Accident Analysis and Prevention 138 (2020) 105468

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

A comparison between Artificial Neural Network and Hybrid Intelligent Genetic Algorithm in predicting the severity of fixed object crashes among elderly drivers

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ARTICLE INFO

Keywords:
Hybrid models
Elderly drivers
Fixed object crashes
Crash severity

ABSTRACT

Run-off-road (ROR) crashes have always been a major concern as this type of crash is usually associated with a considerable number of serious injury and fatal crashes. A substantial portion of ROR fatalities occur in collisions with fixed objects at the roadside. Thus, this study seeks to investigate the severity of ROR crashes where elderly drivers, aged 65 years or more, hit a fixed object. The reason why the present study investigates this issue among older drivers is that, comparing to younger drivers, this age group of drivers have different psychological and physical features. Because of these differences, they are more likely to get injured in ROR types of crashes. This paper applies two types of Artificial Intelligence (AI) techniques, including hybrid Intelligent Genetic Algorithm and Artificial Neural Network (ANN) using the crashe information of California in 2012 obtained from Highway Safety Information System (HSIS) database. Although the results showed that the developed ANN outperformed the hybrid Intelligent Genetic Algorithm, the hybrid approach was more capable of predicting high-severity crashes. This is rooted in the way the hybrid model was trained by taking advantage of the Genetic Algorithm (GA). The results also indicated that the light condition has been the most significant parameter in evaluating the level of severity associated with fixed object crashes among elderly drivers, which is followed by the existence of the right and left shoulders. Following these three contributing factors, cause of collision, Average Annual Daily Traffic (AADT), number of involved vehicles, age, road surface condition, and gender have been identified as the most important variables in the developed ANN, respectively. This helps to identify gaps and improve public safety towards improving the overall highway safety situation of older drivers.

1. Introduction

Careful consideration and understanding the factors that result in the occurrence of high-risk types of road traffic accidents seems to be essential. This procedure allows us to propose some specific prevention measures, which can help significantly reduce the total number of serious injuries and fatalities. In this regard, prediction models can be employed to estimate the probability that a crash will fall into one of the various levels of crash severity (Amiri et al., 2018). As a result, researchers have tried to employ more efficient approaches and develop models that estimate the crash severity more accurately regarding the contributing factors.

In general, road traffic accidents may include only one or at least two road users. Crashes that include only one or at least two vehicles are known as single-vehicle crashes (SVCs) and multiple-vehicle crashes (MVCs), respectively. SVCs have always been a major concern since this type of collision is usually associated with a considerable number of serious injury and fatal crashes (Alruwaished, 2014). National Traffic Safety Administration (NHTSA) confirmed that SVCs comprise 60 % of all fatal crashes (LeRoy et al., 2008).

SVCs can be classified into two main groups of on-road (OR) crashes, and run-off-road (ROR) crashes. On the other hand, ROR crashes mostly involve a single vehicle, but it may also involve more than one vehicle such as head-on crashes (Alruwaished, 2014). ROR crashes take place when a vehicle leaves the roadway, which causes 70 % of the total fatal SVCs. Different factors can contribute in the likelihood of ROR

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https://doi.org/10.1016/j.aap.2020.105468
Received 24 September 2019; Received in revised form 6 January 2020; Accepted 7 February 2020
Available online 14 February 2020
0001-4575/

crash occurrence, including age, gender, distraction, fatigue, sleep, alcohol use, weather condition, rural roads, traveling at high speed, design of the roadway, and curved road segments (Liu and Subramanian, 2009).

Various age groups have different physiological and psychological features which can affect the type of reactions that the driver shows in dealing with the unexpected driving situations. Because of physiological factors, such as vision, reaction time, risk-taking behaviors, and decline with aging, older drivers are more likely to get involved in the ROR type of crashes (Gong and Fan, 2017; Hwang and Hong, 2018; Anstey et al., 2012; Clarke et al., 2010). Moreover, there is a greater risk of mortality among older drivers involved in this type of crash because of increased fragility, due to age-related declines in physical health (Etehad et al., 2015; Loughran et al., 2007; Christopher, 2013; Wisch et al., 2017; Johannsen and Müller, 2013).

ROR crashes include head-on crashes, crashes that occur due to lane shifts, and crashes where the vehicle leaves its designated travel lane and collides with a fixed object or overturns. On a national scale, a considerable portion of ROR fatalities occurs in collisions with fixed objects at the roadside (Holdridge et al., 2005). According to the report released by National Highway Traffic Safety Administration (NHTSA), although fixed object collisions and non-collisions comprise 19 % of all reported crashes, they contribute to 44 % of all fatal crashes (Facts, 2003), only a few number of studies have merely focused on the severity of this specific type of crash (Holdridge et al., 2005; Yamamoto and Shankar, 2004; Dissanayake and Lu, 2002).

Developing an effective approach and a more in-depth understanding of contributing factors associated with the severity of fixed object-related type of ROR crashes among older drivers can bring helpful insights into how to reduce the likelihood of fatality among this particular age group. This is especially necessary considering the growing number of elderly drivers in an aging society; as compared to other age groups, due to their physical differences, they are more likely to get killed or injuried. By developing a systematic knowledge about epidemiological patterns of road traffic injuries among elderly drivers, they can be prevented by providing valuable information for further planning. International Road Assessment Program (iRAP) can be a valuable example for such planning programs. Star Ratings and Safer Roads, two main protocols of iRAP, have been developed based on the relationships between the three major types of crashes, including intersection, head-on, and ROR crashes, and their severity and likelihood of occurrence. It should also be noted that careful attention to vulnerable road users is an important key in all such road safety programs. To address this issue, the present study investigates the severity of ROR crashes where older drivers, aged 65 years or more, hit a fixed object.

