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Design and experiment verification of a novel analysis framework for recognition of driver injury patterns: From a multi-class classification perspective

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ABSTRACT

Detecting driver injury patterns is a typical classification problem. Crash data sets are highly skewed where fatalities and severe injuries are often less represented compared to other events. The severity prediction performance of the existing models is poor due to the highly imbalanced samples of different severity levels within a given dataset. This paper proposes a machine learning based analysis framework from a multi-class classification perspective for accurate recognition of the driver injury patterns. The proposed framework includes preprocessing, classification, evaluation and application of a given dataset. This framework is verified based on the three years single-vehicle ROR (run-off-road) crash records collected in Washington State from 2011 to 2013. At first, thirteen most important safety-related variables are recognized through random forests. Then, the four driver's injury severity levels viz., fatal/serious injury, evident injury, possible injury, and no injury are predicted by integrating the decomposed binary neural network models to achieve better performance. Finally, a sensitivity analysis is carried out to interpret variables' impacts on the decomposed injury severity levels. The study shows that lack of restraint, female drivers, truck usage, driver impairment, driver distraction, vehicle overturn (rollover), dawn/dusk, and overtaking are the leading factors contributing to the driver fatalities or severe injuries in a single-vehicle ROR crash. Most of the findings are consistent with the previous studies. The experimental results validate the effectiveness of the proposed framework which can be further applied for pattern recognition in traffic safety research.

1. Introduction

Investigation of the injury severity patterns in traffic crashes is a fundamental step to develop effective countermeasures for traffic safety improvement, and the prediction of such injury patterns can be viewed as a typical classification problem. Taking the granularity of the crash output variables into consideration, different injury severity levels have been employed in the previous studies. In (Abellán et al., 2013; Zhang et al., 2013 Abu-Zidan and Eid, 2014; Mujalli et al., 2016 Ma et al., 2017 Theofilatos, 2017), the binary injury output levels are considered. On the other hand, several recent studies considered multiple injury severity levels (Kim et al., 2012; Almutairi, 2013; Palamara et al., 2013 Dissanayake and Roy, 2014; Roque et al., 2015 Das and Sun, 2016; Gong et al., 2016 Albdairi and Hernandez, 2017; Gong and Fan, 2017).

The crash datasets usually have much fewer records of fatal and severe injuries compared to other types of accidents as they occur less frequently (Mujalli et al., 2016). When learning from the imbalanced dataset, the traditional classifiers tend to have several problems: (i) These classifiers tend to produce a high accuracy over the majority class but behave badly in minority class (Delen et al., 2006; López et al., 2013; Mujalli et al., 2016). (ii) The training procedure is affected by the considered performance evaluators such as accuracy, which may cause biased learning (Loyola-González et al., 2016). (iii) If the dataset is highly skewed, then the rare samples may be simply treated as noise and vice-versa as discussed in (Beyan and Fisher, 2015). Therefore, the main challenge in the analysis of several injury severity levels is to avoid the imbalanced learning in highly skewed accident observations.

Some efforts have been made to deal with the challenges mentioned above in the crash safety analysis including resampling techniques (Mujalli et al., 2016; Mussone et al., 2017) and feature selection procedure (Mujalli and De, 2011; Yu and Abdelaty, 2013; Chen et al., 2015b Chen et al., 2016a,b; Prati et al., 2017). In (Mujalli et al., 2016),

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the performances of different resampling methods are studied and pointed out that with an imbalanced dataset, the Bayes models are incapable of determining the real influence of the sub-categories “killed” or “severe injury”. In (Mujalli and De, 2011), different feature selection methods are analyzed using Bayesian networks and found that a model built with few important variables can produce more useful results. Most of these studies have focused on a selected step in crash analysis without discussing to build a unified analysis framework for imbalanced learning. On the other hand, novel methods such as data mining and machine learning algorithms, which are the newly developed and promising, can be employed for the implementation of the framework for driver injury severity pattern recognition.

In fact, various approaches have been developed in different stages to deal with the imbalanced learning problems in other fields. Several surveys regarding the imbalanced learning have been published (He and Garcia, 2009; Sun et al., 2009 Galar et al., 2012; Fernández et al., 2013; López et al., 2013 Branco and Ribeiro, 2016; Guo et al., 2016). In (Guo et al., 2016), a thorough overview of learning from imbalanced data tasks is provided that include both techniques and applications. It showed the available promising algorithms, plenty of existing applications and future directions. However, the traffic safety-related research is not mentioned. In fact, (Delen et al., 2006) gave a good attempt about imbalanced learning techniques applied to traffic safety research. Their research stressed the imbalanced classification problem and investigated the partitioning methods to measure the variable importance in different decomposed models. Furthermore, this paper proposed a machine learning based analysis framework to deal with the imbalanced learning problem in transportation safety research. This unified framework includes four steps as preprocessing, classification, evaluation and application. Each step can try to apply different analysis methods in different applications. Resampling techniques, feature engineering and cost-sensitive learning (Fernández et al., 2013; Li et al., 2016) can be used in the preprocessing step. Classification step contains binary decomposition, ensemble methods and classifier modifications (Sun et al., 2009; Galar et al., 2012), while the performance metrics like accuracy, Receiver Operating Characteristics (ROC), Area Under Curve (AUC) and F-measure (De et al., 2011; Chen et al., 2015a,b) can be applied in the evaluation step. Compared with (Delen et al., 2006)’s previous research, this paper put more focus on the design and experiment verification of the proposed analysis framework while partitioning methods only played one important processing step in it. At the same time, adoptions of robust variables importance ranking method, ensemble method for integration of the decomposed models results and discussions of variable impacts towards driver injury severity levels contributed more to the differences between this study and Delen’s research.

Run-off-road (ROR) crashes have been a major cause of fatalities and serious injuries in the United States. Statistics from the Fatality Analysis Reporting System (FARS) illustrate that the traffic fatalities due to ROR crashes in the United States count up to about 38% of the total traffic fatalities in 2007–2016 (NHTSA, 2017). Since the ROR crashes are more likely to cause either fatalities or severe injuries than the other type of vehicle crashes, it has drawn a lot of attention not only in the United States (Lee and Mannering, 2002; Dissanayake, 2003; Peng and Boyle, 2012; Roy and Dissanayake, 2013; Dissanayake and Roy, 2014; Albdairi and Hernandez, 2017) but also across the world (Palamara et al., 2013; Petegem and Wegman, 2014; Shawky et al., 2014 Roque et al., 2015). The proposed framework is implemented and verified on three years of single vehicle ROR crash records in this study.

The rest of the paper is organized as follows: Section 2 describes the data and preprocessing operations. Model description and implementation specifications are introduced in Section 3. Section 4 discusses the injury pattern from the aspects of variable impact and elasticity. Conclusions and summary of the future direction are presented in Section 5.

2. Data description

This study focuses on three-years single-vehicle ROR crash data collected from 2011 to 2013 in Washington State. The raw data were provided by the Washington State Department of Transportation (WSDOT) which is recording the traffic accident information among all the state routes statewide. The entire dataset consists of five parts regarding the traffic accident: four crash related variables including (i) spatial-temporal information, (ii) environmental information, (iii) driver demographic characteristics, (iv) vehicles related data and one output variable of driver injury severity levels when accidents occurred.

1) The spatial-temporal information describes the crash time, crash location and roadway type.
2) Environmental information consists of weather conditions, road surface conditions, lighting condition and road’s geographical features.
3) Driver demographic characteristics refer to driver’s age, gender, sobriety degree, behavior, ejection, and restraint usage.
4) Vehicles related data composed of vehicle type, manufacture, usage and movement.
5) Driver injury severity levels record the ROR crash outcomes and are the dependent variables in this study.

