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Depression Detection Model Based on Discrete Wavelet Transform Associated with Genetic Algorithm

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Abstract

The purpose of this research is to study the possibilities of implementing machine learning algorithms into human population with the purpose of detection of depression. This paper delves into predictive analysis techniques to further investigation how depression is detected. It shows how certain tangibles can be converted into mathematical inputs to present a variable output. These inputs are represented numerically through a variety of machine learning algorithms. We introduce a novel model based on the Wavelet family and a genetic algorithm to predict depressive states based on EEG data in this study. First, we took raw EEG signals from a common database. Preprocessing, feature extraction, feature selection, and classification are the four essential processes in our model.

Keywords: *Machine learning; electroencephalogram (EEG); Discrete Wavelet Transform (DWT); Genetic Algorithm (GA).*

1 Introduction

Through surveying many different previous studies, we have found that most of the models that were built to identify disease states or emotional states of humans based on EEG signals pass through four basic stages, namely: Signal preprocessing stage, features extraction stage, feature selection stage, and classification stage. These stages will be explained in detail and we will review the best techniques used in each stage, and this step is important to explain and clarify the mechanism that was proposed in our model [1-3].The main purpose of this step is to remove the noise signal, which is unneeded elements; it can be performed easily by using filters. In this stage, sometimes the method of capturing data or signals is clarified, and then the proposed method for signal preprocessing is clarified. Pre-existing databases, sometimes called benchmark database or standard database. Simply, the above-mentioned databases are a set of signals that are captured by special devices, these devices contain a set of sensors that are placed on humans, and then the

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signals produced by the human body are recorded and captured. There are two popular ways to capture brain signals:

I. The direct method is the electroencephalogram (EEG).

II. The indirect method, which is the electromyography (EMG).

With regard to the current research we are interested in the common brain signals which is commonly called Electroencephalogram (EEG) signals, this method measures the electrical potentials on the scalp and sometimes on the cortex of the brain, here the signals or waves are captured, the signals are defined as recording the fluctuating electrical changes in the brain, which are obtained through electrodes placed on the outside of the head, this generates EEG signals, it is sampled at 256Hz and consists of five different frequencies, delta $\delta(< 4\text{Hz})$, theta $\theta(4 - 7\text{Hz})$, alpha $\alpha(8 - 15\text{Hz})$, beta $\beta(16 - 31\text{Hz})$ and gamma $\gamma(> 31\text{Hz})$[4],[23]. The EEG signals (500 Hz sampling rate) were captured indicating activity from mastoid electrons associated with both electronically and using a cap system with 30 electrodes placed on the scalp according to a 10-10 system [5],[27]. Figure 1 shows the standardized electrode placement scheme.

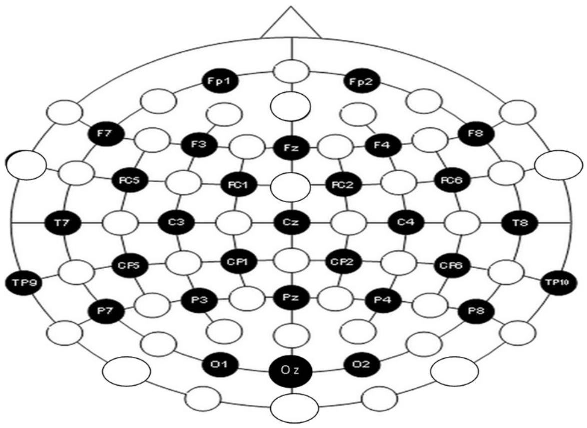

Figure 1. Scheme of standardized electrode placement

Thus, EEG signals are extracted from 30 electrodes. These locations are conventionally named as follows: FP1, FP2, F7, F3, Fz,F4, F8, PC5, PC1, PC2, PC6, T7, C3, Cz, C4,T8, TP9,CP5, CP1, CP2, CP6, TP10,P7,P3,Pz, P4,P8, O1, Oz,O2.

2 Features extraction

After the signal has passed through the previous stage, most of the noise has been removed, and then features of the EEG signals are extracted. The feature extraction stage aims to re-describe with the least number of resources required for a large set of data accurately, in other words this stage is described as a re-representation of the signal with the smallest amount of data that expresses this signal.

In order to extract features from EEG signals, a variety of techniques are utilized, including wavelet entropy, approximation entropy, and sample entropy [6], [12]. While Hjorth employed variance [7], Mean Square, and PP Mean for a total of linear characteristics, activity, mobility, complexity, and other features were also used. There are other often employed techniques in addition to those already described, and the most well-known of them can be summed up as follows: mean energy, petrosian fractal dimension, rényi entropy, spectral entropy, permutation entropy, approximate entropy, wignerville coefficients, wavelet transform, mean curve length, and hurst exponent [8],[11].

In data mining, a variety of search algorithms are used to find the best answer to a problem through the process of natural selection. These algorithms are used in the areas of signal recognition and classification, where these techniques are applied in the feature selection stage. The genetic algorithm is one of the most popular algorithms for selecting the best features, and it is used in many studies such as [9],[24]. Other studies that used the technique of minimal-redundancy-maximal-relevance (MRMR) to obtain optimal features include [10],[16].

Furthermore, numerous studies have used more than one feature selection strategy. For example, Zhao[13-15] identified two types of brain wave signals using a nonlinear feature selection approach based on partial mutual information (PMIS) and a rapid nonlinear classification using the Extreme Learning Machine (ELM) algorithm.

Additionally, Liu proposed a technique for enhancing the selection of motion features by fusing the Firefly algorithm with a learning automaton (LA) [17]. They created high-dimensional feature sets by combining local characteristic scale decomposition (LCD) and common spatial patterns (CSPs), which were afterwards recognized by the Spectral Regression Discrimination Analysis (SRDA) classifier.

