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Emotion recognition using deep neural networks and dynamic features of EEG signal

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Abstract

The aim of this paper is to evaluate the results of deep learning networks and other methods for emotion classification. According to the obtained results, the support vector machine achieved the highest classification accuracy for identifying four emotional states with 94.1% accuracy. Also, the proposed convolutional neural network identified the desired emotional states with an accuracy of 80%. The performance of the deep learning network will be improved if more features are used. In addition, the deep learning method has significant advantages over simple classification methods due to its resistance to noise and automatic processing.

Keywords: emotion quantification, vital biopotentials, wavelet transform, principal component analysis, intelligent classifiers
2020 MSC: 68T07, 97P80

1 Introduction

Emotions play an important role in human life. The design of systems capable of recognizing different emotions has been considered. To design the system, the DEAP database, which includes the physiological signals of EEG, ECG, EMG, and respiration rate recorded from 32 male and female participants, with the application of video music stimulation over a period of 120 minutes, has been used. For every minute, labelling is done based on a face video review by an expert. For emotions, four classes including anger, happiness, sadness and satisfaction were considered. In the first stage of system implementation, the EEG signals obtained by the DEAP method with a sampling rate of 512 Hz are subjected to noise removal and filtering. For this purpose, two filtering stages are performed, one in the frequency domain and the other in the time-frequency domain. Time-frequency domain filtering (wavelet transform) with MATLAB software's default coefficient is used to remove noise with unknown signal sources. In the next step, the alpha, beta, and gamma subbands of the EEG signal are extracted based on the detail coefficients and general coefficients of the Daubechies 4 wavelet transform at eight decomposition levels, and then the signal is reconstructed with the desired coefficients. Linear and dynamic features are extracted from the alpha, beta and gamma subbands of the EEG signal. By determining the desired features, the extracted features are applied in the first step as input to common classification methods such as decision tree, nearest neighbours and support vector machine, and in the next

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step as input to the convolutional neural network. Also, in a study, the EEG signal was considered as the input of the deep classification structure. The aim is to evaluate the results of deep learning networks and other methods for emotion classification. According to the obtained results, the support vector machine achieved the highest classification accuracy for identifying four emotional states with 94.1% accuracy. Also, the proposed convolutional neural network identified the desired emotional states with an accuracy of 80%. The performance of the deep learning network will be improved if more features are used. In addition, the deep learning method has significant advantages over simple classification methods due to its resistance to noise and automatic processing.

Nowadays, due to wearability, price, portability and ease of use, new wireless EEG devices have come onto the market. Therefore, EEG-based emotion recognition can now be used in various fields, such as entertainment, e-learning, virtual world or e-health care applications and may be used for many purposes, such as instant messaging, online games, assisting therapists and psychologists when used for doing their work [2, 4].

EEG signals are common and accessible in many brain and computer classification (BCI) applications, such as emotion recognition, due to their simplicity for analysis and appropriate time and distance resolution.

Previous studies show that by recording EEG signals, we can get very good results in the temporal classification of emotions. Also, a decision was made to review and explain some studies related to the classification of emotions through EEG signals.

In previous studies regarding the automatic identification of emotions, the low accuracy in detecting emotional states and the dependence and sensitivity of simple classification methods for noise have caused the ineffectiveness of the methods. In this research, it has tried to eliminate the disadvantages of the previous methods by presenting an efficient and practical emotion identification algorithm. Also, the main goal of this research, in addition to providing an efficient emotion recognition algorithm, is to investigate the performance of deep learning networks and other EEG signal classification methods so that we can choose the best method for emotion recognition. The algorithm presented in this article uses Sailfish Optimizer (SFO) for optimization.

