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Research Paper

Negative Emotions Recognition While Driving Using Electroencephalogram Signal

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Abstract

The role of the human factor has been confirmed as the number one cause of driving crashes and emotions are known as one of the most important factors of driver distraction. Although biological signals have a great potential for detecting emotions, so far few studies have been conducted to use these signals to develop emotion recognition systems while driving. Therefore, in this paper an electroencephalography (EEG) based classification model presents for recognizing low-valence high-arousal (LVHA) emotions (known as negative emotions) of drivers. For this purpose, two driving tests were designed in a driving simulator, one for driving under normal conditions and the other for driving in the negative emotional state. 18 people participated in these tests and the activity of four channels of their brain signals was recorded during the tests. The energies of delta, theta, alpha, beta, and gamma frequency bands, and the total signal energy along with gender were employed as inputs for classification models and emotional state was considered as output. Different models were used for subject-independent classification, among which the neural network classifier with an accuracy of 95% had the best performance. The results of the analysis showed that all channels are effective in increasing the accuracy of classifiers; also, gender has a relative impact on the accuracy of classification models. Assessing the effects of different frequency bands revealed that alpha and gamma bands have a greater effect on the accuracy of models than do other bands. At the end, different combinations of EEG channels were used to recognize negative emotions while driving, and the results indicated that using only two channels can help recognize these emotions with an accuracy of 89%.

Keywords: emotion recognition, negative emotions recognition while driving, Advanced Driver Assistant Systems (ADAS), driving simulator study, promoting traffic safety

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1. Introduction

According to the World Health Organization (WHO), about 1.35 million people die every year in car crashes. The results of previous studies have shown that the human factor (driver) is the most important cause of traffic crashes [Cai and Lin, 2011, Jeon et al., 2014, Asadamraji et al., 2017, khalifeh et al., 2021], implying that the former is by far more influential. But, which driver characteristic really increases the risk of traffic crashes?

The Fuller's task–capability interface model [Fuller, 2000] and task difficulty theory [Fuller, 2005] both state that driver's ability is influenced by various human factors such as attitude, motivation, fatigue, sleepiness, distraction, stress, and emotions. Also, the driving environment is heavily influenced by emotions and driver distraction is a major contributor to crashes [Cunningham and Regan, 2016, Hayley et al., 2017]. These factors can significantly diminish the driver's ability to perform well. Other studies also demonstrate that driving in inappropriate emotional states could increase tenfold the probability of accident [Cunningham and Regan, 2016]. Therefore, Distraction, and lack of concentration due to an unfavorable emotional state (e.g., anger, fear, and anxiety) [Jeon et al., 2014, Hayley et al., 2017, Braun et al., 2019, Chen et al., 2019, Karimi et al., 2021] are among the most common risky behaviors of drivers that can result in traffic crashes.

Emotion is a sophisticated concept that has three components: subjective experience, emotional experience, and biological response. The biological response means that the human body is biologically aroused or shows physical reaction during an emotion experience [M. Ali et al., 2018]. The results of numerous studies on emotion recognition using biological signals have established that these signals are very efficient and suitable for designing emotion recognition systems [Al Machot et al., 2011, M. Ali et al., 2016, Samara et al., 2016, Minhad et al., 2017, Azman et al., 2018, Wang et al., 2018]. Indeed, The association of biological signals with the autonomic nervous system (ANS) and the central nervous system (CNS) has been established [Murugappan, 2014]. It suggests that the biological response of emotions, unlike other reactions (e.g. facial expression, bodily gesture, tone), is not within human control. Therefore, it is a useful source for developing emotion recognition systems and designing Advanced Driver Assistant Systems (ADAS) to recognize emotions by using biological signals can greatly improve driver performance and consequently increase safety.

Among various emotions that the driver experiences while driving, low-valence high-arousal (LVHA), known as negative emotions (e.g. angry, anxious, and fear), are more common and cause more risky behaviors [Taylor, 1964, Zuckerman, 2007, Koornstra, 2009, Jeon and Walker, 2011, Jeon et al., 2011, Schmidt-Daffy, 2013, Jeon, 2016] specially among young people [Jeon and Walker, 2011] which can interfere with proper driving and endanger both the driver and other traffic participants. According to the [Yerkes and Dodson, 1908] law (Figure 1) negative emotions due to high emotional arousal can lead to a severe drop in the performance of the driver. Consequently, since they are more common while driving, it is crucial to address them.

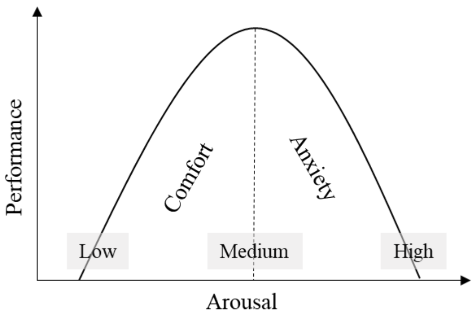


Figure 1. Yerkes and Dodson rule; relationship between performance and emotional arousal

Researchers have recently better understood the importance of emotions in traffic crashes, and yet few studies have investigated this issue. There are several research gaps in previous studies which this paper aims at filling. First, despite the fact that negative emotions are common emotions while driving, studying various aspects of these emotions needs to attract more attention of researchers. Second, no research has yet deployed the ElectroEncephaloGraphy (EEG) signal to identify negative emotions of young drivers while driving. Third, the accuracy achieved in most of previous related studies still has the potential to improve. Thus, to the best of our knowledge, this paper is the first which utilizes EEG signals to provide a classification model for negative emotions recognition while driving with high precision.

The rest of this paper is organized as follows. In section 2, the essential concepts of emotion recognition and characteristics of previous studies are explained. At the end of this section, a comparative table is presented that can be used by researchers to conduct new studies. In Section 3, the details of the experiments including the characteristics of the participants, the experimental procedure, the method of provoking desired emotions, and the features of EEG signals are provided. Section 4 is devoted to analyzing the recorded data. In Section 5, the results of data analysis are presented and discussed from various aspects. Finally, Section 6 concludes the paper.

2. Background and Previous Studies

Studies on emotions and emotion recognition started decades ago, and so far numerous studies have been undertaken in this regard. Various categories have been established for research in this field. Classification based on the emotion(s) in question and how to stimulate those emotion(s) and modeling based on subject-independent or subject-dependent methods and the information used to recognize emotions are among the most important of these categories.

In the case of exploring certain emotions, there are two basic models for emotion recognition [Atkinson and Campos, 2016]. In the first model, known as the dimensional model, emotions are considered continuously. Valence and arousal are two dimensions of this model. Valence expresses the pleasure of an emotion, which can be positive or negative with varying degrees. On the other hand, arousal indicates the severity of an emotion, ranging from low to high [Jerritta et al., 2011]. In Figure 2 the two-dimensional diagram of this model is given. As illustrated in the figure, this model can determine emotions continuously. In another model, known Ekmans' *Atlas of Emotions*, emotions are regarded to be discrete. Happiness, discomfort, excitement, anger, fear, and disgust are the basic emotion categories in this model [Ekman, 1992].