3 Data classification

At this level, numerous approaches are routinely utilized, although machine learning algorithms are the most prevalent. Thus, machine learning techniques may be widely applied in a variety of classification and identification domains; these technologies are accessible in a variety of forms, including supervised learning, unsupervised learning, semi-supervised learning, and so on. However, supervised learning is commonly employed in the field of classifying instances based on brain signals (EEG). We can deduce that some classifiers are more common than others. Nave Bayesian (NB), Decision Tree (DT), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Random Forest (RF), and support vector machines (SVM) are among the classifiers used.

4 The Proposed Method

EEG monitors the brain's electromagnetic activity at relatively low pressure, which also obstructs the signal sent by some internal and extrinsic components. The pulse, the body's movements, the activity of the limbs, and the mind's focus are all indicators of inherent irregularities. Brain function measurements may be impacted by artifacts, synthetic noise, and frequency components.

One of the main steps are to decrease the electronic amplifier, power line, and external intervention noise. When capturing and recording EEG signals, they may be affected by different types of interference and distortions. These interferences can change the signals and affect them negatively, which means that the original signals generated from the brain may be distorted. To solve this problem, we will use the band pass filter for removing noise then DWT will be applied for signal processing.

There are many filters that are used in the processing stage. The band pass filter is one of the most popular and used of these filters, as studies like [18] have shown that it has achieved good results in eliminating interference and a high ability to eliminate noises and artifacts in EEG signals. Thus, the signals are passed onto the band filter so that the filter allows the signals to pass within the frequency to pass through, rejecting anything outside that range, and then the filtered signals are represented as time series vector s = {s1, s2, … , sr}, recorded in different temporal states from 1 to r.

Many methods used in signal processing, but we will use DWT. There are justifications that prompted us to use Discrete Wavelet Transform (DWT); EEG signal usually consists of two types of frequencies, high frequencies which contain short range information and low frequencies with long time intervals. Thus, electromagnetic interference occurs between the high frequencies that are recorded from the oscillators, and the low frequencies that are recorded from eye blinking and stretching of muscles, and here we can say that the EEG time-series signals are not stable because they contain a lot of information with both frequencies.

Thus, obtaining information from these frequencies is a challenging task, particularly when brain activity is taking place. To address this issue, we need a practical method for handling the signals that provides a more precise and detailed analysis of the data. To do this, we will use the Wavelet Transform (WT), one of the approaches that applies high and low frequency spectral methods and multi-resolution analysis to examine the signals across various frequency spectra.

There are two primary variants of WT: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). CWT suffers from redundancy as its main flaw, but DWT is more effective thanks to the frequency filter bank that is used to cut down on undesired frequencies. It separates the signal into distinct levels by employing five decomposition layers, each of which has a sample separated into two components. The first step in DWT implementation is to select the proper mother wave. However, several mother waves are generated when applying various DWTs to the same EEG segment, which causes case identification algorithms to offer inconsistent findings. According to Faust [15], there are now seven wavelet families that are widely used: Biorthogonal (bior), Coiflets (coif), Daubechies (db), Reverse biorthogonal (rbio), Symlets (sym), Discrete Meyer (dmey), and Haar. According to Table 1 below from a study [17], these seven families are split up into 54 sub-families.

The procedure of determining the proper mother wave and the number of levels of analysis is critical in DWT signal analysis. It is frequently used with multiple types of wavelets, and the one with the highest efficiency is chosen [18]. The smoothing property of the daubechies wave of order 4 (db4) makes it more suitable for detecting changes in EEG signals from other waves that are symmlet of arrangement. 10 (sym10), Coiflet 4 (coif4), and Daubechies 2 (db2), for example, according to the study presented by [19].

The EEG signals are divided into approximation (A) and detailed (D) components when DWT is applied. It is applied up to level 7, which means that it is divided into detailed components (D1–D7) and one remaining approximation (A7). The results of Gaos' study [19] showed that the bands A7, D7, D6, and D5 correlate to the delta, theta, alpha, and beta waves, respectively. In this stage, we obtain four frequency bands with 320 samples each, which serve as the building blocks for the EEG correlation feature.

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Table 1: Fifty-four Mother Wavelets [17]

Mother Wavelet	**Family**

bior_1.1, bior_1.3, bior_1.5, bior_2.2, bior_2.4, bior_2.6, bior_2.8, bior_3.1, bior_3.3, bior_3.7, bior_3.9, bior_4.4, bior_5.5, bior_6.8	Biorthogonal (bior)
coif_1, coif_2, coif_3, coif_4, coif_5	Coiflets (coif)
db_1, db_2, db_3, db_4, db_5, db_6, db_7, db_8, db_9, db_10	Daubechies (db)
rbio_1.1, rbio_1.3, rbio_1.5, rbio_2.2, rbio_2.4, rbio_2.6, rbio_2.8, rbio_3.1, rbio_3.3, rbio_3.7, rbio_3.9, rbio_4.4, rbio_5.5, rbio_6.8	Reverse biorthogonal (rbio)
sym_2, sym_3, sym_4, sym_5, symu_6, sym_7, sym_8	Symlets (sym)
Dmey	Discrete Meyer (dmey)
Haar	Haar (Haar)

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This step of feature extraction analyzes vectors for signals; it aims to acquire the appropriate features. These features are important to perform a good test of EEG signals. This step is to increase the accuracy for the model and gives the classifier a better handled data, for this phase we will use many method included: Mean Absolute Value (MAV), Average Power (AVP) Standard Deviation (SD), Variance(V), Mean (M), Skewness (SK), energy(E), normalized energy(nE), Channon Entropy (ChEn), zero crossing value, variance value, values of maximum, minimum, mean energy, petrosian fractal dimension, rényi entropy, spectral entropy, permutation entropy, approximate entropy, wignerville coefficients, kurtosis, normalized standard deviation (nSD).

