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TRANSPORT FINDINGS

Exploring Pedestrian Injury Severity by Incorporating Spatial Information in Machine Learning

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Findings

Using the random forest classification technique, this study explored the role of different factors such as demography, pedestrian and drivers' conditions, collision characteristics, road characteristics, and weather in predicting pedestrian injury severity from automobile-related collisions in Toronto. Spatial information was incorporated in the models to capture spatial autocorrelation. The results revealed the importance of spatial information in predicting pedestrian injury severity. Other important predictors of pedestrian injury severity include aggressive driving, driver's conditions (e.g., inattentive, slowly stopping, driving properly, failing to yield right of way), pedestrian conditions (e.g., normal, inattentive) and dark lighting conditions.

1. Questions

Pedestrian safety is a major concern in the transportation industry since pedestrians are the most vulnerable group to be injured in motor vehicle-related traffic collisions (Beck, Dellinger, and O'neil 2007; Toronto Public Health 2012, 2015; Pour-Rouholamin and Zhou 2016). In Toronto, Ontario, pedestrians accounted for 44% and 62% of all fatalities from traffic collisions in 2022 and in 2023 (as of October 16, 2023), respectively (City of Toronto 2023). An understanding of the relevant factors that contribute to injury severity due to collisions can provide insights to improve pedestrian safety. Accordingly, by incorporating spatial information, this study explored the role of different factors such as demography, pedestrian and drivers' conditions, collision characteristics, road characteristics, and weather in predicting pedestrian injury severity from automobile-related collisions.

2. Methods

The traffic collision data of the City of Toronto from 2006 – 2022 is obtained from the Toronto Police Service's public safety data portal (http://data.torontopolice.on.ca/datasets/ksi/data). The injury severity of each individual involved in the collision was recorded in five categories: None – Minimal – Minor – Major – Fatal. Collision-related data were also available in the database, including age of the individual(s) involved, type of vehicle(s) involved, condition(s) of the individuals involved, time of occurrence, visibility, lighting condition, collision location (e.g., intersection, non-intersection, near private driveway), type of traffic control at the collision location, road condition, etc. As this study focused on automobile-related pedestrian injury, collision data involving other vehicle types were excluded from the analysis. The information on drivers' and vehicle passengers' injury levels in pedestrian-automobile collisions were also excluded but drivers' age and information on their conditions during the collision (e.g., impaired driving, inattentiveness, etc.) were included to explore whether these factors contribute to pedestrian injury severity. Finally, 2021 observations were selected for analysis. The distribution of injury severity class is – Fatal: 13%, Major: 80%, Minor: 4%, Minimal: 2%, None: 1%. Please refer to the Supplemental Information to be informed about the class imbalance in the dataset and how it has been resolved.

The analysis was conducted using a non-parametric machine learning technique known as random forest (RF) classification model which is widely used in injury severity analysis (e.g., Li et al. 2017; Rezapour et al. 2021). Predictor variables used in model development are presented in Table 1. As multicollinearity does not affect the prediction accuracy in RF algorithm, no tests were conducted to check for multicollinearity among the predictors.

One of the frequently reported limitations of machine learning models is that there is no standard method of incorporating spatial information into the model, and as a result, they cannot minimize spatial autocorrelation (Islam et al. 2022). To address this limitation, a RF model for pedestrian injury severity prediction in pedestrian-automobile collisions was developed first without incorporating spatial information (model 1). To incorporate spatial information, two different approaches were followed. First, a RF model was developed where latitude and longitude were used directly as predictors (model 2). Second, the eigenvector spatial filter method was applied to extract approximated eigenvectors from spatial coordinates of the collision location [see Supplemental Information section]. Later, the vector for all approximated eigenvectors (EV) was extracted and included as a predictor within the random forest model (model 3). A comparison of three RF models was made to determine which model demonstrates better performance in terms of predicting pedestrian injury severity in pedestrian-automobile collisions.

