**Data Driven Road Safety Transformation-Canada**

A Holistic Approach to Detect Accidents and Predict Severity

**Group 1**

**Capstone Project**

Abigail Sunil Dsilva

Aesha Bhavanisinh Rathod

Ann babu Treeza

Srinivas Venuvanka

**Data Driven Road Safety Transformation-Canada**

Abigail Sunil Dsilva, Aesha Bhavanisinh Rathod, Ann Babu Treeza, Srinivas Venuvanka

**ABSTRACT**

*Traffic collisions remain a pressing public safety concern worldwide, consistently ranking as a leading cause of fatalities, particularly among children and young adults. This grim reality underscores a profound socio-economic impact, compelling a reevaluation of road safety strategies. Our comprehensive project, grounded in the analysis of Canada's National Collision Database (NCDB) and the deployment of advanced machine learning techniques, endeavors to align with Canada's vision of achieving the world’s safest roads by substantially mitigating collision injuries and fatalities.*

*In the first segment of our study, we meticulously analyzed collision data spanning from 2000 to 2020, sourced from the NCDB. Our methodical approach included extensive data cleaning, exploratory data analysis (EDA), and the application of machine learning models such as Random Forests to interpret complex datasets effectively. Through these techniques, we identified critical predictors of accident severity, such as collision configuration, road conditions, and safety device utilization. This phase of the project revealed surprising insights, including the prevalence of severe collisions in non-intersection areas lacking adequate traffic control, and a majority of fatal outcomes occurring under ostensibly normal weather conditions. Our findings challenge conventional wisdom on accident causation, emphasizing the often-overlooked influence of mundane factors on road safety.*

*Complementing our statistical analysis, the second part of our project employed a Convolutional Neural Network (CNN) model to detect accident occurrences from visual data. This innovative approach aimed to harness the capabilities of deep learning to identify accidents in real-time, particularly in remote areas where traditional monitoring systems might fail to recognize or report incidents promptly. The CNN model was trained on a diverse dataset of images depicting various traffic scenarios, achieving commendable accuracy in distinguishing between accident and non-accident scenes. This technology promises significant improvements in emergency response times and resource allocation, potentially saving lives by enabling quicker deployment of first responders to accident sites.*

*Both components of our project converge on a holistic strategy that not only anticipates and classifies the severity of accidents but also enhances proactive road safety measures. By integrating findings from both the Random Forest and CNN models, we propose a multifaceted approach to traffic safety that includes timely updates to road conditions, optimized deployment of traffic control measures, and targeted educational campaigns that address identified risks. Furthermore, we have deployed these models into a practical, interactive application using Flask, making our system accessible to traffic management bodies and emergency response teams in real-time. This deployment facilitates the immediate application of our findings and models in a user-friendly environment, enhancing the practical impact of our research.*

*Ultimately, our project contributes to the academic and practical domains of traffic management and road safety, offering evidence-based recommendations that could inform policy and infrastructure planning. With the dual application of Random Forest and CNN models, we demonstrate the power of a data-driven approach in crafting effective, responsive road safety strategies that prioritize human life and well-being. As we continue to refine our models and expand our analysis, we remain committed to the goal of transforming road safety in Canada and setting a benchmark for the world.*

***KEYWORDS****: Motor Vehicle Collisions, Road Safety, Data Analysis, NCDB, CNN, Random Forest, Machine Learning, Traffic Management, Emergency Response, Public Health, Flask Deployment.*

1. **INTRODUCTION**:

The analysis of road collision data in Canada is crucial, reflecting its significant socio-economic and personal impacts. In 2020 alone, the social cost of road collisions was estimated at $35.98 billion, constituting 1.92% of the GDP. This underscores the critical need for effective road safety strategies, as these incidents also impose a substantial financial burden on individuals, averaging $946.65 per capita and $1,334.00 per licensed driver. [1]