SFO algorithm

One of the interesting examples of social behaviour in groups of arthropods, fish, birds and mammals is group hunting. In group hunting, hunters do not need much effort to kill prey compared to when hunting alone. In the simplest form of group hunting, predators attempt to kill prey with little or no coordinated attack, while in the complex form of group hunting, predators use specific roles to herd and capture prey. One of the complex strategies of group hunting is the frequency of attacks. This strategy provides an opportunity for the predator to conserve energy while other predators injure the prey. One example of this type of strategy is group hunting of sailfish, which alternate their attacks to hunt training sardines in each behavioural state of group hunting of sailfish. Sailfish are the fastest fish in the ocean, which can reach a maximum speed of about 100 km/h. They hunt in groups and bring smaller fish-like sardines to the surface. The manoeuvrability and acceleration of sardines during the attack are very challenging for sailfish. A sailfish will either make a slashing motion with its rostrum, injuring several sardines, or strike a sardine and destabilize it. Because the sailfish has one of the highest accelerations ever recorded in an aquatic vertebrate, the sardines cannot swim fast enough to avoid the sailfish's rostrum tip and cannot do anything in response to the group's predation. According to the observed behaviour of sardines, it was shown that injured sardines are separated from the hunting grounds and cannot move with the school, so they are quickly hunted by sailfish. Most sailfish attacks do not result in sardine deaths, and only a few percent of sardines are directly caught. But with the frequent attacks by sailfish, more sardines are damaged. This type of hunting is mostly for animals that hunt in packs, such as wolves. However, this group of sailfish regularly breaks up and is reformed with new members. During the attack, the sailfish keeps its large dorsal fin and pelvic fins straight, presumably to stabilize its body. Also, they change their body color with bluish-silvery sides that darken just before they attack. The reason for the color change is not clear, but it must be some kind of communication between the sailfish. It is possible to prevent injury by a fellow countryman. Sailfish use their body changes to signal it. The main inspiration of the SFO algorithm is based on the attack alternation strategy of group hunting sailfish [**?**].

The steps of this algorithm are as follows and Fig. 2 shows the convergence curve of this algorithm.

1. Initialization
2. Elitism
3. Attack alteration strategy
4. Hunting
5. Catching prey

The design of the emotion recognition system in this research is done in six stages, which we will examine in order.

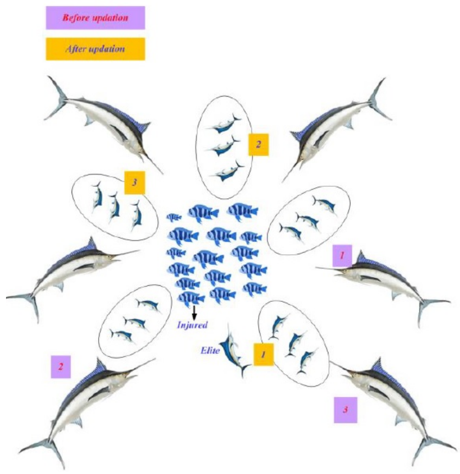

Figure 1: SFO algorithm

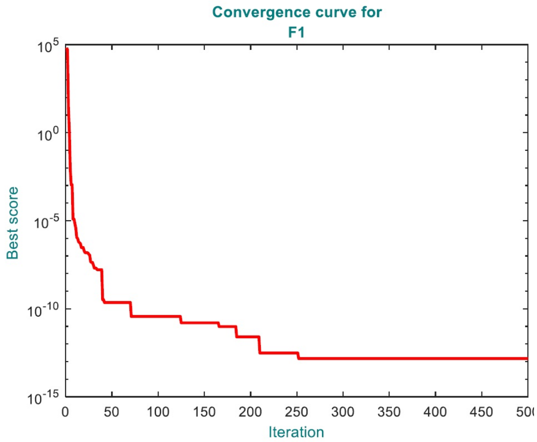

Figure 2: Convergence curve of SFO algorithm

In the first step, vital (brain) biopotential signals are recorded and obtained clinically from a group of male and female volunteers after stimulation with music. In this study, the DEAP database is used, so that a vital signal recorded from the anterior part of the face is recorded and obtained. This signal is an informational signal from the EEG signals from the frontal brain area, muscles of the forehead and face, which is done in the conditions of recording the response to stimulation (stimulation is music, color, film or images).

In the second step, data is pre-processed in order to reduce noise. For this purpose, suitable filtering of the frequency domain or wavelet transformation in the time-frequency domain is used.

In the third step, due to a large amount of data and the number of electrodes, it is necessary to extract a set of representatives for each signal, which firstly creates a significant difference for each class of emotions, and secondly, its calculation in terms of the computational volume is reasonable. In this research, time characteristics, frequency and dynamic characteristics are extracted.

The purpose of this study is to investigate the performance of other classifiers with neural networks with deep learning for emotion classification. For this purpose, in the fourth step, linear classification structures such as support vector machine, non-linear structures such as nearest neighbours and deep classification are used in order to label emotions. The input of the classifier structure is the extracted features and its output is the emotion class label. In the fifth step, once the pre-processed signal is entered into a convolutional neural network and the raw signal will be entered into the network. All simulations are implemented under MATLAB2020 software, and in order to validate the method, clutter matrix analysis and calculation of accuracy, sensitivity and determinability criteria are used.