In this paper, driving in the negative emotional states is investigated. Negative emotions refer to an area in the two-dimensional model where emotional valence is low and emotional arousal is high (LVHA). Angry, fear, stress, and anxiety are the most important emotions in the LVHA area that are more frequent in the driving context.

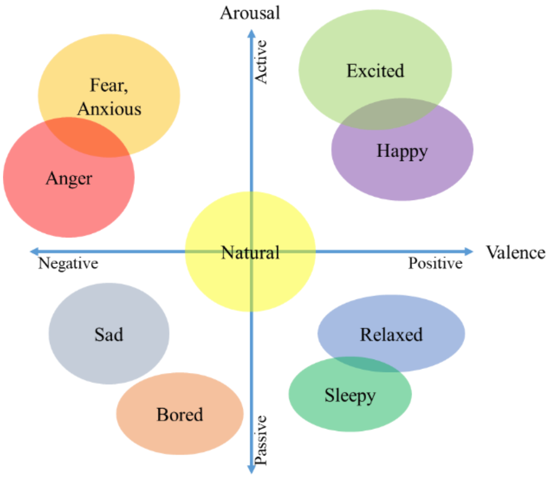


Figure 2. categorize emotions based on dimensional model

One of the most challenging issues in studies on emotion is how to stimulate the desired emotion [Cai and Lin, 2011]. Various approaches have been proposed to this end, including the use of short films, music, the International Affective Picture System (IAPS) [Lang et al., 1997], and International Affective Digital Sounds system (IADS) [Bradley and Lang, 1999]. IAPS is one of the most widely used options here. It is a database of pictures developed by the Center for the Study of Emotion and Attention at the University of Florida. This database, produced through a survey of different people, contains 956 color pictures that score the stimulated emotion of the observer. Each picture identifies the associated emotion based on two dimensions of valence and arousal. IADS also uses this two-dimensional model to determine the emotion associated with each audio track.

Another issue in studies on modeling emotion recognition is related to the quality of being subject-dependent or subject-independent. Subject-dependent means that both the training data and the test data of a classifier are from one person, and the emotion recognition system is dependent on the subjects [M. Ali et al., 2016]. Although subject-independent systems are more practical, many studies on emotion recognition are subject-dependent. It should be noted that subject-dependent systems make it possible to achieve higher accuracy than do subject-independent ones.

So far, different data have been used to recognize emotions. Facial expressions, the speech signal, bodily gestures, and biological signals are the most common data used to detect emotions. As mentioned, the use of biological signals due to their connection with the autonomic nervous system (e.g. skin resistance) and the central nervous system (e.g. EEG signal) is more reliable than other methods for emotion recognition. Also, the development of instruments for recording these signals has encouraged researchers to come up with systems to recognize emotions based on biological signals.

Using driving simulators has had a significant impact on the development of driving-related studies. Controllability, repeatability, low cost, and safety are the most important features of a driving simulator. These features have encouraged many researchers to study driver behavior using driving simulators. For example, [Sheikholeslami et al., 2020] analyze the effect of hazard properties on driving accident likelihood by a driving simulator and 90 participants. [Asadamraji et al., 2019] used the driving simulator to assess the effect of demographic, lifestyle, and driver cognition variables on hazard perception sensitivity index. In another paper, [Vlakveld et al., 2021] perform the driving test in a driving simulator for analyzing gaze and driving behavior of drivers who used smartphones in one hand or a dashboard-mount. In an interesting study, [Y. Ali et al., 2020] investigated driver behavior and safety improving when additional information about the environment provides for the driver. To achieve this purpose, an innovative driving simulator experiment was designed to mimic a connected environment. Several studies conducted in recent years for drawing future lines of driving behavior analysis. [Vilaca et al., 2017, Kaye et al., 2018, Abou Elassad et al., 2020, Alkinani et al., 2020, Mantouka et al., 2020] presented in this regard, so interested readers can refer to them for more information.

Although studies on emotions and emotion recognition started decades ago, researchers have just lately discovered the importance of emotions in driving and their role in traffic crashes. So far, few studies have been done to recognize emotions while driving [Katsis et al., 2008, Al Machot et al., 2011, Wan et al., 2014, M. Ali et al., 2016, Ganesh et al., 2017, Minhad et al., 2017, M. Ali et al., 2018, Azman et al., 2018, Izquierdo-Reyes et al., 2018]. For this reason, in order to better understand how to study emotions, other fields have been considered in reviewing the literature. However, most of studies, in driving context, make use of subject-independent models, and anger detection is one of the main concerns they deal with.

Table 1 compares the characteristics of various studies performed in the field of emotion recognition. At the end of this table, the few studies conducted in the context of driving are presented. Subsequently, the characteristics of the current study are outlined. Several gaps exist in the previous studies which this paper presented to fill them. First of all, studying emotion detection while driving needs more attention, and such studies can pave the way for future works in this regard, especially using the potential of the biological signals for emotion recognition while driving. Second, this paper presented to investigate negative emotion detection while driving to achieve a subject-independent classification model with higher accuracy. Third, conducting a comparison among classification models to determine their performance for negative emotion recognition while driving was elaborate in this study for the first time.

Table 1. Characteristics of previous studies

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
[Samara et al., 2016]	×	32	Video	×	Valence, Arousal	✓																	✓		✓		✓		80
[Zhang et al., 2016]	×	32	Video	×	Valence, Arousal	✓																			✓			✓	81
[Gong et al., 2016]	×	-	Music	×	joy, anger, sadness, pleasure		✓	✓		✓	✓										✓								92
[Gong et al., 2016]	×	32	Video	×	terrible, love, hate, sentimental, lovely, happy, fun, shock, cheerful, depressing, exciting, melancholy, mellow	✓												✓					✓		✓			✓	92
[Kolodyazhniy et al., 2011]	×	34	Movie clips	✓	fear, sadness, neutral	✓																				✓			subject dependent: 81 subject independent: 78
[Shin et al., 2017]	×	30	Video	×	amusement, fear, sadness,	✓	✓																					✓	98

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
					joy, anger, and disgust																								
[Agrafioti et al., 2012]	×	44	IAPS Video game	✓	valence, arousal		✓																			✓			Valence: 52-89 Arousal: 76
[Wen et al., 2014]	×	-	Video	✓	amusement, grief, anger, fear, baseline		✓				✓						✓												74
[Kim and André, 2008]	×	3	Music	✓	valence, arousal		✓	✓		✓	✓															✓			subject dependent: 95 subject independent: 77
[Zong and Chetouani, 2009]	×	-	Music	×	joy, anger, sadness and pleasure		✓	✓		✓	✓														✓				76
[Valenza et al., 2012]	×	35	IAPS	✓	5 level valence 5 level arousal		✓			✓	✓																	✓	90
[Wong et al., 2010]	×	-	Music	×	joy, anger, sadness, pleasure		✓	✓		✓	✓							✓											86
[Mirmohamadsadeghi et al., 2016]	×	32	Music Movie clips	×	valence, arousal			✓		✓															✓				Valence: 74 Arousal: 74
[Wu et al., 2012]	×	33	Movie clips	×	love, sadness, joy, anger, fear					✓													✓						88