After applying the previous statistical functions, the resulting values are considered a new representation of each signal. These values are actually the features that are derived from the signals. The values of the statistical functions are stored consecutively to form vectors, and thus the features of each signal have a vector. These vectors contain some dimensionality that may subsequently negatively affect the accuracy of the classification, and to solve this problem we will use PCA, this technique has proven its worth in several studies such as [20],[26]. PCA is one of the most popular statistical tools that mainly use an eigenvector, which uses singular value decomposition, which converts a set of interconnected features into disconnected features, major components or computers. The extracted features can be expressed as, the PCA coefficients (Z) can be represented as:

$$Z = X\phi \qquad (1)$$

Where ϕ is the training set underlying basis vector, then the underlying basis vector is applied to the extracted featuresof the test set, X', to obtain principal components of the test set, as:

$$Z' = X'\phi \qquad (2)$$

After applying the previous step, it is noticeable that there are a large number of features, therefore we need to apply an algorithm to select the best features, and according to [21] studies, the use of the Genetic Algorithm (GA) for such cases achieves impressive results, for this reason we will use GA to choose the best features.

It is one of the most popular random search algorithms; it is widely used in order to choose the best option for a problem using the natural selection process in the field of data mining. In GA, "chromosomes" are randomly generated to represent features of data as genes. Each gene is encoded by a string of zeros or ones, with (0) indicating the feature has not been chosen in that particular chromosome, and (1) indicating that a feature has been chosen.

In the paper presented by Mohammadi, he considered the locations of EGG signals as genes, while in our study we will consider every feature to be a gene, and thus the chromosome is expressed by a vector.

We apply (7) levels of DWT, this yields (7) detailed and one approximate, and there are 54 sub-families of DWT. Also, we have (25) statistical functions; thus, the total number of features becomes 10800 (8*54*25). Based on future work that [16] study indicated, we will apply independent component analysis (ICA) technique to the extracted features. The signals obtained from the previous step are inputs for this step, depending on these features; this step can classify the signals automatically. For this purpose, we have used six popular machine learning classifiers; all of these are supervised classifiers. In addition, we will use the Adaboost classifier used in Ahmad's study. The performance of Naïve Bayesian (NB), Bayesian Network (BN), Decision Tree (DT), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), and Random Forest (RF), and Support Vector Machines (SVM) machine learning classifiers were applied on the extracted features of publicly available dataset.

The Adaboost Classifier is one of the most popular methods used in the field of classification. It is considered one of the lighter versions of the probabilistic boosting tree method, which is used to classify states based on signal analysis [22], [25]. Basically, PBT is a decision tree trained on two types of samples: the negative sample (signal of a depressed person) and the positive (the healthy person signal), the Adaboost algorithm takes its power by combining a weak set of classifiers.

5 Results, Analysis and Discussions

According to the database, there are two main cases: the first is indications of people who suffer from depression (infected) and the second is for people who do not suffer (healthy or normal). Each of these cases was recorded while the volunteer had open eyes or closed eyes. This means that we have four different cases of signal.

The figures below are examples of what the original signal looks like for each of the four cases.The first and second figures of people with depression, the first one is of a person with depression, his eyes were open while recording the signal (see figure 1), and the second one is of a person with depression, his eyes were closed during the recording of the signal (see figure 2), while the third and fourth figures are of normal non-depressed people, the third was for a person with closed eyes (see figure 3), and the fourth for a person with open eyes (figure 4).