The RF models were developed based on 80% of the observations (training dataset: 1617 observations) and tested on the remaining 20% (testing dataset: 404 observations). Two hyperparameters (*mtry* and *ntree*) were specified. The *mtry* parameter controls how many predictors are to be considered in a decision tree at any given point in time. The *ntree* parameter represents the number of decision trees to be developed for the RF models. A 10-fold cross-validation procedure is used to select the optimal hyperparameter values which involves testing multiple values of the hyperparameters and selecting the optimal values[1] (Ahmed and Roorda 2021). The values tested for the hyperparameters are: *mtry* = 1 to 10 and *ntree* = 100, 150, 200, 300, 400, 500, 1000. Based on the results of the cross-validation procedure, the following hyperparameter values were selected[2]:

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1 It is expected that enough trees and parameters (in each tree) are considered to stabilize the prediction error and optimize model performance, but using too many trees or parameters involves more computational time.

2 A slight difference in hyperparameter values is expected as there were differences in variables (i.e., spatial information) included in the dataset.

Table 1. Predictors used in pedestrian injury severity in RF models.

Predictor	Note	Percentage
Non-spatial predictors		
Major_Arterial	Dummy variable. 1 if the collision occurred on a major arterial road.	72%
ACCLOC_Intersection	Dummy variable. 1 if the collision occurred in an intersection.	70%
TRAFFCTL_NoControl	Dummy variable. 1 if there is no traffic control at the collision location.	44%
TRAFFCTL_TrafficSignal	Dummy variable. 1 if there is a traffic signal at the collision location.	46%
VISIBILITY_Rain	Dummy variable. 1 if it was raining at the time of collision.	16%
LIGHT_Dark	Dummy variable. 1 if the light condition at the time of collision was dark.	43%
RDSFCOND_Wet	Dummy variable. 1 if the road surface condition was wet at the time of collision.	24%
PED_0_to_19years	Dummy variable. 1 if the age of the pedestrian was between 0 to 19 years.	11%
PED_20_to_34years	Dummy variable. 1 if the age of the pedestrian was between 20 to 34 years.	25%
PED_35_to_49years	Dummy variable. 1 if the age of the pedestrian was between 35 to 49 years.	20%
PED_50_to_64years	Dummy variable. 1 if the age of the pedestrian was between 50 to 64 years.	18%
PED_65_to_79years	Dummy variable. 1 if the age of the pedestrian was between 65 to 79 years.	16%
PED_80years_n_above	Dummy variable. 1 if the age of the pedestrian was 80 years or above.	10%
PEDCOND_Normal	Dummy variable. 1 if the pedestrian was in normal condition.	58%
PEDCOND_Impaired_Alcohol_Drugs	Dummy variable. 1 if the pedestrian was ability impaired due to alcohol or drug use.	2%
PEDCOND_HadbeenDrinking	Dummy variable. 1 if the pedestrian had been drinking at the time of collision.	7%
PEDCOND_Inattentive	Dummy variable. 1 if the pedestrian was inattentive at the time of collision.	16%
PEDCOND_Disability	Dummy variable. 1 if the pedestrian had a medical and physical disability.	2%
DRV_15_to_19years	Dummy variable. 1 if the age of the driver was between 15 to 19 years.	5%
DRV_20_to_34years	Dummy variable. 1 if the age of the driver was between 20 to 34 years.	24%
DRV_35_to_49years	Dummy variable. 1 if the age of the driver was between 35 to 49 years.	19%
DRV_50_to_64years	Dummy variable. 1 if the age of the driver was between 50 to 64 years.	18%
DRV_65_to_79years	Dummy variable. 1 if the age of the driver was between 65 to 79 years.	16%
DRV_80years_n_above	Dummy variable. 1 if the age of the driver was 80 years and above.	9%
DRV_Going_Ahead	Dummy variable. 1 if the driver was going ahead.	55%
DRV_Turning_Left	Dummy variable. 1 if the driver was turning left.	27%
DRV_Turning_Right	Dummy variable. 1 if the driver was turning right.	6%
DRV_Slowing_Stopping	Dummy variable. 1 if the driver was slowing or stopping.	3%
DRV_Driving_Properly	Dummy variable. 1 if the driver was driving properly.	44%
DRV_Failed_ROW	Dummy variable. 1 if the driver failed to yield the right of way.	31%
DRV_Disobeyed_TRAFFCTRL	Dummy variable. 1 if the driver disobeyed traffic control.	4%
DRV_Improper_Turn	Dummy variable. 1 if the driver was making an improper turn.	4%
DRV_Lost_CTRL	Dummy variable. 1 if the driver lost control of the vehicle.	4%
DRVCOND_Normal	Dummy variable. 1 if the driver was in normal condition.	61%
DRVCOND_Impaired_Alcohol_Drugs	Dummy variable. 1 if the driver was ability impaired due to alcohol or drug use.	2%
DRVCOND_HadbeenDrinking	Dummy variable. 1 if the driver had been drinking at the time of collision.	2%
DRVCOND_Inattentive	Dummy variable. 1 if the driver was inattentive at the time of collision	20%
Aggressive_Driving	Dummy variable. 1 if the collision was caused due to aggressive driving.	46%
Spatial predictors		
Latitude	Latitude of the collision location	
Longitude	Longitude of the collision location	
EV	Vector of all approximated eigenvectors extracted by applying spatial filtering approach.	

