUC of 1, while an AUC of 0.5 suggests no better performance than random guessing. In essence, the aim is to have the ROC curve as near as possible to the upper-left corner of the plot, signifying a high TPR and low FPR, and an AUC score close to 1, highlighting excellent classification performance.

For multi-class problems, the AUC is computed per class:

- **SEVERITY Class-Specific AUC Scores**:
    - **Other Injury** (AUC = 0.72)
    - **Serious Injury** (AUC = 0.70)
    - **Fatal Accident** (AUC = 0.89)
- **Micro-Average AUC**: Combines the performance of all classes, yielding an AUC of 0.87, reflecting the model's overall capability to distinguish between accident severity levels – very strong overall predictive capability.

While ROC curves were plotted for all models, only the Tuned XGBoost model is shown here due to its superior performance and importance. XGBoost outperformed all other models, achieving the highest AUC scores across all severity classes and the best micro-average AUC (0.87), indicating its superior overall performance in distinguishing between Other Injury, Serious Injury, and Fatal Accident cases. These results reinforce XGBoost's reliability as the best model for predicting accident severity. Its high AUC for Fatal Accident (0.89) is particularly crucial since this class represents the most severe and life-threatening outcomes. Correctly predicting fatal accidents allows authorities to prioritize interventions in high-risk areas, potentially saving lives. The micro-average AUC score of 0.87 reflects excellent overall model performance across the dataset, despite the inherent class imbalance (more Other Injury cases and fewer Fatal Accidents). This aligns with the project's goal to accurately predict severe accident outcomes, supporting Victoria's Road Safety Strategy 2021-2030 by identifying accident severity and targeting preventive actions towards high-risk scenarios.

Ultimately, the ROC curve reaffirms the Tuned XGBoost model as the most effective model, confirming its suitability for deployment in real-world scenarios where accurate and reliable accident severity prediction is essential for improving road safety and reducing severe outcomes on Victorian roads.



This bar plot highlights the top 10 features ranked by gain-based importance in the tuned XGBoost model, the best-performing model for predicting accident severity in our project. Gain quantifies the improvement in the model's accuracy when a specific feature is used to split the data at a decision node, making it a key metric for identifying the features with the greatest impact on the model's performance. The feature importance scores in the plot reflect each feature's relative contribution to predicting accident severity in Victoria. Higher scores indicate greater influence on the model's ability to predict accident severity accurately – making it a crucial metric for understanding which features have the greatest impact on the model's classifications on SEVERITY.

Key Insights:

1. **POLICE_ATTEND_Yes**:
    - This feature stands out as the most influential, with a significantly higher importance score of 128.19 compared to the other features.
    - This suggests that the presence of police at the scene of an accident provides critical information in predicting the severity of an accident; supplies the most valuable information for predicting the severity of unseen accidents in Victoria compared to all other features.
2. **POLICE_ATTEND_No**:

- The counterpart to the previous feature, this indicates situations where police were not present, with an importance score of 27.73.
- Together, these two features demonstrate the strong role of police attendance in accident severity classification.

3. **ACCIDENT_TYPE_Collision with vehicle**:
   - With a score of 26.95, this feature highlights the importance of the type of collision in determining the severity of an accident.
4. **MOTORCYCLE**:
   - This feature, with a score of 20.17, shows the impact of motorcycle involvement in severe accidents.
5. **DCA_CODE_HEAD ON (NOT OVERTAKING)**:
   - This specific accident type also has significant predictive power, scoring 10.83, emphasizing the severity of head-on collisions.
6. **SPEED_ZONE_100 km/hr**:
   - High-speed zones are associated with severe accidents, as indicated by their importance score of 8.78.
7. **OLD_PED_65_AND_OVER**:
   - This feature (7.92) reflects the vulnerability of older pedestrians in traffic accidents, contributing significantly to severity prediction.
8. **DCA_CODE_REAR END (VEHICLES IN SAME LANE)**:
   - Rear-end collisions have a score of 6.98, highlighting their role in predicting less severe accidents.
9. **MOTORCYCLIST**:
   - Related to motorcycle involvement, this feature (6.42) supports the critical nature of motorcycle accidents in severity classification.
10. **NO_OF_VEHICLES**:
    - The number of vehicles involved in an accident (5.87) is also a crucial factor in predicting accident severity.

Essentially, this plot provides valuable insights into the factors that most strongly influence the prediction of accident severity in Victoria according to our best performing

model (Tuned XGBoost). Understanding these key features allows for targeted strategies, supporting data-based recommendations to enhance road safety and aligning with the project's goal of reducing accident severity through actionable insights.

DATA-DRIVEN RECOMMENDATIONS

Based on the comprehensive actionable insights gained through Exploratory Data Analysis, Modelling, and Results Analysis, the following actionable recommendations have been developed to support Victoria's Road Safety Strategy 2021-2030. These recommendations are aligned with the project's goal to mitigate severe traffic accidents, reduce fatalities, and enhance road safety through data-driven strategies.