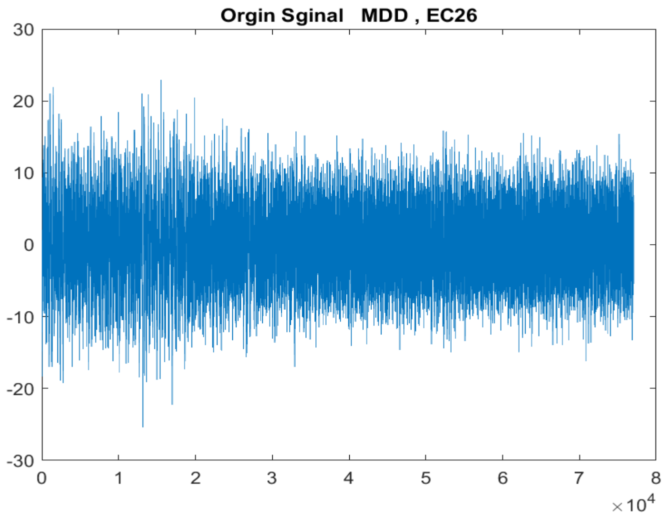

Figure1: Signal of a depressed person with closed eyes

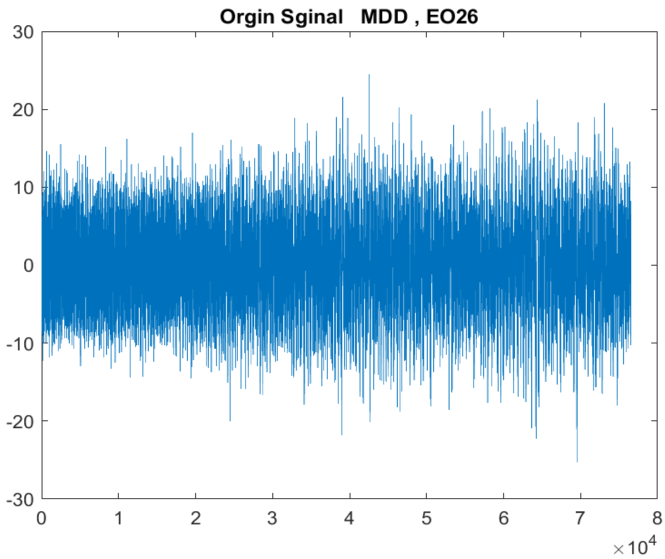

Figure 2. Signal of a depressed person with open eyes

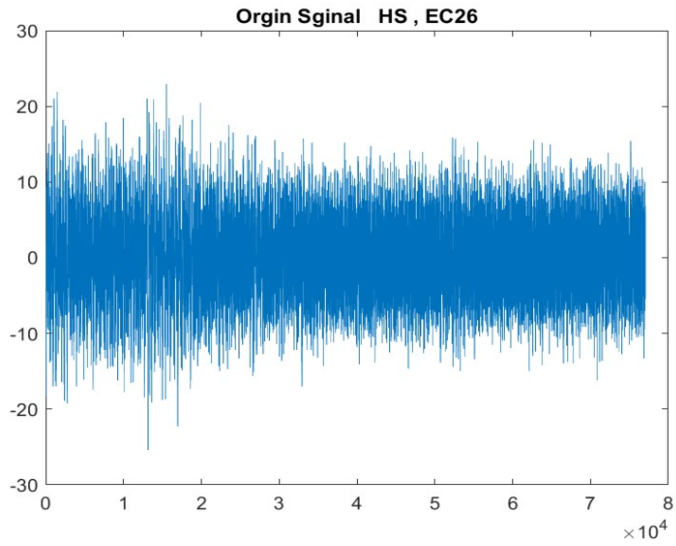

Figure 3. Signal of a normal person with closed eyes

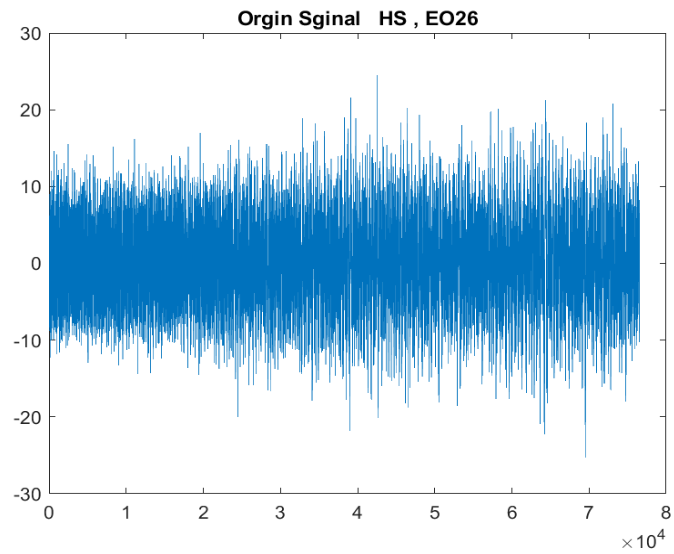

Figure 4. Signal of a normal person with open eyes

In the first stage of our proposed model, we apply a band-pass filter to the signals to get rid of the noise, the image below shows the shape of the signals after applying this filter, and the following figures below (figure 5, figure 6, figure 7 and figure 8), show the filter results on the same four signals with the four different states mentioned above.

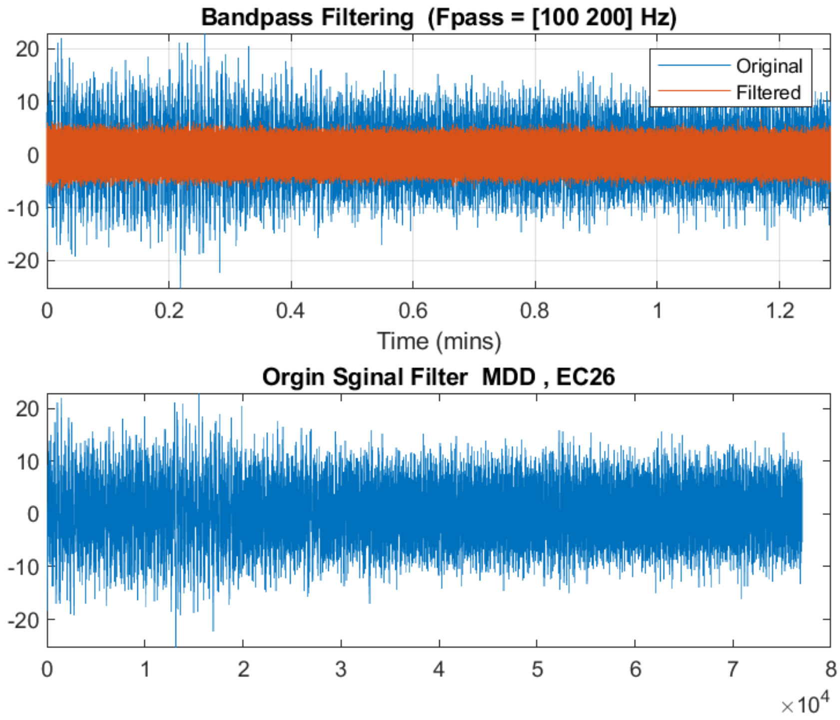

Figure 5. Signal of a depressed person with closed eyes after applying the band pass filter