To pursue the above mentioned objective, different models can be utilized, such as statistical techniques, Artificial Intelligence (AI), data mining, and machine learning approaches. Data mining is one of the recent methods that functions as a foundation for both AI and machine learning. Besides, machine learning, at its core, is simply a way of developing AI. On the other hand, Discrete Choice and Logistic Regression models are the most well-known statistical approaches. For more than two decades, discrete choice models such as Multinomial Logit (MNL), Nested Multinomial Logit (NMNL), and Mixed Logit (ML) have drawn the most attention in the field of crash severity prediction. However, these statistical methods are created based on strong assumptions and pre-defined underlying relationships between variables. In contrast, AI approaches have been proven to be more efficient and effective in the modeling process (Abduljabbar et al., 2019). In this regard, to pursue the research objectives, this paper applies two types of AI techniques, including hybrid Intelligent Genetic Algorithm and Artificial Neural Network (ANN). Subsequently, the results of these two approaches will be compared using Coefficient Confusion Ratio (CCR) and Root Mean Square Error (RMSE) to determine which model performs better regarding the study limitation and characteristics.

Following a brief overview of previous studies, the data used in this research and study methodology are explained comprehensively. Finally, the results of these methods are compared with each other and the best method is proposed, followed by a conclusion.

2. Literature review

The main objective of this study is to investigate the severity of fixed object crashes, among older drivers. Following is a brief overview of previous studies relating to the subject of this paper.

Many studies have been carried out to compare SVCs with MVCs, where considerable differences were found between these two types of crashes (Chen and Chen, 2011; Geedipally and Lord, 2010; Martensen and Dupont, 2013; Savolainen and Mannering, 2007; Ma et al., 2016). Moreover, until now, many studies merely focused on single-vehicle types of crashes in which contributing factors associated with crash frequencies and severities were investigated (Wu et al., 2016; Behnood and Mannering, 2017; Naik et al., 2016; Osman et al., 2018). Accordingly, some studies evaluated SVCs based on their types of collision, ROR crashes and on-road (OR) crashes. Out of these two, ROR crashes have drawn the most significant attention among traffic engineers since they have always been associated with a considerable number of road accident fatalities. As a result, several studies have investigated injury severities of ROR crashes, with regard to driver factors, vehicle characteristics, and road conditions (Lee and Mannering, 2002; Dissanayake and Roy, 2014; Peng and Boyle, 2012; Eustace et al., 2014; Gong et al., 2016). Generally, the likelihood of ROR crashes occurrence is higher on rural roads compared to urban areas. Thus this type of crash comprises 80.6 % and 56.2 % of all reported crashes on rural and urban roadways, respectively (Xie et al., 2012). Moreover, Liu and Subramanian (2009) stated that the types of driving that take place in rural roads are inherently different from those in urban areas (Liu and Subramanian, 2009).

Fixed object crashes as well as crashes due to overturning are two major types of ROR crashes. Although overturning crashes have frequently been investigated (Funk et al., 2012; Krull et al., 2000; Hu and Donnell, 2011), only a few studies have been conducted with the focus on fixed object crashes. Annually, fixed object crashes contribute to a considerable part of all fatal crashes and the total number of ROR crashes. Considering the fact that this issue is more critical among older drivers, the need for an in-depth analysis of this type of ROR crash is felt more than ever.

There is clearly no single way to group individuals by age, as much depends on the characteristics they share and the number of observations included in each study. According to the research conducted by Liu and Subramanian (2009), after young drivers, aged 15–24, elderly drivers, aged 65 or more, are more likely to get involved in fatal ROR crashes (Liu and Subramanian, 2009). Because physical and cognitive abilities decline with aging and this age group needs longer perception-reaction times while driving (Gong and Fan, 2017; Hwang and Hong, 2018; Anstey et al., 2012; Clarke et al., 2010). Accordingly, Cicchino and McCartt (2015) stated that frequent surveillance errors committed by elderly drivers are mainly because of their looking but not seeing. This can be the result of a decrease in information processing speeds and declining abilities to divide visual attention (Cicchino and McCartt, 2015). More importantly, because of the greater amount of physical fragility due to aging, elderly drivers are more likely to be killed or injured. Previous studies have confirmed that older traffic victims show more skeletal injuries associated with internal injuries than younger victims in whom internal injuries usually present without rib fractures (Etehad et al., 2015; Loughran et al., 2007; Christopher, 2013; Wisch et al., 2017; Johannsen and Müller, 2013). Similarly, Loughran et al. (2007) concluded that the likelihood of fatality among passengers riding in a car driven by a middle-aged driver is 6.73 times less than those riding in a car that is driven by an older individual (Loughran et al., 2007).

To investigate the severity of fixed object crashes, different modeling techniques can be used regarding their limitations and advantages, among which AI, Data mining, and machine learning techniques are the most frequently used techniques. Since this study only used a specific type of AI technique, the rest of the literature review only addresses a brief overview of previous studies that used AI in predicting crash severity.

AI techniques themselves can be classified into several subsets such as Artificial Neural Network (ANN), Fuzzy Logic (FL), and Evolutionary Computation (EC) and so forth. EC usually involves metaheuristic optimization algorithms such as Evolutionary Programming (EP), Learning Classifier Systems (LCS), Evolution Strategy (ES), Genetic Algorithms (GA), and Swarm Intelligence (SI). SI itself includes Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) (Bittermann, 2010). To date, different types of AI techniques have been employed in modeling traffic safety problem. ANN is the most well known AI approach which has frequently been used in predicting traffic crash severity based on a set of contributing factors (Behbahani et al., 2018).

In some cases, researchers combine two different AI techniques to benefit both simultaneously to overcome the shortcomings of each technique, which consequently leads to a more accurate result. In this regard, both PSO and GA can be used to optimize other AI techniques, such as ANN, by minimizing the related error. Xiaodong et al. (2005) compared the performance of these two techniques in the optimization process. Accordingly, compared with GA, the PSO showed better performance in real function optimizations; however, in the case of optimizations with discrete encoding, the results were the opposite (Xiaodong et al., 2005).

Gu et al. (2018) compared Support Vector Machine (SVM) optimized with hybrid PSO with other similar technologies in predicting road traffic fatalities. According to the results, particle swarm with mutation optimization-support vector machine was identified as the most accurate technique in pursuing the study objective (Gu et al., 2018). Similarly, Dizaji and Gharehchopogh (2016) proposed a hybrid approach for classification of road crash severities using Differential Evolution (DE) algorithm and ANN. The authors used the ANN algorithm to classify information based on features of classification determined by DE algorithm (Dizaji and Gharehchopogh, 2016). Chong et al. (2005) compared the performance of neural networks trained using hybrid learning approaches, support vector machines, decision trees, and a hybrid decision trees-neural network to analyze road accident severities, where the last one showed the best performance (Chong et al., 2005). Chen et al. (2016) applied a multinomial logit model-Bayesian network hybrid approach to analyze the severity of rear-end crashes (Chen et al., 2015). Similar to this study, Chen et al. (2016) utilized a decision table/Naïve Bayes (DTNB) hybrid classifier to pursue the same objective. The results showed that both hybrid approaches performed satisfactorily well (Chen et al., 2016).

