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A review on neural network techniques for the prediction of road traffic accident severity

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ABSTRACT

The occurrence rate of death and injury due to road traffic accidents is rising increasingly globally day by day. For several decades, the focus of research has been on getting a deeper understanding of the significant factors that influence the risk of road traffic fatalities. In today's modern world, neural network (NN) approaches play a crucial role in identifying the contributing factors that describe the frequency and severity of road accidents. Over the years, many researchers used neural network models for predicting the impact of such factors on road accident injury severity. Deep learning methods such as the recurrent neural network (RNN) and the convolutional neural network (CNN) has recently been successfully used for the prediction of road accidents and demonstrate their high accuracy and efficiency. This study overview and summarizes the different forms of neural network models such as the single layer perceptron (SLP) neural network, the multilayer layer perceptron (MLP) neural network, the radial basis function (RBF) neural network, the recurrent neural network, and the convolutional neural network used as a prediction method for the severity of road crash injuries and includes a discussion of future planning and difficulties. This article also summarizes the model input parameter or independent variable and output or dependent variable, as well as various performance assessment methods.

1. Introduction

One of the most common causes of injury and death worldwide is road traffic accidents and for people of all age groups, it is the 8th leading cause of death. Every year approximately 1.35 million people died on the road around the world, 20–50 million injured, and with an average rate of 27.5 deaths per 100,000 population (WHO, 2018). The highest rates of road traffic fatalities are 26.6 deaths per 100,000 people in Africa and 20.7 deaths per 100,000 people in South-East Asia (WHO, 2018). Recent studies have estimated that the fifth leading cause of death worldwide will be traffic crashes in 2030 (Sameen, and Pradhan, 2016).

Road traffic accidents are uncertain, random events and can occur anyplace at any time. Researchers have continually found ways to obtain a deeper understanding of the factors that influence the risk of accidents, with the immense costs for society arising from road accidents. It is an expectation that they will be able to predict the risk of an accident and provide recommendations for strategies and preventive measures to minimize the number of accidents (Lord and Mannering, 2010). It is therefore of greatest importance to forecast possible traffic incidents in order to understand the severity of the issue and speed up decision-making to mitigate it (Ebrahim and Hossain, 2018; Lee et al. 2020). Forecasting models for traffic accidents are very effective tools for road safety assessment and considering their ability to determine the frequency of accidents and identifying the contributing factors that transport policies should then address (Abdulhafedh, 2017; Pradhan and Sameen, 2020). For the effective implementation of an Intelligent Transport System (ITS), an adequate and reliable model of severity prediction is expected in traffic accidents (Zeng et al. 2019). In particular, studies on traffic accident prediction, statistical approaches, and neural networks have been used in recent years (Sameen et al. 2019).

Statistical methods such as linear regression models were first used for road accident prediction in the 80s and early 90s to model the incidence of highway accidents (Joshua and Garber, 1990). Researchers soon found that the frequency of crashes could be best suited to a Poisson regression model and they developed and suggested these models to investigate the relationship between risk factors and crash frequency (Basyouny and Sayed, 2009; Abdulhafedh, 2016; Shaik and Hossain, 2019). The Poisson regression model has over dispersion problem and Negative binomial (Poisson-gamma) and Gamma

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regression model were applied widely as an alternative to Poisson regression in road accident prediction (Oh et al. 2006; Geedipally, 2012; Llau and Ahmed, 2016; Naghawi, 2018; Shaik and Hossain, 2020). The Poisson-lognormal method was established for the purpose of overcoming the constraints of the negative binomial models and also handle better under dispersed problems than gamma regression (Miaou et al. 2005; Lord and Miranda-Moreno, 2008; Daniels et al. 2010). With regard to road safety problems, the Conway-Maxwell Poisson model has recently been studied and this method can also be adversely affected by low mean sample, limited sample error (Li et al. 2008; Lord and Mannering, 2010). Other statistical models such as Random-Parameter models were developed to predict road accident on two-lane divided roads (Dinu and Veeraragavan, 2011), K-Nearest Neighbors (K-NN) (Zhang et al. 2013) for predicting the duration of traffic accidents, and Support Vector Machine (SVM) (Li et al. 2008) for the prediction of motor vehicle crashes. There are strengths and strong limitations of each statistical model in the application that are found by all researchers.

Apart from statistical models, neural network models have also been developed for road accident prediction and effectively used in several transport research areas, including traffic safety study with high performance (Chang, 2005; Li et al. 2008). Artificial Neural Networks are used to incorporate flexibility, precision, generalization, and powerful forecasting capacity than some traditional statistical models. (Delen et al. 2006; Xie et al. 2007; Flood, 2008; Moghaddam et al. 2011; Ahmed and Pradhan, 2019). ANN is one of the techniques of Artificial Intelligence (AI) that can outperform all other models for the prediction of road accident which can also easily model non-linear functions without statistical simulation at all (Singh and Deo, 2007; Rusul et al. 2019; Ahmed and Pradhan, 2019; Profillidis and Botzoris, 2019). Many researchers have used ANN models successfully to forecast traffic injuries and severity in transport studies, and it has shown greater precision in forecasting deaths and injuries compared to other conventional approaches (Dougherty, 1995; Abdelwahab and Abdel-Aty, 2001; Dursun et al. 2005; Akin and Akba, 2010; Alkheder et al. 2017; Soto et al. 2018; Chakraborty, 2019). Deep learning approach such as RNN and CNN has gained great interest at present, has heated research topics from researchers and academics in several scientific fields and also plays an important role in the prediction of road traffic accidents (Sameen et al., 2019; Zeng et al., 2019; Gutierrez-Osorio and Pedraza, 2020).

The main aim of this study is to review the developments of accident prediction model by different types of neural network models including deep learning techniques. This paper also reviews the performance of several NN techniques, learning algorithms, and contributing factors of road traffic accidents. It also presents an open analysis of the challenges of current NN-based models as well as forecasts potential road accident prediction accuracy.

The remaining part of the paper is organized as follows. Some theoretical aspects that are required for traffic accident prediction are described in section 2. The “Taxonomy of the Reviewed Systems” section classifies the models reviewed for proper comprehension. The “Literature on developed systems” section explains and summarizes the different types of road accident prediction neural network models that have been studied in recent years. The “Open discussion and future challenges” are depicted in section 5. Lastly “Conclusions” concludes this article.

2. Theoretical considerations

Neural networks are arrays of simple computer functions that are highly interconnected and strongly constructed on brain structure. Remarkable progress has been made to NNs over the past couple of decades, and many model architectures have also been developed and suggested for the prediction of road traffic accidents by a greatly increased number of researchers globally.

2.1. General structure and basic function of neural network

A neural network is a group of algorithms that simulates the way the human brain works, attempt to identify underlying relationships in a set of data. Neural networks, in this context, apply to neuron structures, either biological or artificial in process.

Fig. 1 shows a general neural network structure. An ANN has an input layer (receiving various external signals), an output layer (sending various external signals), and one or more hidden layers (nonlinear input transformations that have been entered into the network) (Profillidis and Botzoris, 2019).

Fig. 2 depicts the basic function of a neural network. Basic functions of all types of neural networks are data receipt from the external situation or sources, decide if this data will be activated and taken into account or is discarded as negligible, analysis or error minimization by iteration of the data, and finally the output or performance for the entire trial. In an artificial neuron, therefore, the first stage is the summation of the different Xi inputs multiplied by their corresponding weights of the relation Wi. The Wi.Xi products are then fed into the summation function and minimization of error by iteration (Profillidis and Botzoris, 2019).

2.2. Training algorithm

For road accident prediction, there are several different optimization algorithms used in NN models development. Methods of optimization are used to calculate the input weights (network training) by eliminating the loss function.