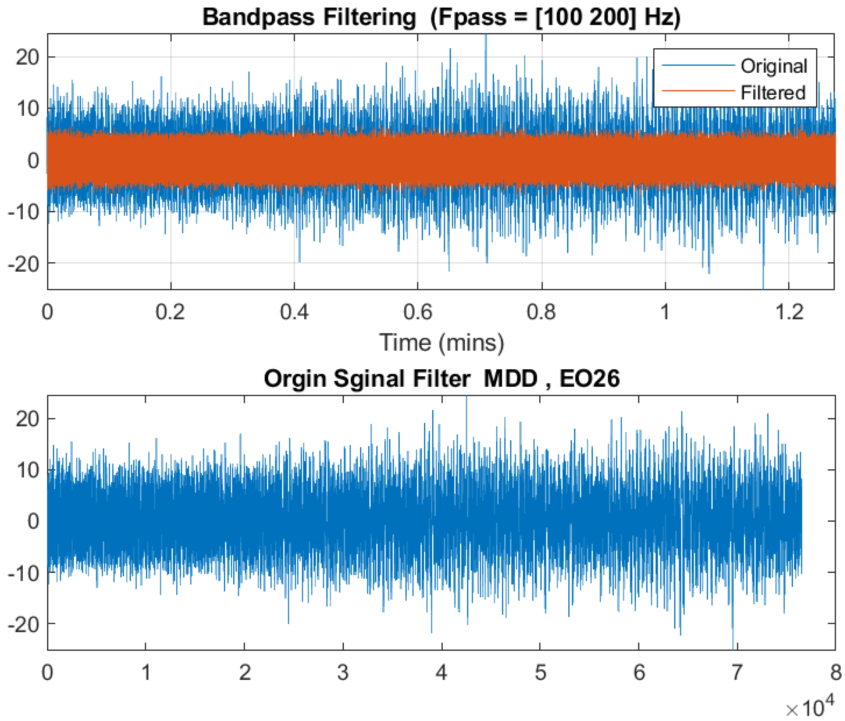

Figure 6. Signal of a depressed person with open eyes after applying the band pass filter

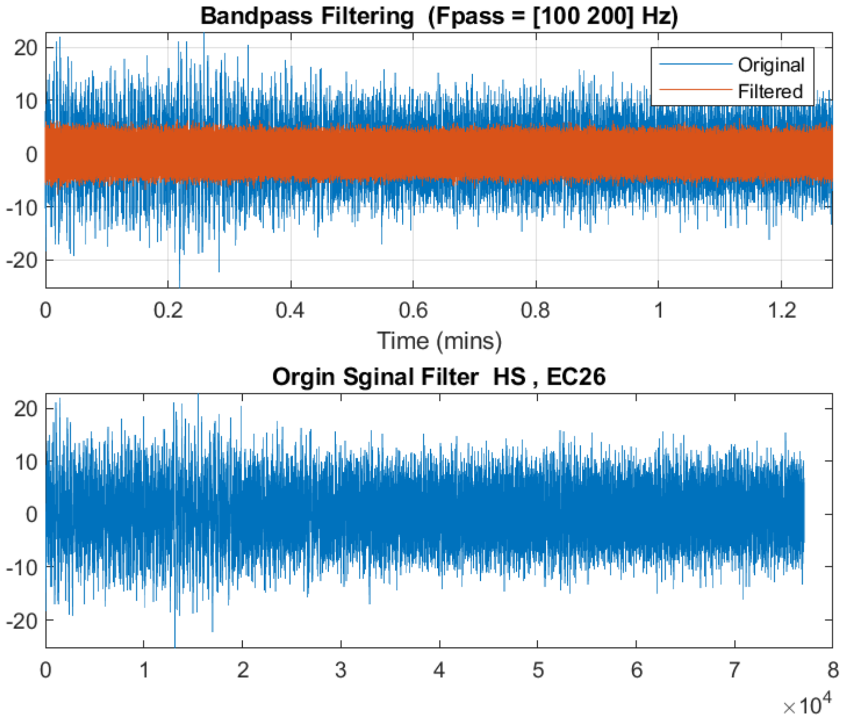

Figure 7. Signal of a normal person with closed eyes after applying the band pass filter

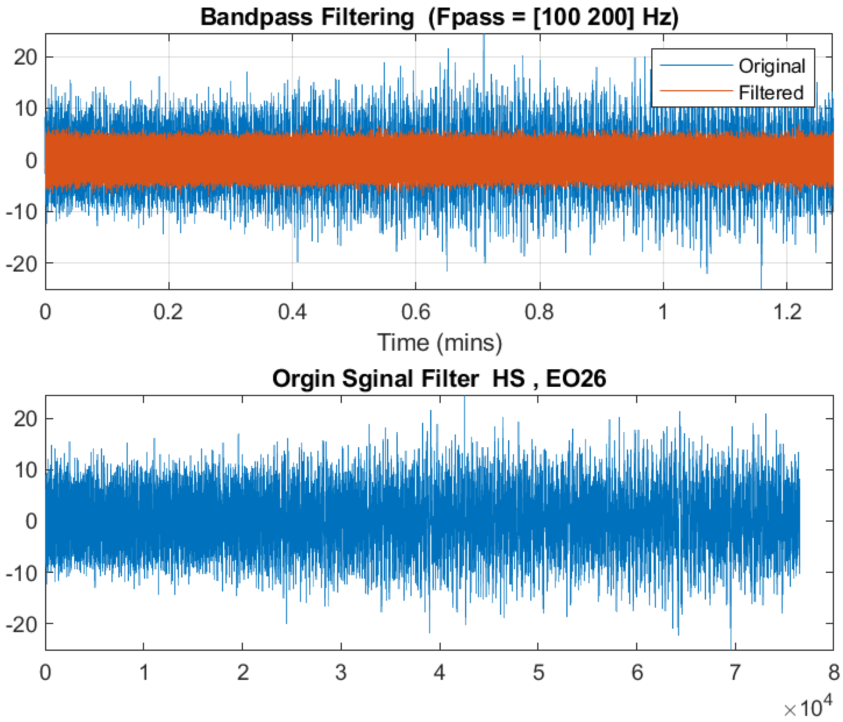

Figure 8. Signal of a normal person with open eyes after applying the band pass filter

The second step of the first stage is the use of the DWT, as it was previously mentioned there are 54 types of DWT family, and each one of this family will be applied to more than one level, it was applied from the first level to the seventh level, and as we mentioned previously that the signal after the seventh level dissipates and becomes not valuable. The figure below (figure 9) shows one of the previous signals after applying the filter, this figure illustrates applying the DWT in the first level, as it results in two signals, the detailed signal, and the approximate signal, while the rest of the figures (figure 10 to figure 15) are for the rest of the levels from the second to the seventh respectively.