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
[Lisetti and Nasoz, 2004]	×	14	Video	✓	sadness, anger, fear, surprise, frustration, and amusement		✓	✓		✓	✓		✓																84
[Maaoui and Pruski, 2010]	×	10	IAPS	✓	amusement, contentment, disgust, fear, sadness, and neutral			✓		✓	✓			✓											✓	✓			subject dependent: 90 subject independent: 45
[Kim, 2007]	×	3	Video	✓	Valence, Arousal		✓	✓			✓	✓		✓	✓								✓						subject dependent: 92 subject independent: 55
[Petrantonakis and Hadjileontiadis, 2010]	×	16	IAPS	✓	happiness, surprise, anger, fear, disgust, sadness	✓																	✓				✓		85
[Wang et al., 2018]	×	-	Video	✓	Various	✓																			✓			✓	57-75
[Ganesh et al., 2017]	×	32	Video	✓	Valence	✓																	✓		✓				81
[M. Ali et al., 2018]	×	30	Video	✓	Valence, Arousal		✓			✓	✓							✓											89
[Li et al., 2016]	×	32	Video	×	Valence, Arousal	✓																						✓	Valence: 72

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
																													Arousal: 74
[Guendil et al., 2015]	×	-	Music	×	joy, anger, sadness, and pleasure		✓	✓		✓	✓														✓				95
[Lin et al., 2010]	×	26	Music	✓	joy, anger, sadness, and pleasure	✓												✓							✓				82
[Valenza et al., 2014]	×	-	IAPS	✓	Valence, Arousal		✓																		✓				Valence: 79 Arousal: 83
[Cheng and Liu, 2008]	×	-	-	×	joy, anger, sadness, and pleasure			✓																				✓	75
[Basu et al., 2015]	×	-	IAPS	×	Valence, Arousal					✓	✓	✓	✓													✓	✓		HVHA: 98 HVLA: 96 LVHA: 93 LVLA: 97
[Liu et al., 2016]	×	32	Video	×	Valence, Arousal	✓																	✓					✓	Valence: 70 Arousal: 71
[García et al., 2016]	×	32	Video	×	Valence, Arousal	✓		✓	✓	✓	✓	✓		✓											✓				Valence: 88 Arousal: 90
[Guo et al., 2016]	×	25	Movie clips	×	Positive, Negative		✓																		✓				71

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
[Monajati et al., 2012]	×	13	-	×	Negative, Natural					✓	✓		✓															✓	94
[Lan et al., 2016]	×	5	IADS	×	Positive, Negative	✓																			✓				73
[W.-L. Zheng et al., 2017]	×	47	Video	×	Valence, Arousal	✓																						✓	Dataset 1: 70 Dataset 2: 91
[Izquierdo-Reyes et al., 2018]	✓	15	Drivin g Events	×	Joy, Natural, Surprise	✓																						✓	-
[Katsis et al., 2008]	✓	10	-	✓	High Stress, Low Stress, Disappointment, Euphoria		✓		✓	✓	✓							✓							✓				79
[Minhad et al., 2017]	✓	69	Audio Visual	✓	Happy-Anger		✓																		✓				83
[Wan et al., 2014]	✓	30	Driving Events	×	Anger	✓				✓	✓		✓					✓							✓				85
[Azman et al., 2018]	✓	-	-	×	Anger											✓									✓				97
[M. Ali et al., 2016]	✓	30	video	✓	Valence, Arousal		✓				✓	✓						✓					✓		✓				82
[Al Machot et al., 2011]	✓	-	-	✓	Fear, Sadness, Neutral, Happiness, Anger		✓	✓			✓	✓		✓	✓													✓	33-93

Reference	While driving	Sample size	Elicitation method	Subject-independent	Emotion(s)	Used signals												Classifiers											Accuracy
						EEG	ECG	EMG	EOG	RSP	EDA	ST	HR	BP	Speech	Facial	Others	ANN	DT	CHAID	C 4.5/ 5.0	QUEST	KNN	K-Means	SVM	LDA	QDA	Others	
This paper	✓	18	IAPS IADS	✓	LVHA emotions, Natural	✓												✓	✓	✓	✓	✓				✓			95

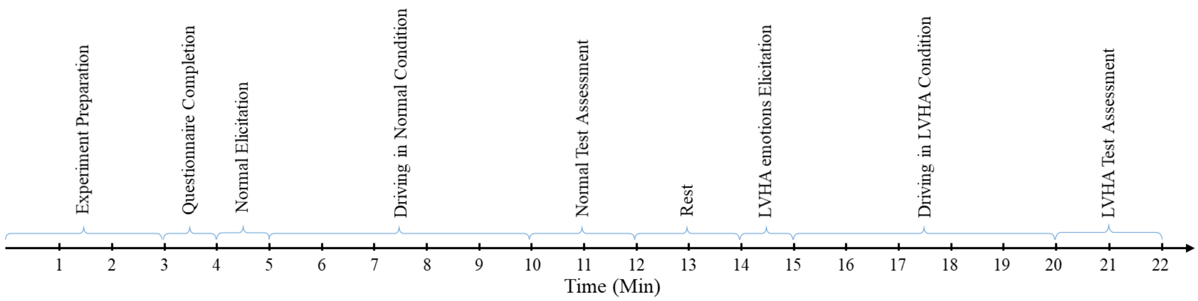


Figure 3. timeline for conducting the experiments

3. Methodology

3.1. Experimental Procedure

The details of the experiments are laid out in this section. The experiments included two tests performed in the Nasir driving simulator which were designed and validated by the virtual reality group in the K. N. Toosi University of technology. This simulator has various capabilities include recording driving data (such as speed, acceleration, steering wheel degree, lateral and longitude positions, break status, and Round per Second (RPS)), modifying environmental characteristics, and designing desired scenarios.

The first test was driving under normal conditions and the second was driving in the negative mode. Driving routes and traffic conditions (Figure 4) were the same for both tests, and completion of each test required about 5 minutes. In both tests, the traffic congestion was moderate, so participants had to pay enough attention to their route and speed, especially at intersections, to avoid accidents. Participants were also asked to adjust the car speed between 60 and 80 km under normal circumstances. In order to familiarize the participants with the simulator environment as well as the rules of the tests, before starting the experiment procedure, all participants drove in preparative driving mode. Preparative driving continued until the participant announced that he/she was sufficiently familiar with the simulator and the executive team confirmed his/her readiness.