From 2000 to 2019, the staggering toll of road accidents included over 6.9 million incidents, resulting in nearly 47,000 fatalities and more than 3.6 million injuries. These statistics highlight the profound loss of human life, extensive suffering, and the immense economic burden placed on communities. Our project, "Data-Driven Road Safety Transformation," stems from this dire context, emphasizing the value of each life and the broad impact of road accidents on communities. [2]

Our analysis is anchored in the robust dataset provided by the National Collision Database (NCDB) [3] and is further informed by regional reports such as Manitoba's Traffic Collision Statistics Report. We have expanded our analysis to a national level, examining a wide range of variables from collision timings to weather conditions. Our objective is to uncover patterns and risk factors that contribute to these incidents at a granular level. The insights gained are intended to inform the development of targeted strategies aimed at reducing traffic collisions across Canada and enhancing overall road safety. [4]

Through our comprehensive analysis, we aim to identify conditions and times of high risk, informing the development of specific preventative strategies. Moreover, our project seeks to enhance the preparedness and efficiency of emergency response teams, including paramedics, firefighters, and police officers, through predictive modeling. This proactive approach is designed to ensure timely and effective medical care for victims, particularly during peak accident times. Additionally, by assessing road surface conditions and other environmental factors, we aim to provide actionable insights for necessary road infrastructure adjustments.

Our analysis has revealed critical insights into the demographics of accident involvement. Males are more frequently involved in these accidents than females, with 3.6 million male involvements compared to 2.8 million female. The age group most affected is those aged 21 to 30 years, experiencing 1.3 million cases, followed closely by the 31 to 40-year-old cohort. [5]

Temporal patterns also emerged, with the months of August and July recording the highest incidence of accidents, and April the lowest. Interestingly, most accidents occur during weekends and peak between the hours of 3 to 8 PM. Furthermore, a significant number of these incidents take place on straight and level roads, with fewer but still substantial occurrences on curved roads.

These findings underscore the necessity of tailoring our strategies to address the specific demographics, timings, and road conditions associated with higher accident risks. In response, our project is developing targeted interventions aimed at these high-risk groups and scenarios. By implementing these strategies, we aim to significantly reduce road accidents and enhance the safety and quality of life for all road users. In conclusion, our data-driven approach is dedicated to forging safer roads and fostering a more resilient emergency response system, thereby enhancing safety for all road users and reducing the overall impact of road accidents in Canada.

1. **METHODOLOGY**

Our methodology for the "Data-Driven Road Safety Transformation" project includes a comprehensive approach to analyze road traffic collisions in Canada using datasets from the National Collision Database (NCDB). We outline our methods across several stages, from data acquisition and preprocessing to in-depth analysis and visualization, followed by the application of advanced machine learning techniques.

**Data Acquisition:**

We collected 20 distinct datasets from the Canada Open Data Portal, spanning from 1999 to 2019. These datasets encompass all police-reported motor vehicle collisions on public roads in Canada, providing a broad spectrum of data related to fatal and injury collisions.

**Data Merging and Loading:**

We employed Python scripts to consolidate the datasets, using the pandas library to read and merge individual Excel files, ensuring a consistent year-wise distinction with a 'C\_YEAR' column. The unified dataset was saved in a CSV format for more efficient handling. Data analysis was enhanced with the use of Python libraries such as NumPy, matplotlib, seaborn, and tools like Google Colab for execution and data loading.

**Data Preprocessing:**

This stage involved the systematic renaming of columns for better clarity and handling null values in critical features. We replaced placeholder values with NaN or median values where appropriate and converted categorical data to numerical formats, adjusting data types to facilitate accurate statistical analysis.

**Data Cleaning and Transformation:**

Our focus was on transforming various features into more analyzable formats, such as extracting year information from string formats, converting categorical data to numerical values, and effectively managing outliers and missing values.

**Exploratory Data Analysis (EDA):**

Our EDA encompassed univariate, bivariate, and multivariate analyses using Python. We inspected data types, verified for null values, and performed a statistical summary to grasp the distribution and characteristics of the data. This included the use of histograms, line graphs, and bar graphs to visualize data distributions and relationships.