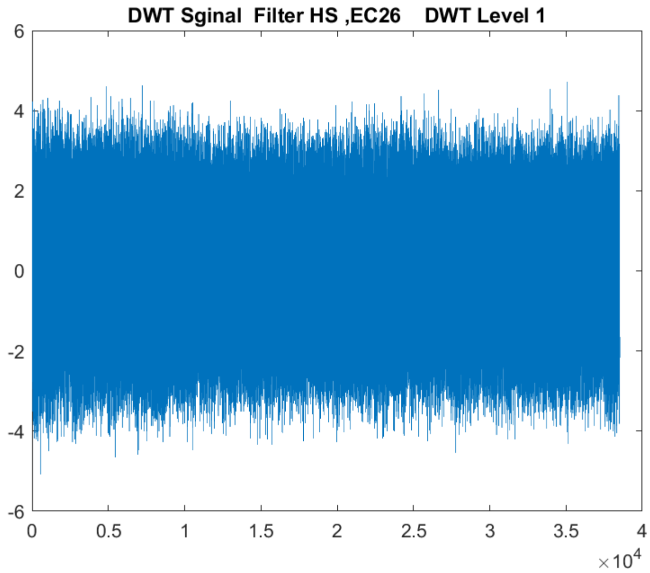

Figure 9. DWT for depression signals at level 1.

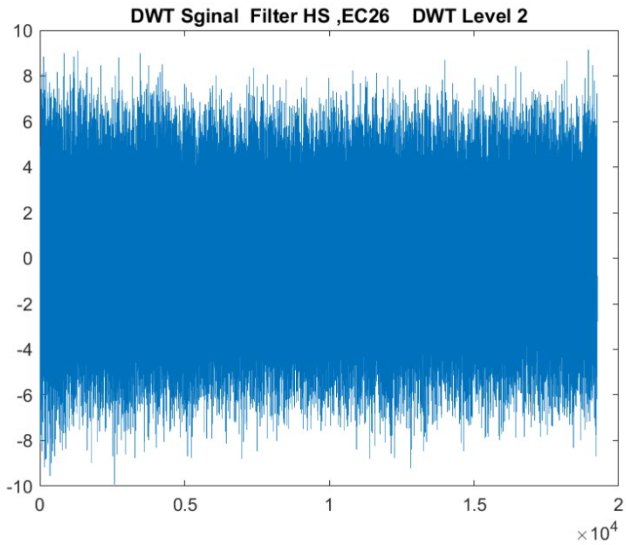

Figure10. DWT for depression signals at level 2.

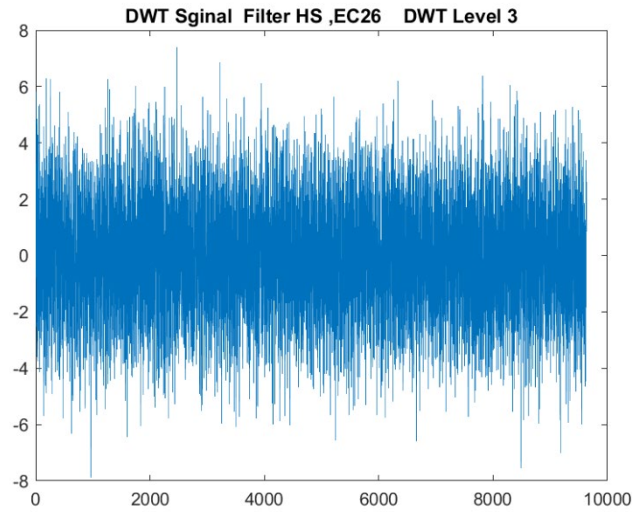

Figure11. DWT for depression signals at level 3.

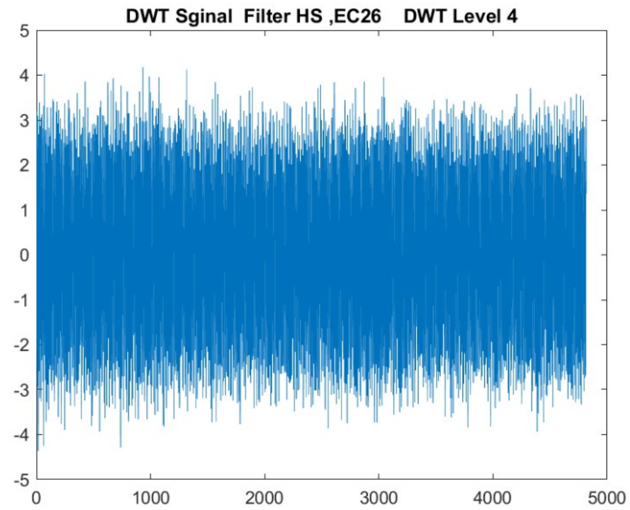

Figure12. DWT for depression signals at level 4.

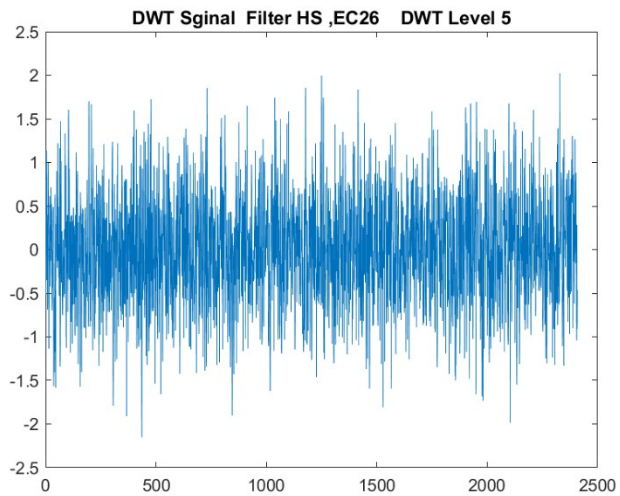

Figure13. DWT for depression signals at level 5.