2 Designing emotion recognition system using EEG signal

The quantification of emotions and the automatic analysis of behaviour and mood based on vital biopotentials have received much attention. Several studies have been conducted from the perspective of biomedicine, psychology and cognitive neuroscience in the field of quantifying emotions from EEG, ECG and other vital signals. In this research, a new vital signal, recorded from the anterior part of the face, is recorded and obtained. This signal is an information result of EEG signals from the frontal brain region. The main goal of this research is to compare different signal-processing methods for emotion recognition, including deep learning-based neural networks and other classifications. Fig. 3 shows the block diagram of vital signal processing steps.

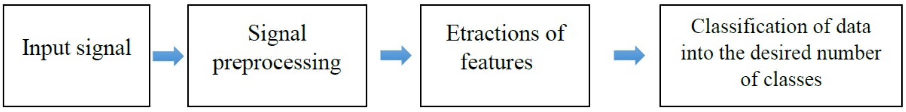

Figure 3: Block diagram of different stages of critical signal processing

First, we will use the desired vital signal. This signal may be used from the database or from our own recorded signals. The second step is signal preprocessing, in which operations are performed on the raw data so that it can be used. In the next step, we use the features to create a representative of each signal, and in the last step, we enter these features into the classifier for the purpose of classification. In the following, we will examine each of these cases.

2.1 Database

The DEAP database was used in this research. A set of healthy samples of both men and women without mental, cardiac or neurodegenerative diseases or epilepsy were selected. The average age of the samples will be between 15 and 55 years. This database includes 32 people from two samples of men and women who were stimulated by the video music, the duration of the video was 120 minutes (40 video recordings for each person), and for each minute of the person's emotions, they were labelled based on the examination of the video of the face that was done by a psychologist [7].

This database contains 46 recording electrodes, of which 32 EEG channels, one ECG channel, and 13 channels of other vital signals (4 EOG signal channels, 4 EMG signal channels from the thigh muscle, and one channel of the conduction response). Skin is a respiratory signal channel and a body temperature channel and a photoplethysmography signal channel and a status recording channel) [7]. The videos that were broadcast to people during the experiment were carefully selected and reviewed.

2.2 Preprocessing

In this study, for the purpose of data preprocessing of the DEAP database according to recent research [1, 3, 13, 14], at first the signal with a sampling rate of 512 Hz was converted to a signal with a sampling rate of 128 using the down sample technique, then in filtering in the frequency domain, a low-pass filter is used in the range of 4 to 45 Hz with a limited impulse response [1, 14]. Also, in order to reduce noise, Daubechies 4 wavelet transformation (which is suitable for vital signals) is used. The considered level of analysis is eight levels and the default coefficients of MATLAB2020 software are used to achieve the goal.

2.3 Extraction of features

In the second step of signal processing, it is necessary to extract a set of features from the raw signal and use them to check the behaviour of the signal. In the following, we will examine the features used in this research.

2.4 Linear feature

The first category of the features used in this research is the statistical features that we will examine.

2.5 Statistical feature

The mean and standard deviation are obtained from relations (2.1) and (2.2), respectively. The standard deviation examines the dispersion of the data.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2.1}$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{2.2}$$

N refers to the number of signal samples and x_i is the target signal for processing. Skewness is a measure of symmetry or, more precisely, asymmetry. A distribution or data set is symmetric if it looks the same to the left and right of the center. Skewness is calculated from Eq. (2.3).

$$x_s = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^3 \tag{2.3}$$

N refers to the number of signal samples and x_i is the target signal for processing. Kurtosis is a statistical operator that is used to describe the statistical distribution, and by analyzing the histogram chart, it gives us useful information about the flatness of the data. Elongation is calculated from Eq. (2.4).

$$x_K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 \tag{2.4}$$

2.6 Hjorth parameters

Hjorth parameters are a set of non-linear features based on statistical calculations that have been used in many studies to effectively describe EEG signal characteristics [6, 9, 10]. For the first time in 1970, the statistical parameter was introduced under the name of Georgeth's parameter and it includes three basic parameters named activity, mobility and complexity [10]. The signal strength is calculated by the activity parameter. This parameter is calculated using Eq. (2.5).

$$\text{Hjorth} = \sigma_x^2 \tag{2.5}$$

The average frequency of a signal is calculated by the dynamic parameter. Eq. (2.6) represents the dynamic parameter.