2.2.1. Back propagation

The back-propagation developed by Paul Werbos in 1974, which was later rediscovered by Rumelhart and Parker, is the most popular learning algorithm for neural networks. With the back propagation learning algorithm, which is the most common learning principle, a large percentage of NN applications use the multilayer perceptron framework (Garrido, 2014). This back propagation algorithm is used by many researchers in transportation applications, especially traffic accident prediction. Back-propagation has almost the same architecture as a multilayer perceptron neural network (Pradhan and Sameen, 2020). Back propagation is a widely used algorithm for supervised learning to train MLP neural networks using gradient descent. The aim of back propagation training is to adjust the weights between the neurons sequentially in a pattern that minimizes the error. The error between the network output and target output was measured and sent again from the last layer to the previous one during learning, thus correcting the weight coefficients using the back-propagation algorithm (Rumelhart, 1986). In traditional back propagation, the error function (E_f) is minimized by using the following equation (1):

$$E_f = 0.5N \sum_{i}^{N} \left(\widehat{p}_i - p_i \right)^2 \tag{1}$$

Where,

p_i = Target value
$\widehat{p_i}$= Calculated output
i= Output layer
N= Number of nodes (output layer)

2.2.2. Levenberg-marquardt algorithm

The levenberg-marquardt algorithm (LMA) was developed to actually work with hidden layers, which consist of a squared error sum. LMA is commonly used as a regular algorithm to solve problems with nonlinear least squares (Du and Stephanus, 2018). This algorithm begins from an arbitrary set of randomly selected interconnection weights from a uniform value distribution between 0 and 1; then the algorithm

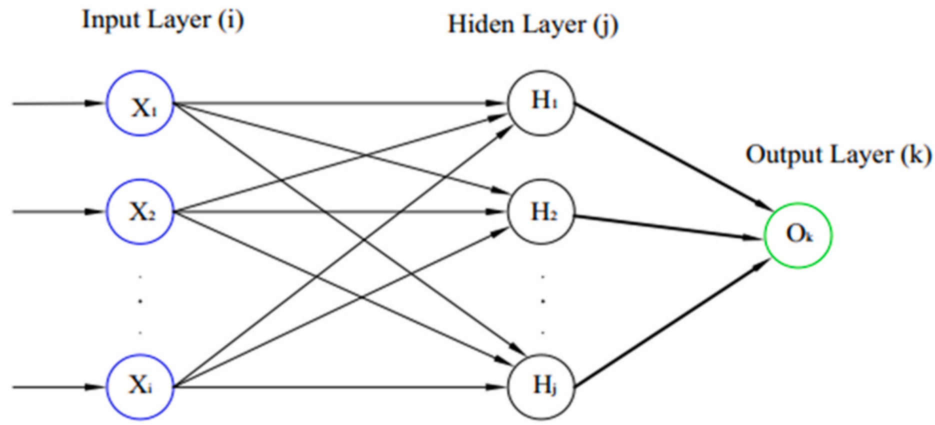

Fig. 1. General neural network structure.

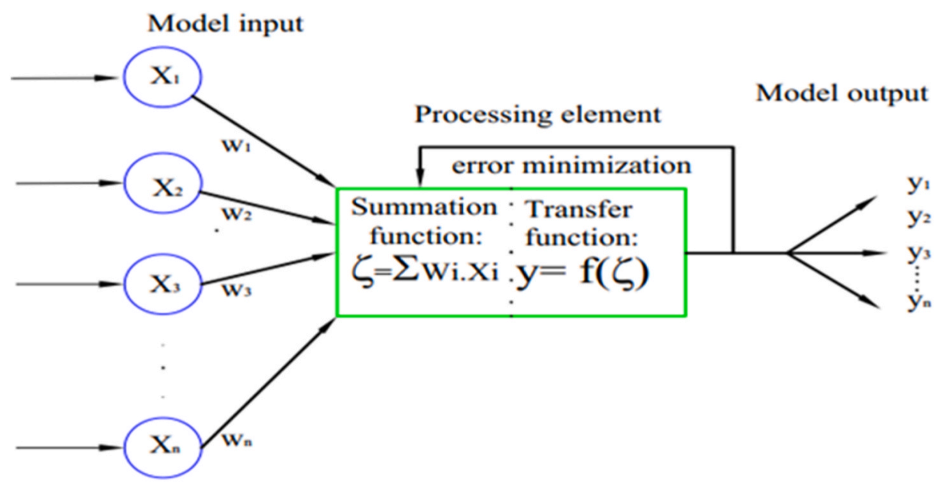

Fig. 2. The basic function of a neural network.

attempts to reduce the discrepancies between the output of the network and the required outputs (Abdelwahab and Abdel-Aty, 2001). The algorithm will become slow when Back-Propagation (BP) is displayed as gradient descent and does not provide an optimal solution (Hagan and Menhaj, 1994). There is a combination of gradient descent and Gauss-Newton techniques in the Levenberg-Marquardt algorithm and also can ensure problem solving abilities through its adaptive functioning (Guler and Ubeyli, 2006; Du and Stephanus, 2018). This Levenberg-Marquardt algorithm is also used as a learning algorithm like back-propagation to train MLP neural networks for the prediction of traffic accidents (Abdelwahab and Abdel-Aty, 2001; Çodur and Tortum, 2015). The Levenberg-Marquardt algorithm adjusts neuron weights and improves the efficiency of the BP algorithm (Xioa et al. 2014). In case of several neural networks training, the Levenberg-Marquardt algorithm could be the best option.

2.3. Software and evaluation of model performance

Most of the researchers used MATLAB software in developing NN models for the prediction of road traffic accidents, driver injury severity, which is also used for machine learning, signal and image processing, etc. Statistical software R is also used in NN models development for road accident prediction by some researchers. More recently, Python is also used and has become more popular in deep learning techniques for developing road accident severity prediction models. Generally, the prediction performance of NN models is measured and compared by the following methods: mean squared error (MSE), root mean square errors (RMSE), mean absolute errors (MAE), mean absolute percentage errors (MAPE), coefficient of correlation (R), coefficient of determination (R^2) and mean absolute deviation (MAD), etc. The general description of these various methods are given below:

MSE: The mean squared error (MSE) represents the average difference between the observed values and the actual value of the squares of the errors. Mathematically it is expressed as:

$$MSE = \frac{1}{N}\sum_{i}^{n}\left(p_i - \overline{q}_i\right)^2 \tag{2}$$

Where.

N= trained data samples.

p_i= observed values.

$\overline{q}_i$= estimate value/predicted value.

RMSE: The root-mean-square error (RMSE) is defined as the square root of the mean square error.

$$RMSE = \sqrt{MSE} \tag{3}$$

MAE: The mean absolute error (MAE) is a measure of errors expressing the same hypothesis between paired observations. Mathematically it is expressed as:

$$MAE = \frac{1}{N}\sum|p_i - q_i| \tag{4}$$

MAPE: The mean absolute percentage error (MAPE) is a measure of the prediction accuracy of a forecasting system, often used as a loss function for machine learning regression problems. Mathematically it is expressed as:

$$MAPE = \frac{1}{N}\sum\left|\frac{p_i - q_i}{p_i}\right| \tag{5}$$

R and R^2: The proportion of variance in the dependent variable that is predictable from the independent variable(s) is the coefficient of determination, denoted R^2 or R squared. However, the square of the coefficient of correlation (R) is the coefficient of determination. Mathematically it is expressed as

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}(p_i - q_i)^2}{\sum_{i=1}^{N}\left(p_i - \overline{p}_i\right)^2}} \tag{6}$$

Where,

$\overline{p}_i$=mean estimate value/mean predicted value

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(p_i - q_i)^2}{\sum_{i=1}^{N}\left(p_i - \overline{p}_i\right)^2} \tag{7}$$

SD: The standard deviation (SD) measures the sum of a set of values to differ or disperse.