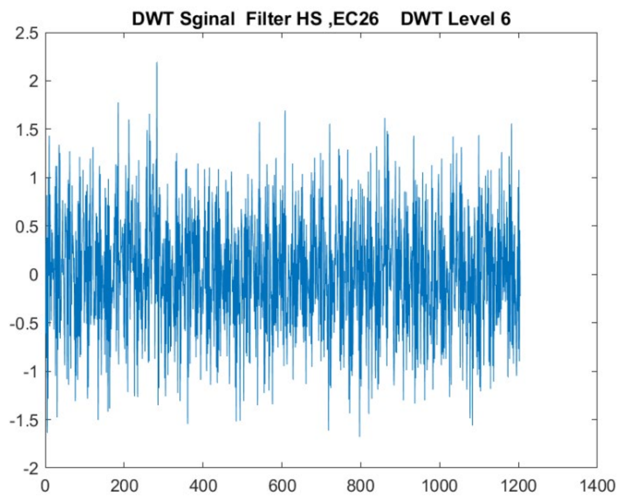

Figure14. DWT for depression signals at level 6.

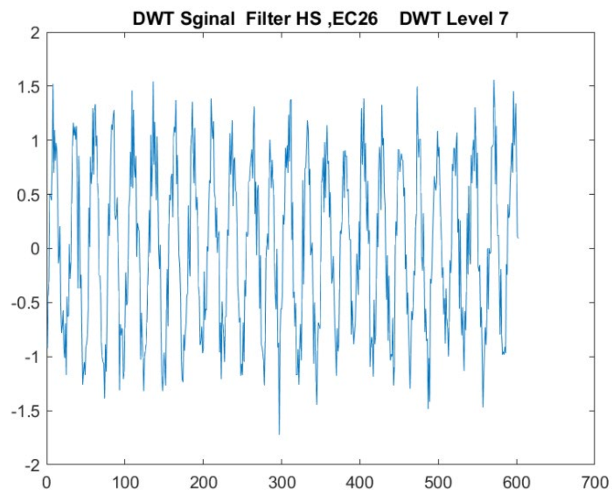

Figure15. DWT for depression signals at level 7.

The table below represent the results of applying the classification algorithm before and after PCA, and after applying the genetic algorithm. Table 1, represents the results of the performance of the proposed model and its ability to classify depressive states, as the results are presented from four well-known types of system performance measures, Accuracy, Precision, Recall, and the F-scale in addition to time.

Table 1. Evaluation performance measures with all features

	ACC	PRE	RECALL	F	TIME
KNN	56.89	0.571	0.569	0.569	**0.01**
ADBOOST	37.97	0.379	0.379	0.379	1.98
DT	**62.09**	0.629	0.621	0.618	0.4
SVM	44.8	0.445	0.448	0.445	1.2
RF	62.069	0.622	0.621	0.621	1.92

Figure 16 below, illustrates the evaluation in terms of accuracy and time measures in case of all features.

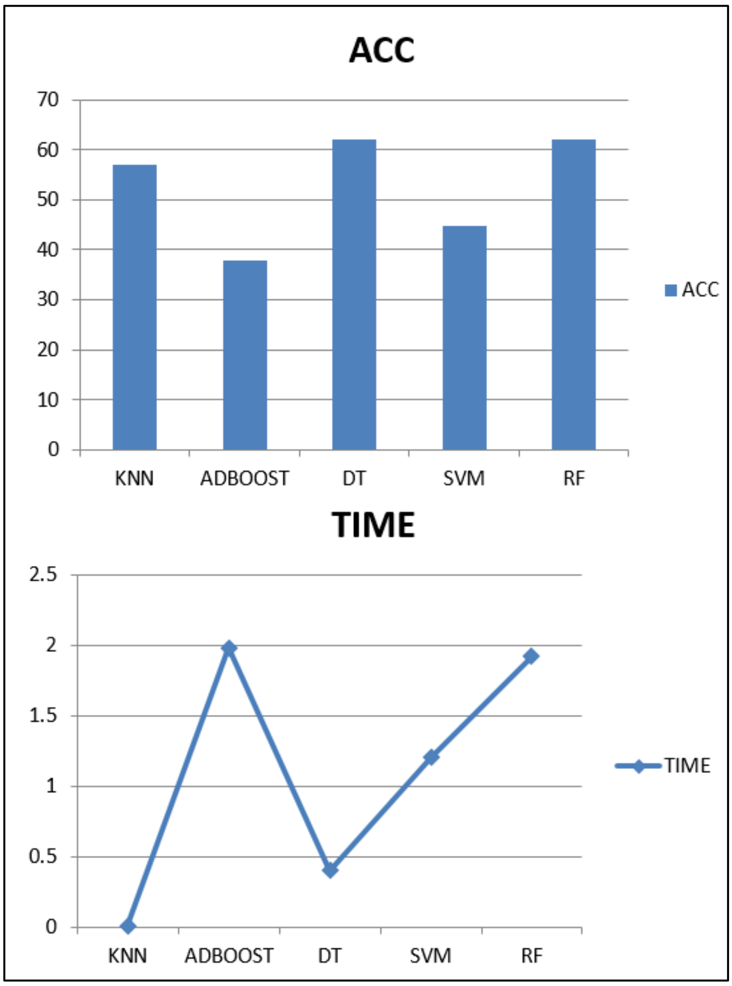

Figure 16. Accuracy and time measures in case of all features

Table 2 displays the results of applying PCA to the extracted features. The results show that the system performance has been improved in terms of accuracy and it has been improved significantly in terms of speed and amount of time consumed.

Table 2. Evaluation performance measures after PCA

	ACC	PRE	RECALL	F	TIME
KNN	50.1	0.506	0.490	0.490	**0.001**
ADBOOST	**74.13**	0.743	0.741	0.740	0.03
DT	62.1	0.625	0.621	0.62	0.04
SVM	68.96	0.691	0.690	0.690	0.04
RF	60.1	0.603	0.603	0.603	0.06

Figure 17 below, illustrates the evaluation in terms of accuracy and time measures after applying PCA.

