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Offering a machine learning based algorithm, with the purpose of emergency brake during simulated driving based on EEG signal

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Abstract Providing safe driving conditions has a great impact on reducing the amount of road accidents and deaths which are caused by them. The necessity of intelligent brake system for increasing the safety during driving has been taken into consideration in today's cars. The automatic emergency braking system is responsible for informing the driver of impending accidents and using the ultimate potential of the vehicle's braking before a collision occurs. In this paper, the purpose is to predict the brake based on brain EEG signals. For this purpose, the standard bnci database which is defined in this field is used. The aim of the proposed method of this article, is to predict emergency brake during simulated driving, using after error propagation neural network algorithm. The innovative aspect of this paper is the combined use of the dimension reduction algorithm, after-error propagation neural network, and training by the means of K cross validation algorithm for reducing neural network learning error. The proposed method is trained with dataset feature vectors so that after feature vector entry, test recognizes that if emergency brake is necessary or not. Results obtained from proposed method show that the accuracy of this method is more than 90 percent, which has a better performance in comparison with other methods.

Keyword: After Error Propagation Neural Network, EEG Signal, Emergency Brake.

1 Introduction

In recent years, issue of car safety has become particularly important and a lot of research has been recently carried out on it. Intelligent driver monitoring systems are among the issues that have been considered in car safety, so that these systems try to help and warn the driver by intelligently detecting accident-causing conditions. By using such intelligent systems, traffic accidents can be significantly reduced [1].
The most important equipment that has been considered for smart vehicles so far includes emergency brake assist systems, front crash warning, exiting from road lines warning, detecting driver blind spots, smart headlights, and detecting drowsiness that among these

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items, the driver drowsiness detection system is extremely important in preventing fatal road accident [2].

The detection of drowsiness is not only used in driving, but it is also extremely important in the jobs and areas that are very sensitive and need full awareness that flight related jobs and pilotage, care and monitoring systems, military systems, and medical research and studies are examples of this.

For this reason, extensive research has been conducted on this topic for about 50 years.

In 1970s, aviation industry experts succeeded in inventing a powerful camera with the ability to film, computer processing of eye image, and detect the amount of gazing that due to its very complex structure and high costs, it could not be used except for pilots and users of extremely sensitive military systems. But now in the automotive industry, large companies such as Volvo, Mercedes-Benz, Mitsubishi and Toyota have started designing systems to detect driver drowsiness [3].

The automatic emergency braking system is responsible for informing the driver of impending accidents and using the ultimate potential of the vehicle's braking before a collision occurs. These systems are very different from each other; but in general, it can be said that all of these systems pursue three general purposes.

The first purpose, includes braking performance at low velocity, which is specially designed for the city and operates with the help of low-range radars. The second purpose is to brake at high velocities in which high-range radars are active and prepare the car for braking according to the road conditions. The third purpose in the automatic braking system requires more powerful technologies which include pedestrian observation and operate with images received from car cameras and radars [4].

The process of falling asleep behind the wheel of a car can be considered as a gradual decrease in driver awareness. The most important issue to consider about intelligent drowsiness detection systems is how accurately and quickly they can detect drowsiness in the early stages.

Unfortunately, there is no exact standard for detecting drowsiness and it is generally tried to determine the driver’s level of consciousness by examining its effects. Accordingly, several methods have been proposed to detect drowsiness, each of which has its own weaknesses and strengths [5].

In these methods, various parameters are used to detect drowsiness that may be related to the car or driver. These parameters can include eye movements, brain signals, the shape of the driver's face, the driver's body position, steering wheel rotation, braking, speed, vehicle position on the road, and so on.

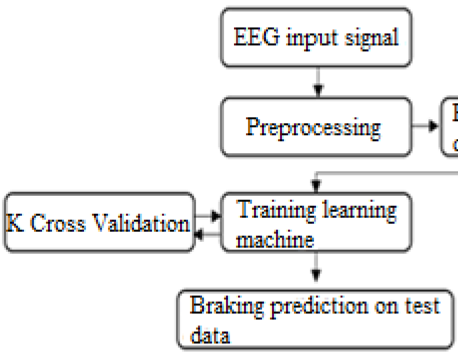

Fig.1 The proposed model

In general, these methods can be divided into three main groups based on the symptoms they use, based on physiological symptoms, based on driver and vehicle performance, and based on the driver's situation and appearance [6].
For categorizing brain signals to control car brakes, the artificial intelligence model is used. In this regard, different machine learning architectures and their various parameters are tested and the model with the least amount of the prediction error is proposed.
The innovative aspect of this paper is the combined use of the dimension reduction algorithm, after-error propagation neural network, and training by the means of K cross validation algorithm for reducing neural network learning error. The proposed algorithm for predicting emergency braking in simulated driving has not been implemented in previous studies. The proposed method can provide better accuracy than other existing methods.