Improved Road Safety:

- **Identified Hotspots**
    - **Recommendation**: Prioritize interventions in high-risk areas such as Melbourne's urban regions, major arterial roads (e.g., Princes Highway), and identified clusters with high accident frequencies.
    - **Justification**: Geospatial analysis highlights urban Melbourne as a major accident hotspot, while rural highways show higher concentrations of severe and fatal accidents.

- **Predictive Insights**
    - **Recommendation:** Deploy predictive models, particularly the tuned XGBoost model, to forecast accident severity based on key features such as speed zones, atmospheric conditions, and vehicle types.
    - **Justification**: The model's high recall and precision can identify potential severe accidents, enabling proactive safety measures in high-risk scenarios (e.g., 100 km/h speed zones).

- **Guided Infrastructure Improvements**
    - **Recommendation**: Implement targeted road safety improvements such as better lighting in dark areas without streetlights, enhanced road markings, and increased signage in high-speed zones and areas with frequent rear-end and head-on collisions.

- **Justification**: Features such as *LIGHT_CONDITION* and *SPEED_ZONE* have a strong influence on accident severity, highlighting infrastructure deficits that contribute to severe outcomes.

- **Accident Type-Specific Interventions**

  - **Recommendation**: Introduce tailored interventions for specific accident types, such as additional rumble strips for head-on collisions or advanced driver-assistance systems (ADAS) for rear-end collision prevention.
  - **Justification**: Insights show that head-on collisions and rear-end accidents (DCA_CODE) are prevalent and severe, particularly on rural highways and urban arterials.

- **Motorcycle Safety Enhancements**

  - **Recommendation**: Develop motorcycle-specific safety programs, including advanced rider training, dedicated motorcycle lanes, and increased enforcement of helmet and speed regulations.
  - **Justification**: Motorcycles significantly contribute to severe and fatal accidents, as reflected in the feature importance of MOTORCYCLE and MOTORCYCLIST.

Resource Allocation:

- **Efficient Use of Funds**

  - **Recommendation**: Allocate funds to regions and road types with the highest severity ratios, focusing on undivided roads, rural highways, and intersections with no traffic control.
  - **Justification**: These locations show disproportionately high rates of serious injury and fatal accidents, offering the highest potential return on investment in safety improvements.

- **Emergency Response Planning**

  - **Recommendation:** Optimize the placement of emergency services, focusing on areas with high accident frequencies and serious injury ratios.
  - **Justification:** Insights into police-attended accidents and severity predictions highlight areas where faster response times could save lives and reduce injury severity.

- **Resource Allocation Optimization**

- **Recommendation**: Use the XGBoost model's predictions to prioritize resource deployment during peak accident times, such as weekends and evenings.
- **Justification**: Data shows Friday and high-traffic periods have increased accident rates, allowing for proactive resource deployment.

Policy and Decision-Making:

- **Policy Development**

  - **Recommendation**: Introduce stricter regulations for high-risk scenarios, such as enforcing lower speed limits in rural and urban high-speed zones or requiring advanced safety features in vehicles used on high-speed roads.
  - **Justification:** The *SPEED_ZONE* and *VEHICLE_TYPE* features demonstrate a strong correlation with accident severity, indicating areas where regulatory changes could significantly reduce risk.

- **Regulatory Improvements**

  - **Recommendation:** Implement mandatory safety audits for undivided roads and intersections with no traffic control, along with stricter penalties for unlicensed drivers and those involved in alcohol-related accidents.
  - **Justification**: Features such as *UNLICENSED* and *ALCOHOL* reveal the increased risk associated with these factors, supporting the need for enhanced regulation.

- **Predictive Insights**

  - **Recommendation**: Integrate predictive modelling into policy planning to forecast and mitigate future accident risks based on current trends.
  - **Justification:** The model's ability to predict severe accidents provides policymakers with data-driven insights for proactive decision-making.

- **Regulations for Vulnerable Populations**

  - **Recommendation**: Establish stricter protections for vulnerable road users, including older pedestrians (OLD_PED_65_AND_OVER) and cyclists. This could involve longer pedestrian crossing times and safer cycling infrastructure.
  - **Justification**: Older pedestrians and cyclists are disproportionately involved in severe accidents.

Public Awareness and Education:

- **Community Engagement**

- **Recommendation**: Launch community-driven safety initiatives in identified accident hotspots, encouraging local residents to contribute to road safety improvements.
- **Justification:** Community awareness and participation can address localized issues such as poor lighting or road maintenance, which might not be captured in broader analysis.

- **Targeted Awareness Campaigns**

  - **Recommendation**: Develop educational campaigns targeting high-risk behaviours, such as speeding in 100 km/h zones, driving under the influence, and unlicensed driving.
  - **Justification:** Features like *SPEED_ZONE* and *ALCOHOL* emphasize the need to address specific behaviours contributing to severe accidents.

- **Targeted Campaigns for High-Risk Demographics**

  - **Recommendation**: Create targeted campaigns addressing specific high-risk groups, such as young male drivers and older pedestrians, focusing on the unique risks they face.
  - **Justification**: Male drivers and older pedestrians exhibit higher rates of severe accidents, underscoring the need for focused awareness efforts.