The severity criterion of driver injury adopted by most Department of Transportation in different states was KABCO: fatality (K), incapacitating injury (A), visible injury (B), complaint of injury (C), and no apparent injury (O). In imbalanced learning problem, if the proportion of minority class samples is less than 35% of the dataset, then the dataset is considered imbalanced (Li and Sun, 2012). The available ROR dataset was scrutinized and presented in Table 1, and it was found that different driver injury severity levels have an imbalance distribution. Therefore, four categories of injury severity levels are employed in this study as follows: (i) fatality or serious injury(F/S), (ii) evident injury (EI), (iii) possible injury (PI), and (iv) property damage only (PDO).

The observations of ROR crashes were obtained through screening the candidate variables “driver sequence 1”, and the events with records “Ran off the road” were selected. A ROR crash dataset including 12,788 single-vehicle ROR accident observations was formed from overall 133,579 accidents. Further, eighteen variables were selected from the original reports according to the previous driver injury severity studies (Huang and Abdel-Aty, 2010; Savolainen et al., 2011 Mannering and Bhat, 2014) and engineering experience, all of which were categorical variables and were coded numerically. Variables composed of multiple attributes and highly skewed in frequency were decomposed, for example, road characteristics were divided into road curvature and road grade. Similarly, for multi-categorical variables, those values with similar contributions were merged, for example, “apparently asleep” and “apparently fatigued” under the variable “driver action” were reduced to “fatigue”. From these records, the incomplete and “unknown” crash records were screened out. Such processing is consistent with the existing literature in driver injury severity analysis. A detailed variable definitions and data description are shown in Table 1. The interpretation of variables as well as the numerical coding value for each sub-category within every variable are illustrated, accompanied with driver injury severities corresponding to the value.

3. Methodology

3.1. Multi-class imbalanced learning framework

To gain more insight into the mechanism of accident crashes, a higher prediction performance and a better understanding are essential. This article proposed the multi-class imbalanced learning framework into the analysis of accident crashes.

Table 1
Variable definitions and data descriptions.

Variable	Categories		Driver Injury Severity								Total
	Information	coding	PDO	Percentage	PI	Percentage	EI	Percentage	F/S	Percentage	
Time variables											
1 Quarter											
	Q1(Jan.-Mar.)	0	2738	73.60%	495	13.31%	428	11.51%	59	1.59%	3720
	Q2(Apr.-Jun.)	1	1658	66.13%	415	16.55%	368	14.68%	66	2.63%	2507
	Q3(Jul.-Sep.)	2	1660	62.93%	450	17.06%	430	16.30%	98	3.71%	2638
	Q4(Oct.-Dec.)	3	2825	72.01%	568	14.48%	449	11.45%	81	2.06%	3923
2 Day of week											
	Week Day	0	6084	69.58%	1370	15.67%	1099	12.57%	191	2.18%	8744
	Weekend	1	2797	69.16%	558	13.80%	576	14.24%	113	2.79%	4044
3 Hour 24											
	Night(0:00am-5:00am)	0	1590	67.06%	349	14.72%	346	14.59%	86	3.63%	2371
	Morning(6:00am-11:00am)	1	2617	70.79%	586	15.85%	435	11.77%	59	1.60%	3697
	Afternoon(12:00pm-17:00pm)	2	2687	70.05%	567	14.78%	496	12.93%	86	2.24%	3836
	Evening(18:00pm-23:00pm)	3	1987	68.90%	426	14.77%	398	13.80%	73	2.53%	2884
Environment variables											
4 Weather											
	Clear or partly cloudy	0	3995	65.08%	1026	16.71%	931	15.17%	187	3.05%	6139
	Overcast	1	1521	68.33%	333	14.96%	315	14.15%	57	2.56%	2226
	Rain	2	2032	74.71%	368	13.53%	275	10.11%	45	1.65%	2720
	Snow/fog/crosswind	3	1296	78.69%	194	11.78%	143	8.68%	14	0.85%	1647
	Other	4	37	66.07%	7	12.50%	11	19.64%	1	1.79%	56
5 Road surfaces											
	Dry	0	3840	63.62%	1024	16.96%	969	16.05%	203	3.36%	6036
	Wet	1	2720	73.47%	528	14.26%	392	10.59%	62	1.67%	3702
	Snow	2	1204	80.27%	163	10.87%	125	8.33%	8	0.53%	1500
	Ice	3	1064	72.18%	203	13.77%	179	12.14%	28	1.90%	1474
	Other	4	53	69.74%	10	13.16%	10	13.16%	3	3.95%	76
6 Intersection											
	Not at Intersection	0	7251	68.05%	1655	15.53%	1491	13.99%	259	2.43%	10656
	At Intersection	1	1438	76.09%	244	12.91%	166	8.78%	42	2.22%	1890
	At Driveway	2	114	82.61%	13	9.42%	9	6.52%	2	1.45%	138
	Other	3	78	75.00%	16	15.38%	9	8.65%	1	0.96%	104
7 Lighting condition											
	Daylight	0	4738	68.82%	1095	15.90%	913	13.26%	139	2.02%	6885
	Street lights	1	1421	74.71%	259	13.62%	178	9.36%	44	2.31%	1902
	Dark	2	2188	67.26%	470	14.45%	488	15.00%	107	3.29%	3253
	Dawn/Dusk	3	531	71.47%	103	13.86%	96	12.92%	13	1.75%	743
	Other	4	3	60.00%	1	20.00%	0	0.00%	1	20.00%	5
8 Road curvatures											
	Straight	0	5542	70.04%	1166	14.74%	1029	13.00%	176	2.22%	7913
	Curve	1	3339	68.49%	762	15.63%	646	13.25%	128	2.63%	4875
9 Road grades											
	Level	0	5151	68.73%	1136	15.16%	1009	13.46%	199	2.66%	7495
	Grade	1	3538	70.52%	753	15.01%	625	12.46%	101	2.01%	5017
	In sag	2	105	72.92%	17	11.81%	21	14.58%	1	0.69%	144
	Hillcrest	3	87	65.91%	22	16.67%	20	15.15%	3	2.27%	132
10 Urban/Rural											
	Urban	0	4390	74.55%	840	14.26%	566	9.61%	93	1.58%	5889
	Rural	1	4491	65.10%	1088	15.77%	1109	16.07%	211	3.06%	6899
Vehicle variables											
11 Vehicle types											
	Passenger car	0	4796	70.69%	1028	15.15%	816	12.03%	145	2.14%	6785
	Pickup	1	3629	67.08%	831	15.36%	801	14.81%	149	2.75%	5410
	Truck	2	435	77.54%	63	11.23%	55	9.80%	8	1.43%	561
	Other	3	21	65.63%	6	18.75%	3	9.38%	2	6.25%	32
12 Vehicle actions											
	Going Straight Ahead	0	7642	68.26%	1743	15.57%	1533	13.69%	278	2.48%	11196
	Slowing	1	96	75.59%	13	10.24%	17	13.39%	1	0.79%	127
	Changing Lanes	2	265	69.92%	65	17.15%	42	11.08%	7	1.85%	379
	Turning	3	612	86.44%	54	7.63%	37	5.23%	5	0.71%	708
	Merging (Entering Traffic)	4	97	82.20%	15	12.71%	6	5.08%	0	0.00%	118
	Overtaking and Passing	5	161	64.40%	38	15.20%	39	15.60%	12	4.80%	250
	Other	6	8	80.00%	0	0.00%	1	10.00%	1	10.00%	10
13 Vehicle sequential action after ROR											
	Collision involving fixed object	0	7625	72.23%	1476	13.98%	1218	11.54%	238	2.25%	10557
	Overturn (Rollover)	1	1153	55.01%	439	20.94%	440	20.99%	64	3.05%	2096
	Other	2	103	76.30%	13	9.63%	17	12.59%	2	1.48%	135
Demographic variables											
14 Driver impairments											
	Not impaired	0	7994	71.53%	1667	14.92%	1322	11.83%	193	1.73%	11176
	Impaired	1	887	55.02%	261	16.19%	353	21.90%	111	6.89%	1612
15 Driver ages											

(*continued on next page*)

Table 1 (*continued*)

