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Severity Prediction of Traffic Accident Using an Artificial Neural Network

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ABSTRACT
In this paper, an artificial neural network (ANN) was used to predict the injury severity of traffic accidents based on 5973 traffic accident records occurred in Abu Dhabi over a 6-year period (from 2008 to 2013). For each accident record, 48 different attributes had been collected at the time of the accident. After data preprocessing, the data were reduced to 16 attributes and four injury severity classes. In this study, WEKA (Waikato Environment for Knowledge Analysis) data-mining software was used to build the ANN classifier. The traffic accident data were used to build two classifiers in two different ways. The whole data set were used for training and validating the first classifier (training set), while 90% of the data were used for training the second classifier and the remaining 10% were used for testing it (testing set). The experimental results revealed that the developed ANN classifiers can predict accident severity with reasonable accuracy. The overall model prediction performance for the training and testing data were 81.6% and 74.6%, respectively. To improve the prediction accuracy of the ANN classifier, traffic accident data were split into three clusters using a *k*-means algorithm. The results after clustering revealed significant improvement in the prediction accuracy of the ANN classifier, especially for the training dataset. In this work, and in order to validate the performance of the ANN model, an ordered probit model was also used as a comparative benchmark. The dependent variable (i.e. degree of injury) was transformed from ordinal to numerical (1, 2, 3, 4) for (minor, moderate, sever, death). The R tool was used to perform an ordered probit. For each accident, the ordered probit model showed how likely this accident would result in each class (minor, moderate, severe, death). The accuracy of 59.5% obtained from the ordered probit model was clearly less than the ANN accuracy value of 74.6%.

KEY WORDS accident data; artificial neural network; ordered probit; severity prediction; WEKA; clustering

INTRODUCTION

Traffic accidents in the Middle East are a primary concern for governments and local communities owing to the large numbers of fatalities, injuries and economic losses. Factors affecting accident severity and frequency are mainly related to one or more of the following: driver characteristics, highway characteristics, vehicle characteristics, accident characteristics and atmospheric factors (Kopelias *et al.*, 2007; Chang and Wang, 2006). Accident data form an enormous database that covers different accident attributes. Many analytical methods have been used in the literature to analyze the accidents database. One of the recent methods in this domain is the data-mining technique. Data mining uses various tools to analyze accident data, including database technology, statistics, machine learning, high-performance computing, pattern recognition, neural networks, data visualization, information retrieval, image and signal processing and spatial data analysis (Baluni and Raiwani, 2014; Shanthi and Ramani, 2011). These models can determine the interactions between variables that would be impossible to establish directly, using ordinary statistical modeling techniques (Baluni and Raiwani, 2014; Shankar *et al.*, 1996). Furthermore, artificial neural networks (ANNs) are an adaptive system that changes its structure based on external or internal information that flows through the network (Baluni and Raiwani, 2014; Haykin, 1999). In this paper, one technique of data mining, namely ANN, was used to predict the injury severity of traffic accidents in Abu Dhabi, UAE.

In the work of Abdelwahab and Abdel-Aty (2001), ANNs were used to relate driver injury severity to various accident factors covering driver, vehicle, roadway and environment characteristics. Of 13 variables, only six were significant: gender of driver, fault, vehicle type, seat belt, point of impact and area type. A comparison was made between the ANN results with the ordered probit model (OPM), showing a higher accuracy for the ANN model.

Another work, by Delen *et al.* (2006), used ANN to model injury severity of road accidents through classifying the injury severity into five categories (no injury, possible injury, minor non-incapacitating injury, incapacitating and fatality). From 150 parameters they selected the most significant ones (a total of 17 parameters), using appropriate parameter selection algorithms, that mostly affect the injury level of drivers. ANN was used to classify the injury

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severity level, resulting in a low total accuracy of 40.71%. Montella *et al.* (2012) studied powered two-wheeler (PTW) crashes in Italy using eight binary multilayer perceptron (MLP) neural network models. Different levels of injury severity ranging from no injury to fatality were used as the dependent variable. All models were found to have better predictive power as compared to a model with a five-category outcome variable. In addition, this structure helped in identifying the important explanatory variables at each level of distinction between the injury severities (Baluni and Raiwani, 2014).

