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Database for an emotion recognition system based on EEG signals and various computer games – GAMEEMO☆

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ABSTRACT

In this study, electroencephalography-based data for emotion recognition analysis are introduced. EEG signals were collected from 28 different subjects with a wearable and portable EEG device called the 14-channel EMOTIV EPOC+. Subjects played 4 different computer games that captured emotions (boring, calm, horror and funny) for 5 min, and the EEG data available for each subject consisted of 20 min in total. The subjects rated each computer game based on the scale of arousal and valence by applying the SAM form. We provide both raw and preprocessed EEG data with.csv and. mat format in our data repository. Each subject's rating score and SAM form are also available. With this work, we aim to provide an emotion dataset based on computer games, which is a new method in terms of collecting brain signals. Additionally, we want to determine the success of the portable EEG device and compare the success of this device with classical EEG devices. Finally, we perform pattern recognition and signal-processing methods to observe the performance of our dataset and to classify EEG signals based on the arousal-valence emotion dimension and positive/negative emotions. The database will be publicly available, and researchers can use the dataset for analyzing signals for their own proposed method in the literature.

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1. Introduction

Emotion can be defined as a reaction to external stimuli and represents human consciousness. It affects peoples' routine lives all the time and plays a vital role. Emotions such as happiness, sadness, boredom, and anger are the basic emotions that, are always used by people intentionally or unintentionally. People make decisions based on their mood; thus, negative emotions can cause not only psychological problems but also physical problems. Unfavorable emotions can lead people to acquiring bad health conditions while positive emotions provide better life standards [31,8].

Many researchers perform studies about emotion recognition in order to understand the nature of emotions. It is difficult to comprehend the emotional state of people since emotion is an abstract concept and there is no subjective conclusion regarding which emotion is reflected from subjects [30]. Furthermore, there is a large number of ways to collect and analyze data from patients who makes the conclusion process more complex and takes time. Due to these reasons, the development of a computer-based system and machine learning is required [50].

1.1. Stimuli

In the emotion recognition system, there are typically three types of stimuli including aural, visual and aural/visual stimuli. In aural stimuli, generally, sounds are applied in order to stimulate the subject's feelings by affecting the sensation. Sounds are labeled based on their genre such as sad, funny, etc. The most well-known aural dataset is IADS (International Affective Digitalized Sounds), which is available publicly for researchers [5]. Visual stimuli consist of various pictures or images labeled with different names. The aim of the stimuli is to affect the subject's eyesight to extract emotions. The most popular stimuli is IAPS (International Affective Picture System) for visual stimuli [24]. However, studies show that these methods are not effective; thus, it is observed that the best stimuli for emotion extraction is aural-visual stimuli [20]. To the best of our knowledge, there is no database on computer games. To fill the gap in the literature, we perform this line of work by providing computer games-based brain signals and alternative aural/visual aided EEG signals.

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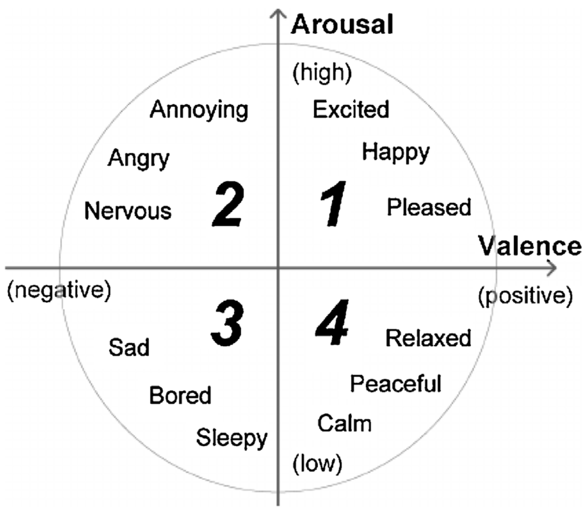


Fig. 1. Arousal-valence emotion model [43].

1.2. Emotion models in the literature

There are two types of emotion models (discrete and dimensional) used in the literature. Discrete emotion models include two types of emotions (positive-negative) and contain eight different main emotions, which are anger, anticipation, joy, trust, fear, surprise, sadness and disgust [11]. On the other hand, the dimensional space includes two models: the arousal-valence coordinate system and emotion wheel. The arousal-valence coordinate model was first introduced by Russel in 1980 [42]. In the arousal-valence coordinate system, emotions are distinguished into four different areas. The left side of the coordinate represents the negative emotions while the right side shows the positive ones. They both represent the valence axis. In other respects, the arousal axis ranges from inactive to active emotions. Fig. 1 illustrates the arousal-valence emotion model. According to Fig. 1, the first area includes high arousal positive valence (HAPV) emotions ranging from pleased to excited. Area 2 ranges from nervous to annoying emotions called high arousal negative valence (HANV). Area 3 consists of three negative emotions (sad, bored and sleepy) and can be represented as low arousal negative valence (LANV). The last area is called low arousal positive valence (LAPV) which includes calm to relaxed emotions. As seen in Fig. 1, the first two zones indicate high arousal (active) emotions, while the last two zones specify the low arousal (inactive) emotions.

Another dimensional model is the emotion wheel defined by Plutchick in 1980 [39]. According to this emotion type, basic and advanced emotions are placed together and create an emotion wheel. In this model:

- Emotions are placed based on their intensity and volume.
- Neighbor emotions are more similar than other emotions.
- Emotions congregate and create more complex emotions.
- Emotions and their oppositions are placed mutually in the wheel.

The basic eight emotions (anger, anticipation, joy, trust, fear, surprise, sadness and disgust) are organized based on colors and create a similar emotion. Basic emotions generate more complex emotions. For instance, surprise and sadness create disapproval. Likewise, trust and fear create submission. Moreover, the intensity of emotions becomes lower while moving in the outer part of the wheel. In the emotion wheel, opposite emotions are also formed with basic emotions. For example, the opposite emotion of grief is joy. Likewise, the opposite emotion of love (joy + trust) is remorse (sadness + disgust). As seen the equation depicts, sadness as the opposite emotion of joy, whereas trust is the adverse emotion of disgust.

The discrete emotion model is easier to implement since it classifies the specific emotions. Nevertheless, it is not universal. In some languages, specific emotions cannot be expressed [41]. On the other hand, arousal-valence is international and well-studied. With this model, emotions are not expressed with their names but their coordinate locations. In this case, anger is represented as HANV.

To collect EEG based emotion signals, the arousal-valence emotion model is applied in this work. We mentioned earlier that the discrete emotion model is not universal since some of the emotions do not have any definition in some languages. To eliminate this problem and to make our dataset universal, a dimensional emotion model is performed in this study.

1.3. Emotion datasets in the literature

Collecting EEG data and generating effective databases for emotion recognition studies play an important role. Recent developments in emotion recognition studies have impelled the creation of novel databases including emotional expressions. These databases generally consist of speech, visual, audio-visual and physiological signals [16,35,10,14,9,36,21]. Visual databases generally include body gestures and/or facial expressions. Audio based databases carry emotional speech in different languages. Physiological signals consist of EEG, EMG, GSR, etc., signals collected from subjects with various stimuli.

