Understanding and Predicting the Risk of Injury Resulting from Vehicle Collisions in Ottawa, Ontario

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Abstract

Road traffic collisions are a serious and on-going threat to human life. Understanding the features of a collision that increase the likelihood of an injury is useful for increasing personal protection, guiding emergency services and advising municipal staff. This study analyzed traffic collisions in Ottawa, Ontario from 2017 to 2022. This study sought to highlight hazardous areas and modes of transportation, and to analyze correlations found with occurrences and severity of injuries. The intersections along the Hunt Club bridge stood out as a frequently hazardous location, while 8th Line Rd and Parkway Rd was considered one of the most fatal ones. Finally, a predictive model was created and achieved 85% accuracy in forecasting injuries. Overall, there were not many features correlated to injuries, however, non-vehicles had a mild positive correlation with injury occurring. Despite limitations, this study provides actionable insights for local authorities to enhance road safety.

ACM Reference Format:
Ben Nikkel and Anja Wu. 2023. Understanding and Predicting the Risk of Injury Resulting from Vehicle Collisions in Ottawa, Ontario. In *Proceedings of Seminar Course (DATA5000).*, 8 pages.

1 Introduction

As the world population continues to grow, road safety remains an important component of social welfare. In their most recent report, the World Health Organization estimated that global deaths due to road traffic was over 1.3 million people per year [16]. They attributed the implementation of road, vehicle and user safety standards as key strategies for countries to use to reduce these deaths.This may help explain why, as of 2021, Canada's number of motor vehicle collision fatalities relative to population size was the second lowest on record [5].

To achieve and maintain a decrease in deaths and injuries due to road traffic collisions, it is useful to understand if the characteristics of a collision increased the risk of death and injury, in general. This risk can depend on small scale characteristics of the vehicle (eg. type, travelling speed) and those injured (eg. age, gender, position/orientation at impact) [15][3]. This risk can also depend on large scale characteristics such as the environment (eg. ice/snow) and infrastructure (eg. speed limits, road lights) [3][18]. Indirect dynamics, such as fuel prices and climate change, can influence the rate of road collisions too [11][13]. The complexity stemming from this wide variety of factors makes accurately predicting the risk of injury a challenge.

Supervised machine learning is well suited to the task of modelling traffic collision injuries and has been undertaken with a variety of approaches. Yuan et al. [22] used Decision Tree/CART approaches to classify the severity of injury using driver, vehicular and environmental factors. Abdi et al. [1] used a boosted Decision Tree to predict disruptions to traffic flow using a variety of collision variables, which can influence the risk of injury [2]. Alternatively, Gatarić et al. [7] used Neural Networks to predict injuries using road engineering features – road section length, traffic volume, surface type, curvature, and road width – among the other previously mentioned types of variables. Sirikul et al. [20] used a variety of methods, including K-Nearest Neighbour, to model the risk of fatal injury while considering drunk driving. These studies set a precedent for applying multiple machine learning methods to traffic collision injury modelling.

To support Canada's trend of decreasing collision fatalities and contribute to a better understanding of traffic collision injuries, we analysed collision data for Ottawa, Ontario, Canada. We wanted to understand the collisions descriptively - where did accidents most occur, how severely were people injured, what features related to injury outcomes, how were non-vehicles affected by collisions, did traffic controls attenuate the occurrence of collisions? Subsequently, we built a model to predict the likelihood of injury by evaluating a variety of machine learning methods. We hoped to warn Ottawa residents of dangerous traffic scenarios and explain what aspect(s) of collisions made them dangerous. We also hope to provide more information for first responders and municipal staff to use when attending to a collision.

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DATA5000, 2023, Ottawa, ON

2 Methodology

2.1 Data Collection and Preprocessing

The data was retrieved from https://open.ottawa.ca/ in September 2023. The data set contained almost 70,000 collisions occurring between 2017-2022. There were 29 features consisting of: location (latitude, longitude, address, and Geo ID), accident date/time, descriptions about the accident, road, environmental, and light conditions at time of accident, traffic control at accident location, number of vehicles, pedestrians, bicycles, and motorcycles involved in collision, number and severity of injuries.

For the data cleaning and preprocessing: the distribution for each variable was checked for outliers and any other inconsistencies. Missing values for integer columns were changed to zeros, after analysis led to concluding they are equivalent. Latitude and longitude values were truncated from five to four decimal points, to allow groupings of identical location strings. A binary injury variable was created where 0 labelled a collision with no injuries and 1 labelled a collision with at least one injury. Ordinal categorical features were converted to a numeric scale. Nominal categorical features were converted to one-hot encoding to allow more granularity in analyzing relationships.