In spite of the steady improvement of methodological innovation in the field of crash analysis, there is no definitive conclusion about which approach performs better. Thus, the present study aims to apply two types of AI techniques, hybrid Intelligent Genetic Algorithm and ANN, for crash severity prediction and subsequently compare them to determine which model performs better.

3. Data description

The crash data was obtained from Highway Safety Information System (HSIS) database comprising 145,143 crashes occurred in the state of California, in 2012. To investigate the severities of fixed object crashes, among older drivers, two filters were applied for this database. First, only those crashes where the vehicle was driven by older drivers, aged 65 years or more, were kept in the database; while other accidents involving other age groups were eliminated. Second, out of all road accident scenarios, those where drivers hit their cars to fixed objects remained in the modeling process. By applying these two filters, a total of 4070 crahses were obtained for developing the models.

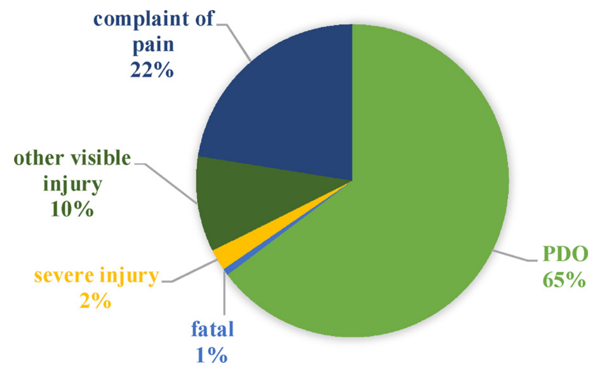

Fig. 1. Severity of road accidents.

The outcome variable of the model is crash severity that is categorized into five levels: Property Damage Only (PDO) (1), Complaint of Pain (2), Visible Injury (3), Severe Injury (4), Fatal (5). Most crashes are PDO followed by complaint of pain and visible injury (Fig. 1). Fatal and severe injury constitute about 3 percent of crashes; however, because of the imposed direct and indirect costs, their importance cannot be understated.

A total of 37 qualitative and quantitative explanatory (independent) variables were used in the present study, from which 14 variables have been found to be significant in the modelling process. The procedure of variables selection can be done in various ways. The presented study used simultaneous method to carry out the modeling process, where variables were imported simultaneously and subsequently, the effect of each parameter in the equation is studied. Accordingly, variables are examined in different combinations and the best combination for the proposed model is chosen based on the outcomes. These 14 variables include cause of collision, time, road conditions, road light conditions, the number of vehicles involved in collision, the number of road lines, type of median, type of access control, Annual Average Daily Traffic (AADT), left shoulder, right shoulder, type of surface, driver age, and gender. As shown in Table 1, the mentioned variables are divided into different categories (codes) with their descriptions. These are among the influential human, environmental, road and vehicular factors in crash occurrence.

Different approaches can be employed in order to group drivers by age, as much depends on the characteristics they share as individuals and the number of observations included in each study. However, in this study, to investigate the factor of age among elderly drivers, these drivers have been categorized into two subgroups: drivers aged between 65 and 75 and drivers older than 75.

4. Methodology

In predicting road accident severities, different types of statistical models, especially regression methods, have been broadly applied to determine the contributing factors. Among all forms of regression models, the choice models and logistic regression models have been employed more frequently. Nonetheless, the majority of regression models have been developed based on some predefined assumptions and relationships, which can significantly affect the accuracy of the model. This is why the presented study used two types of AI techniques including ANN and hybrid Intelligent Genetic Algorithm.

Although ANN has been frequently used in predicting crash severity, hybrid Intelligent Genetic Algorithm can be considered as an emerging modeling technique in the field of traffic safety. Hybrid Intelligent Genetic Algorithm is created by combining neural network and genetic algorithm. Thus, researchers combine the advantages of the aforementioned methods to achieve a more capable modeling technique. As a result, they configure a single framework, which can overcome the

Table 1
Qualitative and quantitative independent variables.

Variable	Abbreviation	Code/Unit	Description	Percentage of total crahes
Cause of collision	Cause	1	Driving Under the Influence (DUI)	7.9
		2	Following too closely	0.1
		3	Failure to yield	2.4
		4	Improper turn	46.8
		5	Speeding	46.9
		6	Falling asleep	19.4
		7	Other volitions (Hazardous)	25.6
Time	Time	1	00:00-06:00	9.6
		2	10:00-16:00	40.7
		3	20:00-24:00	11.5
		4	06:00-10:00 (Rush Hour)	18.0
		5	16:00-20:00 (Rush Hour)	19.9
Road surface condition	RDSURF	0	Dry	82.1
		1	Wet	15.1
		2	Snowy or icy	2.8
Light condition	LIGHT	0	Daylight	69.7
		1	Dusk – Dawn	3.4
		2	Dark - Street Lights	10.7
		3	Dark - Street Lights Not Functioning	0.3
		4	Dark - No Street Lights	15.8
Number of vehicles	Numvehs	1	1 vehicle involved in a crash	87.7
		2	2 vehicles involved in a crash	10.7
		3-15	3 to 15 vehicles involved in a crash	1.6
Number of lanes	NO_LANES	1	2 -3	28.3
		2	4-5	28.5
		3	6-7	18.3
		4	> 8	24.9
Median type	MED_TYPE	1	Undivided	24.8
		10	Divided, Unpaved Median	19.7
		11	Divided, Paved Median	35.1
		12	Divided, Separate Structure	13.3
		13	Divided, Other	7.1
Facility access	ACCESS	1	Conventional - No Access Control	29.8
		2	Expressway - Partial Access Control	9.7
		3	Freeway - Full Access Control	60.5
AADT	AADT	1	2000 >	4.4
		2	2000-4999	7.0
		3	5000-9999	7.8
		4	10000-19999	11.5
		5	20000-34999	10.0
		6	35000-54999	9.9
		7	55000-84999	11.5
		8	85000-124999	10.1
		9	125000-174999	11.6
		10	175000-249999	12.2
		11	> 250000	4.2
Left shoulder	LSHLD	1	No	33.5
		2	Yes	66.5
Surface type	SURF_TYP	1	Portland Concrete	54.0
		2	Asphalt Concrete	46.0
Right shoulder	RSHLD	1	No	22.6
		2	Yes	77.4
Driver age	DRV_AGE	1	65-74	62.5
		2	> 75	37.5
Gender	DRV_SEX	1	Male	68.9
		2	Female	31.1

shortcomings of each technique, which consequently leads to a more accurate result.