**Data Visualization:**

To enhance our analysis and provide interactive insights, we utilized Tableau alongside Python. We developed an interactive dashboard that allowed users to dynamically filter and explore data across different dimensions, such as time, vehicle type, weather conditions, and road surfaces, enabling a deeper understanding of the factors contributing to road traffic accidents.

**Interpretation and Validation:**

We conducted a detailed analysis of patterns and trends in road traffic collisions, leveraging our interactive dashboard to isolate the effects of individual factors and drawing comprehensive conclusions. Our findings were validated against established road safety research to ensure accuracy and relevance.

**Statistical Analysis and Insights:**

Our statistical analysis involved examining correlations, frequency distributions, and average values to derive meaningful insights, exploring relationships between variables like weather conditions, road surfaces, vehicle types, and collision configurations to understand the most prevalent scenarios leading to collisions.

**Machine Learning Models – Random Forest:**

We implemented a Random Forest classifier to analyze patterns and predict outcomes based on the refined dataset. This model helped identify significant predictors of collision severity and suggested areas where interventions could be most effective. Model tuning and validation ensured the robustness of our predictions.

**Machine Learning Models – CNN for Accident Detection:**

In the second phase of our project, we designed a Convolutional Neural Network (CNN) model to detect accidents from images. This model was trained on a curated dataset of traffic images, distinguishing between accident and non-accident scenarios with high accuracy. The CNN model's capability to process and analyze visual data in real-time provides a critical tool for immediate accident detection, especially in remote areas.

**Model Deployment using Flask:**

We deployed our machine learning models into a practical, user-friendly application using Flask. This web application allows real-time data processing and interaction, enabling traffic management authorities to access predictive insights and accident detections instantaneously.

**Integration and Practical Application:**

By integrating the insights from both the Random Forest and CNN models, we formulated a comprehensive approach to traffic safety. This integrated system not only predicts and classifies accident severity but also triggers alerts in real-time, enhancing the responsiveness of emergency services and potentially saving lives by reducing response times.

**A screenshot of a computer screen

Description automatically generated**This detailed methodology underscores our commitment to using a data-driven approach for enhancing road safety in Canada, leveraging cutting-edge technology and comprehensive data analysis to develop effective, evidence-based traffic safety strategies.

1. **DATA ANALYSIS**

From Fig 3.1, it's evident that there has been a total of 6,913,204 reported accidents between the year 2000 to 2019. This considerable number underlines the importance of road safety and accident prevention measures.

A key observation from fig 3.1 is the declining trend in the annual number of accidents. In 2000, there were 155.84K reported accidents, a number that gradually decreased to 108.60K by 2021. This decline of nearly 30% over two decades is significant and may suggest the positive impact of various road safety measures and policies implemented over the years. Two key factors contributing to Canada's success in road safety compared to the US include a preference for smaller vehicles and higher gas taxes. Canadians tend to choose somewhat smaller models of SUVs and trucks, which may be contributing to a lower rate of pedestrian and cyclist fatalities. Additionally, higher gas prices in Canada, partly due to taxes, seem to encourage less driving and the adoption of different travel habits compared to the US, potentially leading to fewer road accidents. [1] It could also reflect advancements in vehicle safety technologies, improved road conditions, and increased public awareness about safe driving practices.

|  |  |
| --- | --- |
| **Passenger severity** | **% of Total** |
| Fatality | 0.72% |
| Injury | 56.01% |
| No Injury | 43.27% |

The demographic analysis of the accident data brings additional critical insights. A notable finding is that most of the accidents involved male drivers, who accounted for 56.07% of the total incidents. This statistic points to a gender disparity in road accidents and may indicate the need for targeted safety campaigns or interventions focused on male drivers. A notable finding is that most of the accidents involved male drivers, who accounted for 56.07% of the total incidents. [2]

|  |  |  |  |
| --- | --- | --- | --- |
| **Gender** | | **Count of Case** | |
| Male | | 3,697,197 | |
| Female | | 2,896,561 | |