2.2 Descriptive Analysis

The number of collisions and collisions with an injury were counted for each unique latitude, longitude and location groupings. The groups among the top 10 highest counts were reported and displayed on a map. Due to how dangerous major and fatal injuries are, an analysis was done separately for the number of major and fatal injury collisions. The groups among the top 10 highest counts greater than one were reported.

Correlation heat maps using Pearson correlation coefficients were created to measure the strength and direction of relationships for a) all predictor features and whether an injury occurred and b) environmental predictor features and the count of each injury severity level.

The proportion of all collisions involving each mode of transportation was calculated. A separate calculation was done for each mode of transportation calculating the proportion of each level of injury severity by the total number of collisions reported for that mode of transportation.

Finally, the frequency of collisions for each type of traffic control was reported.

2.3 Predictive Model

To set up, we split the data into 80-20 training, testing sets. Our final performance was measured on the unseen 20%. For hyperparameter tuning, for our various models, the 80% training data set was further split into 70-30 training and validation sets.

The first model that was analysed was the k-Nearest Neighbours (k-NN), coded using the SciKit-Learn library. Due to the class imbalance, several sampling methods were tried to increase performance: Random OverSampling and SMOTE. These were done using the imblearn.over_sampling library. The final model selected was using six nearest neighbours from hyperparameter tuning.

The second main model that was analysed was the Decision Tree, also coded using the SciKit-Learn library. In order to account for class imbalance, Random OverSampling was tried on a set of iterations of the model, using the imblearn.over_sampling library, and also setting class weights to be balanced to penalise the underrepresented class. Also to help with instability of Decision Trees, the Random Forest bagging technique was tried. The final model selected due to superior performance was the entropy criterion, and a maximum depth of 6.

Finally, PyCaret was used to compare performance of different models. The different models compared were: Ridge Classifier, Linear Discriminant Analysis, Logistic Regression, Gradient Boosting Classifier, Ada Boost Classifier, Random Forest Classifier, Extra Trees Classifier, K-Neighbors Classifier, Decision Tree Classifier, SVM - linear kernel, Naive Bayes, and Quadratic Discriminant Analysis. On top of those, there was also a dummy classifier to give a baseline.

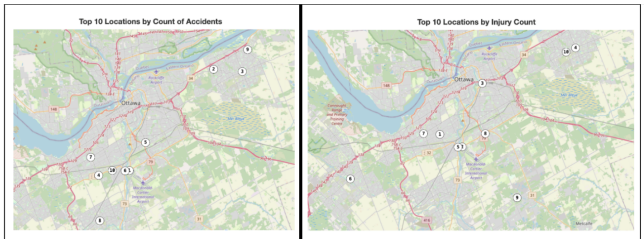
3 Results

The data set described 69,579 collisions that occurred between years 2017 and 2022. The following results are broken down into research questions answered.

3.1 What were the most dangerous locations?

We found the top 10 most frequent locations by number of accidents and by number of accidents with injuries and mapped them (Figure 1).

Hunt Club Rd appeared in 4 of the top 10 locations by number of collisions, with Hunt Club Rd @ Riverside Dr being the location of the most collisions (n = 232). St. Joseph Blvd @ Jeanne D'Arcy Blvd had a similar number of collisions (n = 218) while the other 8 had markedly fewer. For collisions with injuries, Meadowlands Dr @ Merivale Rd was the location with the most (n = 33). Hunt Club Rd appeared in 2 of the top 10 locations, with Hunt Club Rd @ Riverside Dr being one of the locations tied for the second most collisions (n = 32). Innes Rd also appeared in 2 of the top 10 locations, with Innes Rd @ Tenth Line Rd being the location tied for the second most collision (n = 32). All top locations listed were intersections - not midblocks.



Collisions			Collisions with an Injury		
#	Location	n	#	Location	n
1	Hunt Club Rd @ Riverside Dr[a]	232	1	Meadowlands Dr @ Merivale Rd	33
2	St. Joseph Blvd @ Jeanne D'arc Blvd	218	2	Hunt Club Rd @ Riverside Dr[a]	32
3	Innes Rd @ Tenth Line Rd[b]	168	3	Riverside Dr @ Tremblay Rd/Hwy417 Ic117 Ramp52	32
4	West Hunt Club Rd @ Woodroffe Ave	157	4	Innes Rd @ Tenth Line Rd[b]	32
5	Bank St @ Walkley Rd	157	5	Prince Of Wales Dr @ West Hunt Club Rd[c]	29
6	Prince Of Wales Dr @ West Hunt Club Rd[c]	155	6	Hazeldean Rd @ Terry Fox Dr	28
7	Baseline Rd @ Woodroffe Ave[d]	155	7	Baseline Rd @ Woodroffe Ave[d]	28
8	Greenbank Rd @ Strandherd Dr	147	8	Hunt Club Rd @ Bridle Path Dr/Daze St	28
9	St. Joseph Blvd/Old Montreal Rd @ Trim Rd	147	9	Albion Rd @ Mitch Owens Rd	27
10	Merivale Rd @ West Hunt Club Rd	146	10	Innes Rd @ Jeanne D'arc Blvd/Mer Bleue Rd	27

Figure 1. Top 10 Locations in Ottawa, Ontario with the most collisions and the most collisions involving at least one injury. **Top**: geographic maps marked by the locations with the most collisions (**left**) and most collisions with injuries (**right**). **Bottom**: Frequency tables of locations with the most collisions (**left**) and the most collisions with injuries (right). Locations present in both tables are marked with a superscript.