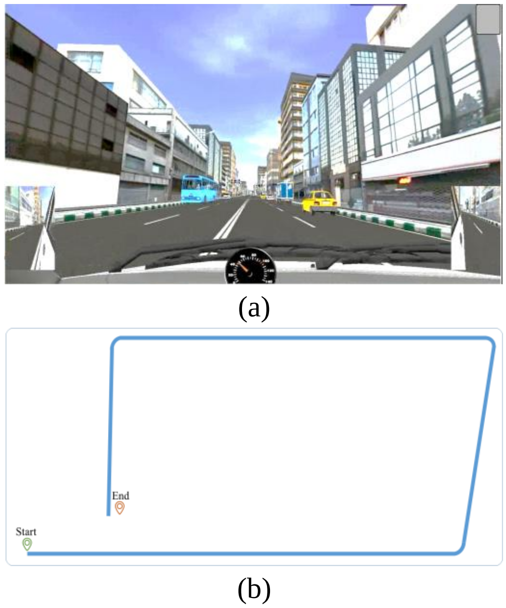


Figure 4. (a). Driving environment, (b). Driving route

Before the tests, participants filled out a demographic questionnaire including age, gender, and education. The timeline for conducting the experiments is given in Figure 3. In order to exclude order effect in experiments, half of the subjects first drove in normal condition then drove in negative emotional condition and others vice versa.

3.1.1. Participants

A total of 18 people participated in the tests, all of whom were young with mean of two-year driving experience. Participants did not have any special disease or disorder. In Figure 5, the gender and age distribution of the study subjects are provided. Investigating negative emotions of young people is one of the innovations of the paper.

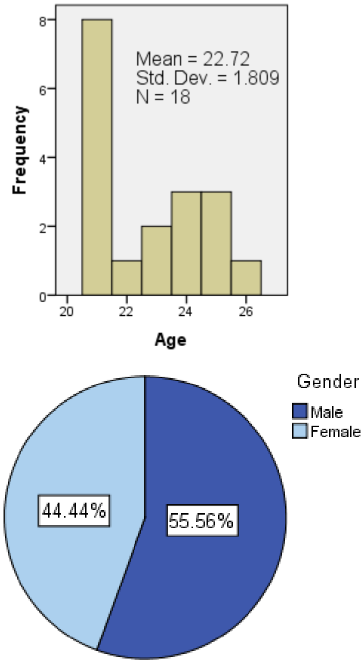


Figure 5. gender and age distribution of participants

3.1.2. Emotion elicitation method

In this study, International Affective Picture System (IAPS) pictures and Affective Digital Sounds system (IADS) sounds were used simultaneously to stimulate normal mode and negative emotional mode in the drivers. By combining several pictures[1] and sounds[2], a one-minute clip was created that was used to fuel negative emotions and fuel normal. To do this, before driving, the driver first watched the one-minute clip with full attention, and after that, he/ she began to drive in the pre-defined route. The clip was repeated in another monitor placed in the side view of the participant while driving. In order to assess the effectiveness of the elicitation method, all drivers were asked to score their emotional state in terms of valence and arousal using the Self-Assessment Manikins (SAMs) scale (Figure 6) both after normal mode elicitation and after negative emotional mode elicitation. The average scores of participants for valence and arousal in normal mode were respectively 5.7 and 4.1, and in negative mode were respectively 1.3 and 8.2, indicating the efficacy of the clip in causing desired emotions.

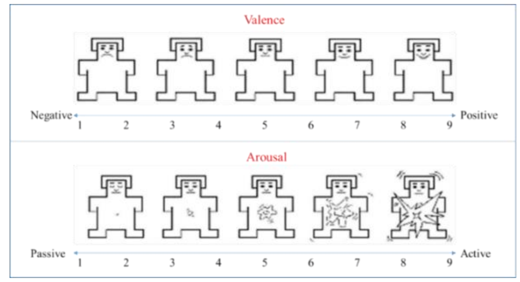


Figure 6. Self-assessment manikin scale

Although the use of SAMs is a standard approach to assessing the effectiveness of the emotion elicitation method, this approach does not provide information about the effect of the emotion elicitation method on the driver's performance and workload. Therefore, we used the National Aeronautics and Space Administration-Task Load Index (NASA- TLX) questionnaire [S. Hart, 1988] to investigate the effect of the used elicitation method on the participant’s workload. This questionnaire measures a person's subjective mental workload, and for this purpose, the total workload is divided into six subjective subscales, including mental demand, physical demand, temporal demand, frustration, effort, and performance [S. Hart, 1988, S. G. Hart, 2006, Bustamante and Spain, 2008, Cao et al., 2009, Grier, 2015].

During each test, the NASA- TLX questionnaire was completed twice by participants, once after driving in normal mode and another after driving in negative emotional mode. The average total workload of the participants after the normal test was 40 and after the LVHA test was 58. Therefore, the obtained results confirm that the method used for negative emotions elicitation has increased the driver's workload.

3.1.3. Biological Signals

The EEG signals of drivers recorded during the experiments included Fp1, Fp2, F7, and F8 channels, which were fixed in suitable locations using special connectors. The location of these channels was determined according to the 10-20 standard (Figure 7).

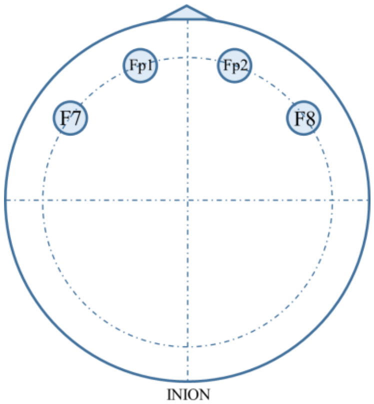


Figure 7. EEG electrode installation site based on the 10-20 standard

There are several reasons for using these channels to record EEG signals for emotion recognition while driving. First, as the theoretical perspective, it is approved that the frontal lobe of the brain is responsible for controlling important cognitive skills in humans, such as emotional expression, and decision making [Davidson and Fox, 1982, Davidson, 1992, W.-L. Zheng and Lu, 2015, W. Zheng, 2016, Masood and Farooq, 2019]. Second, installing EEG electrodes on the head is difficult due to the presence of hair, and their connection may be lost or signal noise could increase. Meanwhile, in this study, the selected channels were located in the forehead and electrodes could be mounted directly on the skin using special connectors. Third, these channels are the most accessible channels such that, as in the studies by [Casson et al., 2010] and [Mihajlović et al., 2015], they can be worn as glasses or headband. Forth, recording EEG signals is intrusive to the primary driving activities, so the fewer the channels are used, the less disturbing the effect will be. It should be noted that using EEG signals to assess negative emotions while driving is another contribution of the paper.