Chong *et al.* (2004) used ANN and decision trees to find the injury severity resulting from traffic accidents. Actual data from the National Automotive Sampling System (NASS)–General Estimates System (GES) were used. Results showed that the model for fatal and non-fatal injury was better than that for other classes. Yang *et al.* (1999) used the ANN approach to detect safer driving patterns that have less chance of causing death and injury when a car crash occurs (Chong *et al.*, 2004). They used Cramer's V coefficient test (Zembowicz and Zytkow, 1996) to identify significant variables that cause injury, thereby reducing the dimensions of the data for analysis. The 1997 Alabama interstate alcohol-related data were used. It was found that by controlling a single variable (such as driving speed or lighting conditions), fatalities and injuries could be reduced by up to 40% (Chong *et al.*, 2004). Mussone *et al.* (1999) used ANN to study intersection-related accidents in Milan, Italy. The study revealed that the highest accident index for running over a pedestrian occurs at non-signalized intersections at nighttime. Dia and Rose (1997) developed a multilayered ANN freeway incident detection model using real-world data. Results showed that ANN could provide faster and more reliable incident detection over the model that was in operation on Melbourne's freeways (Chong *et al.*, 2004).

Garrido *et al.* (2014) used the ordered probit model to investigate the role of driver, accident and vehicle factors in the injury severity faced by motor-vehicle occupants who are involved in road accidents. The results showed that motor-vehicle occupants traveling in light vehicles, on two-way roads and on dry road surfaces tend to suffer more severe injuries than those who are traveling in heavy vehicles, on one-way roads and on wet road surfaces. Also, the study revealed that, first, the driver's seat is the safest seating position; second, urban areas seem to experience less serious accidents than rural areas; and third, women tend to be more likely to suffer serious or fatal injuries than men.

Gray *et al.* (2008) utilized the ordered probit model to highlight accident characteristics that increase the likelihood of accident severity involving young male car drivers in Great Britain. Results showed that driving in darkness, between Friday and Sunday, on main roads, during passing maneuvers, and on single-carriageway roads at a speed limit of 60 mph were the most significant characteristics related to serious and fatal injuries.

Abdel-Aty (2003) used ordered probit to analyze driver injury severity levels at several roadway entities. Three separated models were developed for signalized intersections, roadway sections and toll plazas. Old male drivers, drivers not wearing a seat belt, drivers of passenger cars, vehicles struck at the driver's side and speeding drivers revealed a higher probability of a severe injury in all models.

METHODOLOGY

Data mining, which involves the retrieval and analysis of large amounts of data from a data warehouse, has been successfully used to discover hidden patterns among data in a variety of fields, including business administration, agriculture, medicine, industry and engineering. In the present study, WEKA data mining software was utilized to interrogate the road accidents dataset and build an ANN classifier for predicting the severity of traffic accidents. To validate the performance of the ANN model, ordered probit model was used as a comparative benchmark. The R tool was used to perform the ordered probit. The methodology and techniques used to interrogate the traffic accident data are described in the following subsections.

Traffic accident data collection

Traffic accident data were obtained from Abu Dhabi Emirate for a 6-year period (2008–2013). The total number of accident records obtained for this period was 5973. For each accident record, 48 different attributes were collected at the time of the accident. To investigate the influence of factors on the severity of crashes, the dependent variable (degree of injury) was categorized into four levels, of death, severe, moderate and minor accidents. Descriptions of each category are presented in Table 1. The proportions of each category are shown in Figure 1. Of 5973 traffic accidents, 59% were involved in minor accidents, 31% were involved in moderate accidents, 7% were involved in severe accidents and 3% were involved in fatal accidents. It is important to note that the number of fatal and severe accidents count only for a relatively small proportion of the total accidents.

Data preprocessing

Traffic accident data were obtained in the form of an Excel spreadsheet. Before applying data-mining techniques, the data were first checked out for questionable data, and those that were found to be unrealistic were cleaned up.