$$\text{Hjorth\_mobility} = \frac{\sigma_{x'}}{\sigma_x} \tag{2.6}$$

$\sigma_{x'}$ represents the standard deviation of the derivative of the $x(n)$ signal. The change in signal frequency is calculated by the complexity parameter. This parameter measures the similarity of the signal with a pure sine wave. If the signal is completely similar to a pure sinusoid, the value will be 1. This parameter is calculated according to Eq. (2.7).

$$\text{Hjorth\_complexity} = \left(\frac{\sigma_{x''}}{\sigma_{x'}}\right) \div \left(\frac{\sigma_{x'}}{\sigma_x}\right) \tag{2.7}$$

$\sigma_{x''}$ is the standard deviation of the second derivative of the signal $x(n)$.

2.7 Lyapunov view

In chaotic systems such as the EEG signal, the sensitivity of the system in responding to small stimuli is calculated by the Lyapunov index [6]. In other words, it gives information about the dependence of the system on the initial conditions. In the sense that if we have two initial conditions close to each other such as $x_0, x_0 + dx_0$ and apply M mapping to them, after n consecutive times we will have:

$$dx_n \approx e^{hn} dx_0 \tag{2.8}$$

h is called the Lyapunov view, which is calculated by this method:

$$h = \lim_{T\to\infty} \frac{1}{T} \ln\left|\frac{dx_T}{dx_0}\right| \tag{2.9}$$

$$\frac{dx_T}{dx_0} = \frac{dx_T}{dx_{T-1}} \frac{dx_{T-1}}{dx_{T-2}} \cdots \frac{dx_1}{dx_0} \tag{2.10}$$

$$M'(x_{T-1})M'(x_{T-2}) \cdots M'(x_0). \tag{2.11}$$

So we will have

$$h = \lim_{T\to\infty} \frac{1}{T} \sum_{n=0}^{T-1} \ln |M'(x_n)| \,. \tag{2.12}$$

According to the discussion of the natural boundary for a set, h can also be shown as follows:

$$h = \int \ln |M'(x_n)| \, d\mu(x). \tag{2.13}$$

For one-dimensional mappings, it is proved that such a boundary exists. But in general, the existence of such a boundary has not been proven for high-dimensional systems, and it is still an unsolved problem. But its existence has been investigated numerically in some problems. In any case, a positive Lyapunov view indicates chaos [6].

Lyapunov representation is used to classify any type of steady-state behaviour. It also provides a measure of the rate at which two adjacent points on a state route diverge over time. Lyapunov expressions exponentially express the divergence or convergence of state trajectories in the phase space of a signal. In the state of a stable equilibrium point, all Lyapunov exponents become negative. If the absorber is sensitive to the initial conditions, it will have at least one positive Lyapunov profile. Because this positive coefficient means that two neighbouring paths move away from each other exponentially with the passage of time. Therefore, at least in one dimension, there is infinite sensitivity to changes in initial conditions. Therefore, although an n-dimensional system has n Lyapunov coefficients, in most applications it is sufficient to calculate only the largest Lyapunov coefficient. The Lyapunov expressions of an n-dimensional system are placed in the order $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$ where λ_1 refers to the largest Lyapunov coefficient is and is considered as a feature in this study [6].

The third step in the classical method is to use different classifications to classify the extracted features, which we will examine further.

3 Simulation results

In this section, the four basic steps of this research; That is, examines data collection, preprocessing, processing, and classification. Processing and classification have been done using the SFO algorithm.

As mentioned, the purpose of this research is to provide the best method for EEG processing and comparison between deep learning methods and other methods that will provide us with the best answer for identifying different emotions. For this purpose, in the first step of this research, vital (brain) biopotential signals are clinically recorded and obtained from a group of male and female volunteers after stimulation with music. For this purpose, PowerLab equipment is installed with six bipolar electrodes, four electrodes on the sides of the face and near the ear (temple) and two electrodes on the forehead. In the second step, in order to reduce the noise of the data, pre-processing was done. For this purpose, suitable filtering in the frequency domain or wavelet transformation in the time-frequency domain was used. Fig. 4 shows a view of the used EEG signal before and after noise removal.