In Figure 2, we also found that major and fatal injury collisions occurred at some locations more than once (Figure 2). McCordick Rd @ Roger Stevens Dr, 8th Line Rd @ Parkway Rd, and Russell Rd @ Southvale Cres N all had more than one collision with fatal injuries.

Major Injuries			Fatal Injuries		
Rank	Location	n	Rank	Location	n
1	Bank St @ Dalmeny Rd/Marvelville Rd	3	1	Mccordick Rd @ Roger Stevens Dr	2
1	8th Line Rd @ Parkway Rd[a]	3	1	8th Line Rd @ Parkway Rd[a]	2
1	Hunt Club Rd @ Paul Anka Dr	3	1	Russell Rd @ Southvale Cres N	2
1	St. Laurent Blvd @ McArthur Ave	3			
1	King Edward Ave @ Sussex Dr	3			
1	Aviation Pkwy @ Montreal Rd	3			

Figure 2. Frequency table for locations in Ottawa, Ontario with more than one collision involving major (**left**) and fatal (**right**) injuries. Locations present in both tables are marked with a superscript.

3.2 When were accidents occurring?

As can be seen in Figure 3, most years had similar trends of higher accidents in the winter. Also there was a substantial decrease in years 2020 and 2021; this coincides with the COVID shut downs.

Interesting to note that 2022 had a trend differing from the other years. When further analysis was done, there seemed to be fewer entries for those end of year months, implying this was a problem due to data entry - not due to a true collision trend for that year.

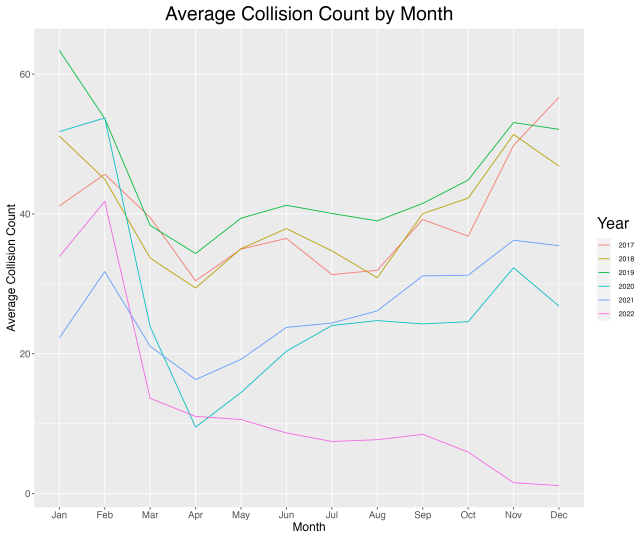


Figure 3. Time trends for average number of collisions by month for each year from the data set.

3.3 Which accident features were correlated to injuries?

We correlated all features with a binary injury variable – whether an injury occurred or not (Figure 4). In general, most of the variables did not correlate with injury occurrence. “classification_of_accident” correlated almost perfectly with injury (0.99) because they held very similar information; “classification_of_accident” was excluded from further analysis. Except for vehicles, the mode of transport (“num_of_vehicles”, “num_of_pedestrians”, “num_of_motorcycles”) had a mild, positive correlation with injury occurrence. These scalar variables referred to the number of entities involved in the collision (eg. 2 pedestrians, 1 motorcycle, etc.). Further analysis of one hot encoding for nominal features still resulted in no correlation.

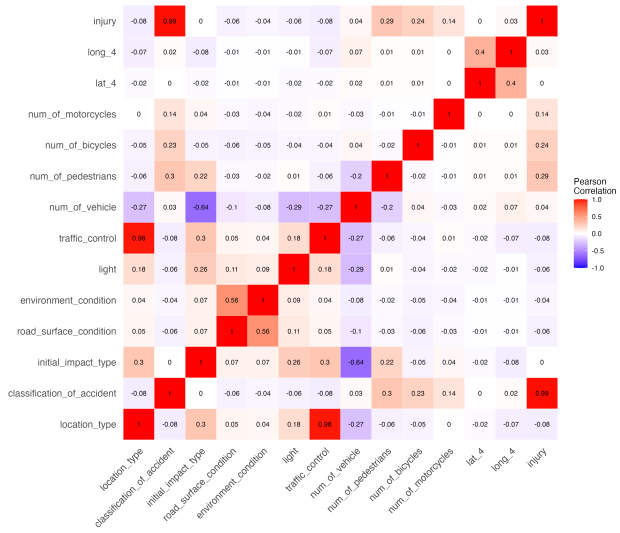


Figure 4. Correlation matrix of all predictor variables and injury occurrence.