In the study of [35], a web-based emotional database (MMI) was created. The database contains spontaneous and posed facial expressions of subjects. Images and videos of subjects were collected from only the frontal and profile perspective. It includes 90 subjects, and 60 of them acted employing different basic emotions, while the remaining ones reacted to emotional videos. One of the most effective databases is the Belfast database (BE) which was generated by the authors in [9]. It includes spontaneous reactions of subjects in TV talk shows. Despite the fact that the database is very rich in facial expressions and body gestures, the diversity in the background makes the data complex and challenging for the emotion recognition process. Later, this database was included in a much larger database HUMAINE [10]. The HUMAINE database consists of nine datasets that include three naturalistic and six induced reactions datasets. The number of subjects change from 8 to 125 in various datasets. Another example of an audio-visual database is VAM (Vera Am Mittag) [14]. Analogous to [28,9], it includes spontaneous reactions of subjects during a German talk show. In the database, 12 h of audio-visual recordings exist and these recordings were labeled as valence, activation, and dominance.

Compared to audio-visual databases, there are fewer publicly available physiological databases. The first affective physiological emotion dataset was created by the authors in [16]. In the dataset, reactions of 17 different drivers under different stress levels were collected. Additionally, the recordings include ECG, EMG, and GSR. Another example of a physiological database is the MANHOB database [36] that includes three different datasets consisting of voice signals, EEG signals and mimics. MAHNOB HCI is the dataset that only contains physiological signals [47]. Thirty different subjects participated in the experiment, and aural-visual stimuli, including movies and pictures, were applied. The researchers used different devices such as a microphone, an eye gaze tracker, ECG and EEG (32 channels) signals and skin temperature. The study includes two parts. In the first part, subjects watched 20 different movies, and after the movie ends, they were asked to rate their emotional feelings based on the valence-arousal scale. In the second part of the experiment, subjects were shown video fragments or images with labels. Participants were asked to press green and red buttons according to the labels to determine which label is correct and wrong, respectively. Images were applied from the IAPS dataset. The detailed information and related works can be found in [15,24]. Another dataset is the DEAP [21] emotion dataset that includes only EEG signals based on aural-visual stimuli (music clips). Thirty-two participants participated in the study, and 32 EEG channels were applied. In the study, 40 different videos were used, and the subjects rated their feelings according to SAM ratings including valence, arousal, familiarity, dominance and liking. In their study, they applied Russel's valence arousal scale [42]. There are many emotion applications that can be found in the literature based on DEAP emotion [34,7,53,37,22,2,38,54,49,26].

As can be seen, while there are sufficient emotion data, we have observed that there are insufficient emotion data based on physiological signals. Consequently, we provide an alternative dataset including physiological signals. Moreover, in the literature, data are collected from traditional 32 channel EEG devices. Similar to our data collection process, MANHOB-HCI and DEAP applied aural-visual stimuli; however, the main difference of our dataset is the type of aural-visual stimuli. In the literature, EEG data are obtained from two different types of stimuli: music clips or short movies. On the other hand, we choose computer games as stimuli rather than traditional types. The main idea behind our approach is, that computer games are effective not only in a physical way but also in a psychological way [44,25]. With short movies or clips, subjects just watch and listen to the sounds of the ambience. However, with computer games, subjects not only watch or observe the stimuli but they also experiment with the scene as a first person. They take on the role model of the gaming characters, and this affects the emotions of the subjects in a different way [6,32]. Emotional states are obtained from games based on two inputs: Game events and gameplay [13]. Game events represent the story, sound, atmosphere, etc., of the game. On the other hand, the gameplay is about the controller of a character. According to the article [44], emotions of people depend on three domains:

- Autonomy: Represents the feeling that is generally used intentionally or unintentionally to control actions, making decisions and thoughts.
- Competence: Is human nature to complete the necessary tasks.
- Relatedness: Represents the capability of people to others. This can be achieved by social interactions or feelings for the greater community.

Their work shows that computer games are a great method to stimulate these domains, and as a result, to observe the emotional states. Another difference in our study is the method for collecting data from subjects. In the literature, researchers obtain EEG data with traditional EEG devices. We propose a database based on a wearable and portable EEG device which has 14 EEG channels. In the later sections, we discuss the performance of our EEG device.

2. EEG dataset

EEG signals are collected from 28 various subjects from students of Firat University Faculty of Technology in the Department of Software Engineering. The range of ages varies between 20-27. The health conditions of subject's were good and there was no disease history. To observe and determine the performance of the portable and wearable EEG, the 14 channel EMOTIV EPOC+ Mobile EEG device is used. Various technical information about the device is provided as follows:

- EEG electrodes are located 16 different scalp zones (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, P3 and P4) since our EEG device has predefined 16 electrode locations. In the literature, well known EEG datasets are generated using a 32-channel EEG device. However, in this study, we used a 14 channel EEG device (16 EEG locations exist, yet two of them, P3, and P4 are reference electrodes) which differs from the existing ones. Reference electrodes, are used to arrange the device to collect signals properly. Therefore, in our dataset 14 EEG channels are applied. Fig. 2 shows the electrode locations.

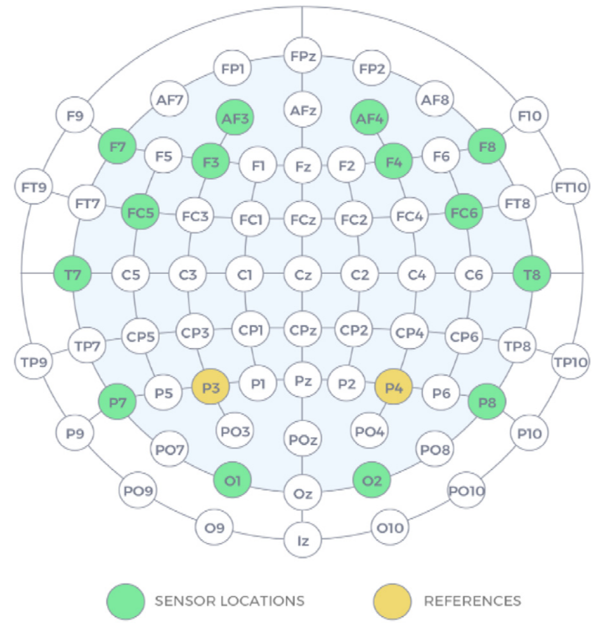


Fig. 2. Sensor and reference electrode locations [12].

- Connectivity established via Wi-Fi.
- The sampling rate of the device is 2048 Hz. However, we downsample the rate to 128 Hz.
- The bandwidth of the signals is 0.16 Hz and 43 Hz. The output of the amplifier is controlled by high and low-frequency filters. The low and high-frequency filter values are used to set the window within which the EEG activity is recorded. This is called bandwidth. It can be emphasized as a range of frequencies that occur in a given band in order to transmit the signal. In our case, the minimum frequency is 0.16 Hz, and the maximum frequency is 43 Hz.
- Our dataset consists of two types of EEG signals: raw and preprocessed. To preprocess the signals, the 5th order sinc filter is applied, which is a built-in filter of this device. We used this filter since the device includes it. The main idea in using the sinc filter is to remove all frequency components above a given cutoff frequency without affecting the lower frequencies. In our case, we used this filter to remove artifacts resulting from movement of hands, head, and arms. The device is able to remove these artifacts and external artifacts.
- The device can be used in various platforms (Windows, MAC, IOS and Android). In our work, the Windows operating system is considered.

The EEG dataset is composed of aural-visual stimuli that correspond to four different computer games that are applied. Each game is labeled according to their genres as boring, calm, horror and funny. We provide the gameplay (first several minutes of these games) in our datasets and mention the game's background information. Genres are determined by the professional game critic services [19,29,48]. Each subject played each computer game for 5 min, and we obtained EEG data that were 20 min long in total from each subject. EEG signals are collected from various EEG channels

Table 1
Comparison of EEG data.