Accordingly, the present study goes one step further by considering the chance of improving ANN performance using an optimization approach. To accomplish this, the developed ANN is combined with an EC technique (GA) to evaluate them in one framework. Comparing the results obtained from ANN and hybrid Intelligent Genetic Algorithm, we can examine the efficiency of using GA in optimizing ANN technique regarding its weights and bias. Following is a brief overview of the AI models used in this study.

4.1. Artificial neural network (ANN)

ANNs are computational models that perform similar to the human nervous system. Several kinds of ANNs can be used in analyzing crash severity. Among all ANN techniques, Multilayer perceptron (MLP) is the most widely known and applied algorithm, which can be used for forecasting by adding memory to its neurons. This is why the present paper utilized MLP, as the representative of ANN models. To train the data, MLP can describe general feedforward network with back-propagation algorithm, where the ultimate objective is to find the global minimum in the loss function. In this way, we can reach the most accurate combiniation of hyperparameters in pursuing the study objectives (Principe et al., 2000; Nelles, 2013).

MLP has an architecture with specific properties:

- No connections within a layer,
- Fully connected between layers,

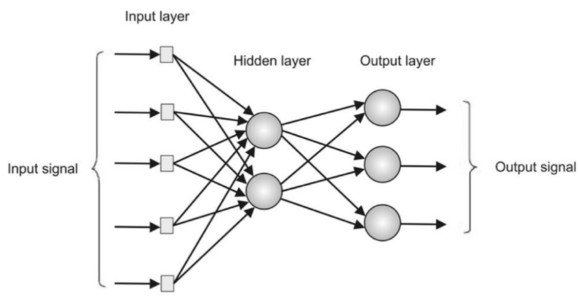

Fig. 2. A simple structure of MLP.

- No direct connections between input and output layers,
- Number of output units does not require an equal number of input units,
- Number of hidden units per layer can be more or less than input or output units,
- Often there are more than three layers.
- Furthermore, there is forward activity and back-propagation of error in MLP, as shown in Fig. 2.

As mentioned, in an MLP, there are no direct connections between the input and output layers. These two layers are connected using a function known as the transfer function (Fig. 3).

Mostly, this function is not linear. However, in some cases transfer function is close enough to linear. The most well-known transfer functions are shown in the following:

$$T\colon tansig(n) = \frac{2}{(1 + \exp^{(-2\times n)}) - 1} \tag{1}$$

$$L\colon logsig(n) = \frac{1}{(1 + \exp^{(-n)})} \tag{2}$$

$$P\colon purelin(n) = n \tag{3}$$

4.2. Hybrid (intelligent) genetic algorithm

Recently, several studies have tried to combine the merits of GA and ANN in the context of hybrid methods. In most cases, the focus has been on employing GAs in order to improve the learning of neural networks. In this regard, GA can be applied to ANN for two specific purposes. Firstly, GA can help ANNs to set their hyperparameters, variables that determine the network structure and variables before the training stage. The number of hidden layers, number of units in the hidden layer, and regularization parameters are some examples of hyperparameters in an ANN. Since the aim of this study was to evaluate the efficiency of GA in improving the developed ANN performance, the comparison is made between an ANN model with a specific topology and hyperparameters to another ANN developed by the same structure, but optimized with GA. As a result, hyperparameters will be the same in both developed models (Montana, 1995).

In addition to setting hyperparameters before the training stage, GA can help ANNs to optimize their weights and bias. Generally, ANNs are

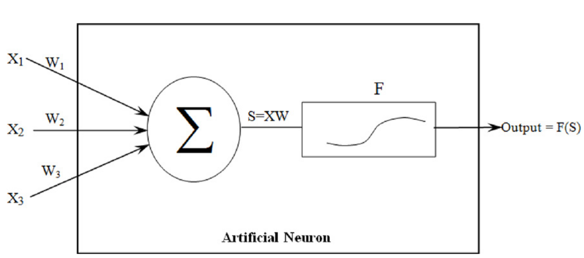

Fig. 3. Artificial neuron with activation function.

trained using analytical gradient-based algorithms with error back-propagation. During training, the network topology, the weights, the biases, and the transfer functions are selected; so that the topology and transfer functions are held fixed, while the space of possible networks is spanned by all possible values of the weights and biases. However, the loss function of a neural net is not convex or bowl-shaped. Indeed, loss function of neural net is much more complex, with many hills and valleys and curves and other irregularities. As a result, there are many local minima, where the loss is the lowest in its own immediate neighborhood, but not necessarily the absolute minimum (global minimum). This means that if we run gradient descent, we might accidentally get stuck in a local minimum. This issue usually gets worse when the complexity and the number of exemplars of the network topology increase. In this case, the complexity of the search space also rises insofar as the error function obtains more and more local minima spread out over a larger portion of the space (Montana, 1995).

In contrast, GAs are remarkably good at efficiently searching complex and large spaces to determine nearly global optima. As the complexity of the search space rises, GAs offer an increasingly attractive substitute for gradient-based techniques such as backpropagation. Even better, GAs are an excellent complement to gradient-based techniques such as backpropagation for complex searches. Furthermore, GAs can optimize not just weights and biases but any combination of weights, biases, topology, and transfer functions. As a result, combining GA into neural networks can be a beneficial approach in tackling the problem of local optima.