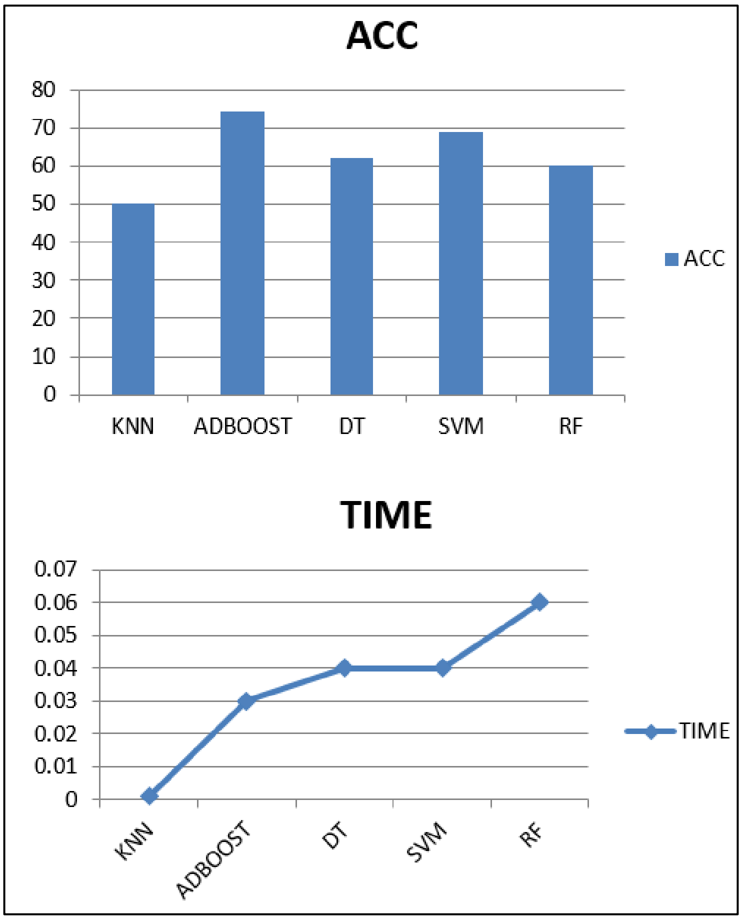

Figure 17. Accuracy and time measures after applying PCA

Table 3 below, shows the results of applying PCA and GA to the extracted features. The results demonstrate that the system performance has been improved significantly in terms of accuracy and it has also been improved significantly in terms of speed and amount of time consumed.

Table 3. Evaluation performance measures after GA

	ACC	PRE	RECALL	F	TIME
KNN	89.5	0.894	0.890	0.892	**0.01**
ADBOOST	**98.54**	0.983	0.981	0.890	0.02
DT	95.1	0.956	0.955	0.955	0.03
SVM	95.96	0.951	0.950	0.950	0.02
RF	95.9	0.958	0.958	0.958	0.06

Figure 18 below, illustrates the evaluation in terms of accuracy and time measures after applying PCA and GA.

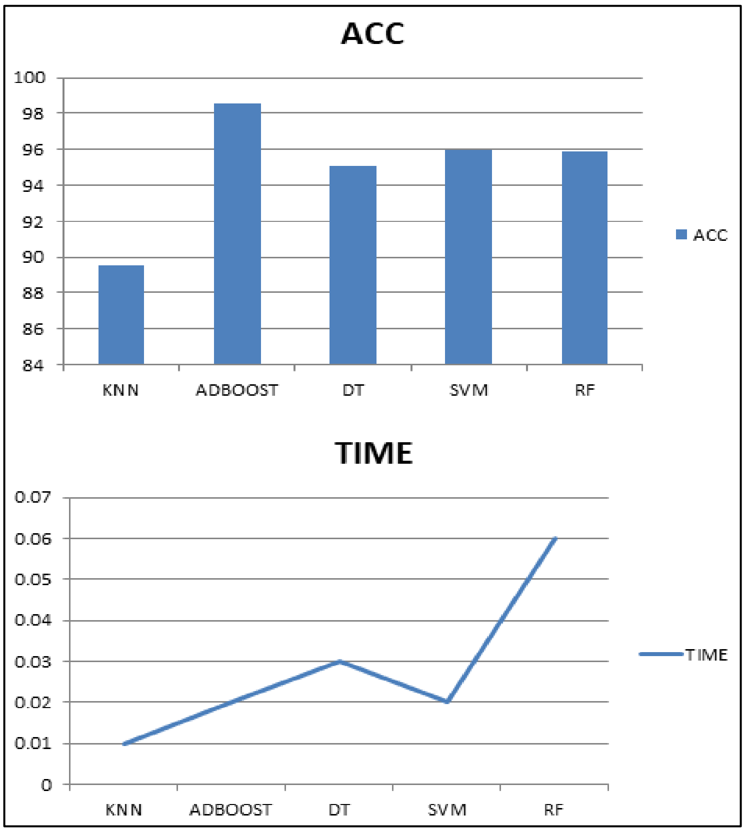

Figure 18. Accuracy and time measures after applying PCA and GA

6 Conclusion and future work

In this section you should present a conclusion of your work together with future work. The ability to use signals derived from human organs, such as brain or heart signals, to identify a person's condition and then detect psychological or pathological conditions in humans has increased as sensor and signal record device development, as well as signal handling and feature extraction techniques, has advanced. This demanded signal classification work in order to boost productivity and performance in signal-based instance categorization. The three basic processes that comprise the proposed model in this study are processing, feature extraction, and classification. To obtain the most precise information from the primary EEG data. Filters are used in signal processing to clean up data and eliminate noise. We aspire to continue working on this important scientific research because of the rapid increase in this phenomenon, which is the prevalence of depression among different age groups. What we plan to do in this regard is to reach a high degree of predictive accuracy by building a comprehensive system in this field by integrating brain signals and other vital parameters obtained by various body systems such as the digestive system, the nervous system, the heart, and hormones as well.

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