Dataset	Subjects	EEG channels	Samples	EEG data
DEAP	32	32	8064	40,960
MANHOB HCI	27	32	540	17,280
GAMEEMO	28	14	38,252	1568

during the data obtaining process, which means that in our dataset, there are 1568 ($4 \times 14 \times 28$) EEG data available that are 20 min long, and the total number of samples is 38,252. Four refers to the applied number of games, 14 means EEG channels and 28 shows the number of subjects. Both.csv and. mat format are also available in our dataset for both raw and preprocessed EEG signals.

Our data are collected from 28 various subjects with 14 EEG channels, which are fewer channels than that used in the existing datasets. However, we have overcome this problem by increasing the number of samples. Table 1 shows the comparison of the datasets with respect to the data.

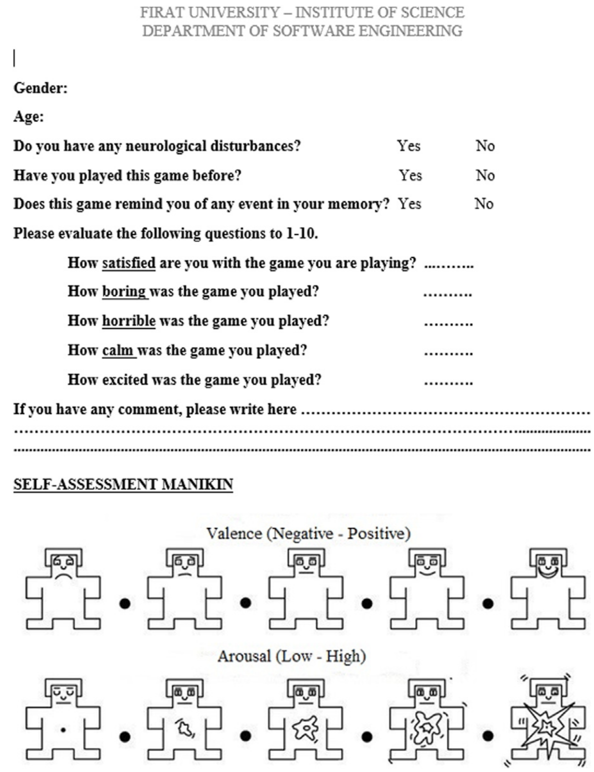
3. Experimental setup

As mentioned earlier, EEG signals are obtained from aural-visual stimuli. Subjects played 4 different computer games and during that time, EEG signals are extracted from them. The experiment was conducted in a dark and quiet room within the university. Video games were played on a notebook computer with a 15.6-inch screen. Various technical information about the computer is as follows:

- Intel Core i7-4710MQ processor with 2.50GHz (boosted to 3.2GHz)
- 16 GB RAM
- 16 GB GTX980M Graphic Card

All computer games are played with ultra-settings to make the screen more realistic and render the object of high quality. During the experiment, subjects wore The EMOTIV EEG device and earphones. Before the experiment began, subjects needed to relax, and they had to focus on the screen. To do that, first subjects closed their eyes for 10 s, and afterward, they opened their eyes again for 10 s. It is a built in procedure of the EMOTIV PRO License, which is an application to collect EEG signals. The PRO license helped us to fit the headset correctly and directed us regarding which EEG channels represent good quality (green light) or bad (red light). By monitoring the EEG channels, we were able to track the problematic electrodes and corrected them. We did not perform the experiment until every EEG channel had good quality. When the quality reached 100%, we applied the next stage. In the next phase, we notified the subjects that he or she can play the game. After starting the play, we performed data collection.

It is essential that players should not move their heads, arms or legs to ensure that signals will not contain many artifacts. However, it is difficult to perform this since playing computer games requires some body movements, mimics and body language. Unintentionally, our data consist of some artifacts generated from subjects' movements; thus, we employed the built-in filter to denoise the signals, as mentioned in Section 2. After 5 min of the game, we notified the subjects to close the game. Then, we stopped the EEG collection. Subsequently, we launched the next game and performed the same procedure until every game (4 games) was played. The application allowed us to track each EEG channel and provided the subject's mental information such as stress, engagement, interest, focus, excitement and relaxation. However, we did not use this information in our study. Subjects did not know the labels of the games, so they could not be influenced by the game itself. We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Gender:

Age:

Do you have any neurological disturbances? Yes No

Have you played this game before? Yes No

Does this game remind you of any event in your memory? Yes No

Please evaluate the following questions to 1-10.

How satisfied are you with the game you are playing? ....

How boring was the game you played? ....

How horrible was the game you played? ....

How calm was the game you played? ....

How excited was the game you played? ....

If you have any comment, please write here ....

SELF-ASSESSMENT MANIKIN

Fig. 3. SAM form used in this study.

presented the games in the same order to each subject, namely, are boring, calm, horror and funny. Boring and horror are negative emotions, while the remaining ones are considered positive emotions. Moreover, we chose these emotions since each emotion has a different location in the arousal-valence dimension. In that way, researchers will be able to use this dataset for both discrete emotion estimation and dimensional emotion estimation applications. In our dataset, games are labeled G1, G2, G3, and G4. G1 refers to the first game which is a boring game; G2 means the second game which is a calm game, and so on. As seen in the process described above, subjects played the games in the same order. This may cause some problems such as cumulative and counteracting effects of emotions for each subject. To overcome this problem and to determine the accuracy of the signals, we implemented the SAM (Self-Assessment Manikin) form for each subject. After each play, subjects filled-in the form to allow us to determine the accuracies of the signals and to help us to decide whether the label of the game and subjects' feelings resemble each other. Fig. 3 shows the SAM sample used in our study. In Fig. 3, there are some questions and the SAM. The main idea behind the questions is to collect the health background of the subject's (disorders, gender, age) and conduct the experiment in an objective way.

The aim of the questions is to determine the objectivity of the signals. The explanations of the questions are given below:

- Have you played this game before? It is asked to understand whether the specific game is new or not for the subjects. If subjects played the game before, it is likely he or she knows the next scene, and feelings do not resemble the right things. The subject will likely know what comes next and can prepare himself/herself such that being afraid or bored or excited, etc., is not shown. In that way, subjects can manipulate their real intentions, which can make the signals unreliable. In this line of work, we observed that no subjects have played these games before.