Table I. Class labels

No.	Accident category	Category description
1	Death	One or more persons die within 30 days of the accident
2	Severe	A person is injured and requires intensive care
3	Moderate	One or more persons are injured and detained in hospital for more than 12 hours
4	Minor	All persons involved are either not detained in hospital or detained for not more than 12 hours

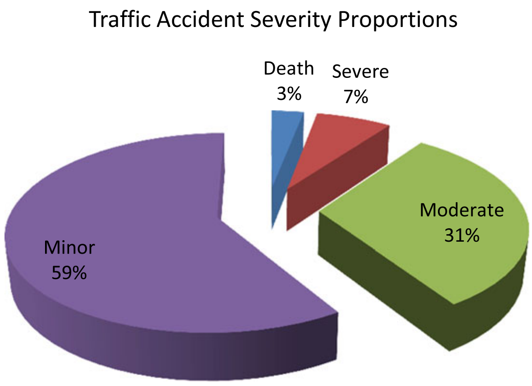

Figure 1. Traffic accident severity proportions

Changes were made to the data that fall under the following categories: deletion of invariant columns, deletion of descriptive columns or columns with so much variety, deletion of redundant columns, deletion of unimportant data and categorization of some columns. After preprocessing the traffic accidents data, the 48 different attributes were reduced to 16 attributes that cover accident, driver, and road/vehicle conditions. Table 2 displays the relevant attributes, data type and their description. Sixteen variables were used with the class variable of degree of injury in an attempt to identify the important variables that affect injury severity of traffic accidents. The data contained information related to accidents, drivers and road conditions. Individual accident records include information about the accident (e.g. year, day, time, accident reason and accident type) and the drive involved (e.g. age, gender, nationality, injury severity level, seat belt). Roadway data include information on road lighting, road surface condition (e.g. dry, wet, sandy, oily), road speed limit and number of lanes. Weather data include the weather conditions prevailing at the time of the accident such as clear, rain or fog.

Data clustering

To improve the prediction performance of the ANN classifier, the traffic accident data were divided into three parts using data clustering. Thus the *k*-means algorithm was used to split the data into three clusters; *k*-means clustering

Table II. Class labels selected 16 attributes with their data type and description (accident, driver and road)

Attribute name	Data type	Description
Accident attribute		
Year	Numeric	Year of the accident
Day	Nominal	Day of the accident
Time	Nominal	Time of day the accident occurred
Reason	Nominal	Reason for the accident
Accident type	Nominal	Type of accident
Driver attribute		
Gender	Nominal	Gender of the driver
Nationality	Nominal	Nationality of the driver
Age rank	Numeric	Age of the driver
Seat belt	Nominal	Use of seat belt when driving
Causality status	Nominal	Whether the causality was driver, passenger or pedestrian
Degree of injury	Nominal	Death, severe, moderate, minor
Road condition		
Lighting	Nominal	Lighting conditions of the road at time of the accident
Road surface	Nominal	Whether the surface of the road was dry, wet, sandy or oily
Speed limit	Numeric	Road speed limit
Lane numbers	Numeric	Number of road lanes
Weather	Nominal	Weather conditions

aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean. More specifically, cluster analysis is a statistical technique that groups items together on the basis of similarities or dissimilarities. For each cluster, a confusion matrix is obtained for use in computing the accuracy. Accuracy is the proportion of the total number of predictions that were correct. The results of clustering are presented in Table 3.

ANN: model development

In data mining, classification is the problem of identifying to which set of categories a new observation belongs, on the basis of a training set of data containing observations whose category membership is known. A total of 5973 records with known values of the degree of injury attribute were obtained, and such information was used to build classifiers that would be able to classify any new accidents and identify whether they would be more or less likely to be death, severe, moderate or minor accident.

In this study, WEKA was used throughout the analysis. WEKA is a collection of machine-learning algorithms for data-mining tasks. WEKA provides a number of useful techniques in classifications. However, the neural network MLP classifier was used. The neural network MLP is a feedforward ANN model that maps sets of input data onto a set of appropriate outputs. MLP was used to build two classifiers. The whole data set was used to train the first classifier, while only 90% of the data was used to train the second classifier.

ANN: model validation

Model validation is possibly the most important step in the model-building sequence. This is the task of demonstrating that the model is a reasonable representation of the actual system. The classifier that was built using the whole set was evaluated on how well it predicts the class of the instances it was trained on (training set). The other classifier, on the other hand, was evaluated on how well it predicts the 10% that was held out for testing (testing set). The original dataset obtained from Abu Dhabi Emirate was divided into two subsets: a training set containing 90% of the data (5376 records), and a testing set containing 10% of the data (597 records). The training set was used to build the models, whereas the testing set was used to validate the models. To validate the prediction performance of the developed ANN model, the 10% dataset was utilized. The prediction results are presented in the next main section.