Furthermore, the most affected age group in these accidents was the 21 to 30 years old demographic, representing 21.34% of the total incidents. This age group, typically characterized by relatively new and less experienced drivers, indicates a critical area for enhanced road safety education and stricter enforcement of traffic laws. It may also reflect lifestyle factors and driving habits prevalent in this age group, which could be addressed through tailored awareness and training programs. Road crashes are a leading cause of death among teenagers, with those aged 20 to 30 particularly vulnerable; alcohol and/or drugs play a role in 24% of these incidents. Males, especially at 19 years old, are more frequently involved, often due to risky behaviors like impaired driving. To mitigate this, it's recommended to intensify awareness and educational campaigns targeted at young drivers, focusing on the dangers of impaired driving, and promoting safer driving practices. [3]

|  |  |
| --- | --- |
| **Passenger Age (group)** | **Count of Cases** |
| 1 to 10 | 326,842 |
| 10 to 20 | 1,043,267 |
| 21 to 30 | 1,375,181 |
| 31 to 40 | 1,089,056 |
| 41 to 50 | 1,041,903 |
| 51 to 60 | 788,437 |
| 61 to 70 | 438,768 |
| 71 to 80 | 245,892 |
| 81 to 90 | 90,109 |
| 91 to 100 | 6,750 |

In terms of severity, there were 46,735 fatalities and a concerning number of injuries at 3,617,076, indicating a with higher traffic volumes. Hourly analysis reveals that accidents peak during evening rush hours, with the highest frequency at 6 PM, underscoring the need for enhanced.

The monthly analysis across the dashboards shows consistent patterns, with higher accident numbers in August, July, January and fewer in April. Weekly data reflects a higher number of accidents on weekdays, particularly on Fridays, which could alter safety measures during these hours.

Collectively, these insights from the dashboards can inform policymakers and stakeholders in traffic management to focus on high-risk times and demographics for targeted interventions.

A screenshot of a graph

Description automatically generatedFig 3.2 presents data on traffic accidents in relation to various conditions and scenarios. Most accidents occurred in clear and sunny weather, with over 4.83 million incidents, suggesting that driver complacency or other factors such as high traffic volumes during good weather conditions might play a significant role. In contrast, fewer accidents happened during adverse weather conditions like overcast/cloudy, rainy, and snowy weather, which together accounted for less than 1.8 million incidents.

When examining the effect of road surface conditions on fatalities, most occurred on dry, normal roads (75.63K), indicating that dangerous driving behavior may not be limited to adverse conditions. The presence of traffic control seems to significantly impact the occurrence of accidents, with a vast majority (76.66%) happening in areas with no traffic control present, highlighting the potential benefits of traffic regulation devices.

The presence of traffic control seems to significantly impact the occurrence of accidents, with a vast majority (76.66%) happening in areas with no traffic control present, highlighting the potential benefits of traffic regulation devices.

A screenshot of a graph

Description automatically generatedLooking at road alignment, accidents predominantly occurred on straight and level roads (77.66%), which might be due to higher speeds or inattention on these stretches. In terms of road configuration, intersections are the most common sites for accidents, with over 3.2 million incidents, more than double the number of non-intersection related accidents, which indicates that intersections are critical points for traffic safety interventions.

This data can be instrumental for traffic safety authorities to prioritize safety measures in clear weather conditions, enhance traffic control presence, and focus on intersection safety to reduce traffic accidents.

fig.3.3 indicates trends and distributions of traffic accidents by vehicle type, passenger position, and vehicle model year. Over the years, motorcycles and mopeds have been involved in the highest number of accidents, followed by bicycles, indicating that two-wheeled vehicles are particularly vulnerable on the roads. Trucks and vans also show a significant presence in accident statistics. When analyzing accidents by passenger position, the driver's seat is A screenshot of a computer screen

Description automatically generatedassociated with the highest number of fatalities and non-fatal accidents, underscoring the high risk for vehicle operators. The front row, right seat (commonly the front passenger seat), is the second most frequent position for fatalities, which could point towards the impact of side collisions, critical need for ongoing road safety education and infrastructure improvement. However, many accidents resulted in no injuries, which suggests that not all reported incidents were severe.