2 Research method

In the proposed method of the present paper, initially preprocessing of lost data is carried out using the relevant algorithms. Then, using Cross-Validation algorithm, machine learning will be performed between test and training data. The learning machine used in the proposed method is the after-error propagation neural network. The proposed algorithm of this paper is shown in Figure 1.

As said before, the suggested algorithm is explained. As it was seen, the proposed method first preprocessed the data and then reduced the size of the features using the dimension reduction algorithm and then learned the features using the after-error propagation neural network.

In this section, first the evaluation criteria and then the database used are described. Then the results of each step of the algorithm will be shown. Finally, the outcomes of the proposed method will be compared and examined with the results of other papers. To evaluate the results of this method, there is a feature vector for each data stored somewhere. To evaluate the results obtained with the proposed method, there is one feature vector for each dataset. As a result, the properties of the Test Dataset vector are compared to the properties of the Train Dataset vector; Whether its output is "braking" or not.
For this purpose, the results of the proposed algorithm have been evaluated using the Accuracy, Precision, and Recall functions. The Precision criterion has been defined as equation number one, the Accuracy criterion has been displayed in equation number three, and the recall criterion has been displayed in equation number two.

1. $$\text{Precision}=\frac{tp}{tp+fp} \tag{1}$$

2. $$\text{Recall}=\frac{tp}{tp+fn} \tag{2}$$

3. $$\text{Accuracy}=\frac{tp+tn}{tp+tn+fp+fn} \tag{3}$$

In equation 4-1, the parameters tp and fp are as below:
[†]Fp: Braking has been declared incorrectly.
[‡]Tp: Braking has been declared correctly.
[§]Fn: No-braking has been declared incorrectly.

Precision criterion displays the percentage of categories on positive data and Recall shows the percentage of categories on negative data. The Accuracy criterion shows the overall accuracy of the proposed algorithm on both groups.

The database used in this paper is taken from the research site bnci-horizon-2020[**]. In this database, information of 18 people with the following names has been collected:

VPae ،VPbba ،VPgab ،VPgag ،VPgam ،VPja ،VPbad ،VPdx ،VPgac ،VPgah ،VPih ، VPsaj ،VPbax ،VPgaa ،VPgae ،VPgal ،VPii ،VPsal.

Their task involved maneuvering a simulated vehicle by utilizing the steering wheel, accelerator/brake pedals and a computer-controlled vehicle. The vehicle will sometimes slow down suddenly. At this time the driver has been instructed to use the emergency brake. In this way, the driver performs the test over a period of 45 minutes with 10-minute breaks.

As mentioned, this database is for 18 people. For each person, a set of modes has been recorded as a data record.

The output of this database can be 5 modes which are mentioned below. The purpose of the proposed method is to predict these 5 modes.

1. Car-brake: The vehicle initiates the process of deceleration.
2. Car-hold: The vehicle ceases braking and decelerates.
3. Reag-emg: The vehicle starts to brake. Here, the start has been detected by EMG.
4. The vehicle starts accelerating again.
5. Car-collision: Indicates a collision between the driver and the vehicle, that hardly occurs.

3 Data

To display the accuracy of the algorithm on the database using the after-error propagation neural network by the 10 cross-validation method, the results are announced separately for each step of the algorithm.

The learning accuracy of the learning machine has been shown in Table 1. The results of the after-error propagation neural network have been presented separately for each stage of cross-validation and finally, in Table 2, the average of the ten stages of training and testing is displayed.

Given that the number of records is divided into ten equal parts by the 10 cross-validation method, finally, 9 parts of the data are selected for testing each time and this is repeated ten times, the results of which are shown in Table 1 in stages.

[†] False positive
[‡] True positive
[§] False negative
[**] http://bnci-horizon-2020.eu/database/data-sets

Table 1 learning accuracy of after error propagation neural network for each run (execution) of 10 Cross-Validation algorithm

Accuracy	precision	Recall	10 Cross validation
0.919	0.895	0.944	1
0.947	0.947	0.947	2
0.919	0.895	0.944	3
0.919	0.895	0.944	4
0.889	0.941	0.842	5
0.919	0.944	0.895	6
0.889	0.941	0.842	7
0.919	0.944	0.895	8
0.947	0.947	0.947	9
0.919	0.895	0.944	10

Table 2 The average accuracy of after error propagation neural network on all ten experimental data sets

Accuracy	precision	Recall
0.919	0.924	0.915

In this section, the results obtained by each of the algorithms will be compared with each other. In this evaluation, first, a comparison of the three methods of the neural network, decision tree, and SVM has been shown in Figure 2. This chart shows the average results. Figure 3 illustrates the comparison of outcomes in the optimal scenario, while Figure 4 presents the comparison of results in the worst case.