In the third step, various statistical, entropy and distance features were extracted from the EEG signal. In the fourth step, from linear classification structures such as support vector machines, non-linear ones such as nearest neighbours and deep classifiers have been used for the purpose of tagging emotions; the input of the structure of the classifiers, the extracted features, and the output of that label, is the class of emotions. In the sixth stage, once the raw signal is and the other time, the pre-processed signal is entered into a convolutional neural network that includes 7 hidden layers with the ReLu activator and the results are checked. All simulations are implemented under MATLAB2020 software, and in order to validate the method, clutter matrix analysis and calculation of accuracy, sensitivity and determinability criteria are used.

Table 1 shows the characteristics of the best classifications used in the proposed method. In the proposed method, three classes of support vector machine, nearest neighbour and decision tree are used.

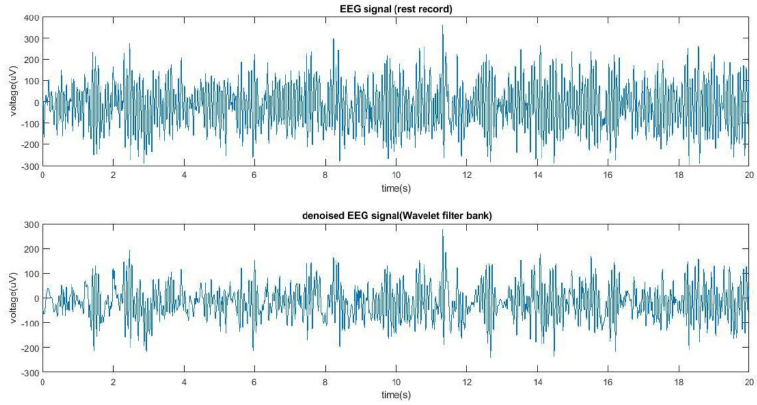

Figure 4: View of the used EEG signal before and after denoising optimized with SFO

Table 1: Specifications of the classifications used in the proposed method

Type of classifier	Specifications
Support vector machine	Gaussian kernel
Nearest neighbors	Based on Euclidean distance and k=3
Decision tree	Coarse decision tree with maximum branching of 4

4 Evaluation of the performance of classifiers

In this section, the results of confused matrix analysis for three classes of nearest neighbor, support vector machine and decision tree in kernels and its different types and convolutional deep neural network are presented. Tables 2 to 4 provide a summary of the simulation results.

In order to calculate the sensitivity index, accuracy and specificity index, the following relations have been used for a two-class problem (Eqs. (4.1)–(4.2)):

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{4.1}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4.2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}. \tag{4.3}$$

T_{pos} is the percentage of correctly classified target classes, T_{neg} is the percentage of correctly classified non-target classes, F_{pos} is the percentage of incorrectly classified target classes, F_{neg} is the percentage of incorrectly classified non-target classes. In the best possible case, when all the results are correctly diagnosed, the value of three parameters - accuracy, sensitivity and specificity - becomes one. Therefore, the closer the value of these three parameters is to the value of one, it means that the simulation response is closer to the ideal response.

The evaluation of SVM, KNN and decision tree classifications was done by the method of cross-validation (k-fold) (K=5). Cross-validation is one of the ways to optimally determine the number of parameters (variables) of the model using the SFO algorithm. If we randomly separate the training data set into k subsamples or "folds" with the same volume, in each step of the CV process, the k-1 number of these layers can be considered as the training dataset and one as the validation dataset.

Table 2 shows the results of accuracy, sensitivity and determinability related to emotion classification using EEG signal with all frequency bands, using support vector machine, nearest neighbours and decision tree classification. It should be noted that all the extracted features are classified.

Table 2: The results of optimization of accuracy, sensitivity and determinability related to classification of emotions with SFO algorithm

Type Of Classifier	Sensitivity	Determinability	Accuracy
Support Vector Machine	91.3%	90.9%	94%
Nearest Neighbors	74.17%	75.8%	79.6%
Decision Tree	73.2%	71.0%	76.3%

Table 3 shows the results of accuracy, sensitivity and determinability related to classification of emotions using EEG signals with all frequency bands, using a convolutional neural network. In this case, the once-processed data enters the deep network, and the raw data is processed in another step.

Table 3: The results of accuracy, sensitivity and determinability related to the classification of emotions using CNN

Network Type	**Data Type**	**Sensitivity**	**Determinability**	**Accuracy**
convolutional neural network	raw data	64.8%	68.01%	70%
convolutional neural network	Processed data	85.1%	87.8%	80.0%

Fig. 3 shows the graph related to decreasing gradient and increasing classification accuracy during classification. As seen in Fig. 5, the classification error has gradually reached its lowest level during 250 repetitions, and this indicates the ability of the classification. Also, this figure shows that the neural network is not stuck in local optima.