- Does this game remind you of any event in your memory? In emotion estimation studies it is important to select the right stimuli. The study in [42] shows that if any event serves to be a remainder of something from the past to the subjects, feelings will become more intense. By using this information, we asked this question to analyze the changes in the signals. It is observed that when the game reminds the subjects of something, their EEG signals show sharp peaks and valleys.
- How satisfied are you with the game you are playing? This question does not have any effect on the experiment. It is used to understand the mental conditions of the subject's to determine whether he or she had a good time and was relaxed or not during the experiment. The subjects rated this question from 1 to 10 according to their feelings. Specifically, 1 means they did not enjoy the game, and 10 indicates that they loved the play in that game.
- How boring was the game you played? The subjects rated this question based on their feelings according to boredom. Boredom increases from 1 to 10 which means the game is not dull if the score is 1, and the game is exceptionally dull when the score reaches 10. Moreover, 5 refers to a neutral feeling on that game. Boring refers to a negative emotion, and it has a location in the third zone (low arousal negative valence) of the arousal-valence dimension space. The first game on the experiment was a dull game which is intended to obtain negative and LANV EEG signals.
- How horrible was the game you played? The subjects rated this question based on their feelings according to fear. If the subjects rate the game as 10, it means that this game is truly scary. On the other hand, a rating score of 1 indicates that the game is not scary at all, and the subject is truly enjoying the game. In addition, 5 indicates the feeling on that game is neutral. Similar to boredom, fear/stressed refers to negative emotions and has a location in the second zone (high arousal negative valence) of arousal-valence dimension space. This was the third game of the experiment, and it is used to stimulate the negative emotions of subjects.
- How fun was the game you played? The subjects rated this question based on their feelings according to funniness. Similar to other questions, this question requires a rating score from 1 to 10. If subjects truly enjoyed the game, they should award it a score of 6 or higher. However, every score less than 5 means that the game is not funny at all. Funny refers to a positive emotion, and it has a location in the first zone (high arousal positive valence) of the arousal-valence dimensional space. This was the last game played during the experiment, and it is used to extract positive emotions from subjects.
- How calm was the game you played? The subjects rated this question based on their feelings according to emotiveness. Emotiveness increases from 1 to 10, which means the game is not calm if the score is 1, and the game is truly relaxing when the score reaches 10. In particular, 5 refers a neutral feeling on that game. Calm refers to a positive emotion, and it has a location in the fourth zone (low arousal positive valence) of the arousal-valence dimension space. The second game in the experiment was a calm game that is intended to obtain a positive emotion.

3.1. Information about the games

In this part, computer games that are used to collect EEG signals are discussed. All computer games are selected based on the global labels and user rated scores. Furthermore, all games are activated through game platforms (Steam, Origin), which means they are all legal games. As mentioned earlier, we applied four different video games including boring, horror, funny and calm types. The following are the games used in this work:

- Train Sim World: We chose this game as a boring game based on global scores, comments and criticisms. It is a simulation game, and it makes gamers control the train. We observed that during an experiment, all of our subjects were bored with this game since some technical information about the trains necessary. Only the machinists or the experienced players who played previous versions of the game can understand the control mechanisms of the game. Nearly all of them did not understand the game, and they just pushed some buttons randomly on the keyboard. In our dataset, we labeled this game as G1. It was applied to extract LANV and negative emotion.
- Unravel: This game was applied as a calm game in our work. In this game, subjects controlled the yarn that tries to fix the broken bonds of the people. It is a relaxing game since the kinds of music, sounds and the atmosphere of the game are slow and relieving. We observed that during the experiment, subjects understood the game mechanics, and we saw they listened to the music of the game. That stimulated their brain and they seemed relaxed. In our dataset, this game is labeled as G2, and we applied this game to extract LAPV and positive emotion.
- Slender – The Arrival: This game was selected as a horror game. In this game, players discover a house and many rooms in order to defect from the place. Players do not have any materials except a camera which shines on the dark places. The atmosphere is quite dark and sounds are very disruptive. It was the most difficult game in our dataset because some of the subjects were scared and splashed during playing the game. In our dataset, this game is labeled as G3, and we employed this game to obtain HANV and negative emotion.
- Goat Simulator: In this game, players acted like a goat and performed some funny things including attacking houses, licking walls, jumping, etc. The atmosphere and sounds are very charming, and we observed most of the subjects had a smile on their faces while playing this game. This was the last game in our dataset and labeled as G4. With this game, we intended to collect HAPV and positive emotion.

In the dataset, all information and background of the games are available. Additionally, we provided the gameplay of each game to enable researchers to correctly comprehend the games and their mechanics, sounds, and atmosphere.

4. Analysis of signals

In this part, we mention the statistical analysis of the data and provide the classification performance based on time-frequency analysis with different classifier algorithms.

4.1. Statistical analysis of the subjects ratings

Some statistical analyses are evaluated and presented in this section. The main idea is to understand and determine the effect of stimuli. First, the standard deviation, variance, mean and distribution of ratings are calculated, and the relationship between the ratings is described. Additionally, ANOVA (analysis of variance) results are presented to determine the effects of the game on the subjects. In the last section of this part, the Friedman test for arousal-valence is also added.

Aural-visual stimuli are selected to obtain emotions from subjects based on the arousal-valence emotional space. In the HAPV zone, arousal and valence ratings should be higher than 5, which means subjects have a good time with the stimuli, and it affects the positive part of the emotions. On the other hand, HANV values should refer to different ratings. Arousal value should be higher than 5 while, the valence value should be lower than 5. Since this

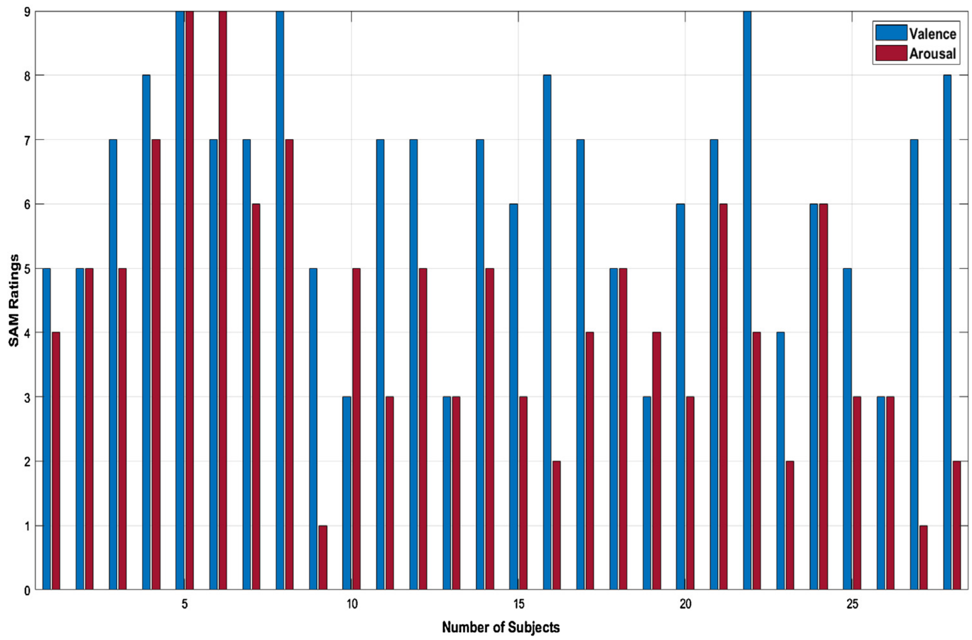

Fig. 4. User SAM ratings for LAPV.

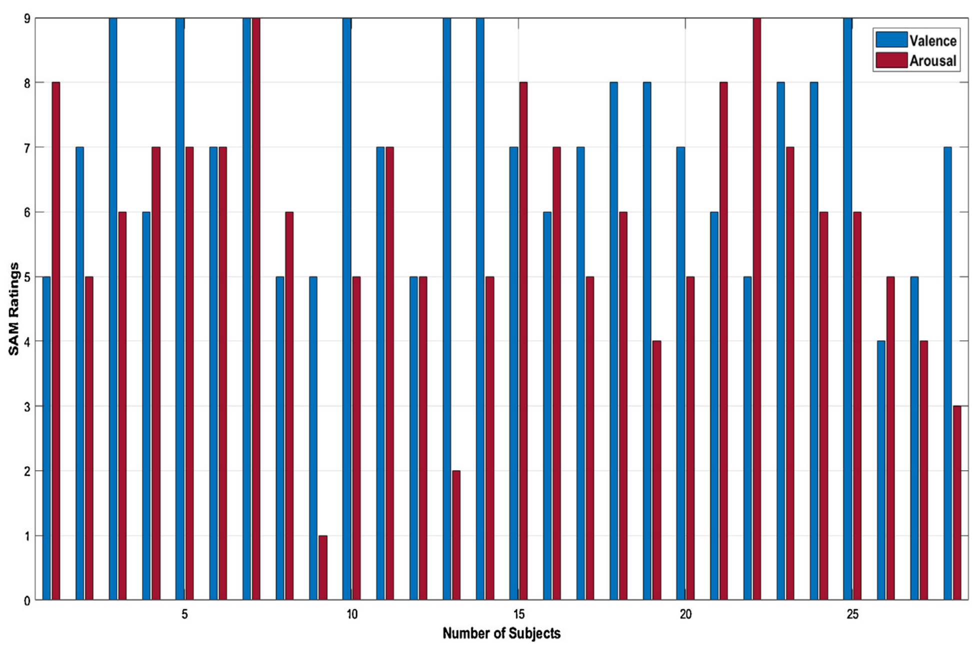

Fig. 5. User SAM ratings for HAPV.