4. Data Analysis

4.1. Feature Extraction

The recorded EEG signals require processing so that their proper features could be extracted for modeling (The desired features are the energy of various frequency bands including delta, theta, alpha, beta, and gamma along with the overall signal energy). To this end, the signal is first filtered to eliminate power-line interference and then, processed to remove eye-blink artifacts. In order to remove eye-blink artifact, spatial filter, which its details described by [Ille et al., 2002] and [Gómez-Herrero et al., 2006], was used. After that, the signal is divided according to the desired frequency bands of Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) [Soleymani et al., 2017]. Finally, the energy of different signal bands is calculated. Equation 1 was used to calculate the power of the $x(t)$ signal in the interval $[1, T]$.

$$PSD = \frac{1}{T}\int_{1}^{T} x^2(t)\,dx \qquad (1)$$

To extract these features from EEG signals, a 30-second window was used. Given that the length of each test was about 5 minutes and 18 people participated in the experiments, we obtained about 180 records for driving in the negative emotional mode and about 180 records for driving in the normal mode. Each record has the features as follow. Feature names are a three-part abbreviated term which in PSD refer to the Power of Spectrum Density of the desired signal, the second part assigned for the EEG channel location, and the last part determines the frequency band of the EEG signal.

- PSD_Fp1_Delta
- PSD_Fp1_Theta
- PSD_Fp1_Alpha
- PSD_Fp1_Beta
- PSD_Fp1_Gamma
- PSD_Fp1_Total
- PSD_Fp2_Delta
- PSD_Fp2_Theta
- PSD_Fp2_Alpha
- PSD_Fp2_Beta
- PSD_Fp2_Gamma
- PSD_Fp2_Total
- Gender
- PSD_F7_Delta
- PSD_F7_Theta
- PSD_F7_Alpha
- PSD_F7_Gamma
- PSD_F7_Total
- PSD_F8_Delta
- PSD_F8_Theta
- PSD_F8_Alpha
- PSD_F7_Beta
- PSD_F8_Gamma
- PSD_F8_Total
- Label

4.2. Data Preparation

In each machine learning project, it is usually necessary to decide on the missing and outlier data before entering the modeling phase. In this paper, IBM SPSS Modeler 14.2 software was used for modeling. After all records were checked, no missing values were found in the data, but there existed some outlier values. Consequently, the Anomaly Node of the software was used and the records containing outlier values were removed. The schematic diagram of the modeling process illustrated in Figure 9.

4.3. Modeling Negative Emotions Recognition While Driving

After preparing data, they should be divided into two groups of training and testing. Thus, 70% of data was used to train the models and the rest were deployed to test the models. The statistical model of the study presented in Figure 8.

Using various classifiers, different models were implemented on the data to create an appropriate subject- independent classifier for negative emotions recognition during driving. The following illustration shows the implemented process in the software. As could be seen in Figure 9, the Neural Network (Multilayer Perceptron), Discriminant, C & R tree, CHAID, Quest, and C 5.0 models have been used for classification, and the Label field has been defined as the target in all of them.

A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output (s). Each unit takes an input, applies a function to it, and then passes the output on to the next layer. Discriminant analysis is a classification method that assumes that different classes generate data based on different Gaussian distributions. Chi-square automatic interaction detection (CHAID), Classification and Regression (C & R) tree, C 5.0, and Quick, Unbiased and Efficient Statistical Tree (QUEST) are the most common methods based on decision tree techniques that can be used for classification purposes.

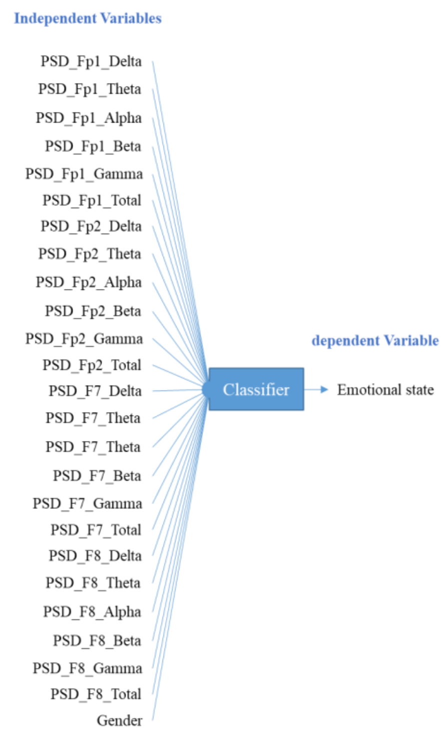


Figure 8. Statistical model of the study

5. Results and Discussions

The results of the used classifiers are shown in Figure 10. Accordingly, the accuracy of the neural network in recognizing negative emotions while driving is better than other models. The confusion matrix for this model is presented in Table 2. As can be seen, the model has a high accuracy for predicting the desired target. The highest accuracy achieved so far for detecting emotions while driving was 97% obtained by [Azman et al., 2018] for subject-dependent anger detection . Also, [Al Machot et al., 2011] could recognize fear while driving by 93% accuracy. Compared to these studies, the results show that we were able to achieve higher accuracy in the detection of negative emotions while driving.