Variable	Categories Information	coding	Driver Injury Severity PDO	Percentage	PI	Percentage	EI	Percentage	F/S	Percentage	Total
	Young 16-25	1	3410	71.53%	654	13.72%	624	13.09%	79	1.66%	4767
	Mid 26-60	2	4591	69.02%	1052	15.81%	844	12.69%	165	2.48%	6652
	Senior > 60	3	880	64.28%	222	16.22%	207	15.12%	60	4.38%	1369
16 Driver genders											
	Male	0	5843	71.78%	1030	12.65%	1063	13.06%	204	2.51%	8140
	Female	1	3038	65.36%	898	19.32%	612	13.17%	100	2.15%	4648
17 Driver actions											
	Distraction	0	495	65.91%	127	16.91%	119	15.85%	10	1.33%	751
	Fatigue	1	774	60.56%	243	19.01%	225	17.61%	36	2.82%	1278
	Did Not Grant ROW	2	155	60.55%	34	13.28%	58	22.66%	9	3.52%	256
	Speeding	3	3781	76.20%	637	12.84%	485	9.77%	59	1.19%	4962
	Impaired	4	1073	54.83%	341	17.42%	409	20.90%	134	6.85%	1957
	Operating Defective Equipment	5	384	74.71%	74	14.40%	50	9.73%	6	1.17%	514
	None	6	359	75.74%	68	14.35%	43	9.07%	4	0.84%	474
	Other	7	1860	71.65%	404	15.56%	286	11.02%	46	1.77%	2596
18 Driver restraints											
	Restraint used	0	8827	70.77%	1866	14.96%	1564	12.54%	216	1.73%	12473
	Restraint not used	1	54	17.14%	62	19.68%	111	35.24%	88	27.94%	315

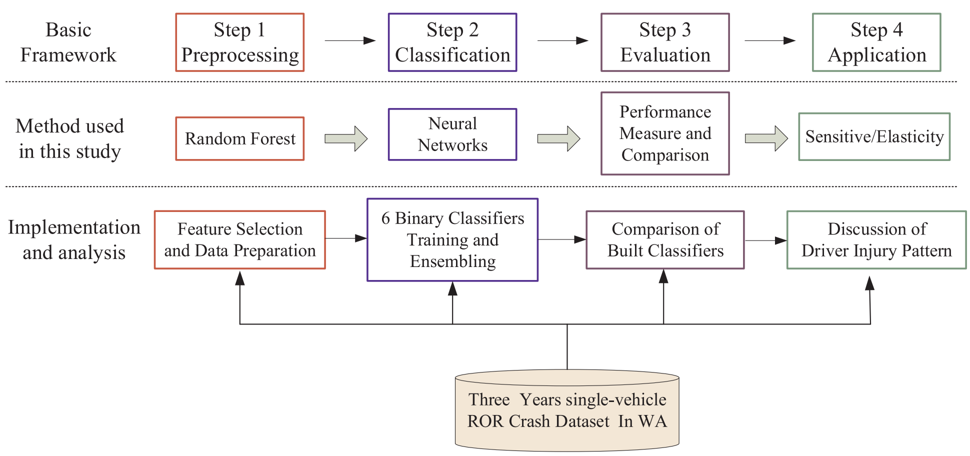


Fig. 1. The proposed framework in this Study.

(Guo et al., 2016) introduced common approaches to deal with imbalanced learning and proposed a general framework. This study extended the above framework for the driver injury pattern recognition task as the top level of Fig. 1. The proposed procedure employs a series of well proven data-driven methods such as Random Forests, Neural Networks and multi-class decomposition to achieve a better classification performance and understanding of the inner mechanism (middle layer of Fig. 1).

The implementations of corresponding steps in our study are shown in the bottom layer of the proposed framework in Fig. 1. At first, the Random Forests (RF) model was utilized to measure the relevance of crash-related variables. A total of thirteen important variables were selected based on their ranking scores. Then, different decompositions of the four output categories in the entire dataset were implemented, and six neural networks were established with different driver injury severities as the binary outputs. An ensemble method was implemented for multi-class imbalanced classification and the performance of all previously built models was evaluated, compared and discussed. Finally, the sensitivity and elasticity analysis were carried out on the outputs of six binary prediction models. The mechanism of ROR driver injury severity pattern was discussed.

3.2. Feature selection with random forests method

The decision tree models are usually employed to identify the relative importance among variables. It is hardly possible to build a "best" tree in decision tree models, thus the importance measurement score utilizing a single tree may be insufficient and unlikely. Therefore, the Random Forests model is employed in this study to select the important variables among all the 18 variables. Feature selection method can help understanding the data, exclude the redundant variables (but may be relevant) (Guyon et al., 2003) and produce more useful results (Mujalli and De, 2011).

Gini reduction was used as the variable importance scores in the RF model (Breiman, 2001; Liaw and Wiener, 2002; Breiman, 2004), and the model was implemented in the SAS Enterprise Miner workstation software (Miguel Maldonado et al., 2014). The variable with the largest scores is marked 100% (normalized), and all the other variables have their scores relatively scaled. The relative importance scores of variables from the RF analysis are shown in Table 2. The calculated "importance" scores here represent the association between variables and driver injury severity levels. The higher the score, the more important the variable. The results presented in this table provide a preliminary perspective of the relationships between the related variables and driver injury severities. The last five variables were removed based on corresponding conclusions from existing peer studies (Yu and Abdelaty, 2013; Chen et al., 2016a Prati et al., 2017); as a result, a total of thirteen variables were identified as the inputs to the Artificial Neural Network (ANN) models. Since the measurement results from RF only manifest the relative significance of a specified dataset, the RF model was used for variable selection only.

Table 2
RF variable importance ranking results based on Gini reduction from Random Forests analysis.

Variable	Importance	Variable	Importance
Driver restraints	**100.00**	**Vehicle types**	**4.78**
Vehicle sequential action after ROR	**69.62**	**Lighting condition**	**3.94**
Driver actions	**69.22**	**Driver ages**	**3.35**
Driver impairments	**33.87**	Intersections	2.43
Urban/Rural	**29.75**	Hour 24	1.74
Road surfaces	**25.03**	Road curvatures	1.10
Driver genders	**24.95**	Day of week	0.83
Vehicle actions	**12.00**	Road grades	0.30
Weather	**12.00**		
Quarter	**8.17**		

The bold values represents the thirteen important variables selected based on RF model as well as their scores.

3.3. Binary decomposition with series of ANN

In this study, the neural network was chosen as the basic classification model. At first, a full back propagation neural network was established and tested with the Bayesian regularization training algorithm. All the 13 selected important variables were given as inputs to the model and all the four injury severity levels defined in Section 2 as outputs. It can be seen from Table 5 that the four class models have an unsatisfactory performance when working with an unbalanced dataset.

A popular approach to improve the learning efficiency of a class-imbalanced dataset was decomposing the multi-class imbalanced problem into a series of binary classification problems. There are three ways to make this decomposition: (i) one-versus-one approach (OVO), (ii) one-versus-all approach (OVA) and (iii) all-versus-all approach (AVA) (Delen et al., 2006; Guo et al., 2016). Based on the principle of OVA, this study puts forward a refined OVA scheme by changing the original four-level classification problem into a set of six binary classifiers as shown in Fig. 2. The series NN models were expected to bring out a satisfactory accuracy in minority class prediction.