Ordered probit model

Ordered probit is one of the most widely used methods in predicting the outcome of an ordinal dependent variable. It is used when the dependent variable has more than two outcomes, where these outcomes can be ordered. This method is considered state of the art in predicting road accident severity . In this work, the dependent variable (i.e. degree of injury) was transformed from ordinal to numerical (1, 2, 3, 4; for minor, moderate, sever, death, respectively). The R tool was used to perform the ordered probit. The Polr function in the MASS library was used as follows:

$$\begin{aligned}&\text{polrFit} < \text{- polr(Degree.of.injury} \sim \text{Year} + \text{Accident.Reason} + \text{Weather} + \text{Roead.Surface} + \\ &\text{Accident.type} + \text{Seat.belt} + \text{Casualty.staus} + \text{Gender} + \text{Nationality} + \text{Day} + \text{Time} + \text{Age.Rank} + \\ &\text{Speed.Limit} + \text{Lanes.number , method} = \text{"probit", data} = \text{data.}\end{aligned} \tag{1}$$

Table III. Traffic accident data clustering

Attribute	Cluster 0 (1976)	Cluster 1 (2280)	Cluster 2 (1717)
Year	2012	2008	2008
Reason	Run a red light	Run a red light	Lack of appreciation of road users
Lighting	Day	Night-high light	Day
Weather	Clear	Clear	Clear
Road surface	Dry	Dry	Dry
Accident type	Vertical collision	Vertical collision	Run over someone
Seat belt	Y	Y	N
Casualty status	Driver	Passenger	Pedestrian
Gender	M	M	M
Nationality	Asia	Asia	Asia
Day	Wed	Fri	Tue
Time	Noon	Evening	Morning
Age rank	18–30	18–30	31–45
Speed limit	62.5101	62.6457	53.7449
Lane number	4	3	4
Degree of injury	Minor	Minor	Minor

Night-high light means that the accident happened during night time but at enough/sufficient lighting at the accident location Vertical Collision means that the accident happened at right angle (i.e. 90 degrees intersection of vehicles).

RESULTS AND DISCUSSION

Sixteen predictor variables (attributes) were used with the class variable injury's severity to build the ANN model (classifier) in order to predict the injury severity of traffic accidents. The software used to build the ANN model was WEKA. The ANN MLP classification technique was applied to traffic accident data. The ANN model was applied to both the full data and to the clustered data. The accuracy of these classifiers is presented and discussed below.

ANN prediction accuracy based on full traffic accident data

In this section, the prediction accuracy of WEKA classifiers is obtained using the 5973 accident records for model building and model validation.

WEKA software was used to build two ANN classifiers. The first classifier was trained and validated using the whole data set (training set). In the second classifier, 90% of the data used to build the model and the remaining data used for validation (testing test). ANN classifier prediction accuracy based on both training set and testing set is presented in Table 4. As shown in Table 4, the crash severity was divided into four classes: death, severe, moderate and minor. The ANN prediction accuracy based on the training data set for death, severe, moderate and minor accidents are 4.5%, 10.2%, 80.1% and 94.5%, respectively. For ANN models, the overall prediction accuracy for the training data is about 81.6%. From these results, it can be observed that the prediction accuracy for minor crash severity accidents is highest, followed by moderate, severe and death accidents, respectively. This seems logical, since the proportions of data available for model training for minor, moderate, severe and death crash severity accidents are 59%, 31%, 7%, and 3% respectively. The more the data available for training, the greater the accuracy will be. Based on the testing data set, ANN prediction accuracy for death, severe, moderate and minor crash severity accidents is 0%, 0%, 78.4% and 82%, respectively. Compared with the prediction accuracy results obtained based on the training data set, the prediction accuracy based on the testing data set is considerably less. This is clearly seen for both death and severe accidents. This could be attributed to data splitting, where only 10% of the traffic accident data is utilized for model testing (validation). Moreover, the numbers of death and severe accident records are small compared with the minor and moderate severity accidents. However, the overall prediction accuracy for the testing data is about 74.6%.