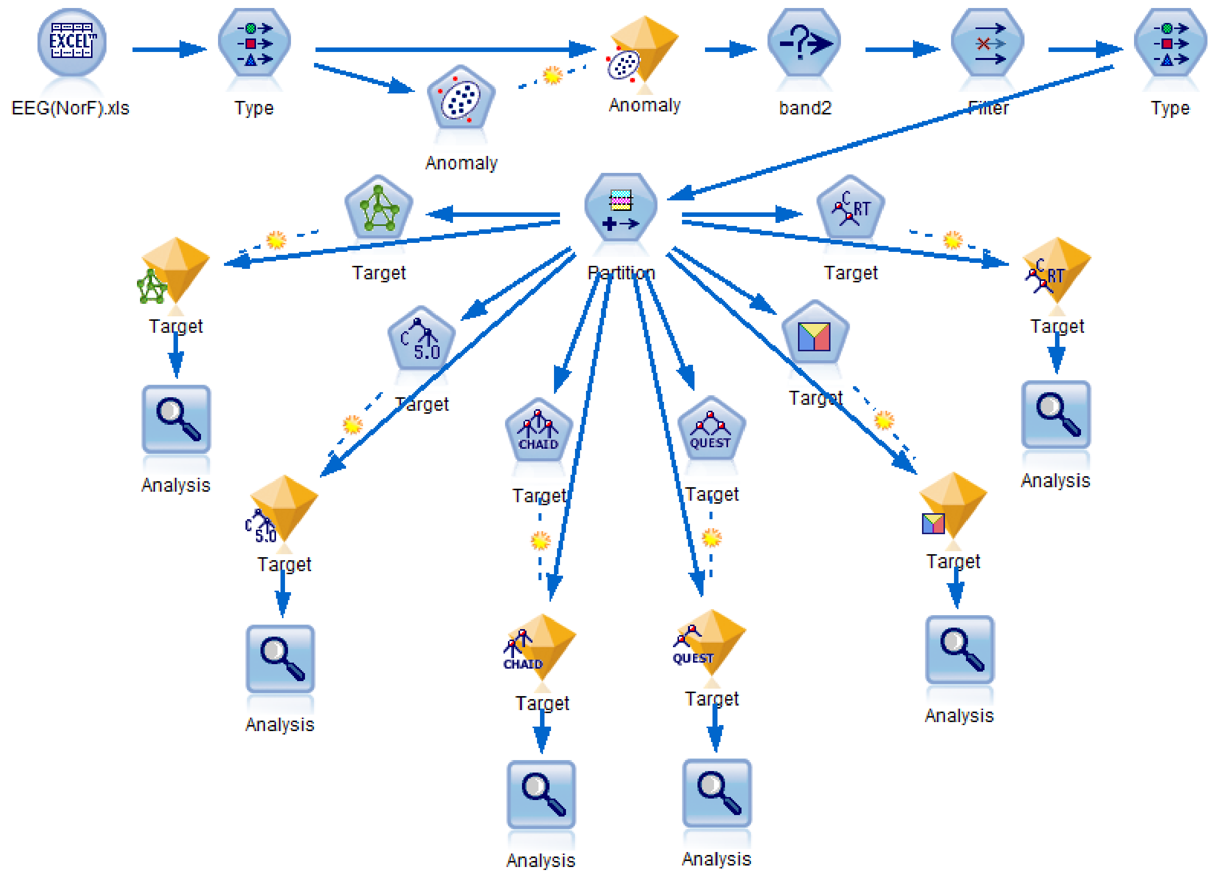


Figure 9. the schematic diagram of the modeling process

Table 2. confusion matrix of neural network classifier

		Actual: Negative	Actual: Normal	Total
Predicted	Negative	41	2	43
Predicted	Normal	3	47	50
Total		44	49	93

Using the confusion matrix, one may calculate the values of error rate, sensitivity, specificity, precision, and prevalence. In the Table 3 and Table 4, the method of calculating these indicators is provided along with their values. The obtained values represent the good performance of the neural network classifier.

Table 3. confusion matrix schematic

		Actual Negative	Actual Normal	Total
Predicted	Negative	TP	FP	Predicted Negative
Predicted	Normal	FN	TN	Predicted Normal
Total		Actual Negative	Actual Normal	Total Samples

Table 4. calculation formula and values of indicators

Indicator	Formula	Value
Error Rate	(FP+FN) /Total	0.05
Sensitivity	TP /Actual Negative	0.93
Specificity	TN /Actual Normal	0.96
Precision	TP /Predicted Negative	0.95

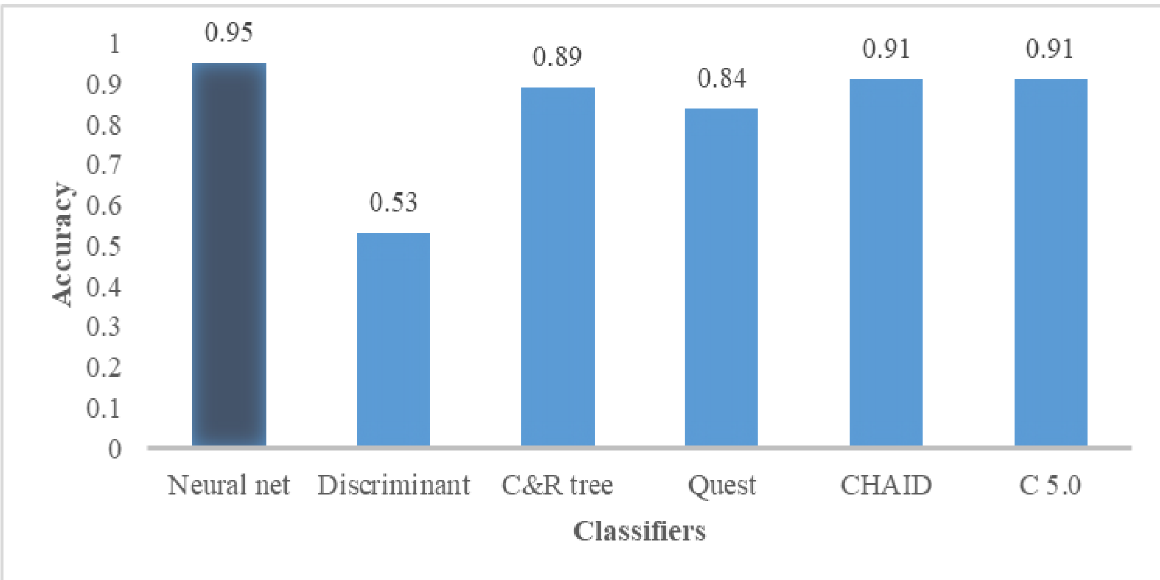


Figure 10. accuracy of different classifiers

Furthermore, it is possible to plot the Receiver Operating Characteristic (ROC) chart by means of the confusion matrix. ROC is a two-dimensional chart representing the true positive rate (Sensitivity) on the y-axis and the true negative rate (1- Specificity) on the x-axis [Gorunescu, 2011, Han et al., 2011]. In Figure 10, the ROC chart for the neural network classifier is drawn.