4.3. Performance evaluation

To compare the predictive performance of the proposed models, three criteria of Root Mean Square Error (RMSE), Correct Classification Rate (CCR), and Misclassification Rate (MCR) were employed. The RMSE shows the sample standard deviation of the differences between predicted and observed values, while CCR indicates the ratio of the number of correctly classified. The misclassification rate/error refers to the number of individuals that we know belong to a category that is classified by the method in a different category. In comparing different models, lower RMSE means that the developed model performs better, while CCR follows the opposite pattern. These indicators are shown in the following formulas:

$$CCR = \frac{Number\ of\ correctly\ classified\ crashes}{Total\ number\ of\ observed\ crashes} \tag{4}$$

$$MCR = 1 - CCR \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{6}$$

Where n is the amount of data for the testing set and y_i and $\hat{y}_i$ are predicted and observed number of crashes, respectively and $\bar{y}$ is the mean of the observed data. CCR can be calculated through Confusion Matrix which is often used to describe the performance of a classification model on a set of data for which the true values are known. In addition, the performance of classification algorithms is sometimes examined by evaluating the accuracy of the classification. Accuracy is a fraction that represents the overall success of the classification (Šimundić, 2008).

To evaluate the performance of models with diverse structucres, we usually increase the complexity of the network to determine which one of them reaches the highest accuracy. More complexity, to some extent, can produce better generalization performance; as they learn different representations in each of their layers. Nonetheless, complicated networks can easily over-fit the training data, creating undesirable generalization capacity and testing performance. Over-fitting happens when a network model with high capacity fits the noise in the data instead of the underlying relationship (Fig. 4).

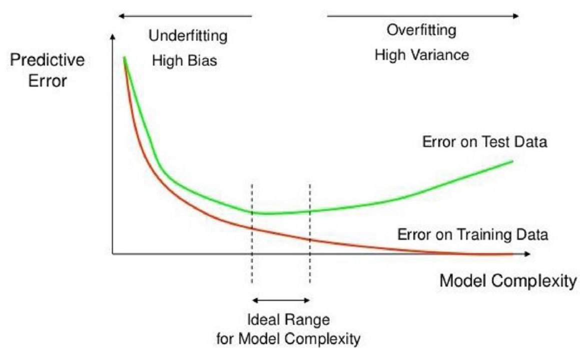

Fig. 4. The over-fitting problem.

When the model is too simple, both the training and test estimates are large because of underfitting. Such a model has high bias but low variance. As complexity increases, the model becomes more accurate and both the training and test estimates decrease. Nonetheless, when the model becomes too complex, specific parts from the training set are captured, reducing the corresponding training error. At the same time, the test estimates become worse as the structure learned from the training set is actually too specific and does not generalize. Thus, the model is overfitting and it has low bias but high variance. As a result, the best structure is the one making the appropriate tradeoff and producing a model that is neither too simple nor too complex. In other words, the most ideal range for model complexity is where the training and testing error begin to diverge from each other.

5. Results and discussion

The present paper applies hybrid Intelligent Genetic Algorithm and ANN in order to investigate the severity of fixed object crashes among older drivers. Subsequently, the results of these two approaches will be compared to determine which model performs better regarding the study limitation and characteristics. Finally, the importance of contributing variables is evaluated using sensitivity analysis.

5.1. Developing ANN

At first, in developing the ANN, the available data (4070 crashes) was divided into 30 % (1221) and 70 % (2849) for testing and learning dataset respectively. Afterward, the inputs were normalized between -1 and +1, and the outputs were classified into five subgroups. To reach the most accurate model structure, different types of neural network topologies and hyperparameters were examined, among which the best one has been identified. Table 2 shows twenty-four different network structures, the accuracy of their prediction and the needed run-time for each one of them. For both stages of training and testing, three comparison criteria has been used in order to compare these different neural network structures, including RMSE, CCR, and MCR.

In Table 2, these different structures have been sorted based on the needed training time. The needed training time for each network structure relates to the complexity of that structure. Indeed, the more complex the structure, the more time it takes to train the model. As mentioned, more complexity, to some extent, can create better generalization performance and less training error. However, complicated networks can easily over-fit the training data, producing poor generalization capacity and testing performance, which is known as overfitting problem.

However, this question may arise as to how we can reach the best network structure which is associated with the least amount of bias and variance. The most ideal range for model complexity is where the training and testing error graphs begin to diverge from each other. For this purpose, this study used MCR as the error criterion. In this regard, Fig. 5 represents the training and testing error graphs in which the divergence has begun from the eleventh structure. Based on this result, it can be concluded that this structure leads to the most accurate results. This model consists of 8 neurons in its hidden layer with Tansig performance function and five neurons in its output layer with Pureline performance function.

As can be seen in Table 2, complexity can not only create overfitting problems but it can also increase the model run-time significantly. According to the result, for training and testing the ANN, with the most accurate model structure (the eleventh one), almost 91.9 and 6.4 ms is needed for each iteration. Comparing this network topology with the others, it can be concluded that more complex structures did not raise the model accuracy even with more running time. These experiments were performed on a personal PC with 1.60 GHz Intel(R) Core(TM) i7 CPU and 8 GB RAM using Windows 10 × 64 operating system.

Fig. 6 shows the most accurate neural network structure. According to the study objective, the second model, the hybrid Intelligent Genetic Algorithm, is also created and subsequently compared with the previously developed ANN to determine which one of them shows a better performance.

Fig. 7 demonstrates the amount of error associated with the developed ANN based on the number of iterations within the training stage. In the process of the model development, since the amount of error remained almost constant after about 20 iterations, the number of iterations was set to 100.

5.2. Developing hybrid intelligent genetic algorithm

In the presented paper, since the aim was to evaluate the efficiency of GA in improving the developed ANN performance, the comparison is made between an ANN model with a specific topology and hyperparameters to another ANN developed by the same structure (Table 3) but optimized with GA. As a result, hyperparameters will be the same in both models. In other words, the topology and transfer functions are held fixed, while the space of possible networks is spanned by all possible values of the weights and biases by taking the advantage of GA.

In this regard, the same ANN topology and hyperparameters are chosen in developing the hybrid model, where the ANN consists of 8 hidden layers with Tansig performance function and 5 output layers with Pureline performance function. Once again, the data is divided into 30 % (1221) and 70 % (2849) for testing and learning dataset, respectively.