- **Alcohol and Substance Awareness**

  - **Recommendation**: Strengthen awareness programs around the dangers of driving under the influence, focusing on the severe outcomes highlighted in alcohol-related accidents.
  - **Justification**: The ALCOHOL feature emphasizes the significantly higher severity in alcohol-related incidents.

Enhanced Urban Planning:

- **Infrastructure Development**

  - **Recommendation**: Prioritize infrastructure investments in urban and suburban areas with high accident frequencies, such as Melbourne and its surrounding regions, focusing on improving road conditions and expanding public transport options.
  - **Justification:** Urban areas see the highest accident rates, and investments here can significantly enhance safety and traffic flow.

- **Traffic Management**
    - **Recommendation**: Deploy dynamic traffic control systems, such as adaptive traffic lights and real-time speed monitoring, in high-risk intersections and high-speed zones.
    - **Justification**: Traffic control features highlight the importance of regulating flow in areas without formal controls, reducing the likelihood of severe collisions.

- **Road Geometry Enhancements**
    - **Recommendation**: Modify road geometries in high-risk areas (e.g., non-intersections and curves) to include safety features like guardrails, widened lanes, and improved road surfacing.
    - **Justification**: ROAD_GEOMETRY insights show that non-intersections often experience severe accidents.

- **Public Transport Integration**
    - **Recommendation**: Encourage public transport usage by improving safety on routes heavily used by public transport vehicles.
    - **Justification**: Accidents involving public transport vehicles show higher severity, suggesting a focus on these routes could enhance overall safety.

These data-driven recommendations, grounded in thorough analysis, aim to significantly enhance road safety in Victoria. By focusing on high-risk areas, optimizing resource allocation, and integrating predictive insights into policy and public awareness, these strategies align with Victoria's Road Safety Strategy 2021-2030, driving towards a future of safer roads and reduced accident severity.

CONCLUSION

This project aims to substantially enhance road safety in Victoria by leveraging advanced data analytics and machine learning techniques. Through a rigorous and systematic approach, we have harnessed the power of data to extract actionable insights from Victorian traffic accident data, ultimately driving data-driven recommendations to optimize road safety. The project began with comprehensive data collection from reputable sources such as VicRoads, the Victorian Government Data Directory, and Kaggle, resulting in a robust dataset covering over a decade of traffic accidents. Following this, data cleaning was meticulously conducted to address inconsistencies, outliers, and irrelevant features, ensuring high data integrity and reliability. Exploratory Data Analysis (EDA) revealed critical patterns and trends, identifying key contributors to traffic accidents, including environmental conditions, vehicle types, and human factors. This phase provided a deep understanding of accident characteristics, uncovering high-risk zones, vulnerable populations, and recurring accident types. Feature selection and engineering further refined the dataset by identifying the most influential features, optimizing it for machine learning models. The modelling phase employed various supervised learning algorithms, with the tuned XGBoost model emerging as the most accurate and reliable. This model demonstrated exceptional performance, achieving the highest recall and precision scores, critical for predicting severe accidents like serious injuries and fatalities. The insights derived from the Results Analysis informed targeted suggestions. Key factors such as police attendance, collision types, speed zones, and vulnerable road users played pivotal roles in predicting accident severity. These findings guided the development of data-driven recommendations, addressing infrastructure improvements, optimized resource allocation, regulatory enhancements, and public awareness campaigns. Ultimately, this project aligns with Victoria's Road Safety Strategy 2021-2030, supporting its mission to halve road fatalities by 2030 and eliminate them by 2050. The actionable recommendations derived from this analysis – ranging from predictive insights and hotspot identification to tailored policy changes hold the potential to significantly reduce severe accidents and fatalities. By implementing these strategies, Victoria can foster a safer road environment, saving lives and minimizing socio-economic impacts. In conclusion, this project demonstrates the transformative potential of data-driven decision-making in enhancing road safety. By systematically addressing each phase; data collection, data cleaning, EDA, feature selection/engineering, modelling, and results analysis – we have provided a robust framework for proactive, evidence-based road safety initiatives. This comprehensive approach ensures a meaningful impact on public health and safety, advancing towards a future of safer roads in Victoria.

While this project has delivered actionable insights and robust predictive models, several avenues exist for future exploration to further improve the outcomes:

1. **Advanced Hyperparameter Tuning:**
   Employing GridSearchCV for hyperparameter tuning could further optimize model performance. Though computationally intensive, this approach ensures the

exhaustive exploration of parameter combinations, potentially boosting predictive accuracy and recall rates, especially in complex models like XGBoost.

2. **Time-Series Analysis:**
   Incorporating a temporal component by analyzing the data through a time-series perspective could identify trends and seasonality in accident occurrences. This would support dynamic risk forecasting and more timely interventions.

3. **Broader Feature Integration:**
   Expanding the dataset by integrating additional features, such as driver behavior (e.g., phone usage) or vehicle-specific safety features (e.g., ADAS systems), could enhance the model's predictive capability.

4. **Real-Time Data Integration:**
   Leveraging real-time traffic and weather data could improve model accuracy for live accident severity forecasting. This would enable authorities to implement immediate safety measures, such as adjusting speed limits or deploying emergency services.

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