zone is about negative emotions, it should stimulate the negative part of the brain. Similar to HANV, LANV is also about negativeness. Both the arousal and valence values should be lower than 5. LAPV is the last zone of the space, and it affects the positive part of the brain. The valence value should be higher than 5, while the arousal value should be lower than 5. Tables 2 and 3 show the mean, variance and standard deviation of all zones. As seen in Tables 2 and 3, all zones resemble the information given before. PV (positive valence) values should be higher than 5 to be considered as positive. Game 4 (G4) and Game 2 (G2) are the positive games, and their average ratings are 7 and 6.1789, respectively for PV or positive emotion. A similar approach can be performed for NV (negative valence). When valence values are lower than 5, it means it is a negative emotion. Game 3 (G3) and Game (G1) are the negative efficient games. As can be seen in Table 1 again, an average value for G3 is 2.6429 and G1 is 3.3571, which are highly good results for negative emotion or NV. Figs. 4 and 5 show the user ratings for PV values for LA (low arousal) and HA (high arousal), respectively. Likewise, Figs. 6 and 7 illustrate the user rated NV values for LA and HA, respectively.

Table 2
The standard deviation, average and variance values of different ratings of arousal (ratings 1–9) on the dimensional zone.

Game	Zone	Average	Std. dev.	Variance
G4	HAPV	5.7500	1.9255	3.7077
G3	HANV	6.3929	2.0063	4.0251
G1	LANV	2.5714	1.2889	1.6614
G2	LAPV	4.3571	2.0943	4.3862

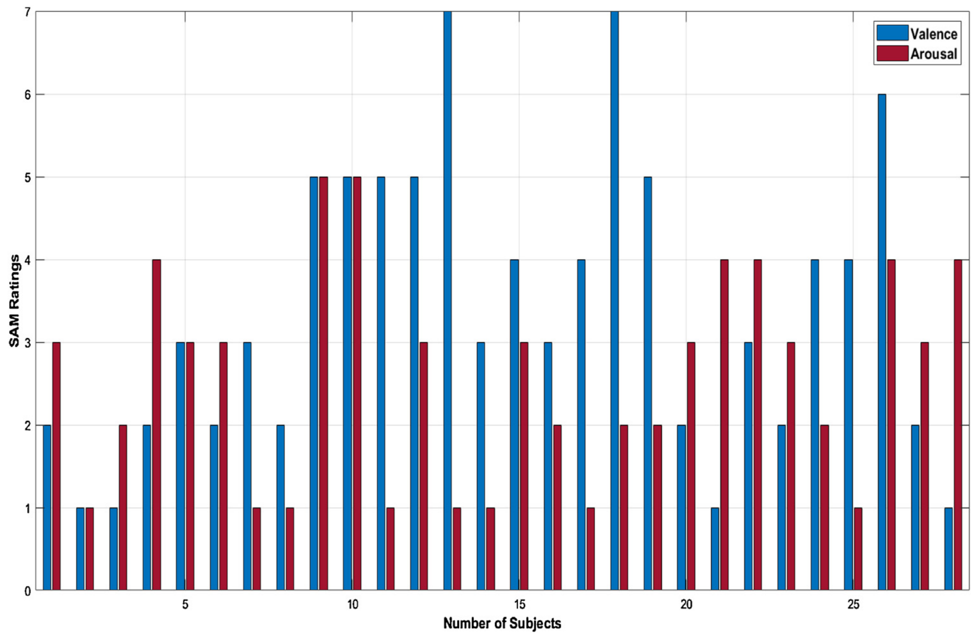

Fig. 6. User SAM ratings for LANV.

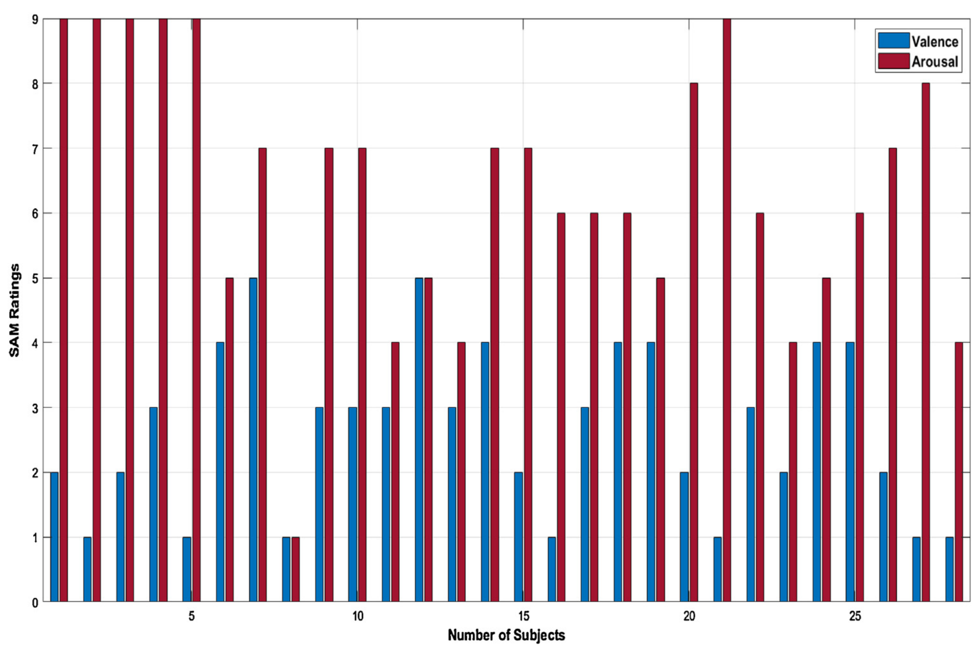

Fig. 7. User SAM ratings for HANV.

Table 3
The standard deviation, average and variance values of different ratings of valence (ratings 1–9) on the dimensional zone.