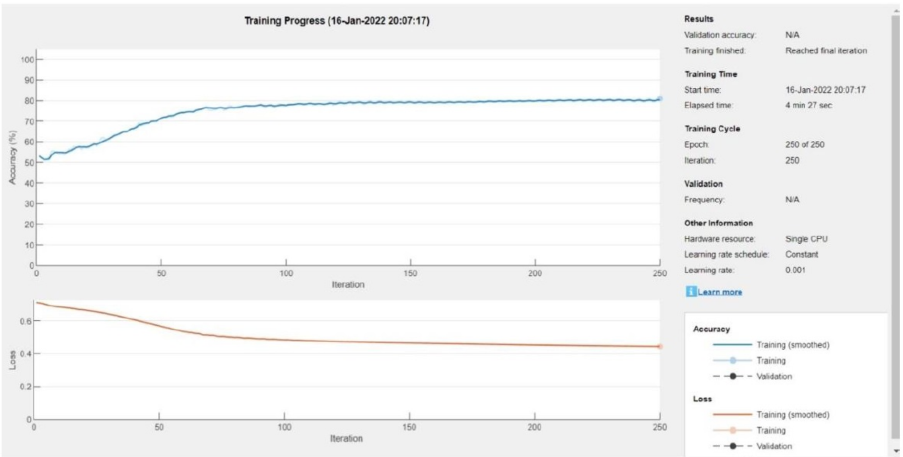

Figure 5: The diagram related to decreasing gradient and increasing classification accuracy

In Table 4, the results of the proposed method for identifying emotions are compared with the methods of researchers in the last few years. As can be seen in the table, the results of the proposed method have provided the best answer.

Table 4: Comparison of the proposed method with recent researches

Reference No	**Year of Publication**	**Database**	**The Proposed Method**	**Number of Emotional States**	**Accuracy**
[9]	2016	DEAP	C-RNN	2 states	73.1%
[12]	2019	DEAP	MLP	4 states	70%
[5]	2019	NNIME	CNN	6 states	52%
[8]	2020	DEAP	RF	2 states	61.8%
The proposed method		DEAP	SVM	4 states	94.1%
The proposed method		DEAP	CNN	4 states	80.0%

5 Conclusion

In this article, an emotion quantification method based on EEG signal processing was presented, which was optimized using the SFO algorithm. In this study, first, a group of data including men and women who were stimulated by video music was used. Since emotions involve the anterior lobe of the brain more, a total of 6 anterior electrodes of the EEG signal were used. The set of these two vital signals was considered as a matrix with seven rows (six rows for the brain signal) as the input of a preprocessing block in order to reduce noise and improve the signal. For this purpose, from two categories of filters, the first category is the frequency domain filter in the significant range of the brain signal (frequency range of 45 Hz) of the type of limited and transient impulse response, and the second category is filters that are used in the time-frequency domain. For this purpose, a wavelet transform filter bank with default coefficients was used to reduce noise from unknown sources.

The reduced noise signals were considered as the input of a processing block, which was for brain signal processing, and extraction of brain alpha and beta bands. To extract EEG signal bands, second and third-level detail coefficients were used for beta and alpha bands with Daubechies 4 mother wavelet, respectively. Processed signals (brain alpha and beta bands and heart rate change rate signals) were considered as the input of a feature extraction block. Time, frequency and nonlinear features were used in this research. The set of features was dimension reduced through PCA and mapped to a space with maximum extra class variance. The dimensions of the features before noise reduction are 32×77, where the first dimension (rows) is equal to the number of samples and the second dimension (columns) is the result of the product of 7 electrodes (six brain electrodes and one cardiac electrode) in 11 features. After reducing the feature space with PCA, this matrix was reduced to 32×8 dimensions.

Also, the results showed that the use of the wavelet transform bank filter has the necessary efficiency in improving the signal and reducing the noise. From the results of the classification based on the movements of the first category, it can be concluded that the perceptron multilayer neural network and support vector machine with a non-linear kernel and the nearest neighbours' classifier with a fine scale have high efficiency in the classification of features. This problem can be justified because the separable features are not linear; linear classifiers do not have the necessary efficiency in classification. Reducing the feature space has been effective in improving the accuracy, precision and sensitivity parameters of all classifications and reducing the calculation time.

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