As shown in Fig. 2, four levels of the original dataset were selected and grouped into six different combinations. Each rearrangement has two combined injury severity levels i.e., Category 0 "−"and Category 1 "+". The Category 0 in each decomposition has a higher injury severity level. Table 3 gives detailed information on the series of binary models. {Model1_1, Model1_2, and Model1_3} specify a decrease in the interested Category 0 while {Model2_1, Model2_2, and Model2_3} have an increased severity level of it. The overall performance of both binary NN classifier and four-level NN classifier were evaluated from the average of stratified 10-fold cross-validations. After six binary NN classifiers (f_1–f_6 in Fig. 3) were trained, the error correcting output codes (ECOC) were generated for a final decision (Dietterich and Bakiri, 1995; Allwein et al., 2000). For example, once the six decompositions are finished, the coding matrix of those binary decompositions is determined (the 4×6 matrix with value 0, -1 and 1 in Fig. 3 for this study). The value 1 in i^{th} row and j^{th} column means the i^{th} class is aggregated as the "+" class in the j^{th} subset, and similarly, the value -1 means the "-" class. The value 0 in i^{th} row and j^{th} column means the observations of the i^{th} class is discarded in the j^{th} subset (For instance, the F/S observations were discarded in Model1_2 and Model1_3). For a test sample, the six binary classifiers generate six predictions ("+1" positive or "-1" negative) as shown at the bottom of Fig. 3. The prediction vector (or prediction coding) was compared with the vector (row vector here) in the coding matrix corresponding to the four classes separately. Either the Hamming distance or Euclidean distance is applied to calculate the distance between prediction vector and the four-class vectors separately. In addition, the labels of these class with minimal distance is assigned as result.

The overall prediction accuracy of these six binary ANN models and their ensemble model were compared with that of the full ANN model with four-level outputs. The confusion matrices of binary and four category models are presented in Tables 4 and 5, respectively. The confusion matrices of binary models show a higher accuracy in overall performance and a stronger capability to recognize the less-represented categories than the four-level models. A noticeable improvement is achieved in the ensemble models compared to four-category models in terms of the number of minority class (PI, EI and F/S) correctly predicted. The four-level NN model is incapable of classifying possible injury and F/S accurately, and inferior in predicting evident injuries. This is consistent with the previous studies that the binary decomposition of multi-category classifications as well as the ensemble techniques can improve the model performance (Delen et al., 2006; Chen et al., 2016a). For comparison purpose, the prediction performance of regression models of both the four-category classifiers and the

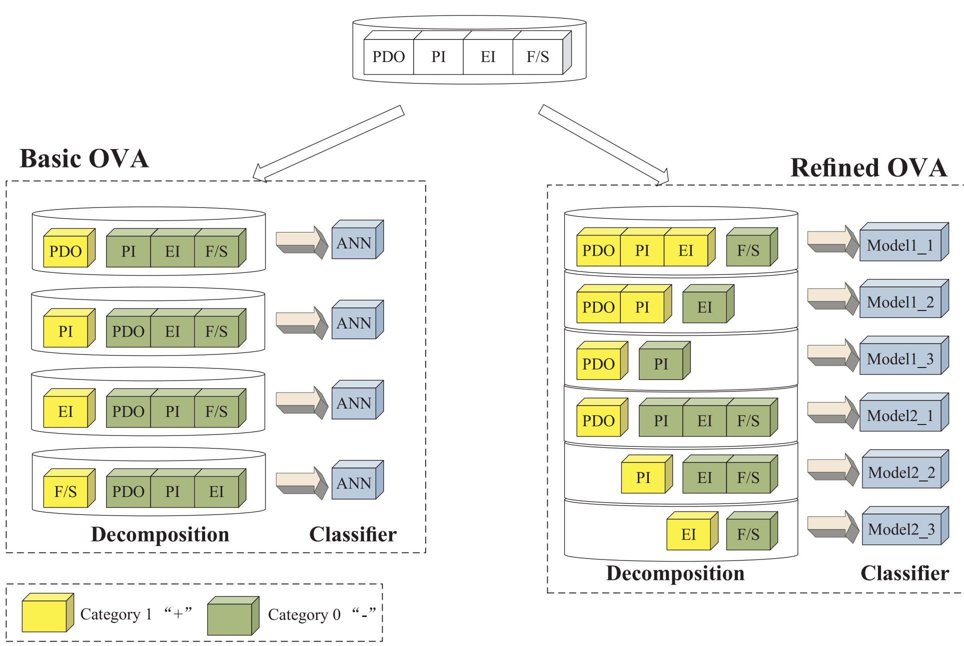


Fig. 2. Graphical representation of disaggregated binary models.

Table 3
Series of binary classification models and injury severity composition.

Model	Target variable (category 1)	Count	Target variable (category 0)	Count	Total
1_1	At most evident injury	12,484(97.62%)	F/S	304(2.38%)	12,788
1_2	At most possible injury	10,809(86.58%)	Evident injury	1675(13.42%)	12,484
1_3	No injury	8881(82.16%)	Possible injury	1928(17.84%)	10,809
2_1	No injury	8881(69.45%)	At least possible injury	3907(30.55%)	12,788
2_2	Possible injury	1928(49.35%)	At least evident injury	1979(50.65%)	3907
2_3	Evident injury	1675(84.64%)	F/S	304(15.36%)	1979

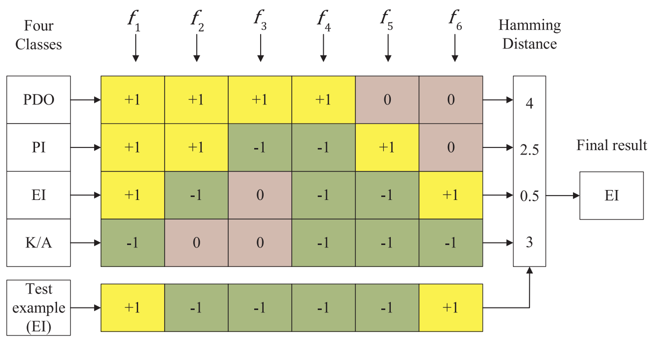


Fig. 3. Error Correcting Output Codes for multi-class classification.

decomposed binary NN models are presented in Tables 4 and 5, respectively. Both the Generalized Linear regression model with "probit" link function (i.e. binary probit model) (Haleem and Abdelaty, 2010) and Multinomial Logit model (MNL) (Ye and Lord, 2014; Chen et al., 2015a) were implemented. It can be seen from the confusion matrices that both the binary NN classifiers and four category NN models perform relatively better compared to the statistical models in terms of the overall accuracy perspective and perform relatively better in minority class prediction.

For binary classifiers, several evaluators such as Sensitivity, Specificity, True Precision, False Precision, F measure and the Area Under the ROC Curve (AUC) were usually employed to examine the model's capability in predicting the less-represented classes (De et al., 2011; Chen et al., 2015a,b). Eqs. (1)–(5) gives their definitions. For instance, the True Positives (TP) denotes the number of positive instances which are correctly predicted (category 1 in this study), True Negatives (TN) denotes the number of negative cases that are correctly predicted (category 0 in this study). Similarly, the False Positives (FP) denotes the number of positive cases which are incorrectly predicted and False Negatives (FN) denotes the number of negative cases that are incorrectly predicted.

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Negative\ Predictive\ Value = \frac{TN}{TN + FN} \tag{4}$$

$$F\ Measure = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \tag{5}$$

Table 6 lists the measurements of the six binary models (NN classifiers and GLMs). Most of the F-measures described in Table 6 are nearly excellent with their values close to 1. Model2_2 only has a lowest value of 69.67%. Its mediocre performance exactly illustrates the vagueness of discriminative boundary between a possible injury and an evident injury. The AUC values of Model1_1 and Model2_3 are obvious higher than other models. One possible interpretation for this

Table 4
Binary classification model performance (Overall Confusion Matrix).

Model 1_1		Target category						Model 2_1		Target category					
		NN classifier			GLM					NN classifier			GLM		
		1	0	ACC	1	0	ACC			1	0	Accuracy	1	0	ACC
Predicted category	1	12462	189		12480	301		Predicted category	1	8294	2811		8447	3167	
	0	22	115		4	3			0	587	1096		434	740	
				98.37%			97.61%					73.61%			71.84%

Model 1_2		Target category						Model 2_2		Target category					
		NN classifier			GLM					NN classifier			GLM		
		1	0	ACC	1	0	ACC			1	0	Accuracy	1	0	ACC
Predicted category	1	10710	1427		10754	1616		Predicted category	1	1352	601		1173	828	
	0	99	248		55	59			0	576	1378		755	1151	
				87.94%			86.61%					70.08%			59.48%

Model 1_3		Target category						Model 2_3		Target category					
		NN classifier			GLM					NN classifier			GLM		
		1	0	ACC	1	0	ACC			1	0	ACC	1	0	ACC
Predicted category	1	8766	1671		8845	1881		Predicted category	1	1643	100		1645	264	
	0	115	257		36	47			0	32	204		30	40	
				83.58%			82.26%					93.43%			85.14%

Table 5
Four category classification model performance (Overall Confusion Matrix).