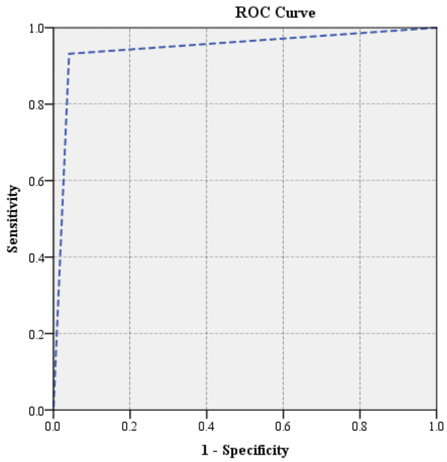


Figure 10. ROC curve of neural network classifier

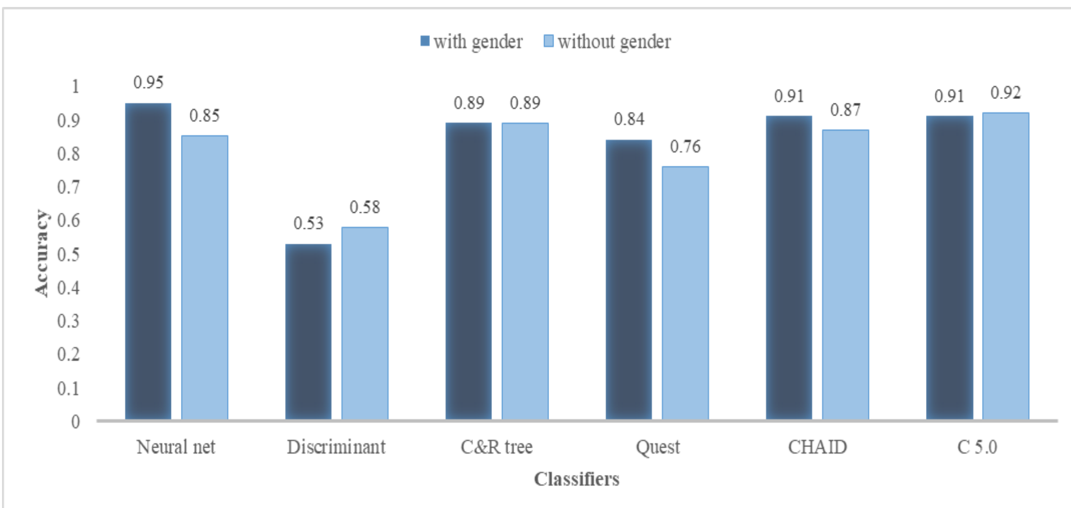
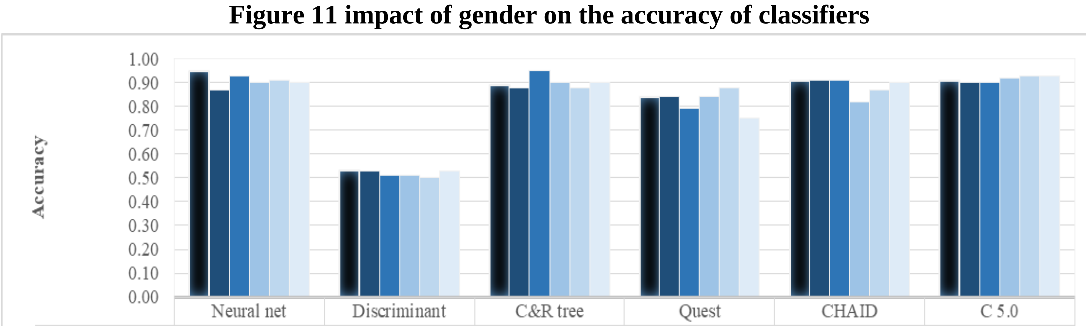
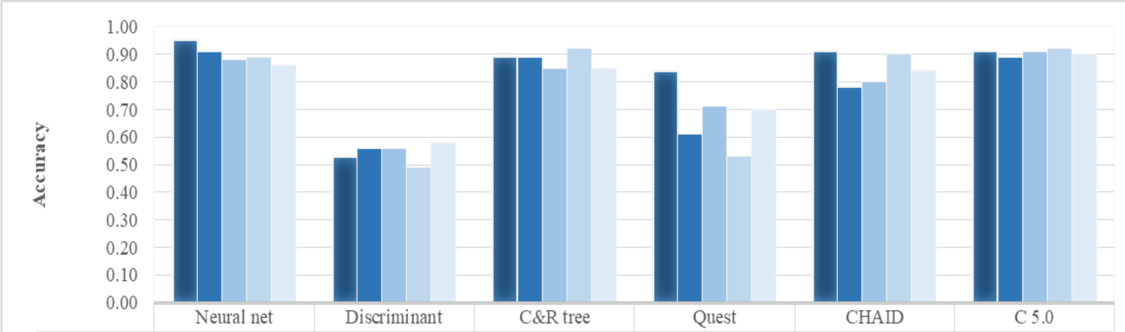


Figure 11 impact of gender on the accuracy of classifiers



	Neural net	Discriminant	C&R tree	Quest	CHAID	C 5.0
All Bands	0.95	0.53	0.89	0.84	0.91	0.91
without Delta	0.87	0.53	0.88	0.84	0.91	0.90
without Theta	0.93	0.51	0.95	0.79	0.91	0.90
without Alpha	0.90	0.51	0.90	0.84	0.82	0.92
without Beta	0.91	0.50	0.88	0.88	0.87	0.93
without Gamma	0.90	0.53	0.90	0.75	0.90	0.93

Figure 12 accuracy of different frequency bands



	Neural net	Discriminant	C&R tree	Quest	CHAID	C 5.0
All channels	0.95	0.53	0.89	0.84	0.91	0.91
without Fp1	0.91	0.56	0.89	0.61	0.78	0.89
without Fp2	0.88	0.56	0.85	0.71	0.80	0.91
without F7	0.89	0.49	0.92	0.53	0.90	0.92
without F8	0.86	0.58	0.85	0.70	0.84	0.90

Figure 13 accuracy of different EEG channels

5.1. Impact of Gender on Emotion Recognition While Driving

In addition to the features derived from the EEG signals, another variable used in the models for negative emotions recognition during driving is gender. An interesting question that can be raised is whether gender is an effective factor in identifying negative emotions while driving? In order to study the impact of this variable on the accuracy of the classifier models, this variable was excluded from the inputs and all classifiers were re-run. The results are provided in Figure 11. As shown, gender does have a significant impact on the accuracy of some of the classifiers. For example, by excluding this variable, the accuracy of the neural network classifier decreased by 10%. The same exclusion, however, has increased the accuracy of some classifiers such as Discriminant and C 5.0. Therefore, this variable has a relative effect on raising the accuracy of classifiers, but it cannot be considered a crucial variable in recognizing negative emotions while driving through EEG signals.

5.2. Importance of Different Frequency Bands of EEG

Another commonly used analysis in EEG-related studies is the assessment of the influence of different frequency bands on the accuracy of classifiers. In this study, the energies of delta, theta, alpha, beta and gamma frequency bands were considered as classifier inputs. In order to investigate the effect of the features of these bands, all classifiers were re-executed five times, and each time the features of a single frequency band was eliminated from the input set of classifiers. The results are given in Figure 12. It seems that the energy of gamma and alpha bands has a greater impact on the accuracy of the classifiers than do other bands.

5.3. Importance of Different Channels of EEG

In order to assess the usefulness of features extracted from each EEG signal channel, all classifiers were performed four times. At each time, the features of one of the EEG signal channels were excluded from the classifier inputs. The results are displayed in Figure 13. It could be inferred that excluding the features of any channel reduces the accuracy of most of the classifiers. Accordingly, all channels play important roles in improving the accuracy of the classifiers, but it is not possible to determine which channel is more effective in this regard.

One of the principal issues in using EEG signals to recognize emotions while driving concerns the limited operational freedom of the driver due to the installation of recording electrodes. This is important because recording EEG signals during driving annoys the driver and, therefore, the fewer the number of electrodes is, the higher the degree of driver's freedom will be. In addition, the use of further channels increases computational costs and reduces speed. Hence, achieving high accuracy with the lowest number of channels is of paramount significance. To this end, the features of different compounds of EEG signal channels besides gender were selected as the inputs of the neural network classifier in identifying the best channel(s) for negative emotions recognition during driving. In Figure 14, the classification results are outlined with different combinations of channels. Based on this figure, it is only through using the features of Fp2 channel that one may identify negative emotions during driving with an accuracy of 80%. If using the features of two channels is desirable, Fp1 and F7 channels or F7 and F8 channels can be chosen to obtain results with an accuracy of 89%. Also, using the features of Fp2, F7, and F8 channels, one may be able to detect negative emotions while driving with an accuracy of 91%.

In simple terms, by using only two channels, proposed system can detect negative emotions of driver with a high accuracy of 89%. Based on these results, the engineering society, especially who focused on the ADAS development by using biological signals, can design and implement the desired systems which have higher computational speed, lower inconvenience, and lower cost.