As shown in Figure 2, the use of the proposed algorithm in the average case has presented the highest accuracy compared to the other two algorithms. After the proposed algorithm, the decision tree has presented a higher accuracy than the SVM method.

Figure 3 shows that in the best-case scenario, the proposed algorithm has presented far better results than the other two methods. After the proposed method, the decision tree has provided the highest accuracy in the best-case scenario, then the SVM has provided lower accuracy than these two algorithms.

Figure 4 shows that in the worst-case scenario, the proposed method using after error propagation neural network algorithm has provided the best response with a long distance compared to the other two methods. As can be seen, the decision tree has presented the best results after the proposed method in the worst-case scenario, then the SVM in the next place has provided the relatively worse results.

As can be seen in the total of three cases of worst, best and average, in all three cases the proposed method has presented the best operation.

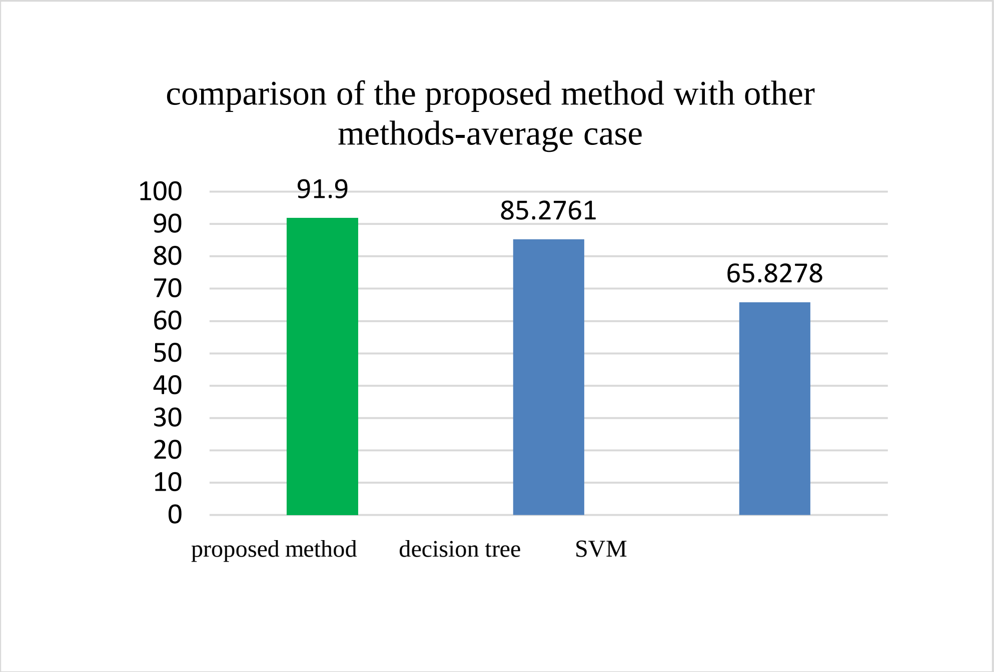

Fig. 2 Comparison of the results of the proposed method and the mentioned methods, in the average case