However, accuracy alone does not completely describe the prediction efficiency, and other means of evaluating the predictive models are necessary. The receiver operating characteristics (ROC) curve, also known as the relative operating characteristic curve, is a comparison of two operating characteristics as the criterion changes. It can be represented by plotting the fraction of true positives (TPR = true positive rate) versus the fraction of false positives (FPR = false positive rate). The area under the ROC curve (AUC) quantifies the overall discriminative ability of a test. An entirely random test has an AUC of 0.5, while a perfect test has an AUC of 1.00.

Since the accuracy of the above model was almost identical, ROC curves were used to further evaluate the developed models, using 10% of the instance data. In all cases, the AUCs were significantly greater than 0.5. These results indicate that all models predicted new instances well.

ANN prediction accuracy based on clustered traffic accident data

To improve the prediction performance of the ANN classifier, the traffic accident data were divided into three parts using data clustering. ANN classifier predictions accuracy based on both training and testing sets are presented in Table 5. As shown in Table 5, the crash severity was divided into four classes: death, severe, moderate and minor. The ANN prediction accuracy based on the training set/cluster 0 for death, severe, moderate and minor crash severity accidents is 60%, 73.5%, 97.2% and 98.9%, respectively. For ANN models, the overall prediction accuracy for the training data/cluster 0 is about 95.2%. From these results, it can be observed that a significant improvement in the prediction accuracy for all severity classes is achieved. This could be attributed to the logic behind data clustering in which each observation belongs to the cluster with the nearest mean. Based on testing

Table IV. Multilayer perceptron model assessment results

Classifier	Test option	Crash severity	Correctly classified instances	Incorrectly classified instances	Accuracy	AUC
		Death	8	169	4.5%	0.661
		Severe	42	371	10.2%	0.745
		Moderate	1464	363	80.1%	0.899
		Minor	3360	196	94.5%	0.896
	Training set	Overall	4874	1099	81.6%	0.880
		Death	0	18	0%	0.561
		Severe	0	28	0%	0.576
		Moderate	149	41	78.4%	0.744
		Minor	297	65	82.0%	0.779
Neural network MLP	Testing set (10%)	Overall	446	152	74.6%	0.752

Table V. MLP model assessment results (clustering)

Classifier	Cluster	Test option	Crash severity	Correctly classified instances	Incorrectly classified instances	Accuracy	AUC
			Death	36	24	60%	0.899
			Severe	111	40	73.5%	0.891
			Moderate	632	18	97.2%	0.983
			Minor	1103	12	98.9%	0.984
		Training set	Overall	1882	94	95.2%	0.974
			Death	0	8	0%	0.503
			Severe	5	10	33.3%	0.547
			Moderate	43	23	65.2%	0.594
			Minor	89	20	81.7%	0.624
	0	Testing set (10%)	Overall	137	61	69.2%	0.603
			Death	28	38	42.4%	0.787
			Severe	108	46	70.1%	0.903
			Moderate	652	41	94.1%	0.984
			Minor	1358	8	99.4%	0.974
		Training set	Overall	2146	134	94.1%	0.967
			Death	0	8	0.0%	0.5
			Severe	6	9	40.0%	0.565
			Moderate	48	20	70.6%	0.763
			Minor	109	27	80.1%	0.735
	1	Testing set (10%)	Overall	163	64	71.8%	0.724
			Death	44	7	86.3%	0.948
			Severe	90	18	83.3%	0.938
			Moderate	469	14	97.1%	0.979
			Minor	1065	10	99.1%	0.985
		Training set	Overall	1668	49	97.1%	0.979
			Death	0	7	0.0%	0.592
			Severe	2	8	20.0%	0.632
			Moderate	33	15	68.8%	0.703
			Minor	89	18	83.2%	0.707
Neural network MLP	2	Testing set (10%)	Overall	124	48	72.1%	0.697

data/cluster 0, ANN prediction accuracy for death, severe, moderate and minor severity accidents are 0%, 33.3%, 65.2% and 81.7%, respectively. Compared with the prediction accuracy results obtained from the training data/cluster 0, the prediction accuracy obtained based on the testing dataset is considerably less. This is clearly seen for both death and severe accidents. This can be contributed to data splitting, where only 10% of the traffic accident data is utilized in model testing (validation). Moreover, the number of death and severe accident records is small compared to minor and moderate severity accidents. However, the overall prediction accuracy for the testing data/cluster 0 is about 69.2%.