Pedestrians also feature prominently in fatality statistics, which highlights the need for better pedestrian safety measures. The yearly trends of accidents over vehicle types seem to have varied fluctuations without a clear increasing or decreasing pattern, suggesting that multiple factors contribute to these accidents over time. In terms of vehicle model years, there is a noticeable decline in accidents involving newer models, possibly reflecting improvements in vehicle safety features. The data from this dashboard can guide targeted safety campaigns and regulatory measures to improve road safety, especially for vulnerable vehicle types and road users.

Fig 3.4 shows driver behavior, including overconfidence and distraction, increases accident risks on straight, non-intersection roads. Alcohol, drugs, and fatigue further exacerbate these dangers. Vehicle factors, such as older cars' lack of safety features and the vulnerability of two-wheeled vehicles, also contribute significantly.

Road characteristics, like the absence of traffic control, poor maintenance, and inadequate signage, increase the likelihood of accidents. Environmental factors, including weather and visibility, affect safety on these roads. Traffic patterns and volume, especially during rush hours, can create hazardous conditions.

Human elements, such as driver age and gender, play a crucial role. Younger, less experienced drivers and males are more prone to accidents. The involvement of bicyclists and pedestrians, particularly on roads without specific safety measures, is also a critical consideration.

1. **MACHINE LEARNING MODEL FOR SEVERITY PREDICTION**

In our "Data-Driven Road Safety Transformation" project, the application of the Random Forest model was pivotal in analyzing and predicting the severity of road traffic accidents based on the data from the National Collision Database (NCDB). Initially, our methodology included a rigorous feature selection process using the Chi-square test to identify the most relevant predictors for collision severity. This statistical approach allowed us to distill the dataset to crucial features that significantly influence outcomes, ensuring the model's focus was on the most impactful data.

To address the challenge of data imbalance, particularly evident in the classification of accident severity where severe accidents were less common than minor ones, we implemented the Near Miss undersampling technique. This method helped in balancing the dataset by reducing the number of instances from the over-represented class, thus providing a more equitable data foundation for training our models. We then developed and compared three different types of machine learning models: Logistic Regression, Decision Tree Classifier, and Random Forest Classifier. Each model was evaluated based on its performance in terms of accuracy, F1 score, and recall. The initial results highlighted the Random Forest Classifier as the most promising model due to its superior ability to manage high-dimensional data and its robustness against overfitting.

Building on this initial success, we fine-tuned the Random Forest model using RandomizedSearchCV, which allowed us to explore a wide range of hyperparameters systematically. This optimization technique not only improved the model's accuracy but also enhanced other critical metrics such as F1 score and recall, essential for ensuring the reliability of the predictions in practical settings. Through careful adjustment and continuous validation against a cross-validated score, we were able to significantly enhance the predictive performance of the Random Forest model, ultimately selecting it as our primary analytical tool for identifying and predicting the severity of road accidents. This approach provided a deep understanding of the underlying patterns in the data, which was crucial for developing targeted interventions aimed at reducing road accidents and enhancing public safety.

1. **V. CNN MODEL – DETECT ACCIDENTS**

In the second phase of our "Data-Driven Road Safety Transformation" project, we developed a Convolutional Neural Network (CNN) model to detect and classify road accidents from images, a pivotal step towards implementing real-time accident detection. This CNN model was designed to process and analyze traffic images to discern whether an accident had occurred, a critical capability for enhancing road safety measures, especially in remote areas where traditional monitoring might not capture every incident. Training the CNN involved a substantial dataset of annotated images that depicted various traffic scenarios, both with and without accidents. This dataset was meticulously prepared, involving the collection, labeling, and augmentation of images to ensure the model was exposed to a wide range of road conditions and accident severities.