Game	Zone	Average	Std. dev.	Variance
G4	HAPV	7.0000	1.5870	2.5185
G3	HANV	2.6429	1.2828	1.6455
G1	LANV	3.3571	1.7683	3.1270
G2	LAPV	6.1786	1.8470	3.4114

In Fig. 8, the distribution of users ratings is given. There are six parameters in the figure (valence (V), arousal (A), boring (B), calm (C), horror (H) and funny (F)) with SAM ratings. According to the scatter plot, there is a high correlation between calm and funny emotions for both PV-based zones HAPV and LAPV. These two emotions are higher than 5, even though one is LA and the other one is HA. The same relation can be deduced for negative emotion in the positive valence dimension. For both HAPV and LAPV, the distribution plot showed that boring and horror are lower than 5, meaning they are negative and do not have any effect on this dimension and the subjects. However, the same correlation was not obtained from the NV-based zones. In HANV, the subject's ratings specified that while they had a fear component from the game, they did not have a boring component from that game. Both of them are negative emotions; however only horror ratings are higher than 5. Calm and funny are lower, which they are supposed to be, yet boring is also lower than 5. Similar to LANV, subjects played a boring game and the ratings showed us the game is truly boring for them. However, the game is also relaxing. They are the contrary emotions, yet in

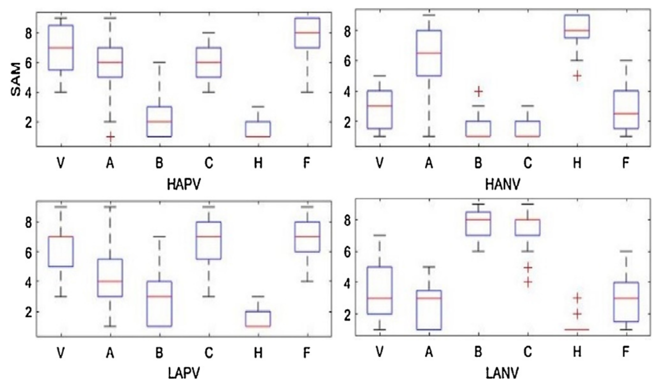

Fig. 8. Distribution of subject's ratings based on different computer games.

Table 4
ANOVA results.

Variable	Variation name	Sum of squares	Dif.	Mean square	f-test	Sig.
Valence	Between groups	377.313	3	125.771	47.007	.000
	Within groups	288.964	108	2.676	–	–
	Total	666.277	111	–	–	–
Arousal	Between groups	244.789	3	81.595	23.684	.000
	Within groups	372.071	108	3.445	–	–
	Total	616.857	111	–	–	–

Table 5
Tukey test results for valence.

Experiment	Subset for $\alpha = 0.5$	
	1	2
G1	–	2.6429
G2	–	3.3571
G3	6.1789	–
G4	7.0000	–
Sig.	0.243	0.364

the LANV zone, their ratings are nearly the same. Moreover, the plot showed us the boring game did not scare the subjects; thus the horror parameter is too low (nearly zero) on that zone. They are both negative emotions (boring and horror), but they do not have the same effect on subjects. The main reason behind this distinctness is that both boring and calm are the LA emotions.

ANOVA results are collected from the SPSS version 20.0 program. Table 4 shows the ANOVA for arousal-valence emotional states. As can be seen in Table 4, the f-test score calculated for valence is 47.007 while the f-test score obtained for arousal emotion is 23.684. The p-values are measured as 0.000, which are lower than 0.0001, meaning they are very significant since at least one of the means shows a difference in the analysis.

To test the different groups, the Tukey test technique is applied with a 0.05 alpha value for both arousal-valence coordinate system. The results for valence are given in Table 5. At the significance level of $p < 0.05$, G1 and G2 form a different group, while G3 and G4 form another group. In other words, the difference between the average values of G1 and G2 is trivial at a significance level of 5%. The same inference can be achieved for G3 and G4.

Table 6 shows the Tukey results for the arousal dimension. At the significance level of $p < 0.05$, G1 forms a group, G2 forms another group, while G3 and G4 form another group. In other words, the difference between the average values of G1 is trivial, G2 is not significant, and G3 and G4 are negligible at a significance level of 5%.

ANOVA results are also given as figures in Figs. 9 and 10 for both valence and arousal, respectively.

Table 6
Tukey test results for arousal.

Experiment	Subset for $\alpha = 0.5$		
	1	2	3
G1	–	2.5714	–
G2	–	–	4.3571
G3	5.8214	–	–
G4	6.3929	–	–
Sig.	0.658	1.000	1.000

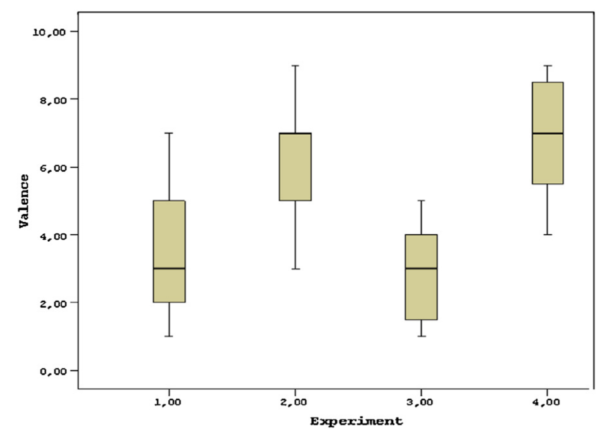

Fig. 9. ANOVA results for valence dimension.

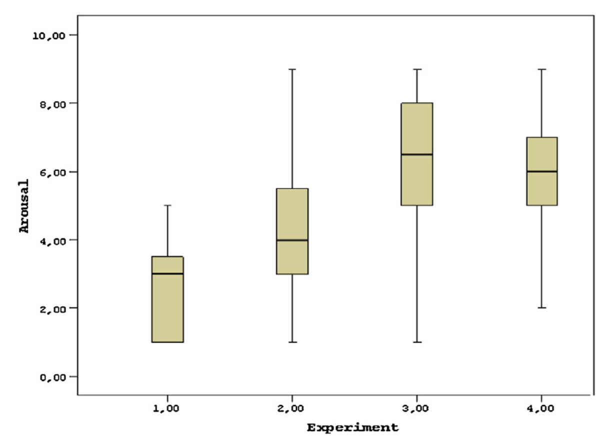

Fig. 10. ANOVA results for arousal dimension.

Table 7
The Friedman test results for the arousal and valence space.

Zone	N	Chi-square	Dif.	Sig
Arousal	28	45.514	3	0.000
Valence	28	52.992	3	0.000

As a result, subjects' ratings show that the selected games for aural-visual stimuli are a good choice since we obtained the desired ratings and EEG signals. Games stimulated the exact parts of the brain, and SAM and the user ratings specified that result.

We also performed the Friedman test to determine the differences between valence and arousal zones. It is a non-parametric analysis that is an alternative the ANOVA analysis. Table 7 shows the Friedman test results for both arousal and valence space.

N represents the number of subjects, which is 28 in our case. Chi-square and degrees of freedom are calculated as 45.514 and 3, respectively, with the significance level 0.000. It can be inferred that at least one of the median arousal and valence scores of these four zone types (LANV, HANV, HAPV, and LAPV) is different. During the calculation of the Friedman test, we also evaluated the mean ranks between these zones. In arousal, LANV and LAPV showed similar mean ranks (1.39 for LANV, 2.16 for LAPV) which specifies that the similar zones show similar results. A similar inference can be made for HANV and HAPV zones since the mean ranks scores are obtained as 3.45 and 3.00, respectively. In valence, LANV, and HANV show close mean rank results, which are 1.91, and 1.45. Additionally, we calculated the mean ranks for the positive valence for low arousal and high arousal as 3.13 and 3.52, respectively. They produce similar results since they are in the positive valence zone.

4.2. EEG-based emotion estimation

In this section, the emotion recognition application is discussed based on this dataset. We perform some time-frequency analysis and feature extraction methods to classify the EEG channels for both the arousal-valence dimension and positive-negative emotions with different classifiers. The main idea of this application is to show the performance and classification accuracies of this dataset and to specify the success of a portable and wearable EEG device against traditional EEG devices.