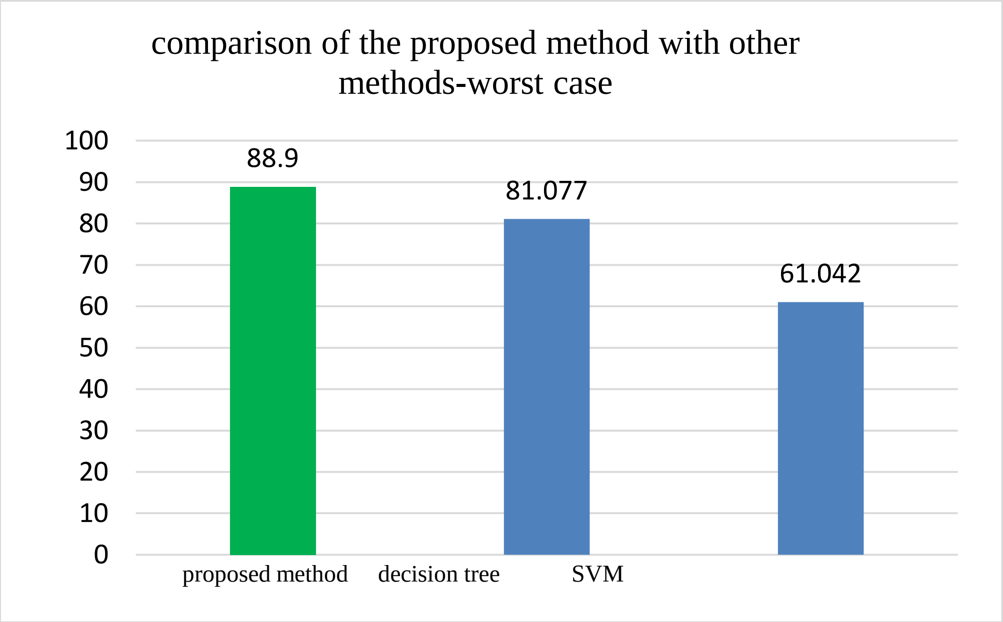

Fig.3 Comparison of the results of the proposed method and the mentioned methods, in the best case

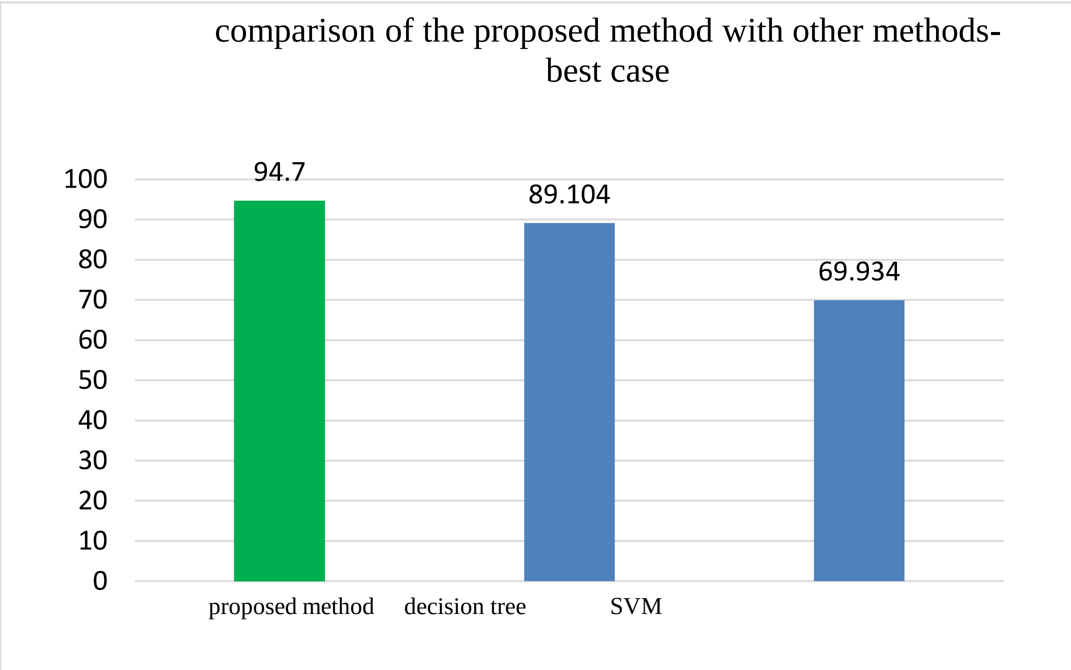

Fig.4 Comparison of the results of the proposed method and the mentioned methods, in the worst case

4 Conclusion

As mentioned, the automatic emergency braking system is responsible for informing the driver of impending accidents and using the ultimate potential of the vehicle's braking before a collision occurs. These systems are very different from each other; but in general, it can be said that all of these systems pursue three general purposes. The first purpose, includes braking performance at low velocity. The second purpose is to brake at high velocities and the third purpose in the automatic braking system requires more powerful technologies which include pedestrian observation and operate with images received from car cameras and radars.

The paper is collected in five sections. The first part of this paper has introduced the research topic, goals, and challenges in learning the state of emergency braking.

In the second part of the paper, the basic concepts of the proposed method were examined. In the background section of the research, regarding the emergency braking of the car based on artificial intelligence algorithms, the advantages and disadvantages of the methods proposed before this research were investigated.

The third section of the proposed algorithm based on machine learning with the aim of emergency braking during simulated driving based on EEG signal was presented. The method being put forward functions using an artificial neural network. The algorithm’s process is that first, the data is preprocessed and then the after error propagation neural network is trained with the training data, and after building the learning machine by the test data, the prediction is done, and finally, in the fourth section, The demonstration of the implemented approach's procedural steps was presented. Within the fourth segment, the change of algorithm variables and its influence on the precision of the suggested approach were investigated. In the continuation of this segment, the outcomes acquired through the suggested approach were shown and compared with other mentioned methods. The results obtained in this section show that suggested approach has performed more effective than alternative approaches.

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