Our initial approach with the CNN model included several layers of convolutional networks that are adept at feature extraction, pooling layers that reduce dimensionality, and dropout layers to prevent overfitting. The architecture was carefully constructed to balance depth—enough to capture complex patterns in the data, but not so much as to become computationally inefficient or overly prone to overfitting. We utilized frameworks such as TensorFlow and Keras for building and training the model, taking advantage of their robust, flexible environments suitable for high-level neural network design.

The training process was rigorously monitored to optimize the model’s parameters and improve its ability to generalize on unseen data. We employed techniques such as real-time data augmentation to artificially expand the training dataset, introducing random transformations to the training images. This approach helped improve the model’s robustness by simulating a variety of accident scenarios under different conditions, thereby enhancing its predictive accuracy. Additionally, we implemented batch normalization and adjustable learning rates to stabilize and expedite the learning process, ensuring that the model rapidly adapted to the nuances of the dataset without overfitting.

After training, the CNN model was evaluated using a separate validation set to assess its accuracy, precision, and recall in identifying accident scenes. The results were promising, demonstrating high accuracy in distinguishing between accident and non-accident images. This success prompted us to deploy the model in a real-world application, where it could provide immediate accident detection in traffic management systems. The deployment was facilitated through a Flask-based web application, allowing for seamless integration with existing traffic monitoring systems. This application provides a user-friendly interface for traffic controllers, emergency responders, and road safety analysts, enabling them to access real-time predictions and visual evidence of road conditions, thereby enhancing the decision-making process and response strategies in critical situations.

1. **MODEL DEPLOYMENT**

**Steps involved in the deployment:**

**Training:** The model is trained using a dataset. This dataset typically consists of features and labels that the model will learn from.

**Saving the Model:** Once the model has been trained to an acceptable accuracy, it is saved in Hierarchical Data Format version 5 (.h5), which is a common storage format for storing the complete state of a machine learningmodel,including its architecture, weights, and training configuration.

**Flask Script:** Used a Flask to create a web server that can handle requests.

This script will: Import the trained .h5 model file.

Define routes that the frontend can send data to.

Include a route (usually /predict) that handles the logic for receiving input, running the model prediction, and sending back the response.

HTML Frontend: Developed an HTML file to create the frontend interface. This file: Includes form elements to allow users to input data. Defines the layout and styling of the webpage. It contains scripts to handle the file selection and to display the model's prediction output after the data has been submitted and processed by the backend.

**Workflow of the Integrated System:**

User Interaction: A user interacts with the web interface by uploading data (like an image) through the form element.

Data Submission: When the user submits the form, the data is sent to the Flask application's /predict route.

Model Prediction: The Flask application takes the input data, runs the model's .predict() method using the uploaded data, and processes the results.

Displaying Results: The prediction result is sent back to the front end and displayed to the user whether there is an accident or not.

**Final Output:**

The Flask application serves the HTML page that allows users to upload their data.

After data submission, the model predicts the result, which is sent back to the HTML page and displayed, completing the end-to-end flow from data input to model output presentation.

1. **INTERPRETATION & LIMITATION**

Incomplete Dataset: The initial dataset does not include province-wise accident records for the 20-year span, necessitating separate data acquisition from each province, adding to the complexity of the project.

Data Format and Integration Challenges: The data received from provinces is in a non-standardized format, comprising results and findings rather than raw data. This necessitates extra effort for interpretation and integration into the overall analysis.

Year-wise Data Segregation: Data for each year was provided in separate Excel worksheets. The team had to first merge 20 years' worth of data using Python, before they could begin deriving insights and creating visualizations. This process added an additional layer of data handling complexity.

Generalizability of Findings: Insights and recommendations are specific to the dataset's geographic and temporal context and may not be applicable in other settings.

CNN model: This model is not generalized, but it is predicting well on the trained and test images.

1. **RECOMMENDATIONS:**

**Control Peak Time Collisions:** To mitigate traffic congestion and accidents during peak times, several effective measures can be implemented: adjusting traffic light timings and speed limits to improve traffic flow and safety; employing quick response strategies like privacy screens and freeway patrols for incidents, alongside ramp metering and active traffic management to control vehicle entry on highways. Enhancing non-motorized transport infrastructure, like segregated bike lanes, and promoting carpooling can significantly reduce the number of vehicles on roads. Additionally, increasing public awareness about traffic safety and using data analytics for smart traffic management are crucial for preempting and addressing potential accident hotspots. [4]

**Traffic Control Setup***:* Install traffic controls at high-risk spots such as non-intersections and curved roads. Place additional traffic management systems at intersections with adjacent parking.