The ANN prediction accuracy based on the training set/cluster 1 for death, severe, moderate and minor severity accidents is 42.4%, 70.1%, 94.1% and 99.4%, respectively. For ANN models, the overall prediction accuracy for the training data/cluster 1 is about 94.1%. Based on testing data/cluster 1, ANN prediction accuracy for death, severe, moderate and minor severity accidents is 0%, 40%, 70.6% and 80.1%, respectively. For ANN models, the overall prediction accuracy for the testing data/cluster 1 is about 71.8%.

The ANN prediction accuracy based on the training set/cluster 2 for death, severe, moderate and minor severity accidents is 86.3%, 83.3%, 97.1% and 99.1%, respectively. For ANN models, the overall prediction accuracy for the training data/cluster 2 is about 97.1%. Based on testing data/cluster 2, ANN prediction accuracy for death, severe, moderate and minor severity accidents is 0%, 20%, 68.8% and 83.2% respectively. For ANN models, the overall prediction accuracy for the testing data/cluster 2 is about 72.1%.

From Table 5, it can be seen that for all severity classes the AUCs were significantly greater than 0.5. These results indicate that all ANN models predicted new instances well.

Ordered probit results

The results of the ordered probit model are presented in Tables 6 and 7. Table 6 shows the coefficient value for each variable. The larger the coefficient value, the higher is its impact on deciding the accident severity. Table 7 shows the Intercepts of the regression model.

For each accident, this method shows the likely outcome in each class (minor, moderate, severe or death). For example, the following information indicates that the accident under consideration is more likely a minor type, whereas the actual status is death. This results in zero accuracy for the first record. However, for the second record,

Table VI. Ordered probit model estimation results

Attribute	Coefficient	SE	*t*-value
Year	0.006596	4.47E − 05	1.47E + 02
Accident. reason failure to comply with stop sign	0.107785	8.85E − 03	1.22E + 01
Accident. reason failure to give right of way	−0.120214	1.97E − 03	−6.09E + 01
Accident. reason fatigue and sleepiness	0.283885	1.21E − 03	2.34E + 02
Accident. reason improper turn	0.077173	4.26E − 02	1.81E + 00
Accident. reason inattention to pedestrian	0.089337	2.49E − 02	3.59E + 00
Accident. reason neglect and lack of attention	−0.128789	4.11E − 03	−3.14E + 01
Accident. reason neglect and lack of attention	−0.028879	4.74E − 03	−6.09E + 00
Accident. reason non compliance with street lines	0.009128	3.86E − 02	2.37E − 01
Accident. reason run a red light	0.103747	3.58E − 02	2.90E + 00
Accident. reason speeding	0.06573	4.20E − 02	1.57E + 00
Accident. reason tailgating	0.056888	2.11E − 02	2.69E + 00
Weather dusty	0.354573	2.61E − 04	1.36E + 03
Weather fog	−0.734732	1.27E − 03	−5.77E + 02
Weather rainy	−0.018654	1.55E − 03	−1.21E + 01
Roead. surface wet	0.083263	5.12E − 03	1.63E + 01
Accident. type hitting a fixed body off the road	−0.226205	3.14E − 03	−7.20E + 01
Accident. type hitting a fixed body on the road	−0.035255	2.11E − 02	−1.67E + 00
Accident. type losing control	0.138377	9.95E − 03	1.39E + 01
Accident. type pedestrian-vehicle	0.12007	2.04E − 02	5.90E + 00
Accident. type rear-end	0.0269	2.57E − 02	1.05E + 00
Accident. type right angle	−0.017193	3.16E − 02	−5.45E − 01
Accident. type sequential collisison	0.405986	2.60E − 03	1.56E + 02
Accident. type sideswipe	−0.029595	3.18E − 02	−9.30E − 01
Seat. beltY	−0.065014	3.88E − 02	−1.68E + 00
Casualty. staus passenger	−0.057496	3.77E − 02	−1.53E + 00
Casualty. staus pedestrian	−0.297486	1.78E − 02	−1.68E + 01
Casualty. staus unknown	−3.944011	5.26E − 07	−7.50E + 06
Gender M	0.027293	3.73E − 02	7.33E − 01
Nationality Asia	0.059091	3.21E − 02	1.84E + 00
Nationality gulf	−0.43353	4.11E − 03	−1.06E + 02
Nationality other	−0.088363	2.66E − 02	−3.32E + 00
Nationality UAE	0.119374	3.88E − 02	3.08E + 00
Day Mon	0.032363	3.79E − 02	8.55E − 01
Day Sat	0.016841	4.01E − 02	4.20E − 01
Day Sun	0.013664	3.89E − 02	3.51E − 01
Day Thr	0.1075	3.74E − 02	2.88E + 00
Day Tue	0.058184	3.99E − 02	1.46E + 00
Day Wen	−0.017846	3.89E − 02	−4.59E − 01
Time evening	−0.016249	2.40E − 02	−6.78E − 01
Time morning	0.008009	2.55E − 02	3.14E − 01
Time noon	0.037501	2.54E − 02	1.48E + 00
Age. rank > 60	0.644835	4.00E − 03	1.61E + 02
Age. rank18–30	0.437576	2.61E − 02	1.68E + 01
Age. rank3145	0.537895	2.53E − 02	2.13E + 01
Age. rank4660	0.430387	3.00E − 02	1.43E + 01
Speed. limit	0.000504	1.47E − 03	3.43E − 01
Lanes. number	−0.037557	2.05E − 02	−1.83E + 00