We perform the discrete wavelet transform (DWT) for the frequency-time analysis process, and original EEG signals are decomposed into 4 different sub-signals since it is known that the beta and gamma sub-signals are the best EEG rhythms for emotion detection systems and provide the most reliable results for the detection processes [21,52]. The Daubechies 2nd order filter is applied and D1, D2, D3, D4, and A4 detailed and approximate coefficients are collected. Then, some feature extraction methods are applied including statistical, chaotic and time-frequency analysis features. Detrended fluctuation analysis, Hjorth features, average energy of wavelet coefficients, Shannon entropy, logarithmic energy entropy, sample entropy, multiscale entropy, standard deviation, variance and zero-crossings are the key features from each EEG channel and each sub-signal. Detailed information for these features can be seen in [45,17,46,3,40,27,1,51,4]. Later, three different (SVM, kNN, and MLPNN) classifiers are used to classify the EEG channels based on positive-negative emotion estimation and arousal-valence dimension classification. Fig. 11 shows all classifiers classification processes for discrimination of emotions.

The parameters for each classification process are given in detail below. Parameters for the kNN (k-nearest neighbor) classifier can be defined as:

- Distance metric is considered as Mahalanobis.
- Number of neighbors (k) is determined as 6.
- Weights for all points in each neighborhood are split equally.
- Max iteration is selected as 300.
- To test the classifier, 10-fold cross-validation is used.
- To determine the performance of the classifier, accuracy and kappa results are obtained.

The main reason for selecting these parameters is based on the trial and error approach. They give the best results for classification of both arousal-valence and discrete emotions within the other parameters; thus, these parameters are considered in our classification process.

Parameters for SVM (support vector machines) classifier can be defined as follows:

- C (penalty parameter) is defined as 1 which is a default parameter for the SVM classifier.
- Kernel function is selected as RBF (radial basis function). All other kernels are also considered including linear, poly, sigmoid, and precomputed; however, the best performance is obtained from this kernel.
- Class weights are determined as balanced; thus, all weights are automatically adjusted based on the input frequencies.
- Max iteration is selected as 300.
- To test the classifier, 10-fold cross-validation is used.
- To determine the performance of the classifier, accuracy and kappa results are obtained.

Similar to kNN classifier, all of these parameters are considered via a trial and error approach. The best performance for each emotion state is obtained from these parameters; thus, they are selected as primary parameters in our study.

The last classification method is MLPNN (multi-layer perceptron neural network) and its parameters are given below:

- Two hidden layers with 10 neurons are applied in this classification process.
- Activation function is selected as ReLU.
- Solver parameter is determined as SGD (stochastic gradient descent).
- Learning rate is set up as adaptive; thus, learning rate is constant as long as training loss keeps decreasing.
- Max iteration is selected as 250.
- Momentum is determined as 0.9 which is a default parameter.
- To test the classifier, 10-fold cross-validation is used.
- Accuracy and kappa results are used as performance criteria.

Similar to other classifiers mentioned earlier, all parameters are chosen based on the best performances. These parameters provide better accuracy results for both binary and multi-class emotion states. Tables 8 and 9 show the classification accuracy with all classifiers for both binary and multi-class classification. The iteration of MLPNN is lower than the other classifiers since we observed that the success of the classification of MLPNN decreases with more than 250 iterations. That is why we select the max iteration as 250 in our study.

As seen in Table 8, the best accuracy is obtained from the AF4 EEG channel in the kNN, which is 55.3%. In general, the kNN classifier did not perform well for our dataset since the kNN is a good classifier when data have some artifacts. When we analyze each EEG channel based on the arousal-valence dimension, the performance for each zone showed different accuracies. The HAPV zone shows the best evolution in the FC5 EEG channel with a 54.0% accuracy. Another positive emotion (LAPV) depicts the best performance in AF4 and F8 EEG channels with the same accuracy of 53.0%. On the other hand, the negative emotional states specify better performance against the positive ones, which can be seen in the same EEG channels. F8 classifies the HANV emotions with 62.0% accuracy, and AF4 discriminates the LANV emotions at 61.2%. On the other hand, for the SVM classifier, the best accuracy is obtained from T8 EEG channel, which is 78.5%. When we analyze each EEG channel based on the arousal-valence dimension, each zone shows different accuracies. The HAPV zone specifies the best evolution in the F7 EEG channel with 85.0% accuracy. Another positive emotion (LAPV) depicts the best performance in O1 with an accuracy of 72.0%. On the other hand, negative emotional states specify at better performance against the positive ones. T8 classifies the HANV emotions with 96.0% accuracy, and P8 discriminates the LANV emotions with 73.2%. MLPNN achieved the best classification results between other classes with an average accuracy of 73%. Similar to kNN classifier, the best accuracy collected from the frontal zone of the scalp with 82.2% in the F4 EEG channel. HAPV emotions are classified with 91.0% accuracy via the AF4 channel, while F4 discriminates the positive emotions on low arousal with 85.8%. Negative emotions are performed best in FC5 and AF3 EEG channels with 83.0% and 94.6% accuracy on high

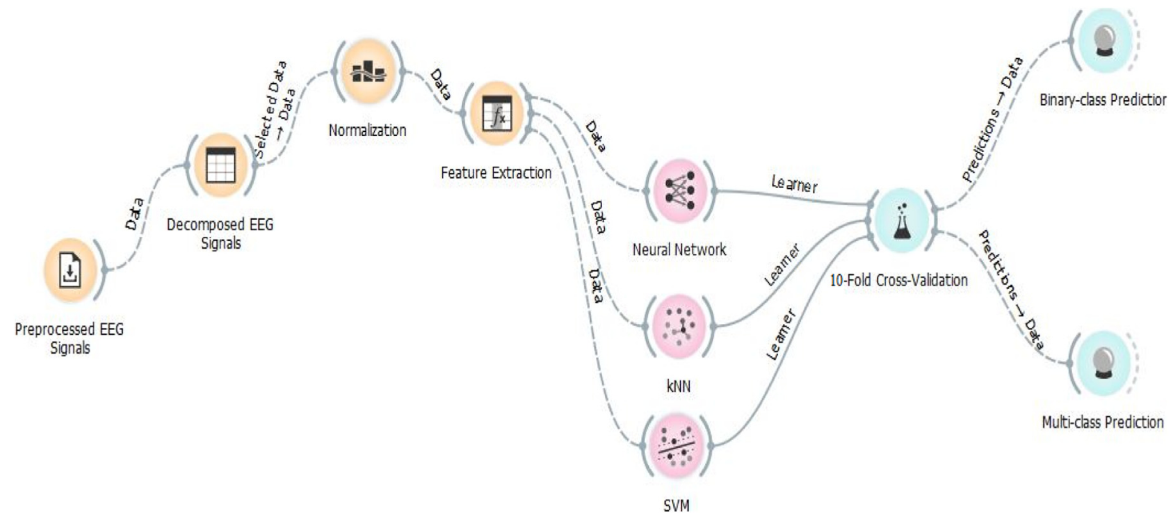

Fig. 11. Workflow of the proposed method.

Table 8
Multi-class classification for both classifiers with all EEG channels.