Note: One of the reasons behind creating dummy variables is to tackle the missing information in certain categories such as the age of the driver, collision location, conditions of the persons involved, etc.

- Model 1 (includes no spatial information): *mtry* = 4, *ntree* = 100,

Table 2. RF model prediction results on training and testing datasets.

Model	Prediction accuracy (%)	
	Training dataset	Testing dataset
Model 1 (no spatial information)	91.51% [OOB estimate of error rate: 11.75%]	83.17%
Model 2 (includes latitude and longitude)	97.09% [OOB estimate of error rate: 8.04%]	84.9%
Model 3 (includes EV)	97.03% [OOB estimate of error rate: 8.84%]	81.69%

- Model 2 (includes latitude and longitude): *mtry* = 5, *ntree* = 400.
- Model 3 (includes EV): *mtry* = 6, *ntree* = 150.

The *R* package *"spmoran"* (Murakami 2023) was used to extract the vector for all approximated eigenvectors (EV), "*ROSE*" (Lunardon, Menardi, and Torelli 2014, 2021) was used to resolve the data imbalance issue, and *"randomForest"* (Liaw and Wiener 2022) was used to develop the RF models.

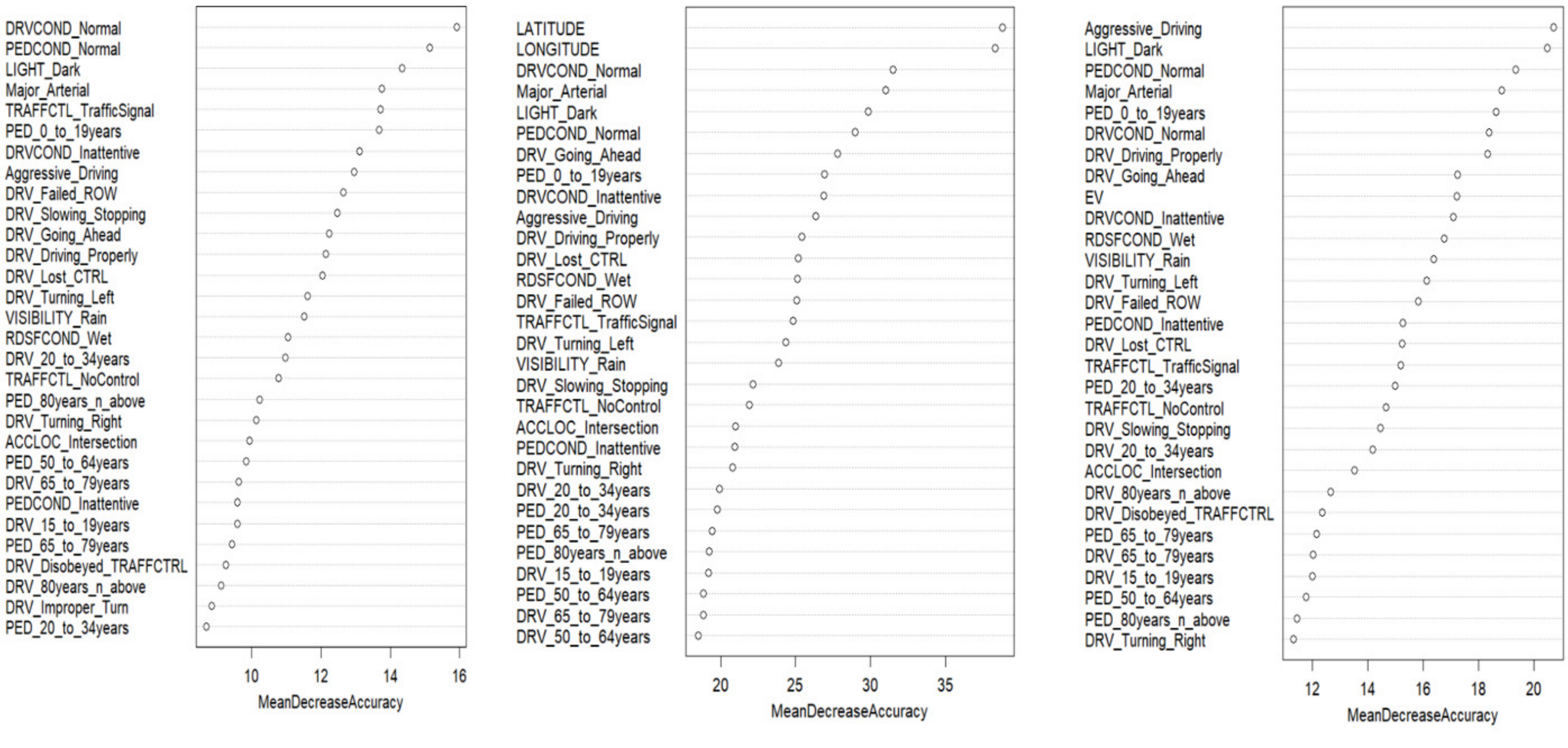
3. Findings

Table 2 shows the prediction accuracy of the three models on both training and testing datasets. Prediction accuracy was calculated by developing a confusion matrix of the actual injury classes and predicted injury classes based on the developed models. The inclusion of spatial information in the RF model improves the prediction performance of the models in the training dataset. In all three models, prediction accuracy is slightly degraded in the testing datasets compared to the corresponding training models. However, the testing dataset is the real-life field data which was not used in the training of the prediction models. Based on the results, it can be concluded that the trained models 1, 2 and 3 will be able to predict out-of-sample injury severity class with 83.17%, 84.9% and 81.69% accuracy, respectively.

The Mean Decrease Accuracy plots of the three RF models are presented in Figure 2. These plots express how much accuracy the models lose by excluding each predictor.[3] The plots for both models 2 and 3 show the importance of spatial information in predicting pedestrian injury severity. Direct use of latitude and longitude plays a more important role in predicting injury severity than EV as model predictors.

The developed model can be used in predicting injury severity in pedestrian-automobile collisions in Toronto. The study results also indicate the importance of developing appropriate countermeasures to increase pedestrian safety, especially related to aggressive driving, and drivers' and pedestrian conditions. In terms of future work, other machine learning techniques such

3 The first thirty predictors are presented in descending order. The more the accuracy suffers, the more important the predictor is for the successful prediction of classification.



Model 1 Model 2 Model 3

Figure 2. Mean Decrease Accuracy plots of the RF models

as gradient boost, XGBoost, and support vector machine (SVM) can be developed and a comparison of the prediction accuracies of the models can be used to determine the optimal prediction model for pedestrian injury severity in pedestrian-automobile collisions in Toronto.

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SUPPLEMENTARY MATERIALS

Supplemental Information

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