Table VII. Model intercept estimation

Intercept	Intercept value	SE	*t*-value
1|2	13.895	0.0005	30077.97
2|3	14.9602	0.0227	659.46
3|4	15.5659	0.0347	447.9465

the model predicts the injury status as minor, which matches exactly the actual severity status, resulting in an accuracy value of 100%.

Accident record	1 (Minor)	2 (Moderate)	3 (Severe)	4 (Death)	Actual Status	Accuracy (%)
1	0.787932	0.180945	0.024372	0.006752	4 (Death)	0
2	0.792212	0.177692	0.023619	0.006477	1 (Minor)	100

Based on this information, the accuracy of this model was calculated using the following equation:

$$\text{Number of correctly classified accidents} \,/\, \text{total number of accidents } 3285 \,/\, 5519 = 59.5\% \tag{2}$$

The accuracy value of 59.5% obtained for the ordered probit model is clearly less than that for the ANN model, which was 74.6%.

CONCLUSIONS

The contribution of this study lies in the development of an ANN model to analyze traffic accident data and to predict the injury severity of traffic accidents based on 5973 traffic accident records occurred in Abu Dhabi over a 6-year period from 2008 to 2013. After data preprocessing, traffic accident data were reduced to 16 attributes and four injury severity classes (death, severe, moderate and minor). Analysis of traffic accident data was performed using WEKA (Waikato Environment for Knowledge Analysis) data-mining software to develop and validate the ANN model (classifier).The following conclusions were drawn based on the results of data analysis and evaluation conducted in this study:

- The overall model prediction performance for the training data and the testing data were 81.6% and 74.6%, respectively.
- The ANN prediction accuracy based on the training data set for death, severe, moderate and minor severity accidents were 4.5%, 10.2%, 80.1% and 94.5%, respectively.
- Based on the testing dataset, ANN prediction accuracy for death, severe, moderate and minor severity accidents were 0%, 0%, 78.4% and 82%, respectively.
- Clustering showed that the overall model prediction performance for the training dataset was 95.2%, 94.1% and 97.1% for clusters 0, 1 and 2 respectively. For the testing dataset, the overall model prediction performance was 69.2%, 71.8% and 72.1 for clusters 0, 1 and 2, respectively.
- The outcome of this study could be used by the United Arab Emirates Traffic Agency to improve traffic safety. For future work, a decision support tool for the Abu Dhabi Emirate Traffic Office will be developed.
- To validate the performance of the ANN model, the ordered probit model was used as a comparative benchmark. Results indicated that ANN (74.6% accuracy value) outperformed the ordered probit model (59.5% accuracy value) in terms of accident prediction accuracy.

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