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(p_i - \overline{q}_i\right)^2} \tag{8}$$

MAD: The mean absolute deviation (MAD) of a dataset is the mean difference between the mean and each data point.

$$MAD = \frac{\sum\left|p_i - \overline{p}_i\right|}{N} \tag{9}$$

AUC: Under the receiver operating curve (ROC), the area under curve (AUC) estimates the area. By plotting a true positive rate, ROC is generated against the false positive rate. In value, the AUC ranges from 0 (100% wrong), vs. 1 (100% right).

Accuracy: Accuracy is one parameter for assessing the classifier model. The accuracy, traditionally, has the following definition:

$$Accuracy = \frac{Corrected\ prediction\ number}{Total\ prediction\ number} \tag{10}$$

3. Taxonomy of the Reviewed Systems

Neural network models especially deep learning methods for road accident prediction increasingly started to show superiority over the other techniques. In this study, a taxonomy of NN models for the prediction of road traffic accidents is presented in Fig. 3. In this research, we have reviewed a total of 33 scientific articles which all were developed for the forecasting of road accident severity. Among them, 20 papers (60.61% of the total reviewed articles) used the MLPNN model for road accident prediction purposes, 6 papers (18.18% of the total reviewed articles) used the RBFNN model for the forecasting of crash frequency, 4 papers (12.12% of the total reviewed articles) used the RNN model for the purpose of traffic accident prediction severity, 3 papers (9.09% of the total reviewed articles) used the CNN, 2 papers (6.06% of the total reviewed articles) used the simple FFNN and also 2 papers (6.06% of the total reviewed articles) used the SLPNN model for the road accident prediction purposes. However, SLPNN, RNN, CNN and MLPNN, RNN, CNN model also developed together for determining their prediction accuracy in some cases.

4. Literature on developed systems

Significant literature studies have offered useful tools and knowledge to predict the magnitude of road traffic accidents. This paper review several neural network models including their input and output parameters and, various model performance measurements.

4.1. Feed forward neural network

The feed forward neural network (FFNN) is one of the first invented artificial neural networks. In this network, the information only moves forward direction through the layers of input, hidden, and output. This function is called feed forward network as there are no feedback links through which the model output is fed back into itself (Sameen et al. 2017; Dong et al. 2018; Rezapour et al. 2020).

Feed forward neural network was used at urban intersections for determining the degree of danger (Mussone et al. 1999). Sameen et al. (2017), developed simple feed forward neural networks with RNN and CNN models for the prediction of injury severities due to traffic accident. They investigated that the RNN model performed 73.76% accuracy, CNN model 70.30%, and FFNN model 68.79%.

4.2. Single layer perceptron neural network

A single neuron called perceptron was generated from the neural network. A feed forward network based on a threshold transfer feature is

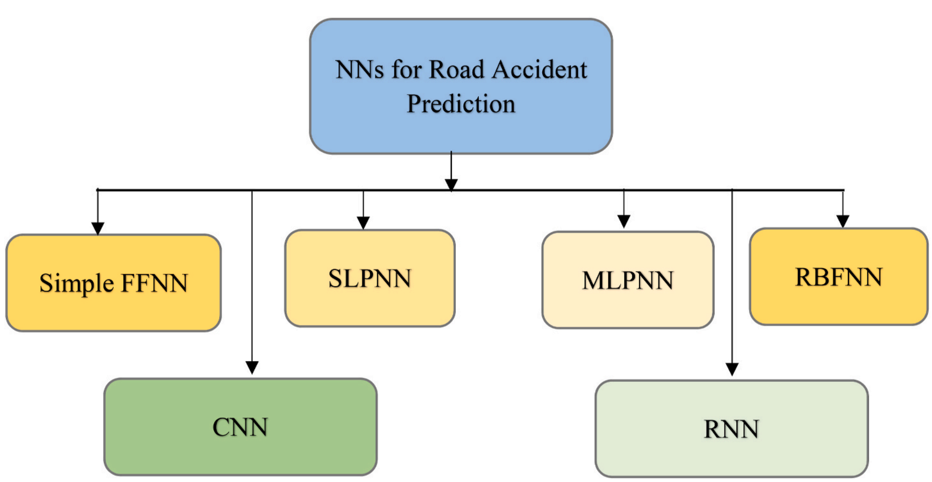

Fig. 3. Taxonomy of the previously developed NN models for road accident prediction.

a single-layer perceptron. SLP neural network is the simplest type of artificial neural network and only linearly separable cases can be categorized by a binary target (Rezapour et al. 2020).

Rezapour et al. (2020) developed a single-layer perceptron neural network with recurrent neural network, multilayer neural network for the prediction of frequency and intensity of motorbike accident, and compared their accuracy. Single layer perceptron was used to analyze in accident research as a distance based pattern matching approach for identifying the correct road segment (Deka and Quddus, 2014). The summary of the SLPNN and simple FFNN based systems for traffic accident prediction is depicted in Table 1 highlighting input/output variables, data partitioning techniques, performance measures, and severity levels.

4.3. Multilayer perceptron neural network

The widely used category of feed forward neural network is a multilayer perceptron neural network. The multilayer perceptron neural network model has the same framework as a single layer neural networks with more hidden layers. An MLP consists of at least three node layers: an input layer, a hidden layer, and a layer of output. In general, MLP uses a supervised learning method called back propagation to train the model. Among several categories of NNs, the multilayer perceptron neural network has become the most common, universal, basic, and necessary for most tasks.

MLPNN and Fuzzy Adaptive Resonance Theory (ART) neural networks were developed for the prediction of injury level of driver and compared with calibrated ordered logit model (Abdelwahab and Abdel-Aty, 2001) and calibrated an ordered probit model (Abdel-Aty and Abdelwahab, 2004). Both of these studies explored a more accurate prediction of injury severity capability for MLPNN over other conventional models.

The genetic algorithm (GA), combined GA and pattern search (PS), and the ANN with MLP architecture were used to predict traffic accident intensity using twelve input variables and three crash severity levels: fatal crash, apparent injury, and no injury (Kunt et al. 2011). With an R-value of around 0.87, the ANN provided the highest prediction performance in this study, followed by a combination of GA and PS with an R-value of around 0.79 and a GA of 0.79. The MLPNN method has been used to forecast crash severity on urban highways and to classify important crash-related factors, and this research (Moghaddam et al. 2011) has shown that the best results are obtained by feed forward back propagation (FFBP) networks such as MLP models. Ogwueleka et al. (2014) developed a MLPNN for predicting road traffic accidents in Nigeria. In 2014, Zadaan et al. 2014 proposed a crash prediction model that analyzes the relationship between accidents and factors influencing them using an ANN and predicts possible traffic accidents on the Jordanian national transport network.

In 2017, Alkedher et al. developed a MLPNN network for predicting the severity of traffic accidents and divided their accident data into three clusters using the k-means algorithm to enhance prediction accuracy. The findings after clustering showed significant improvements in the accuracy of the forecasting. More recently, Chakraborty et al. (2019), using MLPNN, established fatal pedestrian crash frequency models and it was reported that the motorized vehicle's 'approaching speed' has the most important effect on fatal intersectional pedestrian crashes. Soto et al. (2019), introduced a technique to use MLPNN to develop an accident risk prediction model, and this model can be used as an infrastructure management decision-making tool to classify areas of a road network where the number of fatalities is likely to be high and to be able to focus on the factors that cause it.

The summary of the MLPNN based systems for traffic accident prediction is depicted in Table 2 highlighting input/output variables, data partitioning techniques, performance measures, and severity levels.

4.4. Radial basis function network neural network

The radial basis function neural network model explains more specific interactions between the frequency of crashes and factors of risk (Haykin, 2009). This model can quickly replace the redundant nodes (Setiono and Leow, 2000). The characteristics of the RBFNN are good approximation accuracy, high convergence speed which can effectively resolve the deficiencies of BP neural networks (Zhao-hui 2009). In the field of function approximation, problem solving, computer vision,

Table 1
Summary of previous researches that used SLPNN and simple FFNN for traffic accident prediction.