In optimizing the ANN using GA, a population of potential solutions is evolved toward better solutions, which begins from a population of randomly generated weights and biases. This can be considered as an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every combination of weights and bias in the population is investigated; the fitness is typically the value of the fitness function in the optimization problem being solved. More fit values are chosen from the existing population, and each value's genome is changed to create a new generation. Subsequently, the new generation of solutions is utilized in the next iteration of the algorithm. Generally, the algorithm ends when either a satisfactory fitness level has been achieved or a maximum number of generations has been produced. Fig. 8 shows the mean square error of the GA model in terms of the number of generations. As shown, after ten iterations, the amount of error converges to the absolute error; therefore, in the modeling process, the number of iterations was set to ten.

Once the genetic representation and the fitness function are defined, a GA prepares a population of solutions and subsequently improves it by repetitive application of the mutation, crossover, inversion, and selection operators. In the developed GA, the data was divided to 15 %, 50 %, and 35 % for Reproduction, Crossover with a coefficient equal to 0.6, and Mutation, respectively.

Table 2
Different neural networks structures.

Trip	Activation Function	Architecture	RMSEtr	RMSEts	CCRtr	CCRts	MCRtr	MCRts	Training Time (miliseconds per iteration)	Testing Time (miliseconds per iteration)
1	T+P	2HL1	0.3277	0.3330	0.6086	0.6143	0.3914	0.3857	24.362	3.286
2	T+P	4HL1	0.3231	0.3345	0.6188	0.6233	0.3812	0.3767	37.469	2.509
3	T+P	6HL1	0.3215	0.3375	0.6206	0.5987	0.3794	0.4013	61.338	3.277
4	T+L	6HL1	0.3209	0.3393	0.6286	0.6011	0.3714	0.3989	63.331	3.939
5	T+T	6HL1	0.3203	0.3375	0.6311	0.6028	0.3689	0.3972	63.854	4.338
6	L+P	6HL1	0.3209	0.3379	0.6283	0.6052	0.3717	0.3948	65.511	5.707
7	P+L	8HL1	0.3300	0.3326	0.6153	0.6200	0.3847	0.3800	86.793	1.573
8	T+T	8HL1	0.3179	0.3350	0.6378	0.6077	0.3622	0.3923	89.829	3.485
9	T+L	8HL1	0.3165	0.3396	0.6434	0.5880	0.3566	0.4120	89.973	4.189
10	L+T	8HL1	0.3185	0.3389	0.6350	0.5962	0.3650	0.4038	90.738	5.021
11	T+P	8HL1	0.3193	0.3433	0.6346	0.6167	0.3654	0.3833	91.911	6.364
12	L+P	8HL1	0.3172	0.3406	0.6325	0.6061	0.3675	0.3939	93.144	6.066
13	L+P	10HL1	0.3153	0.3419	0.6406	0.6069	0.3594	0.3931	128.379	6.838
14	T+P	10HL1	0.3187	0.3415	0.6304	0.6003	0.3696	0.3997	128.584	6.21
15	T+T	10HL1	0.3152	0.3429	0.6448	0.5880	0.3552	0.4120	130.352	6.407
16	T+L	10HL1	0.3143	0.3455	0.6497	0.5839	0.3503	0.4161	132.954	8.288
17	T+P	12HL1	0.3097	0.3463	0.6553	0.5897	0.3447	0.4103	168.789	6.394
18	T+L	12HL1	0.3098	0.3488	0.6613	0.5733	0.3387	0.4267	170.15	6.362
19	T+T+P	11HL1,6HL2	0.3045	0.3568	0.6701	0.5676	0.3299	0.4324	248.376	7.023
20	T+L+P	12HL1,8HL2	0.3022	0.3588	0.6767	0.5651	0.3233	0.4349	250.354	4.382
21	T+L+P	11HL1,6HL2	0.3046	0.3567	0.6746	0.5930	0.3254	0.4070	262.034	5.988
22	T+T+P	12HL1,8HL2	0.3015	0.3542	0.6722	0.5790	0.3278	0.4210	266.427	5.887
23	T+T+T	11HL1,6HL2	0.3038	0.3554	0.6595	0.5758	0.3405	0.4242	269.587	4.443
24	T+T+T	12HL1,8HL2	0.3009	0.3632	0.6869	0.5782	0.3131	0.4218	271.089	5.078

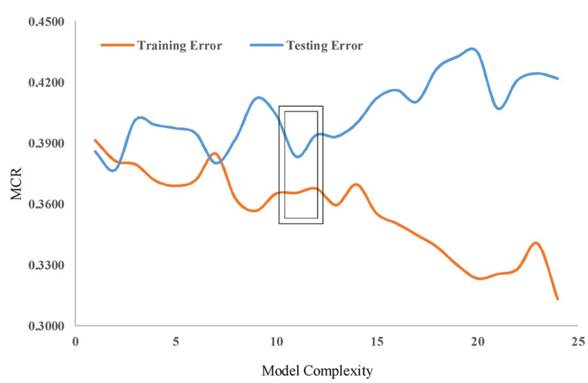

Fig. 5. Error vs Complexity.

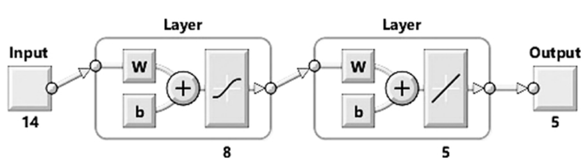

Fig. 6. The developed ANN structure.

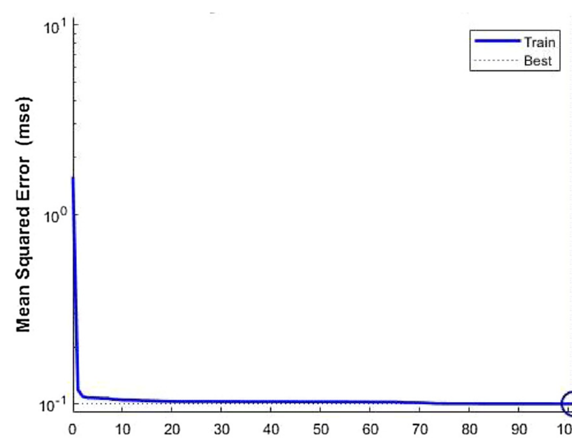

Fig. 7. The associated amount of error based on the number of iterations.