		Target category									
		Four level NN classifier					Ensemble binary NN classifier				
		PDO	PI	EI	F/S	ACC	PDO	PI	EI	F/S	ACC
Predicted category	PDO	**8726**	1736	1422	200		**8231**	1423	1115	134	
	PI	57	**98**	49	11		263	**333**	96	18	
	EI	88	81	**182**	42		341	156	**456**	36	
	F/S	10	13	22	**51**		46	15	8	**116**	
		8881	1928	1675	304	70.82%	8881	1928	1675	304	71.44%

		Multinomial Logit Model No injury	Possible injury	Evident injury	F/S	Accuracy
Predicted category	No injury	**8818**	1860	1557	218	
	Possible injury	3	**4**	3	3	
	Evident injury	51	52	**85**	51	
	F/S	9	12	30	**32**	
		8881	1928	1675	304	69.90%

(ACC: Accuracy). The bold values represents the number of observations correctly predicted in each category.

observation is that the neural networks performed better in Fatal/Injury (Model2_3) and Injury/PDO (Model1_1) cases than differentiating the boundaries among different injury levels. This is consistent with (Delen et al., 2006). The AUC values of NN classifiers are relatively higher than that of the GLM and the measurements concerning the prediction ability of minority classes like Specificity and Negative predictive values in NN classifiers are significantly higher than GLM. This also proves the ability of NN models.

3.4. Sensitivity analysis

Since the neural networks use a black-box approach i.e., without the use of any explicit formula, it is very difficult to understanding and interpreting the model's output. The sensitivity analysis is a prevalent method used in traffic accident studies to understand the internal mechanism of ANN model (Olden and Jackson, 2002; Delen et al., 2006 Mussone et al., 2017). It is capable of measuring the degree to which a given sub-categories contributing to each dependent variable. In this study, we use the six binary models to analyze the variable effects (instead of the ensemble model) to get more insights about the ROR crashes as mentioned in (Delen et al., 2006).

A two-stage sensitivity analysis (Chang, 2005; Yu and Abdelaty, 2013; Chen et al., 2016a) is adopted. Firstly, all the weight coefficients in the trained models from Section 3.3 were kept fixed. The sensitivity analysis was carried out by changing each independent variable with a user-defined step while retaining the value of other input variables. All the variables selected in this study are numerically coded as categorical variables, so every input variable will vary from 0 to its maximum value by a step value of 1. Secondly, to evaluate the impact of significant variables on the specific injury outcome probabilities, an elasticity analysis or pseudo-elasticity analysis (Chang, 2005; Kim et al., 2007 Gong and Fan, 2017) was conducted. After setting one sub-category within each variable as its baseline, the changes in the probability (or elasticity) of each specific sub-category within this variable were calculated and compared to the corresponding base. The elasticity reflects the percentage change in probability of suffering a specific injury severity level involving a certain sub-category compared to the base sub-category of each variable.

Eq. (6) was applied to compute the pseudo-elasticity for each input variable:

$$\mathrm{E}_{X_{ij}}^{P_{ij}} = \frac{P_{ij}(X_{ij} = k) - P_{ij}(X_{ij} = k_{base})}{P_{ij}(X_{ij} = k_{base})} \quad k = 0,1,\ \cdots, max \tag{6}$$

The probabilities P_{ij} specific to an injury severity level j of the i^{th} explanatory variable are calculated when the input variable vector X_{ij} was set to k retaining the values of the other variable vectors. It's the average value for all observations. k is the numerical coding of the sub-categories of the i^{th} variable (for binary variables $k = 0\,or\,1$).

The above two-step process was repeated until all variables were tested. Finally, the influence of each variable on specified driver injury severity levels was obtained.

4. ROR injury pattern discussion

4.1. Variable impact evaluation

Table 7 shows the percentage change in the probability calculated from the two-step sensitivity analysis. The sub-category 'other' was excluded in each model, and only concerned output driver injury severity was discussed. Special attention was devoted to sub-categories that have significant impacts on injury severities i.e., those sub-categories that have high percentage changes in the probability.

Table 6
Model performance measurement.

Measurement	Model1_1		Model1_2		Model1_3		Model2_1		Model2_2		Model2_3	
	NN	GLM	NN	GLM	NN	GLM	NN	GLM	NN	GLM	NN	GLM
Sensitivity	98.51%	97.64%	88.24%	86.93%	83.99%	82.46%	74.69%	72.73%	69.23%	58.62%	94.26%	86.17%
Specificity	83.94%	42.86%	71.47%	51.75%	69.09%	56.10%	65.12%	63.03%	70.52%	60.39%	86.44%	57.14%
Precision	99.82%	99.97%	99.08%	99.49%	98.71%	99.59%	93.39%	95.11%	70.12%	60.84%	98.09%	98.21%
NPV	37.83%	0.99%	14.81%	3.52%	13.33%	2.39%	28.05%	18.94%	69.63%	58.16%	67.11%	13.16%
F Measure	99.17%	98.79%	93.35%	92.79%	90.76%	90.22%	83.00%	82.43%	69.67%	59.71%	96.14%	91.80%
AUC	0.7765	0.8156	0.7222	0.6987	0.7055	0.6636	0.7211	0.6937	0.7564	0.6458	0.8399	0.7265

(NPV: Negative predictive value).

Table 7
Results of variable sensitivity analysis.