**Healthcare Strategy:**To effectively manage peak time accidents, healthcare systems should increase medical personnel and resources, including ambulance services and hospital bed availability, during high-risk periods. Emergency facilities must prioritize critical care spaces like operating rooms and intensive care units, and schedule non-urgent procedures outside peak times to free up resources for emergencies. Additionally, conducting public awareness campaigns and strategically preparing healthcare services for heightened accident rates can significantly enhance emergency response and patient care during these periods.

**Police: Seasonal Hazard Education***:* Increase educational efforts about driving risks during months with historically higher accident rates.

**Road Authorities***:* To reduce traffic accidents, it's crucial to improve traffic control, especially on straight and level roads in clear conditions, and enhance road surfaces, as most fatalities occur on dry roads. Implementing engineering solutions such as improved signage and lane markings, along with promoting vehicle safety features, driver education, and data-driven law enforcement, will significantly boost road safety.

**For Users - Seat Safety Instruction:**Educate drivers and front-row passengers on optimal seat positioning and seat belt usage. Stress the importance of using seat belts correctly to reduce fatalities.

1. **IX. APPENDIX**

**Python file**: The below HTML file contains the Python code utilized in our analysis. This code underpins the data cleaning, EDA efforts described in this document.

https://github.com/abigaildsilva/NCDB-Collision-Analysis

# **REFERENCES**

|  |  |
| --- | --- |
| [1] | "bloomberg.com," [Online]. Available: https://www.bloomberg.com/news/articles/2022-07-01/why-canada-isn-t-having-a-traffic-safety-crisis. |
| [2] | "www.iihs.org," [Online]. Available: https://www.iihs.org/topics/fatality-statistics/detail/males-and-females. |
| [3] | "madd.ca," [Online]. Available: https://madd.ca/pages/programs/youth-services/statistics-links/. |
| [4] | "Breaking the Bottlenecks," [Online]. Available: https://www.caa.ca/app/uploads/2021/01/Congestion-solutions-Summary-ENG-V2.pdf. |
| [6] | "Government of Canada," [Online]. Available: https://tc.canada.ca/en/road-transportation/statistics-data/statistics-data-road-safety/2020-statistics-social-costs-collisions-canada. |
| [7] | [Online]. Available: https://tc.canada.ca/en/road-transportation/statistics-data/statistics-data-road-safety/2020-statistics-social-costs-collisions-canada. |
| [8] | [Online]. Available: https://tc.canada.ca/en/road-transportation/statistics-data/statistics-data-road-safety/2020-statistics-social-costs-collisions-canada. |
| [9] | "[2]," [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/221117/dq221117d-eng.htm. |
| [10] | "[2]," [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/221117/dq221117d-eng.htm. |
| [11] | "Government of Canada," [Online]. Available: https://tc.canada.ca/en/road-transportation/statistics-data/statistics-data-road-safety/2020-statistics-social-costs-collisions-canada. |
| [12] | "statcan.gc.ca," [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/221117/dq221117d-eng.htm. |
| [13] | "open.canada.ca/data," [Online]. Available: https://open.canada.ca/data/en/dataset/1eb9eba7-71d1-4b30-9fb1-30cbdab7e63a. |
| [14] | [Online]. Available: https://www.ricekendig.com/collision-risks-when-traveling-during-peak-hours/. |
| [15] | "open.canada.ca," [Online]. Available: https://open.canada.ca/data/en/dataset/1eb9eba7-71d1-4b30-9fb1-30cbdab7e63a. |
| [16] | "www.mpi.mb.ca," [Online]. Available: https://www.mpi.mb.ca/Documents/TCSR2021.pdf. |