Authors and Study Area	Input/Independent variable	Output/Dependent variable	Data Partitioning	Performances (%)	Severity Levels
Mussone et al. (1999), Italy	Vehicular flows, road geometry, vehicular characteristics	Number of accidents	Training=1037 cases, Testing=1036 cases	RMSE=0.1824	Frontal crashes are the most common at intersections: lateral (56% of the cases), collision (15% of the cases), side (11% of the cases), and accidents involving pedestrians (6% of the cases).
Deka and Quddus (2014), UK	Road name and type, place of crash, direction of vehicle	Mapping of incidents, correct road segment identification	Training=400 accidents, Total samples=560 accidents	Accuracy= 98.2 (road type), 97.3 (run-off road) and 98.4 (other accidents)	N/A
Sameen et al. (2019), Malaysia	Accident time, zone and location, collision type, surface and lighting condition, accident reporting	Injury severities	10-fold cross-validation	SD: RNN=1.24 CNN=0.53 FFNN=2.21 Accuracy: RNN=73.76 CNN=70.30 FFNN=68.79	Property Damage Only (PDO) = 238 (last section), 209 (main route) Evident Injury = 58 (last section), 155 (main route) Disabling injury = 82 (last section), 666 (main route).
Rezapour et al. (2020), USA	AADT, geometric characteristics, winter conditions, area types	Severity of motorbike accident	Training=80%, Testing=20%	AUC: RNN=0.74 MLP=0.58 SLP=0.53 Error rate: RNN=29 MLP=35 SLP=37	Severe/fatal crashes = 34%, PDO = 66%

N/A: Not Appropriately Defined.

Table 2
Summary of previous researches that used MLPNN for traffic accident prediction.

Authors and Study Area	Input/Independent variable	Output/ Dependent variable	Data Partitioning	Performances (%)	Severity Levels
Al-Alawi et al. (1996), Oman	Population growth, gross domestic product (GDP), vehicles number	Number of car accidents	Training= data from 1976 to 1990,	Accuracy=89 MAPE=10.81 R^2=0.898	N/A
Ali et al. (1998), Oman	Population, GDP, cars number	Number of deaths in accidents	Training= data from 1976 to 1994	R^2=0.990	N/A
Abdelwahab and Abdel-Aty (2001), USA	Driver age, gender, alcohol involvement, fault, Vehicle type, speed ratio, day, area type, weather, use of seat belt	Injury severity of driver	Training=2000 cases, Testing=336 cases	MLP: Accuracy=65.6 ARTMAP: Accuracy=60.4	Severity level increases = Rural intersections, female drivers, Speed ratio, Vehicle type, and Drivers in passenger cars, Severity level decreases = Wearing a seat belt.
Abdelwahab and Abdel-Aty (2002), USA	Fatality setting, type of automobile, driver demographics	Place of accident, driver seriousness of injury	Training=85%, Testing=15%	MLP: Accuracy (Training & Testing)=78.7 & 74.3, RBFNN: Accuracy (Training & Testing)=82.6 & 79.2	Severe injuriy = Users of electronic toll collection (ETC), older drivers, and female drivers have a higher risk of serious injury.
Abdel-Aty and Abdelwahab (2004), USA	Different features of driver, vehicle, road environment	Severity of driver injury	Training=1997 crash data, Testing=1996 crash data	MLP: Accuracy=73.5 ARTMAP: Accuracy=70.6	No injury = 6.6%, Possible injury= 36.2%, Evident injury = 44.2%, Fatal injury = 13.0%
Akgüngör and Doğan (2008), Turkey	Vehicles number, fatalities, injuries, accidents, population	Rate of fatalities, accidents, and injuries	Training=data between 1986 and 2000, Testing=data between 2001 and 2005	Accident: MAPE= 5.2 RMSE= 32107 Injury: MAPE= 4.1 RMSE= 4322 Fatality: MAPE= 4.1 RMSE= 254	Fatalities = decreasing trend. Injuries = increasing trend
Akgüngör and Doğan (2009), Turkey	Vehicles number, fatalities, injuries, accidents, population	Rate of fatalities, accidents, and injuries	Training=data between 1986 and 2000, Testing=data between 2001 and 2005	Accident: MAE= 1973 RMSE= 2327 Injury: MAE= 404 RMSE= 452 Fatality: MAE= 37 RMSE= 93	Fatalities = decreasing trend Injuries = increasing trend
Kunt et al. (2011), Iran	Age and gender (driver's), safety belt uses, vehicle type and safety, flow, climate conditions, road surface, speed ratio, crash time and type, collision type	Severity of traffic accidents at freeway	Training=70%, Validation=15%, Testing=15%	MLPNN: R=0.873 MAE=0.162 RMSE=0.229 GA: R=0.792 MAE=0.323 RMSE=0.439	Fatal injuries = 14%, Injuries = 38.4%, and No injuries = 47.6%
Moghaddam et al. (2011), Iran	Human factors, road, vehicle, weather conditions, traffic volume, flow speed	Crash severity, significant factors	Random partitioning	MSE=0.868	Frontal accidents, the type of vehicle at fault, disregarding length and width space, inability to control the vehicle, and exceeding the safety speed, all contribute to the severity of the crash.
Jadaan et al. (2014), Jordan	Registered vehicles number, population, total length of paved roads, GDP	Number of accidents	Training=70%, Validation=15%, Testing=15%	R^2=0.992	N/A
Çodur, and Tortum (2015), Turkey	Years, highway sections, and length (km), (AADT), degree of horizontal and vertical curvature, heavy vehicles (%), Summer (%)	number of accidents	Training=70%, Validation=15%, Testing=15%	MSE= 4.110 RMSE= 2.027 R^2= 0.982 R= 0.991	Summer traffic accidents are more common than other seasons, and those involve heavy vehicles are more frequent than those involve light vehicles.
Ghasemlou et al. (2015), Turkey	Accident numbers and registered passenger car	Number of cyclist and pedestrian accidents	Training=80%, Validation=20%	Pedestrians: R^2=0.68 Cyclists: R^2=0.82	Crash fatalities for pedestrian and cyclists = 20.6% and 3% respectively.
Yilmaz et al. (2016), Turkey	Type of collision, accident type	Fault rates in most frequent PDO accidents	10-fold cross-validation	MFANN: MSE = 0.012/1.551 R=0.999/0.998	Consider 100, 50, and 0% fault rates in most frequent PDO accidents.
Alkheder et al. (2017), United Arab Emirates	Demographics of driver, road and vehicle, weather conditions	Injury severity	Training=90%, Testing=10%	MLP: Accuracy=74.6 Order probit model: Accuracy=59.5	Death = 3%, Severe injury = 7%, Moderate injury = 31%, Minor injury = 59%

(*continued on next page*)

Table 2 (*continued*)

Authors and Study Area	Input/Independent variable	Output/ Dependent variable	Data Partitioning	Performances (%)	Severity Levels
Taamneh et al. (2017), Abu Dhabi	Degree of injury (death, severe, moderate, and minor)	Accidents severity	Training=66%, Testing=34%	AUC: Accuracy=99.8 (cluster 6)	Death = 25%, Severe injury = 55.6%, Moderate injury = 70.3%, Minor injury = 81.5%
Ebrahim and Hossain (2018), Bangladesh	Vehicle type, accidents type, junction type	Traffic accidents, significant factors	Training=70%, Validation=15% Testing=15%	MSE=0.46585 R=0.99995	Person dead = 54% reduction of persons dead Person injured = 73% reduction of persons injured
Soto et al. (2018), Switzerland	AADT, HGV, curvature, slope/gradient	Accident risk	Training=80%, Testing=20%	MLPNN: MAPE (light)=30 MAPE (severe)=27 MAPE (fatal)=22.4 BN: MAPE (light)=51.8 MAPE (severe)=27.5 MAPE (fatal)=21.8	Light injuries = 17.5%, Severe injuries = 32.7%, Severe injuries = 30.6%
Lee et al. (2019), South Korea	Road geometry and location, traffic accident data set precipitation,	Traffic accidents severity	Training=75%, Testing=25%	MLP: MSE=0.102 RMSE=0.319	Fatal = weight of 1.2 Serious Injury and Minor Injury = weight of 0.3
Chakraborty (2019), India	Time, location, and severity of crashes, road geometry, operating speed, vehicular and pedestrian volume	Prediction of accidents for pedestrians	Training=79%, Testing=21%	RMSE=0.4019 MAE=0.3117 R=0.5845	Fatal pedestrian crash frequency = The best-fitted model's accuracy level is nearly 90%.

system identification, and so on, RBFNN has been widely used for its deep physiology foundation, simple network structure, fast learning speed, and outstanding approximate solution abilities (Song and Li, 2011).