3.4 Were road/weather conditions correlated to levels of severity of injuries?

We correlated the environmental predictor variables with each injury class variable (Figure 5). Similar to Figure 3, none of the environmental predictor variables correlated with the count of any injury class.

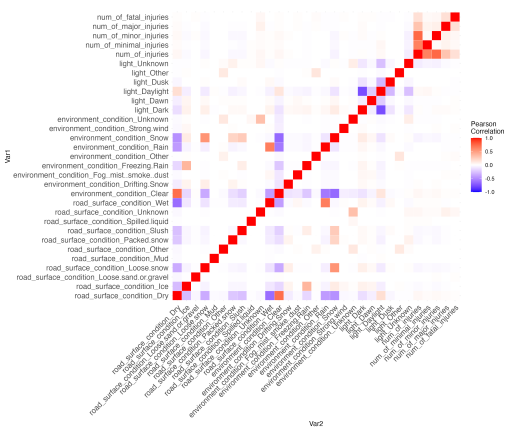


Figure 5. Correlation matrix of environmental predictor variables with one-hot coding injury severity variables.

3.5 Did injuries disproportionately affect drivers, pedestrians, bicyclers or motorcycles?

We found how frequently each mode of transportation was involved in an accident and what class of injury tended to occur when a given mode was involved (Figure 6). Most collisions involved a vehicle while other modes (pedestrian, bicycle, and motorcycles) were involved less frequently. The likelihood of injury occurrence and severity differed by mode. Overall, most collisions involved vehicles (95.28%) and most of these did not involve injury (79.99%). When vehicle injuries did occur, they were usually minimal (8.00%) or minor (10.8%). However, when pedestrians were involved, there was almost always an injury (99.16%); they were often minimal (29.41%) or minor (57.35%). Bicycles and motorcycles were more likely to involve injuries than vehicles. Motorcycle injuries were the most likely to be fatal (3.33%), while pedestrians were the next most likely (2.43%).

		Injury Class				
Mode of Transport	**Collision Involvement (%)**	**None (%)**	**Minimal (%)**	**Minor (%)**	**Major (%)**	**Fatal (%)**
Vehicle	95.28	79.99	8.00	10.87	0.94	0.20
Pedestrian	2.10	0.84	29.41	57.35	9.97	2.43
Bicycle	1.77	12.34	31.95	48.90	6.13	0.68
Motorcycle	0.85	20.13	15.37	46.75	14.42	3.33

Figure 6. Frequency table for (a) how often each mode of transport was involved in a collision and (b) the class of injury per mode of transport.

3.6 Did traffic controls lead to decreases in accidents?

As seen in figures below, we examined the collisions by traffic control to see which control measures were present at a collision. The most common type of traffic control per collision was no control. However when looking at all traffic controls together they tend to account for more accidents than no control. It is important to note that traffic controls correlated with intersections (Figure 4). This means there were confounding variables to influence this result. For instance, intersections tend to have more opportunities for accidents due to more traffic from different directions and more congestion.

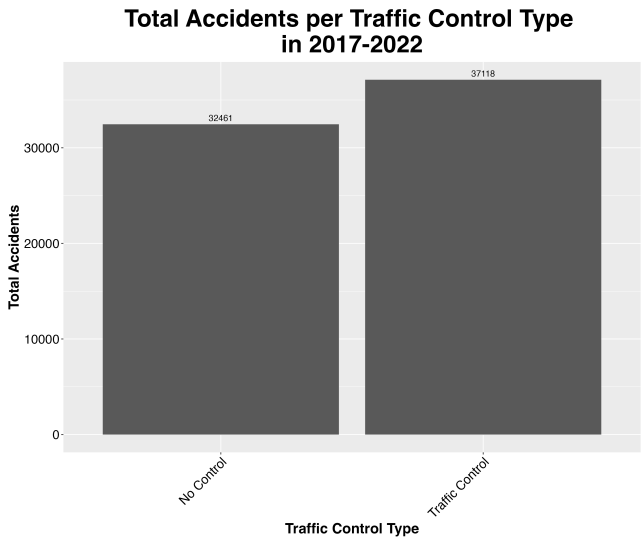


Figure 7. Frequency chart for traffic control versus no control.