Variable	Category											
	Model1_1		Model1_2		Model1_3		Model2_1		Model2_2		Model2_3	
	1(%)	0(%)	1(%)	0(%)	1(%)	0(%)	1(%)	0(%)	1(%)	0(%)	1(%)	0(%)
Quarter												
Q1(Jan.-Mar.) *(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Q2(Apr.-Jun.)	−0.72	59.22	−1.80	14.53	−3.24	17.91	−5.47	14.10	−5.93	6.13	−2.59	19.71
Q3(Jul.-Sep.)	−0.81	66.62	−2.00	16.20	−3.41	18.88	−6.76	17.41	−6.76	6.99	−3.46	26.37
Q4(Oct.-Dec.)	−0.19	15.88	−0.85	6.91	−2.25	12.43	−3.01	7.75	2.02	−2.09	−3.64	27.76
Weather												
Clear or partly cloudy*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Overcast	−0.27	16.41	−0.61	4.47	0.66	−3.16	−1.03	2.36	−6.22	6.18	−0.18	1.11
Rain	−0.04	2.73	−0.36	2.62	2.41	−11.48	1.23	−2.82	−8.61	8.55	0.59	−3.68
Snow/fog/crosswind	−0.10	5.90	−0.79	5.75	4.28	−20.45	5.88	−13.47	−10.90	10.82	1.00	−6.21
Road surfaces												
Dry*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Wet	0.47	−24.34	5.94	−32.40	2.36	−10.53	8.65	−16.86	15.63	−12.79	1.98	−12.28
Snow	0.36	−18.75	8.25	−45.01	6.22	−27.76	15.42	−30.05	18.88	−15.45	0.71	−4.41
Ice	−0.40	20.76	6.71	−36.57	5.51	−24.62	12.26	−23.89	11.66	−9.54	−3.67	22.74
Lighting condition												
Daylight*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Street lights	−0.19	13.40	1.72	−12.29	1.41	−6.77	2.37	−5.33	−0.26	0.27	−2.93	20.66
Dark	−0.34	24.40	1.60	−11.49	1.72	−8.25	2.21	−4.99	−2.58	2.61	−3.35	23.62
Dawn/Dusk	−0.52	36.67	−0.29	2.06	1.02	−4.88	1.63	−3.68	−4.91	4.97	−3.21	22.65
Urban/Rural												
Urban*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Rural	−0.85	77.15	−6.73	69.29	−3.20	17.47	−9.71	26.64	−19.11	23.94	−0.73	4.77
Vehicle types												
Passenger car*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Pickup	0.05	−3.45	−2.05	16.01	−0.51	2.55	−2.95	6.98	−7.56	7.94	0.08	−0.55
Truck	−0.97	61.20	−0.91	7.09	1.02	−5.04	1.11	−2.62	−4.56	4.79	−6.88	44.33
Vehicle actions												
Going Straight Ahead*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Slowing	−0.01	0.59	3.43	−24.34	4.57	−21.71	7.13	−15.75	2.68	−2.60	0.23	−1.51
Changing Lanes	−0.09	5.84	4.61	−32.69	6.66	−31.65	11.23	−24.84	1.52	−1.48	−1.17	7.85
Turning	−0.28	19.34	4.70	−33.33	7.21	−34.25	12.05	−26.65	−2.67	2.59	−2.78	18.69
Merging (Entering Traffic)	−0.82	56.25	2.99	−21.18	6.47	−30.72	9.86	−21.80	−8.61	8.36	−5.40	36.28
Overtaking and Passing	−1.78	122.54	−0.55	3.93	4.83	−22.97	5.10	−11.27	−15.16	14.72	−8.34	56.02
Vehicle sequential action after ROR												
Collision involving fixed object*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Overturn (Rollover)	−0.90	65.91	−10.30	87.11	−14.99	84.15	−24.22	62.99	−8.91	9.01	1.53	−9.74
Driver impairments												
Not impaired*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Impaired	−5.99	504.43	−12.51	106.76	−9.42	48.76	−21.58	54.16	−20.84	22.32	−15.17	111.51
Driver ages												
Young 16-25*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Mid 26-60	−0.26	21.88	1.27	−8.92	−3.50	20.25	−3.11	7.79	7.71	−7.04	−4.11	39.02
Senior > 60	−2.35	199.82	−1.88	13.21	−4.23	24.48	−6.55	16.42	−1.40	1.28	−17.65	167.47
Driver genders												
Male*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Female	−0.15	9.80	−1.44	11.03	−9.68	60.99	−11.10	29.49	14.36	−12.45	−1.14	7.47
Driver actions												
Distraction	−1.59	99.85	−5.34	45.59	−3.48	18.36	−7.41	18.64	−9.83	10.92	−5.23	31.63
Fatigue	−1.25	78.34	−4.57	39.03	−3.22	17.01	−6.72	16.89	−10.63	11.80	−3.62	21.89
Did Not Grant ROW	−1.07	67.37	−3.49	29.79	−2.55	13.45	−5.30	13.33	−10.42	11.57	−2.47	14.93
Speeding	−0.51	31.80	−2.11	17.98	−1.55	8.18	−3.54	8.91	−8.89	9.87	−0.95	5.74
Impaired	−0.14	8.77	−0.88	7.49	−0.62	3.28	−1.87	4.70	−6.03	6.69	0.14	−0.85
Operating Defective Equipment	0.06	−3.51	−0.20	1.71	−0.10	0.52	−0.63	1.57	−2.55	2.83	0.53	−3.21
None*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Driver restraints												
Driver restraint used*(Base)	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Restraint not used	−22.46	2645.48	−39.63	309.20	−37.43	190.70	−65.98	159.85	−50.95	52.27	−34.11	308.36

The bold values represents the categories with the highest possibility in almost all the six binary models.

4.1.1. Time variables

As seen in Table 7 that the pattern for time variables was different. It was found that the drivers are more likely to suffer higher severity injuries in Q2, Q3 and Q4 compared to Q1. This is consistent with (Albdairi and Hernandez, 2017), in which they found that a ROR crash occurred in Oregon between January and April (Q1) increase the probability of no injury outcome. This may be attributed to the harsh temperature in Q1 as the Washington State is located in the northwest of the United States. At low temperatures, drivers are driving more cautiously. The possibility of F/S (in Model1_1 59.22%, 66.62%, 15.88% and in Model2_3 19.71%, 26.37%, 27.76%) in Q2, Q3 and Q4 are greater than that of the Q1 and the possibilities of injury (Model1_2–1_3 and Model2_1–2_2) in Q2 and Q3 are higher than that of the Q1 as well. The probability of F/S in Q3 is significantly higher than Q1 (66.62% in Model1_1 and 26.37% in Model2_3). Considering the distribution of crash events presented in Table 1, it is not difficult to conclude that Q1 and Q4 affect the rate of ROR crashes and Q4 also affects the injury severity in ROR crashes. The number of ROR crashes are less in Q2 and Q3, but such crashes increase the higher injury probability, and there is a subtle distinction in death probability between Q2 and Q3.

4.1.2. Environment variables

The weather conditions are important factors contributing to the ROR crashes and injury severity. Drivers are more likely to suffer F/S and evident injury (Model1_1, Model1_2 and Model2_2) in bad weather conditions when ROR crash occurs and less likely to sustain possible injury severity levels (Model1_3 and Model2_1). It is consistent that the ice on the road tend to induce more F/S with a probability of 20.76% higher than the dry conditions in Model1_1. It was also found that the wet or snow conditions differ from rainy or snowy weather in the sense that wet or snow road surface leads to fewer F/S and injuries. This can be interpreted that the drivers are more cautious and drive at slow speed when the road is wet or snow while under dry roads they tend to be less careful and may increase their speed, thus causing severe injuries during a ROR crash. In (Dissanayake and Roy, 2014; Gong et al., 2016) it was found that the dry surface increases the probability of having an F/S severity in single-vehicle ROR crashes, and in this study the effects of ice surface were also revealed.

When it comes to the lighting conditions, analysis results revealed that the street lights and dark lighting conditions increase the probability of F/S compared to the daylight. Also, the ROR crashes that occur in the dawn or dusk are most likely to cause F/S (36.67% and 22.65% in Model1_1 and Model2_3). This is consistent with (Kim et al., 2012; Gong and Fan, 2017).

It was shown that the ROR crashes on rural roads are more likely to induce higher severity injuries and F/S than the urban roads (Model1_1-Model2_2). This may be due to the differences between country roads and urban environments. On rural roads, there are fewer restrictions for driving than on the urban roads. With fewer restrictions, the drivers will drive relaxed, followed by any unintentional or intentional violations such as speeding, long time driving etc., which will not happen on the urban roads. Furthermore, less guardrail or other protective facilities are utilized on the rural roads due to their long mileage and low traffic flow. These factors lead to short reaction time and less protection for drivers, generating consequences that are more serious when ROR crashes happened. The probability of F/S among urban and rural area in Model2_3 are trivial.

4.1.3. Vehicle variables

Trucks play an important role in the ROR crashes as the crashes involving them have a higher probability of causing higher severity injuries and F/S (Table 7). The trucks are more likely to cause F/S (61.20% in Model1_1 and 44.33% in Model2_3). As explained in previous studies (Chen et al., 2016a,b; Albdairi and Hernandez, 2017; Anderson and Hernandez, 2017; Gong and Fan, 2017; Prati et al., 2017), the trucks are large in size and heavy, which can protect the drivers in car collisions. However, trucks are dangerous because of their large inertia, leading to severe damage in a ROR crash. Pickups are said to be less safe compared to the passenger cars under single vehicle crash condition and here we found that pickups are more likely to induce possible and evident injuries in ROR crashes (Kockelman and Kweon, 2002).

Also, the vehicle's sequential actions after the ROR crashes were examined in this paper. The results show that an overturn or rollover after the ROR crashes are more likely to cause fatalities and higher injuries in all six models (with probabilities 65.91%, 87.11%, 84.15%, 62.99%, 9.01% in Model1_1–Model2_2, respectively) compared to colliding a fixed object. The reasons for this could be that the vehicle skids or irregular tumbling during a rollover or overturn may cause multiple inner collisions which are deadly to drivers. The countermeasures such as the installation of cushion guardrails for high ROR incidence sections can be adopted to avoid vehicle rollover or overturn after a ROR crash. The collisions involving fixed guardrails (i.e., fixed objects) suffer less damage compared to vehicle rollover. As expected from the earlier findings reported in (Roque et al., 2015) that the vehicle's rollover after ROR increases the driver's risk of fatality and severe injury by 120% and 114%, respectively.