MLP and RBF neural networks were analyzed by using the Central Florida freeway program's 1999 and 2000 toll plaza road accident studies and their performance compared with calibrated logit models. The result of this study showed that the RBF neural network was the best model for driver injury severity analysis. This RBF model has shown that older drivers generally have a higher chance of injury in traffic accidents than younger drivers, and female drivers are more likely to experience serious injury compared to male drivers (Abdelwahab and Abdel-Aty,

Table 3
Summary of previous researches that used RBFNN for traffic accident prediction.

Authors and Study Area	Input/Independent variable	Output/Dependent variable	Data Partitioning	Performances (%)	Severity Level
Abdelwahab and Abdel-Aty (2002), USA	Fatality setting, type of automobile, driver demographics	Place of accident, driver seriousness of injury	Training=85%, Testing=15%	RBFNN: Accuracy (Training and Testing)=82.6 and 79.2, MLP: Accuracy (Training and Testing)=78.7 and 74.3	Severe injuriy = Users of electronic toll collection (ETC), older drivers, and female drivers have a higher risk of serious injury.
LIU Zhao-hui (2009), China	Alignment combination, safeguard facilities and sight distance	Equivalent accident number	Training= data during 2003 and 2004, Testing= data during 2005 and 2006	Grey System: MAE=7.0 MAPE=0.042 RBFNN: MAE=4.0 MAPE=0.024 Combined: MAE=3.5 MAPE=0.021	Number of accident = Slightly increases
Song and Li (2011), China	Population, GDP, cars, road mileage	Accident number	Training= data during 1990 and 2005, Testing= data during 2006 and 2007	Relative error= 1.44 and 1.17	Number of traffic accident = Increases
Olutayo and Eludire (2014), Nigeria	Tyre burst, loss of control, and over speeding	Traffic accident (data analysis)	RBFNN: Training= 54.73%, Testing= 40.56% MLP: Training=52.70%, Testing= 45.20%	RBFNN: MAE= 0.3478 RMSE= 0.4484 MLP: MAE= 0.3479 RMSE= 0.5004	Tyre burst, loss of control, and over speeding are the three most common causes of accidents.
Huang et al. (2016), Hong Kong	AADT, lane width, length and gradient, curvature, median shoulder, park rainfall	Crash frequency	Training=80%, Testing=20%	MAD: Trained RBFNN=0.49 Optimized RBFNN=0.14	Number of Crash injury severity = Increases
Behbahani et al. (2018), Iran	Characteristics of crash, traffic flow, and weather condition	Accident frequency	Training=80%, Testing=20%	RBFNN: RMSE=0.8783 MAE=0.9345 MLP: RMSE=0.4727 MAE=0.3164	Model developed to predict accident severity.

2002).

Huang et al. (2016), developed optimized RBF for predicting accident frequency and determining the risk parameters which were more significant for occurring road accidents. The efficiency of its estimation increases while optimizing the RBFNN, although other variables are found to hardly affect the frequency of crash occurrence for the crash data. This study also stated that the RBFNN has a better performance forecasting model than the NB and BPNN models, compared to the standard negative binomial (NB) and back-propagation neural network (BPNN) models for crash level prediction.

The summary of the RBFNN based systems for traffic accident prediction is depicted in Table 3 highlighting input/output variables, data partitioning techniques, performance measures, and severity levels.

4.5. Convolutional neural network

Nowadays, deep learning has drawn considerable interest by academics and also researchers in all fields. The convolutional neural network has become a popular topic of study in many scientific fields as a deep learning technique. CNN is a quick and efficient feed forward neural network that is commonly used in the fields of computer vision, image recognition, and speech recognition and has obtained excellent output (Abdel-Hamid et al. 2014; Mao et al. 2014; Swietojanski et al. 2014).

In recent years, promoting the efficiency of prediction, CNN model was developed as a road traffic accident prediction model for predicting accurately highway road traffic accident (Wenqi et al. 2017). The CNN model in this study showed its advantages in accuracy and efficiency compared to the conventional back propagation neural network model, and the prediction accuracy is 78.5%, which is 7.7% higher than the traditional BP network model.

For road crash severity prediction, Zeng et al. (2019), introduced a deep learning approach with a CNN model by mapping the gradient of the accident data into a grey image representing the weight of the characteristics of the traffic accident. Then the grey image was used as an input for CNN model severity prediction. For the period 2009 to 2016, the Leeds City Council analyzed the effectiveness of this proposed CNN model using traffic accident data and demonstrated higher performance than K-nearest neighbor algorithm, logistic regression, gradient boosting neural network, and support vector machines, and LSTM-RNN.

The summary of the CNN based systems for traffic accident prediction is depicted in Table 4 highlighting input/output variables, data partitioning techniques, performance measures, and severity levels.

4.6. Recurrent neural network

Recurrent neural networks are neural networks generally designed to describe functions and become more efficient with feedback links. They are more functional and technically acceptable than feed forward networks. To resolve the vanishing or exploding gradient problem of the traditional RNNs Long Short-Term Memory (LSTM) algorithm was proposed by Hochreiter and Schmidhuber (1997). A researcher used the LSTM-RNN model with the synthetic minority over-sampling technique (SMOTE) for the prediction of real-time crash risk and compared with the traditional conditional logistic model (Yuan et al. 2019).

The RNN model can be a successful approach for the forecasting of traffic accident injury severity (Sameen and Pradhan, 2017; Sameen et al. 2017; Rezapour et al. 2020). Sameen et al. (2017), investigated a study with three types of neural networks such as RNN, CNN, and simple FFNN for determining the prediction accuracy of traffic accident severity. The results of this study indicated that the model of RNN performed better with an average 73.76% accuracy compared to the 70.30% and 68.79% accuracy of the CNN and FFNN models.

The summary of the RNN based systems for traffic accident prediction is depicted in Table 5 highlighting input/output variables, data partitioning techniques, performance measures, and severity levels.

More recently, the RNN model was also developed as a data-driven predictive model with SLPNN and MLPNN for comparing the prediction accuracy of motor vehicle accident magnitude (Rezapour et al., 2020). The results of this study showed that the RNN model performed better in predicting validating data (29%) and that the validation dataset performed poorly on MLNN and single layer neural network, with an error rate of 37% and 35% of test data respectively.

5. Open discussions and future challenges

This section discusses the previously reviewed models, challenges, and potential future developments of the road accident prediction model based on NNs.

The SLPNN and simple FFNN model description is outlined in Table 1. Generally, most of the researchers used SLPNN and simple FFNN model as a base model for small projects and usually fixed it's as standard for the comparison of deep learning techniques for measuring

Table 4
Summary of previous researches that used CNN for traffic accident prediction.