Classifier	Zone	AF3	AF4	F3	F4	F7	F8	FC5	FC6	O1	O2	P7	P8	T7	T8
kNN	HAPV	45%	52%	34%	42%	42%	53%	54%	34%	51%	43%	46%	39%	38%	50%
	HANV	37%	55%	43%	43%	41%	62%	44%	33%	39%	38%	40%	41%	37%	44%
	LAPV	44%	53%	36%	41%	49%	53%	45%	34%	42%	35%	38%	40%	38%	42%
	LANV	42%	61%	30%	46%	40%	48%	45%	42%	40%	36%	41%	40%	39%	44%
	Avg.	42%	55%	35%	43%	43%	54%	47%	36%	43%	38%	41%	40%	38%	45%
SVM	HAPV	52%	53%	45%	50%	85%	64%	28%	33%	53%	60%	64%	69%	46%	75%
	HANV	51%	58%	44%	48%	67%	65%	35%	35%	48%	54%	75%	69%	41%	96%
	LAPV	56%	34%	38%	67%	65%	58%	43%	35%	72%	48%	63%	68%	46%	71%
	LANV	54%	50%	40%	54%	70%	63%	34%	34%	55%	54%	66%	70%	47%	79%
	Avg.	54%	50%	40%	54%	70%	63%	34%	34%	55%	54%	66%	70%	47%	79%
MLPNN	HAPV	77%	91%	75%	82%	69%	77%	72%	82%	70%	60%	70%	71%	60%	84%
	HANV	72%	73%	77%	80%	66%	70%	83%	73%	81%	64%	66%	69%	61%	78%
	LAPV	78%	66%	73%	86%	67%	68%	74%	71%	65%	71%	65%	76%	64%	76%
	LANV	95%	70%	75%	81%	84%	71%	71%	69%	69%	64%	79%	72%	75%	78%
	Avg.	80%	75%	75%	82%	71%	71%	75%	74%	71%	65%	70%	72%	65%	79%

Table 9
Binary-class classification for both classifiers.

Classifier	Emotion	AF3	AF4	F3	F4	F7	F8	FC5	FC6	O1	O2	P7	P8	T7	T8
kNN	Positive	59%	84%	55%	61%	55%	71%	80%	55%	62%	68%	60%	65%	61%	55%
	Negative	63%	66%	63%	71%	79%	79%	47%	80%	67%	61%	61%	81%	61%	73%
	Avg.	61%	75%	59%	66%	67%	75%	64%	68%	65%	65%	61%	73%	61%	64%
SVM	Positive	77%	95%	59%	71%	81%	81%	65%	68%	56%	79%	57%	83%	56%	90%
	Negative	85%	80%	66%	72%	86%	79%	67%	67%	58%	60%	61%	78%	73%	71%
	Avg.	81%	88%	63%	72%	84%	80%	66%	68%	57%	70%	59%	81%	65%	81%
MLPNN	Positive	81%	86%	84%	93%	87%	84%	82%	95%	76%	79%	81%	75%	80%	83%
	Negative	90%	87%	74%	92%	80%	84%	77%	75%	82%	87%	77%	79%	70%	75%
	Avg.	86%	87%	79%	83%	84%	84%	79%	85%	79%	83%	79%	77%	75%	79%

arousal and low arousal, respectively. Our proposed method shows that MLPNN is better than the SVM and kNN classifier.

In Table 9, binary-class classification is shown based on two classes including positive and negative emotions. When we compare the results of the binary-class with the multi-class for the kNN classifier, the binary-class shows better performance, and the average accuracy is greatly increased from 42.8% to 65.8%. AF4 and F8 channels demonstrate the same average accuracy of 75.0% with different emotional states. Comparison of results between the multi-class and binary-class approaches of the SVM point out that similar to the kNN, the binary-class' performance is better. The accuracy is highly increased from 54.8% to 72.2% in binary-class discrimination. The best performance is obtained from the AF4 channel, which is a completely different channel. In binary-class classification, MLPNN shows great potential for EEG channels, and the average classification accuracy is obtained as 82.0%. When

Table 10
The kappa values of each classifier in multi-class classification process.

Classifier	Kappa value	Asym. std. error
kNN	0.357	0.073
SVM	0.504	0.080
MLPNN	0.664	0.079

Table 11
The kappa values of each classifier in binary-class classification process.

Classifier	Kappa value	Asym. std. error
kNN	0.481	0.117
SVM	0.538	0.121
MLPNN	0.667	0.124

the EEG channels are analyzed independently, the F4 EEG channel gives the most promising result for positive and negative emotions in the order of 93.0% and 92.4%. In general, our dataset gives the best results on frontal zones of the scalp, which are consistent with some studies in the literature [33,18]. The performance of all classifiers for both binary and multi-class processes are determined by Cohen's kappa statistic method. The authors in [23], provided a method to determine the observer agreement for categorical data. According to [23], the kappa value <0 indicates there is no agreement, 0–0.2 indicates there is light agreement, 0.21–0.40 indicates there is fair agreement, 0.41–0.60 indicates there is moderate agreement, 0.61–0.80 indicates there is substantial agreement, and 0.81–1 indicates there is almost perfect agreement between data. We determined the performance of classifiers based on these criteria. Table 10 and 11 show the kappa values for multi-class and binary-class classification.

It can be deduced from Table 10 that, there is fair agreement between the four classes in kNN classifier. The SVM shows moderate agreement between four labels; however, the best agreement is observed from MLPNN, which provides a substantial agreement, with a kappa value of 0.0664.

In binary-class classification, both the SVM and MLPNN showed the same agreement value with the multi-class classification. However, kNN advances its kappa value from 0.357 to 0.481 and has a moderate agreement in binary-class classification.

5. Conclusion

In this study, we provide a database to study emotions based on brain signals. In this database, there are EEG signals collected via 4 different video games and from 28 different subjects. Each subject played different computer games in turn and rated their emotional response with respect to arousal and valence. We present a novel method since there is no EEG emotion dataset based on computer games with different labels. Additionally, we did not apply a traditional EEG device to collect signals; we used new technology (a wearable and portable EEG device) to obtain the signals. To provide the information about the data, we performed some statistical analyses of the signals and relationships of the emotions. In addition, to provide the success of the EEG channels and the signals, we classified emotions with different classifiers. Our dataset achieved a good performance, and we observed that the selected stimuli for the dataset are quite successful according to the subjects' SAM scores. The novelties of this study can be summarized as follows:

- Our data are collected from a wearable and portable EEG device, which is different from the existing EEG channels in the literature. In the literature, researchers applied a 32 channel traditional EEG device. One of the main tasks of this study is to show the performance of the portable device against the traditional devices.
- We performed aural-visual stimuli to obtain the emotion data from subjects. In the literature, existing datasets are formed with the aural-visual stimuli similar to this study. However, researchers applied short movies or music clips rather than computer games. There is no computer-based emotion data existing in the literature. We have already mentioned why we implemented the computer games in our study rather than the existing approaches in the last part of Section 1.

The database will be publicly available to all researchers and we believe that it will provide valuable information and yield good results.

Author contributions

Conception and design of study: T. B. Alakus, I. Turkoglu
Acquisition of data: T. B. Alakus, I. Turkoglu
Analysis and/or interpretation of data: T. B. Alakus, M. Gonen, I. Turkoglu
Drafting the manuscript: T. B. Alakus
Revising the manuscript critically for important intellectual content: T. B. Alakus, M. Gonen, I. Turkoglu
Approval of the version of the manuscript to be published: T. B. Alakus, M. Gonen, I. Turkoglu

Conflict of interest

The authors declare that there is no conflict of interest.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.bspc.2020.101951.

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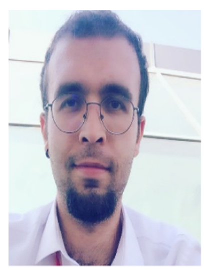

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