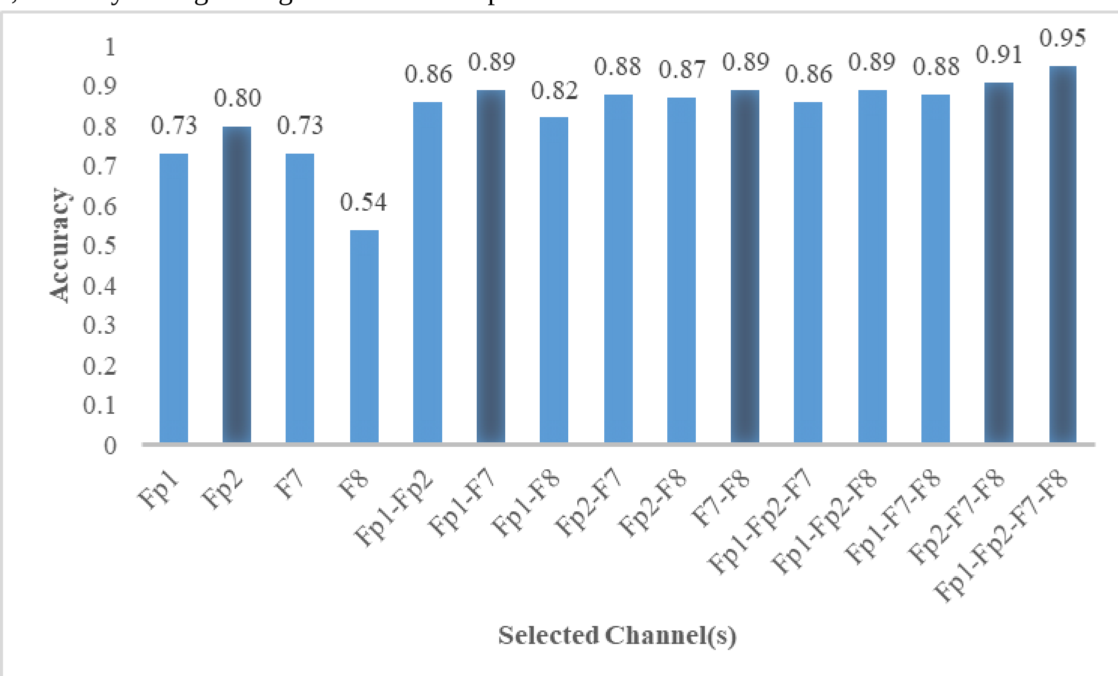


Figure 14. Accuracy of different compounds of EEG channels

6. Conclusion

The results of previous studies have approved that the human factor is the most important cause of driving crashes and that undesirable emotional conditions are one of the main factors of driver distraction which reduce driver performance. In this context, negative emotions are known to be common unpleasant emotion during driving. On the other hand, various studies on emotion recognition have concluded that biological signals are a good source of emotional analysis. Accordingly, it is vital to devise systems that can detect emotional states by monitoring the driver's biological behavior. In this regard, one may design appropriate ADASs using biological signals to recognize the negative emotions of driver and, if necessary, take actions to regulate them. Thus, the purpose of this study was to provide a model for diagnosing negative emotions during driving.

In order to achieve the research goal, an experimental study was conducted in a driving simulator. To stimulate desired emotions, by combining IAPS pictures and IADS sounds, we created a one-minute clip for emotion elicitation during driving. The EEG signal of the four channels Fp1, Fp2, F7, and F8 were recorded during the experiments. The energies of delta, theta, alpha, beta, gamma, and the total signal energy along with gender were used as inputs of the classification models while detecting negative emotions or their absence was considered as the classification target. Six different classifiers were deployed for this purpose, and it was found that the neural network classifier, with an accuracy of 95%, could best recognize the negative emotions while driving.

The results of the analysis demonstrated that all the four channels are effective in increasing the accuracy of the classifiers, and none of them is superior to the others. Also, gender has a relative impact on enhancing the accuracy of some classifiers. Assessing the effect of different frequency bands of the EEG signal revealed that gamma and alpha bands have greater effects on classification accuracy than do other bands. Eventually, in order to reduce the number of EEG recording channels, different combinations of channels were considered as input sets of the classifier model. The results suggested that by using just two channels, the neural network classifier could recognize negative emotional state while driving with an accuracy of 89%, which is a satisfactory level.

The results of this study showed that biological signals are a good source for detecting emotions while driving, as previous studies confirmed [Wan et al., 2014, M. Ali et al., 2016, Azman et al., 2018, Izquierdo-Reyes et al., 2018]. Although detecting only one emotion mode while driving is undoubtedly intertwined with other emotion categories, it has not been possible to achieve 95% accuracy in previous research that focused on a specific emotion while driving [Wan et al., 2014, Minhad et al., 2017, Azman et al., 2018]. In addition, most of them have used a subject-dependent approach for emotion detection while driving while we achieve high accuracy by using a subject-independent approach.

Emotion detection systems for drivers can have a variety of applications. Such systems can communicate with an alarm (audio/ visual) and inform the driver of his/her emotional state so that if the conditions are not suitable to continue driving, he/she will stop for a while or let another person drive in order to reduce the chance of an accident. Moreover, if the driver ignores the warnings, it is possible to ameliorate his/her emotional state and reduce the driving risk by taking interventions such as automatically adjusting the music, air conditioning, or even the speed. In addition to applications this system has inside the vehicle, it can be used outside the vehicle. For example, by announcing the unfavorable emotional state of the driver to neighboring vehicles, the system helps the latter to be more careful and alert when overtaking or following the driver’s vehicle. Reporting the status of vehicles to the police is another application of such systems; thus, if the driver ignores his/her poor performance and the intervention actions are not effective, the police will stop the vehicle to prevent a possible accident.

Exploring the trend of related studies in recent years, an important question raises that can be answered in future research. At present, it is possible to design systems that accurately recognize the driver's emotions, how to control and regulate her/his undesirable emotions in order to improve her/his performance? In fact, it seems that the next step in recognizing emotions while driving is to design interactive intervention systems to control and regulate the driver's emotions, which researchers can focus on.

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Footnotes

1. Number of pictures in IAPS dataset for negative mode elicitation were: 3000, 3010, 3053, 3069, 3080, 3120, 3170, 3266, and 9940 (the mean of arousal and valence score of them were 7.05 and 1.54, respectively); Number of pictures in IAPS dataset for normal mode elicitation were: 1026, 1121, 1303, 1390, 2025, 1560, 1820, 2018, and 1112 (the mean of arousal and valence score of them were 5.15 and 5.16, respectively)

2. Number of sounds in IADS dataset for negative mode elicitation were: 424, 276, 275, 277, 278, 279, 285, and 290 (the mean of arousal and valence score of them were 6.79 and 1.79, respectively); Number of sounds in IADS dataset for normal mode elicitation were: 107, 104, 102, 252, 170, 152, and 132 (the mean of arousal and valence score of them were 5.03 and 5.10, respectively).

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