4.1.4. Demographic variables

Driver's demographic characteristics were found to play a significant role as there are three driver-related factors in the first five important variables presented in Section 3.2. Compared to the sober drivers, the probability of being killed or seriously injured in ROR crashes for impaired drivers are significantly high, about 504.43% and 111.51% in Model1_1 and Model2_3, respectively. Impaired drivers suffer from declined cognitive ability, prolonged perception and reaction time, all of which affect their driving ability and judgments in certain traffic conditions. A monotonous relation was discovered between the driver's ages and injury severity. Compared to a young driver, senior drivers (elder than 60) are fragile and have a higher probability to suffer from all kinds of injuries, especially in F/S ROR cases (199.82% and 167.47% in Model1_1 and Model2_3 respectively). Young drivers are more vulnerable to injuries and fatalities. It is understandable that elder drivers respond slowly to instant traffic and more fragile in ROR crashes.

Gender differences were also identified in different injury severity patterns. Female drivers have a higher probability to experience F/S and possible injuries (9.8% in Model1_1, 11.03% in Model1_2, 60.99% in Model1_3, 29.49% in Model2_1 and 7.47% in Model2_3). These results are consistent with the conclusions from other literature (Das and Sun, 2016). For driver's action, it was found that the distracted drivers are most likely to suffer higher injuries and fatalities as depicted in (WSDOT, 2016). Fatigue, not granting the Right of Way (ROW) and speeding are the major causes of fatalities and severe injuries.

Driver restraint use is one of the most important variables selected in Table 2. It is proven in Table 7 that the drivers without restraint use have alarming probabilities of being killed or severely injured in ROR crashes as discussed in (Kim et al., 2012; Roque et al., 2015 Gong et al., 2016 Gong and Fan, 2017). The estimated probabilities compared to restraint use cases are tremendous: 2645.48%, 309.2%, 190.7%, 159.85%, 52.27%, 308.36% from Model1_1 to Model2_3. The relatively small probability in Model2_2 again proved the vague discrepancy in possible or at least evident injuries. Although the importance of restraint use has been emphasized in policy-making and safe-driving education, it is still urgent and of great pressing to take coercive measures to mitigate the possible injury severity induced by restraint.

4.2. Variable elasticity analysis

The elasticity of variable impacts can reflect the probability of suffering a specific injury severity level involving a certain sub-category compared to the base sub-category of each variable. Table 7 cannot show the discrepancy or distribution among injury severity patterns explicitly. In this section, the elasticity of variable impacts is discussed in a more intuitive and graphical way. The highest probability sub-category of each variable from the six binary models is recorded and summarized in Table 8. The highest probability sub-category in each

Table 8
The highest possible sub-categories within each variable among all the six binary models.

Variable	Model1_1	Model1_2	Model1_3	Model2_1	Model2_2	Model2_3
Quarter[1]	Q3	Q3	Q3	Q3	Q3	Q4
Weather[3]	Overcast	Snow/fog/crosswind	Clear	Overcast	Snow/fog/crosswind	Overcast
Road surface[2]	Ice	Dry	Dry	Dry	Dry	Ice
Lighting condition[2]	Dawn/Dusk	Dawn/Dusk	Daylight	Daylight	Dawn/Dusk	Dawn/Dusk
Urban/Rural[1]	Rural	Rural	Rural	Rural	Rural	Rural
Vehicle type[2]	Truck	Pickup	Pickup	Pickup	Pickup	Truck
Vehicle action[2]	Overtaking and Passing	Overtaking and Passing	Going Straight Ahead	Going Straight Ahead	Overtaking and Passing	Overtaking and Passing
Vehicle sequential action after ROR[1]	Overturn (Rollover)	Overturn (Rollover)	Overturn (Rollover)	Overturn (Rollover)	Overturn (Rollover)	Collision involving fixed object
Driver impairment[1]	Impaired	Impaired	Impaired	Impaired	Impaired	Impaired
Driver age[1]	Senior	Senior	Senior	Senior	Senior	Senior
Driver gender[1]	Female	Female	Female	Female	Male	Female
Driver action[1]	Distraction	Distraction	Distraction	Distraction	Distraction	Did Not Grant ROW
Driver restraints[1]	Restraint not used	Restraint not used	Restraint not used	Restraint not used	Restraint not used	Restraint not used

variable to injury severity levels consist three types.

At first, eight sub-categories viz., (i) Q3, (ii) rural, (iii) overturn or rollover, (iv) impaired, (v) senior, (vi) female, (vii) distraction and (viii) restraint not used were identified as the categories with the highest possibility in almost all the six binary models. These eight sub-categories are most likely to suffer all kinds of injuries and are emphasized with a superscript "1" in Table 8. These circumstances should be set as top priorities in the efforts to reach Target Zero plan. Secondly, the cases with a superscript "2" in Table 8 have two sub-categories occupying the highest probabilities among all the six models, of which one is responsible for higher level injuries, and the other is blamed for lower level injuries in general. All the other cases with a superscript "3" show no obvious rules, which means that these cases are less significant in the analysis of different injury severities.

Similarly, the effects of all sub-categories of a certain variable on six injury severity patterns can be investigated graphically as shown in Fig. 4. Consideringthe vehicle type in Fig. 4**(a)** as an example, the relative influences of all kinds of vehicles have been discussed in Section 4.1.3. It is not surprising that the trucks are the main vehicle types that have high-risk of fatalities or severe injuries. It can be observed from the figure that the trucks are more likely to induce possible injuries and fatality compared to evident injury in Model1_2 and Model2_2. The probabilities of pickup are comparable with the base category, indicating that the effects on injury severities of different vehicle types are different. A consistent conclusion can be reached from the age analysis shown in Fig. 4**(b)**. This discrepancy may be induced by the differences in physiological and behavioral factors across different age groups. The non-monotonic relationships between the crash-related factors and injury severity levels show a better fitting quality of neural network models.

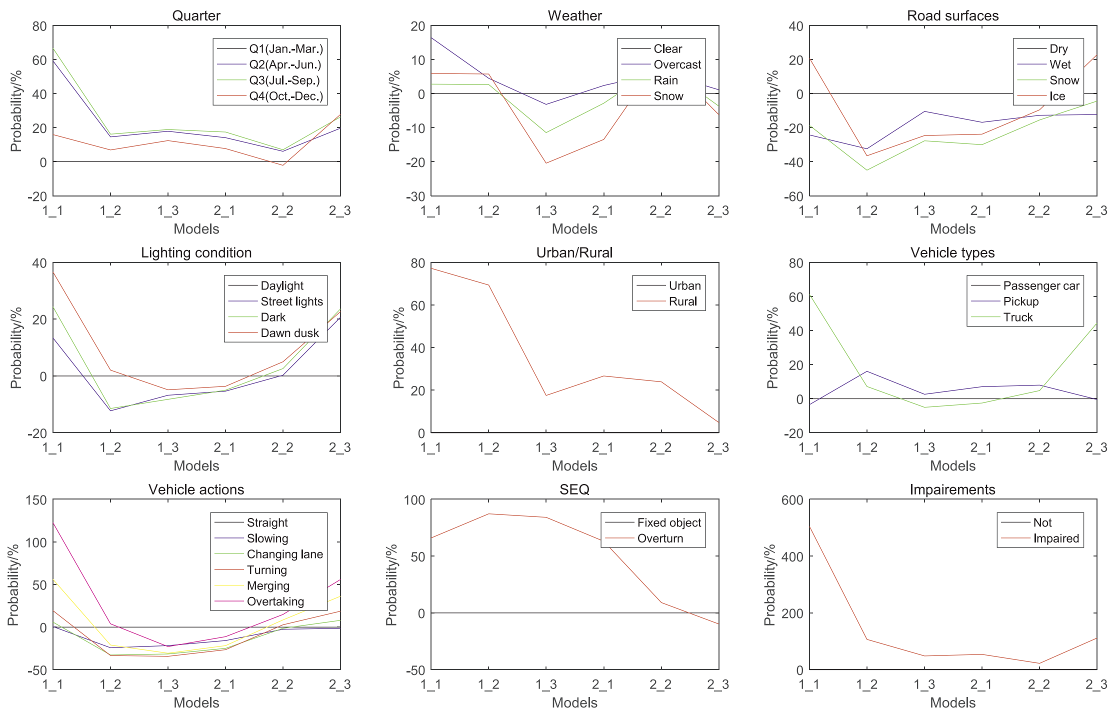
The above variable sensitivity analysis can also be extended to certain pre-determined sub-category combinations to investigate their relative influences on injury severity patterns. An example plot that combinesthe driver's action with road surfaces is illustrated in Fig. 5. The X–Y axis scale represents the sub-category coding, and the highest point i.e., (0,3) represents a distracted driver driving on icy roads is most likely to suffer F/S compared to other sub-category combinations. With better performance, it is more likely to identify and prioritize the granularity effects of crash-related variables (as well as their combinations) on specified injury severities (Mujalli and De, 2011; Mujalli et al., 2016 Mussone et al., 2017).