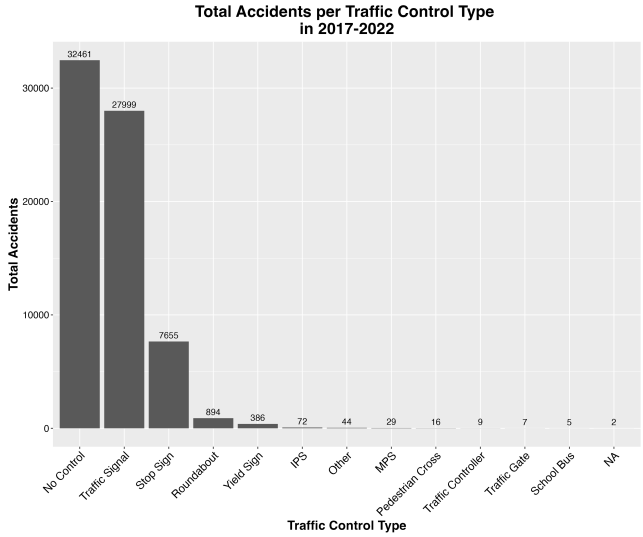


Figure 8. Frequency chart for all different traffic control measures at collision location.

3.7 Can an injury be predicted given collision information?

We wanted to see if the accident features were enough to have a good model for predicting whether an injury would occur or not. There is a ratio of approximately 1:5 imbalance for injury occurring vs not. Models were attempted to increase not only accuracy but also precision-recall (due to the imbalance). The best model on the training and validation set was Decision Tree with criterion = "entropy" and max_depth = 6. See Figures 9 and 10 for the evaluation of this model.

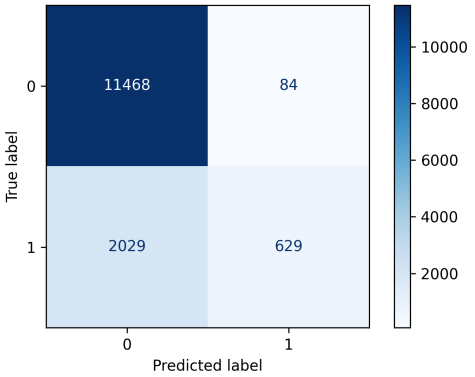
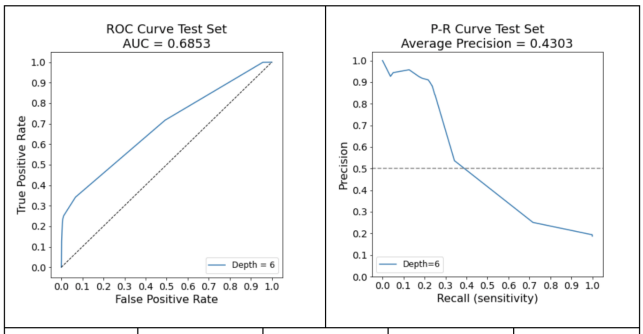


Figure 9. Confusion matrix of collision classification as injury (1) or no injury (0) from the decision tree test set.

In looking at the training and validation set, the k-NN model performed worse than chance (which is about 80% due to class imbalance). k-NN results were not included given this performance.



	Precision	Recall	F1-score	Support
0	0.85	0.99	0.92	11552
1	0.88	0.24	0.37	2658
Accuracy	-	-	0.85	14210
Macro Average	0.87	0.61	0.64	14210
Weighted Average	0.86	0.85	0.81	14210

Figure 10. Evaluation of Decision Tree model: ROC Curve (**top left**), R-C Curve (**top right**) and table of measures - Precision, Recall, F1-Score, and Accuracy (**bottom**).

The Decision Tree and k-NN models were benchmarked against other methods using PyCaret library (Figure 11). There was no model that did well overall given the max F1-score was less than 0.4. However, the Ridge Classifier did the best in this table across the most metrics. Compared the results to our Decision Tree (Figure 8), we actually see our model on the test set had higher accuracy (0.85) and precision (0.88). They had relatively the same F1-score. The only metric Ridge Classifier did better on was recall (by 2%).