5.3. Performance comparison

Tables 1 and 2 show the performance of ANN and GA, respectively. In the stage of testing, by comparing the results obtained from these models, it can be concluded that ANN, with RMSE equal to 0.3433 and CCR equal to 61.6708, showed better performance compared to the developed hybrid Intelligent Genetic Algorithm (with RMSE = 0.3868 and CCR = 52.8256). A similar pattern can be found in the training stage. Generally, in comparing different models, lower RMSE means that the developed model performs more accurately, while CCR follows the opposite pattern.

To compare these two models in more detail, it seems essential to realize how they performed in terms of the level of crash severity. This makes it possible to understand which model can predict a specific level of crash severity more accurately. Table 4 shows and compares the performance of the developed model in prediction of different level of severities in the stage of testing. According to the results, the developed ANN was more accurate in predicting low severity crashes, this model was not able to detect more severe collisions. Although the hybrid Intelligence Genetic Algorithm has not been considered as the best model, in contrast to the developed ANN, it was able to detect a portion of high-severity crashes. In other words, in the hybrid approach, the ANN model that benefits from GA in its training stage, was more capable of predicting crashes associated with higher severities. In terms of sample size, the number of high-severity crashes is generally lower than the frequency of crashes associated with lower severities.

Moreover, confusion matrix, as one of the most capable techniques in analyzing classification problems, can be used in measuring Specificity, Precision, Recall, Accuracy, and AUC-ROC Curve. Accordingly, for both stages of training and testing, the confusion matrixes obtained from ANN and hybrid Intelligence Genetic Algorithm are shown in Tables 5 and 6, respectively. In this confusion matrix, each row shows the severities in an actual class while each column represents the severities in a predicted class. Analyzing them can provide us with a more in-depth insight into how these models performed in different levels of crash severity, based on their structure.

Table 3
The structure of the developed hybrid model.

Activation Function	Architecture	RMSEtr	RMSEts	CCRtr	CCRts	Training Time (seconds per generation)
121.38	52.8256	52.2991	0.3868	0.3873	8HL1	T + P

5.4. Analysis of parameters

As mentioned, the main objective of the presented paper was to investigate the severity of fixed object crashes among older drivers. To address this objective, it is essential to understand what the contributing factors are, and how they contribute to the occurrence of a fixed object crash among older drivers with a specific severity. By acquiring a systematic awareness of epidemiological patterns of road traffic injuries among older people who hit a fixed object, we can prevent them and provide useful information for further planning. Fig. 9 illustrates the importance of contributing factors using Simulink in MATLAB. As shown, the light condition has been the most significant parameter in evaluating the level of severity associated with fixed object crashes among elderly drivers, which is followed by right and left shoulders existence. Following these three contributing factors, cause of collision, AADT, number of involved vehicles, age, road surface condition, and gender have been identified as the most critical variables in the developed ANN, respectively. In the following, some of these important contributing factors are discussed in more detail.

It should also be noted that the exposure of fixed object crashes is higher in roads with lower functional class. For instance, lighting is not common on lower functional class roads; these roads are typically the lowest level of design. Thus, the light condition variable could very well be acting as a surrogate for the facilities design. Furthermore, there are many more fixed objects and narrower clear zones on these routes when compared to the interstate. As a result, if the main objective of the study was to predict the likelihood of crash occurrence, not its severity, functional class would be a key variable in the modeling process.

5.4.1. Light condition

There is a wide range of evidence that suggests RORs and particularly fixed object crashes are more likely to occur after dark than during daylight, and more likely to lead to a severe or fatal injury if they occur after-dark (Alruwaished, 2014). In the developed ANN, light condition has been identified as the most significant contributing variable, which may be rooted in the defective eyesight of elderly drivers. In other words, the lower level of lighting can increase the severity of fixed object crashes among older drivers, where the vehicle leaves the roadway and hits a fixed object alongside the road. Thus, it can be concluded that lighting-related crashes are more likely to be associated with severe injuries or fatalities, where older drivers do not notice the object alongside the road because of their visual disabilities and hit it without decreasing their velocity.

5.4.2. Shoulders existence

In the developed ANN, in terms of the importance of contributing factors, light condition is followed by two variables of right shoulder and left shoulder existence, respectively. Although human factors have always been the main reason for road accident occurrence, roads can be designed in such a way to compensate for the driver's mistakes. This

Table 4
The performance comparison between the developed models.

Crash Severity	No. of test data	Percentage	Accuracy of ANN	Accuracy of the hybrid model
PDO	762	62.4	94.6	78.6
Complaint of pain	213	17.4	7.0	20.2
Visible injury	183	15.0	9.3	0
Sever injury	42	3.4	0	4.7
Fatal	21	1.8	0	4.8
Sum	1221	100		

can be considered as the road forgiveness, which can decrease the severity of an evitable collision. Considering the situation where the vehicle has left the roadway and a crash occurrence is inevitable, the severity of this collision can heavily depend on the road and vehicle characteristics. This is where the importance of right and left shoulders comes into the picture. Since the reaction time among elderly drivers is more than other age groups, a wide shoulder can provide them with additional time to react properly in dealing with unexpected situations.

5.4.3. Cause of collision

Following these three parameters, the cause of collision was considered as the fourth most significant variable. As shown in Table 1, improper turn, speeding, and falling asleep comprise a great portion of causes that led to crash occurrence. Considering physiological and psychological differences between elderly drivers and other age groups and by connecting these differences to the three mentioned causes of collision, an epidemiological pattern can be drawn by which we can prevent them and provide useful information for further planning.

5.4.4. AADT

According to the previous studies, the AADT factor considerably affects both crash frequency and severity, but in different ways. Dong et al. (2017) concluded that the frequency of truck-related crashes increases with increasing AADT, whereas the severity of the truck-related crashes decreases with increasing AADT. Their results showed that the likelihood of fatality is estimated to drop when the AADT is more than 50,000 vehicles per day (vpd) on the road at the time of the crash. Another research conducted by Chang and Xiang (2003) confirmed that accidents that occur during more congested traffic conditions tend to be at a less severe level; as such traffic conditions increase driver awareness and/or encourage more cautious (e.g., slower) driving. In this study, following the cause of collision, AADT has been identified as the fifth most important variable in predicting accident severity of fixed object crashes.