5. Conclusion

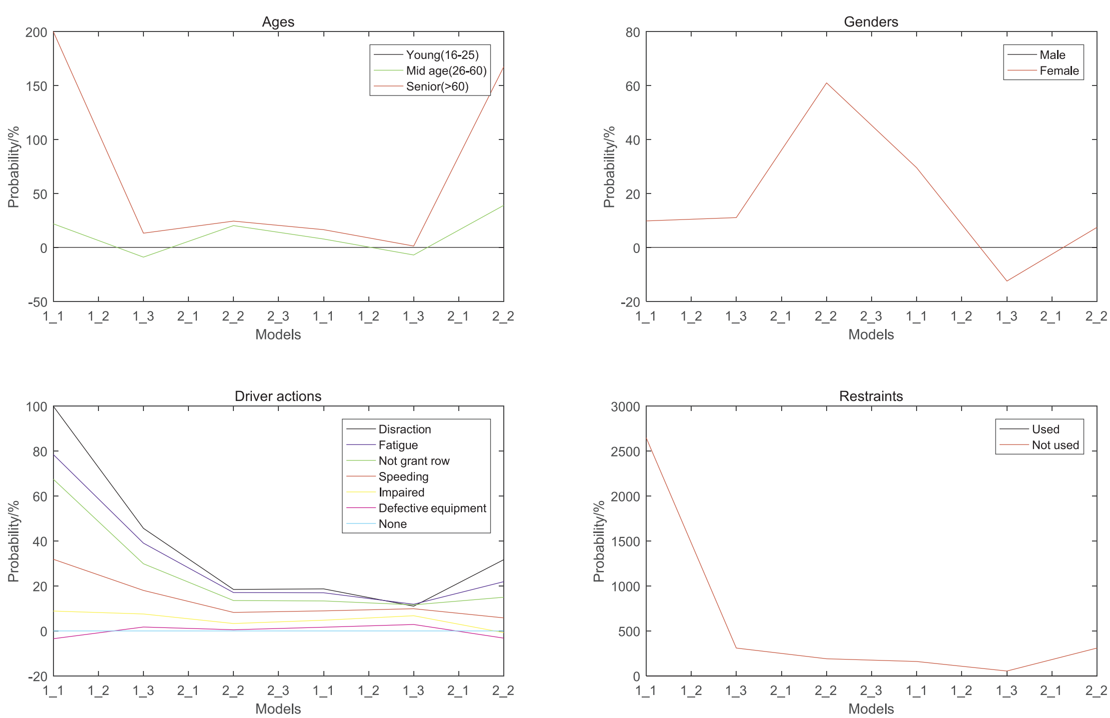
Based on three years crash data from 2011 to 2013 in the Washington State, a study on the driver injury severity patterns of single vehicle ROR crashes is conducted in this paper. With the imbalanced data distribution among different injury severities, an extended multi-class imbalanced learning framework was proposed to investigate the heterogeneous influence of eighteen variables from four main categories viz., time, environment, vehicle and demographic characteristics. At first, the Random Forests model is utilized to provide a preliminary selection of the candidate variables based on their relative importance. Then, the four-level injury severity classification problem is decomposed into six binary classification problems with a different combination of injury severity levels. ANN models are used to establish six classifiers and predict the driver's injury severity levels. Compared to the four-level injury severity prediction model as well as previous studies, the disaggregation models showed a better performance, and the decomposition of the multi-classification problem can help to catch the granular information useful for recognizing the less-presented category. The final prediction results were obtained by integrating the six trained NN classifiers and the ensemble classifier outperformed the four-level NN classifier as well as the statistical models. Finally, the sensitivity and elasticity analyses are performed to identify the degree to which the contributing factors are influencing the injury probabilities of each level of distinction between injury severity patterns. The analysis also revealed the distribution of their probabilistic influence across injury severity levels. Most of the findings were consistent with the previous studies. Thus, the effectiveness of the proposed analysis framework is validated.

In demographic characteristics aspect, it is found that the female drivers are more likely to suffer higher level injuries than male. Senior drivers have a higher likelihood to suffer injuries and fatalities due to their physiological and mental characteristics. Same as the most priority factor concluded from the Target Zero Plan, distraction is an important factor causing fatalities and injuries, this finding is also revealed in this study. For vehicle aspect, trucks increase the chances of being killed or injured in ROR crashes. Other factors that induce higher probability of fatalities or injuries are weak lighting conditions (street lights, dark, dawn/dusk), ice on road surface, snow/fog/crosswind, and crashes happening in Q2, Q3 and Q4.

Eight sub-categories are found most likely to suffer all kinds of driver injury severities. They are Q3, rural, trucks, overturn or rollover, impaired, female, distraction and restraint not used. These findings tell that the most effective way to improve the driver's safety is to take the required mandatory measures or law enforcement statewide concerning those sub-categories. The effects of various variable combinations were tentatively examined with driver's action and road surface. The result shows that a distracted driver driving on icy roads are most likely to suffer fatalities. These results illustrate the inner mechanism of the complex relationship among contributing variables and their impacts on injury severity patterns in ROR crashes. These findings can provide useful information for policymakers, transportation designers and



(a)



(b)

Fig. 4. Variable impact on various injury severity patterns (SEQ: Vehicle sequential action after ROR).

researchers.

There are still some limitations that need to be addressed in future investigation. Firstly, collecting more crash data may help to model and interpret the driver injury pattern better. Secondly, optional classification algorithms can be investigated to improve the performance of ensemble model since this study only uses neural networks as the base

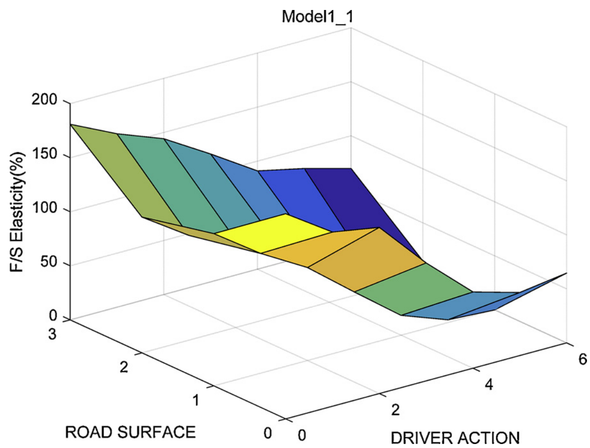


Fig. 5. Multivariable sensitivity analysis.

classifier, and modifications on the base classifier can also be implemented for application in reality. Finally, with the advancements in the big data era, monitoring data collected from different sensors could be accessible to researchers. With the large-scaled multi-sources and heterogeneous data resources, multi-source information fusion can be used in traffic crash analysis.

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