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
ridge	Ridge Classifier	0.8412	0.0000	0.2610	0.6931	0.3790	0.3088	0.3576	1.3380
lda	Linear Discriminant Analysis	0.8325	0.7064	0.2913	0.6018	0.3924	0.3086	0.3361	1.0320
lr	Logistic Regression	0.8242	0.7176	0.2872	0.5521	0.3777	0.2871	0.3080	3.9570
gbc	Gradient Boosting Classifier	0.8218	0.6780	0.2551	0.5442	0.3472	0.2593	0.2845	12.9670
ada	Ada Boost Classifier	0.8206	0.6591	0.2558	0.5367	0.3462	0.2571	0.2810	3.6010
rf	Random Forest Classifier	0.8202	0.6976	0.2577	0.5337	0.3473	0.2575	0.2806	4.8450
et	Extra Trees Classifier	0.8191	0.7028	0.2714	0.5256	0.3577	0.2648	0.2845	3.5250
knn	K Neighbors Classifier	0.8153	0.6719	0.2799	0.5058	0.3602	0.2626	0.2784	1.8880
dummy	Dummy Classifier	0.8142	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6000
dt	Decision Tree Classifier	0.7551	0.5914	0.3308	0.3376	0.3340	0.1841	0.1841	0.8070
svm	SVM - Linear Kernel	0.7287	0.0000	0.4309	0.4790	0.3697	0.2346	0.2690	1.0200
nb	Naive Bayes	0.3185	0.7279	0.9568	0.2089	0.3429	0.0545	0.1418	0.6210
qda	Quadratic Discriminant Analysis	0.2301	0.5376	0.9968	0.1940	0.3248	0.0200	0.0968	1.3040

Figure 11. Model benchmark results using PyCaret. The model with the highest value for each measure was highlighted.

4 Discussion

4.1 Descriptive

The most hazardous Ottawa location for collisions and injuries was the Michael J.E. Sheflin Bridge (aka Hunt Club Bridge). The intersections on both sides of the bridge (Hunt Club Rd @ Riverside Dr and Prince Of Wales Dr @ West Hunt Club Rd) appeared in both Top 10 lists (Figure 1). According to a previous transportation development report, congestion and collisions have been issues with this area that have arguably have not improved [9]. More broadly, the most frequently hazardous locations in the city involved arterial roads - urban roads with higher speed limits that accommodate large traffic volumes [4]. In terms of regulating these roads for safety purposes, reducing vehicle speed can reduce traffic volumes but may or may not reduce the rate of collision-caused injury overall [8][19]. For the locations with the most major and fatal collisions, additional features such as road straightness, which relates to speed, and driver negligence may be important [17]. The intersection of 8th Line Rd and Parkway Rd has had numerous articles written about the danger of the intersection, most recently in 2021 [6] and 2023 [14], highlighting the negative impact of fatal collisions on the area residents and their understanding of why the area is prone to these collisions.

Given our correlation analysis, we do not have evidence of weather/road condition or environmental light having a significant influence on traffic injuries occurring. This disconnect may be due to environmental factors being represented categorically instead of quantitatively; Lio et al. [10] found a significant relationship between road traffic injuries and temperature, humidity and wind speed. This relationship likely existed for Ottawa too, given the consistent seasonal collision pattern (i.e. more collisions in the winter when temperature and humidity were lower), and may have been uncovered if environment variables had been quantitative.

The higher fatality rate for collisions involving motorcycles and pedestrians is consistent with previous work. Vanlaar et al. [21] analyzed fatal and serious injury collisions at a national scale over 12 years; they found that these non-vehicle modes of transportation became a greater proportion of these collisions over time. They cite some of the previously mentioned features that partially explain the risks of motorcycle collisions - speeding, substances, driver behaviour, wildlife and the environment. They also noted that elderly pedestrians are particularly affected given their increased reliance on walking rather than driving and physical vulnerability to injury. We were unable to assess pedestrian age in our study; this and other demographic details are likely related to collision injuries.

Determining the relationship between collision injuries and traffic control was confounded by traffic control existing where collisions were frequent. As previously explored, locations with the most collisions were intersections, which also have traffic lights - the most common form of traffic control. To uncover the impact of traffic control, an intervention study would need to be performed to detect how collision rates change before and after the implementation of traffic control. Marchant et al. [12] studied the effect of collisions as road lighting was installed. They were able to isolate the effect of installed lighting from daylight and did not find that collisions decreased as more lights were installed. Overcoming confounding aspects was necessary for this conclusion to be drawn and was essential for attributing intended injury outcomes to traffic control strategies.

4.2 Predictive

As can be seen when comparing metrics for various models (figure 8 and 9), the Decision Tree with depth 6 and entropy criterion performed the best overall. Leading to the belief that this was the best model with our specific data set. Yuan et al. [22] found that drunk driving, speed, weather, and traffic lights factored into the severity of injuries when looking at specifically intersection collisions. It is interesting to note that when weather and traffic lights are applied to all types of collisions they tend to not have as much of a relationship with severity.

In Figure 9, it can be seen that the model tends to over predict no injury leading to a decrease in recall score for injury prediction (Figure 10). Even with oversampling of the minority class the overall model was not improved. This can indicate that the features we are looking at are generally not good at being used to distinguish injury vs. none. It is interesting to note that the number of accidents with injury that were classified as no injury is very low. This could imply that we had a feature or two that are really representative of injuries but they did not occur often. For instance, the number of bikes, pedestrians, and motorcycles were highly underrepresented in this data set. We saw that almost 80% of motorcycle accidents ended in an injury yet only accounted

for less than 1% of all accidents. This could be an example of why the model was good about not misclassifying non injury as injury.