5.4.5. Number of involved vehicles

In some cases, the actions of another driver can cause a fixed-object

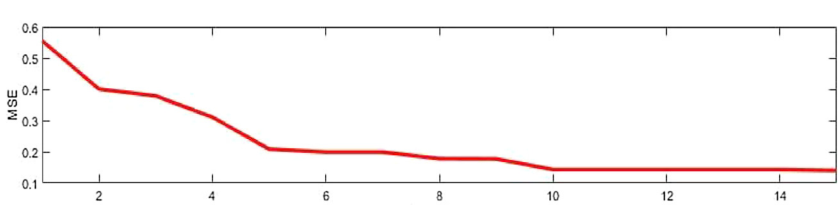

Fig. 8. The amount of error in terms of the number of generations.

Table 5
Confusion Matrix obtained from the developed ANN.

		Predicted Classes									
		Testing stage					Training stage				
		PDO	Complaint of pain	Visible injury	Sever injury	Fatal	PDO	Complaint of pain	Visible injury	Sever injury	Fatal
Actual Classes	PDO	721	21	20	0	0	1717	14	21	0	0
	Complaint of pain	191	15	7	0	0	428	47	10	0	0
	Visible injury	163	3	17	0	0	374	22	44	0	0
	Sever injury	39	0	3	0	0	107	6	10	0	0
	Fatal	21	0	0	0	0	46	1	2	0	0

crash, even if the negligent driver's vehicle does not collide with one crashing into the object. For example, a driver who is speeding and tailgating another vehicle could cause that driver to speed up, lose control of his car, and crash into a nearby fixed object.

5.4.6. Age

According to the results, the parameter of age is considered as the seventh most important variable, which has been categorized into 2 subgroups of 65–75 and more than 75. The results showed that the second group of drivers are more likely to get injured in fixed object crashes. This issue is the result of physiological and psychological differences, such as vision, reaction time and risk-taking behaviors, between these two age groups. However, we should not disregard the importance of this fact that there is a greater risk of mortality among the second age group of elderly drivers involved in this type of crash because of increased fragility, due to age-related declines in physical health.

5.4.7. Gender

Gender is another contributing factor in the severity level of fixed object crashes among older drivers; however, this association was not considered highly significant. It means that the driver's gender does not significantly contribute to the severities caused by ROR crashes where the driver hits a fixed object.

6. Conclusion

The present paper compared two approaches of hybrid Intelligent Genetic Algorithm and ANN in order to investigate the severity of fixed object crashes among elderly drivers. The outcome variable of the model is crash severity that was categorized into five levels: PDO (1), Complaint of Pain (2), Visible Injury (3), Severe Injury (4), Fatal (5). Since one of the main objectives was to evaluate the efficiency of GA in improving the developed ANN performance, the comparison is made between an ANN model with a specific structure and hyperparameters to another ANN developed by the same structure, but optimized with GA. As a result, the same ANN structure is chosen in developing the hybrid model, where the ANN consists of 8 hidden layers with Tansig performance function and 5 output layers with Pureline performance function.

Although in the hybrid Intelligence Genetic Algorithm, GA was supposed to improve the learning of the developed ANN, the results showed that ANN performed better compared to the mentioned approach. To compare these two models in more detail, it seems essential to consider this fact that ANN was more accurate in predicting low-severity crashes, while it was not able to detect more severe crashes. In contrast to the developed ANN, although the hybrid model has not been considered as the best model, it was able to detect a portion of high-severity crashes. This is rooted in the way the hybrid model was trained by taking advantage of GA.

The results also showed that light condition has been the most significant parameter in evaluating the level of severity associated with fixed object crashes among elderly drivers, which is followed by right and left shoulders. Following these three contributing factors, Cause of collision, AADT, Number of vehicles, age, road surface condition, and gender have been identified as the most important variables in the developed ANN, respectively. Identifying contributing factors and more in-depth understanding of their impact on the occurrence of fixed object crashes among elderly drivers will help to identify gaps, and improve public safety towards improving the overall highway safety situation of older drivers.

CRediT authorship contribution statement

Amir Mohammadian Amiri: Conceptualization, Data curation, Methodology, Writing - original draft, Validation, Visualization. **Amirhossein Sadri:** Methodology, Software, Resources, Formal analysis, Data curation. **Navid Nadimi:** Investigation, Writing - review & editing, Supervision, Project administration. **Moe Shams:** Software, Writing - review & editing, Validation.

Declaration of competing inserest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 6
Confusion Matrix obtained from the developed hybrid approach.

		Predicted Classes									
		Testing stage					Training stage				
		PDO	Complaint of pain	Visible injury	Sever injury	Fatal	PDO	Complaint of pain	Visible injury	Sever injury	Fatal
Actual Classes	PDO	599	103	6	44	10	1377	228	19	115	13
	Complaint of pain	151	43	5	13	1	338	99	5	40	3
	Visible injury	139	35	0	8	1	310	90	8	29	3
	Sever injury	35	4	1	2	0	83	30	2	6	2
	Fatal	14	4	0	1	1	39	5	0	5	0

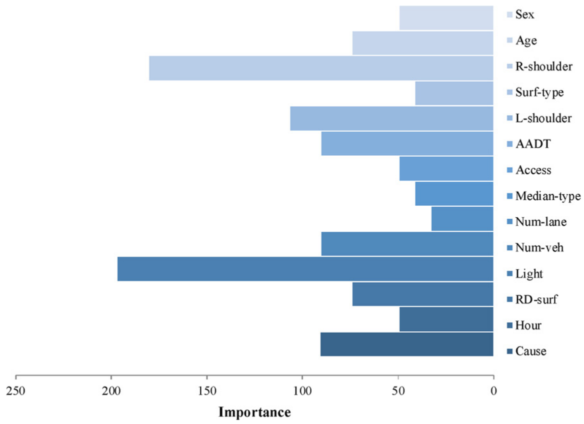

Fig. 9. The importance of the contributing factors.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2020.105468.

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