Authors and Study Area	Input/Independent variable	Output/ Dependent variable	Data Partitioning	Performances (%)	Severity Level
Sameen et al. (2019), Malaysia	Accident time, zone and location, collision type, surface and lighting condition, accident reporting	Injury severities	10-fold cross-validation	SD: RNN=1.24 CNN=0.53 FFNN=2.21 Accuracy: RNN=73.76 CNN=70.30 FFNN=68.79	PDO = 238 (last section), 209 (main route) Evident Injury = 58 last section), 155 (main route) Disabling injury = 82 (last section), 666 (main route)
Wenqi et al. (2017), USA	Traffic flow, weather, light	Traffic accidents	Training= 150 accidents samples, Testing= 100 accidents samples	CNN: Accuracy=78.5 Traditional BP: Accuracy=70.8	N/A
Zeng et al. (2019), UK	Street category, time of accident, number and type of vehicles, road surface, lighting conditions, climate conditions, casualty class, sex and age of casualty	Severity of traffic accident	5-fold cross-validation	Micro_F1score=0.84	slight accident = 0.893 (Average Precision) serious accident = 0.248 (Average Precision) fatal accident = 0.063 (Average Precision).

Table 5
Summary of previous researches that used RNN for traffic accident prediction.

Authors and Study Area	Input/Independent variable	Output/Dependent variable	Data Partitioning	Performances (%)	Severity Level
Sameen and Pradhan (2017), Malaysia	Location, road-bound, accident zone, lighting condition, surface condition, collision type, vehicle type	Injury severity	Training=80%, Validation=20%	R^2: RNN: BLR=0.72 RNN: MLP=0.38 Validation Accuracy: RNN=71.77 MLP=65.48 BLR=58.30	PDO = 65.4% Possible/Evident Injury = 15.2% Disabling injury = 19.4%
Sameen et al. (2019), Malaysia	Accident time, zone and location, collision type, surface and lighting condition, accident reporting	Injury severities	10-fold cross-validation	SD: RNN=1.24 CNN=0.53 FFNN=2.21 Accuracy: RNN=73.76 CNN=70.30 FFNN=68.79	PDO = 238 (last section), 209 (main route) Evident Injury = 58 (last section), 155 (main route) Disabling injury = 82 (last section), 666 (main route)
Rezapour et al. (2020), USA	AADT, geometric characteristics, winter conditions, area types	Severity of motorbike accident	Training=80%, Testing=20%	AUC: RNN=0.74 MLP=0.58 SLP=0.53 Error rate: RNN=29 MLP=35 SLP=37	Severe/fatal crashes = 34%, PDO = 66%
Yuan et al. (2019), USA	Crash data, travel speed data, signal timing data, loop detector data, weather characteristics	real-time crash	Training=70%, Testing=30%	LSTM-RNN: Sensitivity=60.67 False Alarm Rate=39.33 Conditional Logistic Model: Sensitivity=56.72 False Alarm Rate=43.28	Intersection areas = 50.37%, Intersection entrance areas = 34.59%, Intersection exit areas = 13.53%

their performances.

Table 2 illustrates the summary of the previous researches that used the MLPNN model for traffic accident prediction. This study showed that a common data set such as population, GDP, different driver attitude, road geometry, number of vehicles, and accidents were used as an input variable by the MLPNN based developed systems. Most of the model determined and predicted the injury severity or accident frequency and the number of people dead and injured. Some of the researchers also established a prediction model for identifying the significant risk parameters for road (Moghaddam et al. 2011; Ebrahim and Hossain, 2018) and crash rate (Yilmaz et al. 2016).

Table 3 depicts the summary of previous researches that used the RBFNN model for road traffic accident prediction. The RBFNN framework illustrates more explicit correlations between accident rates and contributing risk parameters and can perform better than the MLPNN in terms of feature interpretation and learning speed (Huang et al. 2016). Researchers found that RBF is used as an activation function for the key distinction between RBFNN and FFNN with a radial basis function. Several authors used unsupervised learning strategies in RBFNN such as the orthogonal least square method (Behbahani et al. 2018) and recurrent least squares algorithm (Huang et al. 2016).

Tables 4 and 5 depicts the previous study of road accident prediction based on deep learning techniques such as RNN and CNN. Some research has shown that the accuracy of the various machine learning/deep learning approaches is greatly affected by different hyperparameters, so it is necessary to change the variables of the models before presenting the output. Recently, the Feature Matrix to Grey Image (FM2GI) algorithm (Sameen et al. 2017) was developed and suggested to facilitate the predictive performance of traffic accident's severity by combining the estimation of feature weights, filling the features into the all-zero matrix, and finally transforming them into images as a CNN input (Zeng et al. 2019). This study showed that these deep learning models are a new paradigm to obtain higher efficiency for road traffic accident prediction and the use of high-dimensional crash accident data.

Since the latest trend for prediction or analysis of road traffic accidents is based on deep learning techniques, there are also some specific challenges. Although deep learning techniques are highly automated, the development of a robust framework for forecasting purposes requires broad and heterogeneous data sources. In order to develop an effective prediction model, gathering all contributing factors of road accidents, including geo-spatial data, adverse weather data, vast elements of human behavior, and psychological data, is a major challenge.

Developing an appropriate road crash risk forecasting model is a high priority task in traffic accident mitigation. While the chance of a traffic accident in that certain area can really be forecasted, we can use that information to alert nearby drivers or persuade them to take a less dangerous route. Road users have really managed to avoid being dead or gravely wounded using machine learning (ML) approaches. It might be accomplished by effectively utilizing an intelligent traffic system that can detect a driver who is at a greater risk of colliding with other vehicles (Rezapour et al. 2020). Due to the intricacies of traffic accident data, deep learning techniques are presently being effectively used to the road accident alert system and demonstrate their high accuracy and efficiency, which can assist people to avoid traffic accidents by guiding them to safer places.

Table 6 illustrates the summary of prediction types, reasons, and considerations for selecting NN models. The key objective of all NN models development is analyzing and predicting the road traffic accidents, as well as determining the most important risk factors that contribute to road accidents. SLPNN and a simple FFNN model were used as base models to examine if various techniques may improve the model's performance when compared to this simple model. MLPNN is a multi-layer feed-forward network with hidden sigmoid and linear output neurons that could dynamically suit multi-dimensional mappings tasks. It is a supervised learning strategy for categorization that has been used to solve a variety of complex situations. MLPNN is commonly

Table 6
Summary of prediction types, reasons, and considerations for selecting NN models.

NN Techniques	Types of Prediction	Reasons and Clues
SLPNN/ FFNN	• Road accident prediction	• Only classify linearly separable cases with a binary target.
MLPNN	• Road accident prediction	• MLP networks are more successful for modeling data with categorical inputs because they are compact, less sensitive to add unnecessary inputs, and less sensitive to include unnecessary inputs.
RBFNN	• Road accident prediction • Time series prediction	• Short training, simple configuration, and fast convergence. • Approximation ability to any nonlinear function has a significant advantage.
CNN	• Road accident prediction • An innovative method for predicting traffic accidents	• The feature combination, and deeper feature correlations from traffic accident's data. • Neurons in adjacent layers have different patterns of connection. • Predict the results with a lower cost of computations. • Use a specialized layer known as the pooling layer, the CNN decreases the model's variable size.
RNN	• Road accident prediction • Time series prediction • An innovative method for predicting traffic accidents	• By using hidden layers, information can be transferred from one layer to the next. • Predict the outputs with less computational costs • More effective for sequential data • Real-time data sources are processed and classified

utilized to construct road accident severity prediction models because it can separate data that is not linearly separable. As MLP networks are compact, less susceptible to add needless inputs, and less sensitive to include unneeded inputs, they are more successful at modeling data with categorical inputs. RBFNN is well-known for its strong physiological base, simple network architecture, quick learning speed, and excellent approximate solution capabilities. Deep learning methods such as RNN and CNN are a relatively new strategy to predict road traffic accidents with high precision and embrace the use of the integration of many data sources.

The following aspects need to be evaluated too for future research. For predicting the severity of traffic accidents, it is recommended more balance data sets and observations in future research. The computer program based accident reporting database system should be developed by each and every nation and implemented to collect and store all the features of road accidents. Evaluating neural network architectures on broader datasets can potentially transform the industry's deep learning models for use in operation. The application of the LSTM approach to non-sequential datasets is also suggested for future research.