4.3 Limitations

A significant limitation to our analysis was the data's form. Many variables that other studies showed to be relevant [10] were not correlated to injuries. Additionally, the data did not contain traffic speed and volume measures, which are also important [7]. Future analysis should include these measures and current measures should be in a quantitative form as much as possible.

A more elaborate time analysis is also worth future study. While we noted consistent seasonal trends across years, weekly and daily collision patterns could also be explored. Also in terms of time, assessing the impact of traffic controls, such as speeding cameras, depends on data for before and after implementation. Traffic control effects can be confounded by their presence in collision-prone environments.

5 Future work

For future work, several avenues warrant exploration to enhance the depth and breadth of our analysis. First and foremost, incorporating the variable of speed could refine the predictive model, providing a better understanding of accident injury outcomes. Additionally, delving into the consideration of traffic volume could enable a more comprehensive comparative analysis across various locations. Furthermore, our examination of time trends reveals a decrease in accidents post-COVID (years 2020-2022), prompting a closer inspection into the proportional nature of this decline. Specifically, investigating whether hybrid work arrangements, with individuals commuting to offices only 2-3 times per week, result in a $\frac{2}{5}$-$\frac{3}{5}$ reduction in accidents compared to previous years could yield valuable insights.

The exploration of seasonal trends represents another intriguing avenue, as we aim to discern if specific weather or environmental conditions during particular months correlate with the severity of injuries. Potentially incorporating quantitative measures of weather (e.g. amount of snow) could yield a better predictive model.

Lastly, once the 2023 collision data is released, it can be used to see if we are able to predict whether an injury can occur using new data.

6 Conclusion

Our analysis covered many aspects of Ottawa's recent history of traffic collisions. Answering many quantitative questions along with providing a predictive model for collision injuries.

6.1 Summary

In analyzing accident and injury data, several notable locations stood out as high-risk areas: Hunt Club and Riverside/Prince of Whales, Innes and Tenth Line, and Baseline and Woodroffe. Among these, 8th Line and Parkway was a particularly concerning spot for major and fatal injuries. An examination of correlated features revealed a slight correlation between modes of transportation (including pedestrian, bike, and motorcycle) and the severity of injuries sustained. Notably, although motorcycles represent less than 1% of accidents, a substantial 14% of collisions resulted in major injuries and 3% in fatal injuries. Similarly, pedestrians, accounting for 2% of accidents, with approximately 2.5% resulting in fatal injuries and more than half (57%) in minor injuries. Encouragingly, a predictive model developed for the data set demonstrated an 85% accuracy rate, surpassing random chance.

6.2 Application

This study contributes to the City of Ottawa, by providing a comprehensive list of locations deemed "dangerous". This will enable the City to conduct a qualitative analysis to better understand and address the factors contributing to these locational risks. The examination of injury levels across various modes of transportation not only sheds light on the associated risks but also lays the groundwork for targeted Public Service Announcements aimed at promoting safety for each mode. The development of a predictive model, which performed better than chance, signifies a good starting point in accident prediction for the City of Ottawa. This model holds the potential for further refinement through the integration of additional data sources, such as speed-related information. As a result, our study not only enhances the current understanding of accident patterns but also offers practical insights that can be leveraged to implement proactive measures for improving road safety and preventing accidents in the future.

Acknowledgments

To Mahmud Hasan, for obtaining/certifying data.

References

[1] A. Abdi, S. Seyedabrishami, and S. O'Hern. 2023. A Two-Stage Sequential Framework for Traffic Accident Post-Impact Prediction Utilizing Real-Time Traffic, Weather, and Accident Data. *J Adv Transp* (2023).

[2] D. Albalate and L. Fernández-Villadangos. 2010. Motorcycle injury severity in Barcelona: The role of vehicle type and congestion. *Traffic Inj Prev* 11 (2010), 623–631.

[3] K. Amin, M. Skyving, C. Bonander, M. Krafft, and F. Nilson. 2022. Fall- and collision-related injuries among pedestrians in road traffic environment – A Swedish national register-based study. *J Safety Res* 81 (2022), 153–165.