6. Conclusions

The prediction of traffic accident severity is a significant phase in the intelligent transport and traffic management system in order to classify drivers at higher risk of serious accidents and thereby prevent them from crashing. In general, statistical analyses are often used for simple problems or small datasets, whereas simple neural network models or deep learning based neural network models can be used when problems become more complex because they can address larger datasets and nonlinear characteristics. The multilayer perceptron neural network is the most prevalent, universal, simple, widely used for road accident prediction, and essential for most activities among several categories of NNs. More recently, deep learning techniques such as RNN and CNN is developed and outperform the MLPNN, and single layer perceptron neural network for accident severity prediction. RNN and CNN are evaluated as successful road accident prediction and traffic safety evaluation techniques.

Declaration of competing interest

The work presented in this paper is original research article. On behalf of all the authors, the corresponding author states that there is no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eastsj.2021.100040.

References

Abdel-Aty, M.A., Abdelwahab, H.T., 2004. Predicting injury severity levels in traffic crashes: a modeling comparison. J. Transport. Eng. 130 (2), 204–210.
Abdel-Hamid, O., Mohamed, A.R., Jiang, H., Deng, L., Penn, G., Yu, D., 2014. Convolutional neural networks for speech recognition. IEEE/ACM Trans. Audio Speech Language Proc. 22 (10), 1533–1545.
Abdelwahab, H., Abdel-Aty, M., 2001. Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized intersections. Transport. Res. Rec.: J. Transport. Res. Board 1746 (1), 6–13.
Abdelwahab, H., Abdel-Aty, M., 2002. Artificial neural networks and logit models for traffic safety analysis of toll plazas. Transport. Res. Rec.: J. Transport. Res. Board 1784 (1), 115–125.
Abdulhafedh, A., 2016. Crash frequency analysis. J. Transport. Technol. 6, 169–180.
Abdulhafedh, A., 2017. Road crash prediction models: different statistical modeling approaches. J. Transport. Technol. 7 (2), 190–205.
Ahmed, A.A., Pradhan, B., 2019. Vehicular traffic noise prediction and propagation modelling using neural networks and geospatial information system. Environ. Monit. Assess. 191 (3), 190.
Akin, D., Akba, B., 2010. A neural network (NN) model to predict intersection crashes based upon driver, vehicle and roadway surface characteristics. Sci. Res. Essays 5 (19), 2837–2847.
Akgüngör, A.P., Dogan, E., 2008. Estimating road accidents of Turkey based on regression analysis and artificial neural network approach. Adv. Transport. Studies, 2008 (16), 11–22.
Akgüngör, A.P., Doğan, E., 2009. An artificial intelligent approach to traffic accident estimation: model development and application. Transport 24 (2), 135–142.
Al-Alawi, S.M., Ali, G.A., Bakheit, C.S., 1996. A novel approach for traffic accident analysis and prediction using artificial neural networks. Road Transp. Res. 5 (2), 118–127.
Ali, G.A., Al-Alawi, S.M., Bakheit, C.S., 1998. A comparative analysis and prediction of traffic accident causalities in the sultanate of Oman using artificial neural networks and statistical methods. J. Sci. 3, 11–20.
Alkheder, S., Taamneh, M., Taamneh, S., 2017. Severity prediction of traffic accident using an artificial neural network. J. Forecast. 36 (1), 100–108.
Behbahani, H., Amiri, M.A., Imaninasab, R., Alizamir, M., 2018. Forecasting accident frequency of an urban road network: a comparison of four artificial neural network techniques. J. Forecast. 37 (7), 767–780.
Chakraborty, A., Mukherjee, D., Mitra, S., 2019. Development of pedestrian crash prediction model for a developing country using artificial neural network. Int. J. Inj. Control Saf. Promot. 26 (3), 283–293.
Chang, L., 2005. Analysis of freeway accident frequencies: negative binomial regression versus artificial neural network. Saf. Sci. 43 (8), 541–557.
Çodur, M.Y., Tortum, A., 2015. An artificial neural network model for highway accident prediction: a case study of erzurum, Turkey. Promet - Traffic & Transp. 27 (3), 217–225.
Daniels, S., Brijs, T., Nuyts, E., Wets, G., 2010. Explaining variation in safety performance of roundabouts. Accid. Anal. Prev. 42 (2), 392–402.
Deka, L., Quddus, M., 2014. Network-level accident-mapping: distance based pattern matching using artificial neural network. Accid. Anal. Prev. 65, 105–113.
Delen, D., Sharda, R., Bessonov, M., 2006. Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. Accid. Anal. Prev. 38 (3), 434–444.
Dinua, R.R., Veeraragavan, A., 2011. Random parameter models for accident prediction on two-lane undivided highways in India. J. Saf. Res. 42 (1), 39–42.
Dong, C., Shao, C., Li, J., Xiong, Z., 2008. An improved deep learning model for traffic crash prediction. J. Adv. Transport., 3869106
Dougherty, M.A., 1995. Review of neural networks applied to transport. Transport. Res. C 3 (4), 247–260.
Du, Y., Stephanus, A., 2018. Levenberg-marquardt neural network algorithm for degree of arteriovenous fistula stenosis classification using a dual optical photoplethysmography sensor. Sensors 18 (7), 2322.
Dursun, D., Sharda, R., Bessonov, M., 2005. Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. Accid. Anal. Prev. 38 (3), 434–444.