[4] G. Berhanu. 2004. Models relating traffic safety with road environment and traffic flows on arterial roads in Addis Ababa. *Accid Anal Prev* 36, 5 (2004), 697–704. https://doi.org/10.1016/j.aap.2003.05.002

[5] Transport Canada. 2022. *Canadian Motor Vehicle Traffic Collision Statistics: 2021.* Retrieved September, 2023 from https://tc.canada.ca/en/road-transportation/statistics-data/canadian-motor-vehicle-traffic-collision-statistics-2021

[6] Sara Frizzell. 2021. *Latest serious crash leads to more calls to improve Metcalfe intersection.* Retrieved October, 2023 from https://www.cbc.ca/news/canada/ottawa/8th-line-parkway-road-metcalfe-safety-crash-1.6153797

[7] D. Gatarić, N. Ruškić, B. Aleksić, T. Đurić, L. Pezo, B. Lončar, and M. Pezo. 2023. Predicting Road Traffic Accidents—Artificial Neural Network Approach. *Algorithms* 16 (2023).

[8] R.F. Hunter, C.L. Cleland, J. Busby, G. Nightingale, F. Kee, A.J. Williams, P. Kelly, M.P. Kelly, K. Milton, K. Kokka, and R. Jepson. 2022. Investigating the impact of a 20 miles per hour speed limit intervention on road traffic collisions, casualties, speed and volume in Belfast, UK: 3 year follow-up outcomes of a natural experiment. *J Epidemiol Community Health* 77 (2022), 17–25.

[9] R.T. Leclair and Michael J. Flainek. 2002. *Modifications at the Intersection of Hunt Club Road.* Retrieved September 15, 2023 from https://app06.ottawa.ca/calendar/ottawa/citycouncil/ttc/2002/07-17/ACS2002-TUP-TRF-0026.htm

[10] Cheong H. H. Un C. H. Lo I. L. Tsai S. Y. Lio, C. F. 2019. The association between meteorological variables and road traffic injuries: A study from Macao. *PeerJ* (2019), 1–13.

[11] A. Liu, S.I. Soneja, C. Jiang, C. Huang, T. Kerns, K. Beck, C. Mitchell, and A. Sapkota. 2017. Frequency of extreme weather events and increased risk of motor vehicle collision in Maryland. *Sci Total Environ* 580 (2017), 550–555.

[12] P. Marchant, J. D. Hale, and J. P. Sadler. 2020. Does changing to brighter road lighting improve road safety? Multilevel longitudinal analysis of road traffic collision frequency during the relighting of a UK city. *J. Epidemiol. Community Health* 74 (2020), 467–472.

[13] N.K. Naqvi, M. Quddus, and M. Enoch. 2023. Modelling the effects of fuel price changes on road traffic collisions in the European Union using panel data. *Accid Anal Prev* 191 (2023), 107–196.

[14] CBC News. 2023. *1 dead, 5 injured in collision at rural Ottawa intersection.* Retrieved October, 2023 from https://www.cbc.ca/news/canada/ottawa/collision-rural-southeast-ottawa-1.6842397

[15] S. Nogayeva, J. Gooch, and N. Frascione. 2021. Science Justice The forensic investigation of vehicle – pedestrian collisions: A review. *Sci Justice* 61 (2021), 112–118.

[16] World Health Organization. 2018. Global Status Report on Road Safety 2018. *Geneva: World Health Organization* (2018).

[17] W. Pawłowski, K. Goniewicz, D. C. Schwebel, J. Shen, and M. Goniewicz. 2019. Road traffic injuries in Poland: magnitude and risk factors. *Eur J Trauma Emerg Surg* 45, 5 (Jan. 2019), 815–820. https://doi.org/10.1007/s00068-019-01093-6

[18] J. Pineda-Jaramillo, H. Barrera-Jiménez, and R. Mesa-Arango. 2022. Unveiling the relevance of traffic enforcement cameras on the severity of vehicle–pedestrian collisions in an urban environment with machine learning models. *J Safety Res* 81 (2022), 225–238.

[19] I. A. Rossi, D. Vienneau, M. S. Ragettli, B. Flückiger, and M Röösli. 2020. Estimating the health benefits associated with a speed limit reduction to thirty kilometres per hour: A health impact assessment of noise and road traffic crashes for the Swiss city of Lausanne. *Environ Int* 145 (2020).

[20] W. Sirikul, N. Buawangpong, R. Sapbamrer, and P. Siviroj. 2021. Mortality-risk prediction model from road-traffic injury in drunk drivers: Machine learning approach. *Int J Environ Res Public Health* 81 (2021).

[21] W. Vanlaar, M. Mainegra Hing, S. Brown, H. McAteer, J. Crain, and S. McFaull. 2016. Fatal and serious injuries related to vulnerable road users in Canada. *J Safety Res* 58 (2016), 67–77. https://doi.org/10.1016/j.jsr.2016.07.001

[22] Y. Yuan, S. Wang, Z. Liu, G. Cui, and Y. Wang. 2022. Influencing factors analysis of side right-angle collisions severity at intersections based on decision tree. *Int J Crashworthiness* 27, 5 (2022), 59–69.

Received 8 December 2023