Ebrahim, S., Hossain, Q.S., 2018. An Artificial Neural Network Model for Road Accident Prediction: a Case Study of Khulna Metropolitan City. KUET, ICCESD-2018; 2018.
El-Basyouny, K.7, Sayed, T., 2009. Collision prediction models using multivariate Poisson-lognormal regression. Accid. Anal. Prev. 41 (4), 820–828.
Flood, I., 2008. Towards the next generation of artificial neural networks for civil engineering. Adv. Eng. Inf. 22 (1), 4–14.
Garrido, C., Oña, R. de, Oña, J. de, 2014. Neural networks for analyzing service quality in public transportation. Expert Syst. Appl. 41 (15), 6830–6838.
Geedipally, R., Lord, D., Dhavala, S., 2012. The negative-binomial lindley generalized linear model: characteristics and application using crash data. Accid. Anal. Prev. 45, 258–265.
Ghasemlou, K., Aydi, M.M., Yildirim, M.S., 2015. Prediction of pedal cyclists and pedestrian fatalities from total monthly accidents and registered private car numbers. Arch. Transport 34 (2), 29–35.
Guler, I., Ubeyli, E.D., 2006. A recurrent neural network classifier for Doppler ultrasound blood flow signals. Pattern Recogn. Lett. 27 (13), 1560–1571.
Gutierrez-Osorio, C., Pedraza, C., 2020. Modern data sources and techniques for analysis and forecast of road accidents: a review. J. Traffic Transport. Eng. 7 (4), 432–446.
Hagan, M.T., Menhaj, M.B., 1994. Training feed forward networks with the Marquardt algorithm. IEEE Trans. Neural Network. 5 (6), 989–993.
Haykin, S.S., 2009. Neural Networks and Learning Machines, third ed. Prentice Hall, New York.
Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9 (8), 1735–1780.
Huang, H., Zeng, Q., Pei, X., Wong, S.C., Xu, P., 2016. Predicting crash frequency using an optimised radial basis function neural network model. Transportmetrica: Transport. Sci. 12 (4), 330–345.
Jadaan, K.S., Al-Fayyad, M., Gammoh, H.F., 2014. Prediction of road traffic accidents in Jordan using artificial neural network (ANN). J. Traffic Log. Eng. 2 (2), 92–94.
Joshua, S.C., Garber, N.J., 1990. Estimating truck accident rate and involvements using linear and Poisson regression models. Transport. Plann. Technol. 15 (1), 41–58.
Kunt, M.M., Aghayan, I., Noii, N., 2011. Prediction for traffic accident severity: comparing the artificial neural network, genetic algorithm, combined genetic algorithm and pattern search methods. Transport 26 (4), 353–366.
Lee, J., Yoon, T., Kwon, S., Lee, J., 2020. Model evaluation for forecasting traffic accident severity in rainy seasons using machine learning algorithms: seoul city study. Appl. Sci. 10 (1), 129.
Li, X., Lord, D., Zhang, Y., Xie, Y., 2008. Predicting motor vehicle crashes using support vector machine models. Accid. Anal. Prev. 40 (4), 1611–1618.
Llau, A., Ahmed, N.U., 2016. Identification of an accident prediction model for red light camera analysis. Biometr. Biostat. Int. J. 4 (3), 94–99.
Lord, D., Mannering, F., 2010. The statistical analysis of crash frequency data: a review and assessment of methodological alternatives. Transport. Res. Pol. Pract. 44 (5), 291–305.
Lord, D., Miranda-Moreno, F., 2008. Effects of low sample mean values and small sample size on the estimation of the fixed dispersion parameter of Poisson-gamma models for modeling motor vehicle crashes: a bayesian perspective. Saf. Sci. 46 (5), 751–770.
Mao, Q., Dong, M., Huang, Z., Zhan, Y., 2014. Learning salient features for speech emotion recognition using convolutional neural networks. IEEE Trans. Multimed. 16 (8), 2203–2213.
Miaou, S.-P., Bligh, R.P., Lord, D., 2005. Developing guidelines for median barrier installation: benefit–cost analysis with Texas data. Transport. Res. Rec. 1904 (1), 2–19.
Moghaddam, F.R., Afandizadeh, S., Ziyadi, M., 2011. Prediction of accident severity using artificial neural networks. Int. J. Civ. Eng. 9 (1), 41–49.
Mussone, L., Ferrari, A., Oneta, M., 1999. An analysis of urban collisions using an artificial intelligence model. Accid. Anal. Prev. 31 (6), 705–718.
Naghawi, H., 2018. Negative binomial regression model for road crash severity prediction. Mod. Appl. Sci. 12 (4).
Oh, J., Washington, S.P., Nam, D., 2006. Accident prediction model for railway-highway interfaces. Accid. Anal. Prev. 38 (2), 346–356.
Ogwueleka, F.N., Misra, S., Ogwueleka, T.C., Fernandez-Sanz, L., 2014. An artificial neural network model for road accident prediction: a case study of a developing country. Acta Polytechnica Hungarica 11 (5), 177–197.
Olutayo, V.A., Eludire, A.A., 2014. Traffic accident analysis using decision trees and neural networks. Int. J. Inf. Technol. Comput. Sci. 6 (2), 22–28.
Pradhan, B., Sameen, M.I., 2020. Review of traffic accident predictions with neural networks. In: Laser Scanning Systems in Highway and Safety Assessment, Technology & Innovation (IEREK Interdisciplinary Series for Sustainable Development). Springer, Cham, pp. 97–109.
Profillidis, V.A., Botzoris, G.N., 2019. Chapter 8 - artificial intelligence—neural network methods. In: Modeling of Transport Demand Analyzing, Calculating, and Forecasting Transport Demand, pp. 353–382.
Rezapour, M., Nazneen, S., Ksaibati, K., 2020. Application of deep learning techniques in predicting motorcycle crash severity. Eng. Rep. 2 (7), e12175.
Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning representations by back-propagating errors. Nature 323, 533–536.
Rusul, A., Hussein, D., Sohani, L., Saeed, A.B., 2019. Applications of artificial intelligence in transport: an overview. Sustainability 11 (1), 189.
Sameen, M.I., Pradhan, B., 2016. Assessment of the effects of expressway geometric design features on the frequency of accident crash rates using high-resolution laser scanning data and GIS. Geomatics, Nat. Hazards Risk 8 (2), 733–747.
Sameen, M.I., Pradhan, B., 2017. Severity prediction of traffic accidents with recurrent neural networks. Appl. Sci. 7, 476.
Sameen, M.I., Pradhan, B., Shafri, H.Z.M., Hamid, H.B., 2019. Applications of deep learning in severity prediction of traffic accidents. In: Global Civil Engineering Conference. Springer, Singapore, pp. 793–808.
Setiono, R., Leow, W.K., 2000. Pruned neural networks for regression. In: PRICAI 2000 Topics in Artificial Intelligence. Springer Berlin Heidelberg, pp. 500–509.
Shaik, M.E., Hossain, Q.S., 2019. Accident prediction by using Poisson regression for unsignalised junction in Khulna Metropolitan City, Bangladesh. In: Proceedings of International Conference on Planning, Architecture and Civil Engineering, RUET, ICPACE-2019, 2019.
Shaik, M.E., Hossain, Q.S., 2020. Application of statistical models: parameters estimation of road accident in Bangladesh. SN Comput. Sci. 1, 261.
Singh, P., Deo, M.C., 2007. Suitability of different neural networks in daily flow forecasting. Appl. Soft Comput. 7 (3), 968–978.
Song, C., Li, Q., 2011. The prediction model of macro-road traffic accident basing on radial basis function. Appl. Mech. Mater. 97–98, 981–984.
Soto, B.G. de, Bumbacher, A., Deublein, M., Adey, B.T., 2018. Predicting road traffic accidents using artificial neural network models. Infrastruct. Asset Manag. 5 (4), 132–144.
Swietojanski, P., Ghoshal, A., Renals, S., 2014. Convolutional neural networks for distant speech recognition. IEEE Signal Process. Lett. 21 (9), 1120–1124.
Taamneh, M., Taamneh, S., Alkheder, S., 2017. Clustering-based classification of road traffic accidents using hierarchical clustering and artificial neural networks. Int. J. Inj. Control Saf. Promot. 24 (3), 388–395.
Wenqi, L., Dongyu, L., Menghua, Y., 2017. A model of traffic accident prediction based on convolutional neural network. In: 2nd IEEE International Conference on Intelligent Transportation Engineering, pp. 198–202.
WHO, 2018. Global Status Report on Road Safety 2018. Geneva 2018.
Xiao, L., Chen, X., Zhang, X., 2014. A joint optimization of momentum item and Levenberg Marquardt algorithm to level up the BPNN's generalization ability. Math. Probl Eng. 653072, 1–10.
Xie, Y., Lord, D., Zhang, Y., 2007. Predicting motor vehicle collisions using bayesian neural networks: an empirical analysis. Accid. Anal. Prev. 39 (5), 922–933.
Yilmaz, A., Aci, C., Aydin, K., 2016. Traffic accident reconstruction and an approach for prediction of fault rates using artificial neural networks: a case study in Turkey. Traffic Inj. Prev. 17 (6), 585–589.
Yuan, J., Abdel-Aty, M., Gong, Y., Cai, Q., 2019. Real-time crash risk prediction using Long short-term memory recurrent neural network. Transport. Res. Rec.: J. Transport. Res. Board 2673 (4), 1–13.
Zhang, L., Liu, Q., Yang, W., Wei, N., Dong, D., 2013. An improved K-nearest neighbor model for short-term traffic flow prediction. 13th COTA international conference of transportation professionals (CICTP 2013). Procedia - Soc. Behav. Sci. 96, 653–662.
Zhao-hui, L., 2009. A study on multifactorial prediction model for the road traffic accidents. In: Ninth International Conference of Chinese Transportation Professionals (ICCTP), Harbin, China, Critical Issues in Transportation Systems Planning, Development, and Management ©2009 ASCE.
Zheng, M., Li, T., Zhu, R., Chen, J., Ma, Z., Tang, M., Cui, Z., Wang, A.Z., 2019. Traffic accident's severity prediction: a deep-learning approach-based CNN network. IEEE Acc. 7, 39897–39910.