Wavelet transform based feature extraction for EEG signal classification

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Abstract: - This study focused on the classification of EEG signal. The study aims to make a classification with fast response and high-performance rate. Thus, it could be possible for real-time control applications as Brain-Computer Interface (BCI) systems. The feature vector is created by Wavelet transform and statistical calculations. It is trained and tested with a neural network. The db4 wavelet is used in the study. Pwelch, skewness, kurtosis, band power, median, standard deviation, min, max, energy, entropy are used to make the wavelet coefficients meaningful. The performance is achieved as 99.414% with the running time of 0.0209 seconds.

Key-Words: - Wavelet transform, db4, EEG, feature vector, eye state, classification

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1 Introduction

The human brain is composed of neurons. Data between the brain and the human body is passed by these neurons. One of the methods that help to record brain activities is Electroencephalogram- EEG. EEG signal is important for BCI system. Because it has the potential to control applications such as computer games, health care and bio-medical systems, emotion tracking, a smart home device controlling and internet of things, military, and detection of car driving drowsiness [1]. Postalcioglu et al. are used wavelet analysis for feature extraction of the faults [2,3]. Qaysar and Jayanthy are studied wavelet transform for classifying autism spectrum disorder [4]. Subasi et al are studied EEG-based emotion recognition using Q wavelet transform [5].

Many previous studies focused on the detection of eye state from EEG signals. Reddy and L. Behera get the performance as 97.5% for classification of the EEG dataset. Running time for classification is calculated as 1.9 seconds for 3-layer architecture neural network [6]. Al-Taei gets the performance as 97.27% for the study [1]. Ma and Gao get an accuracy of 0.93 for eye behavior prediction [7].

This study includes detecting the condition of eyes with two-dimensional eyes closed or open from EEG signal for control applications. The main aim of this paper is to develop a classification method that is more robust and higher in performance. So it could be applied to the real-time implementations. BCI systems turn these signals into device signals that are controllable at the level of thought. Classification of motor movements is a crucial problem in the field of BCI for immediate applications. Such, a significant amount of work has been done so far for classification methods for distinguishing between various motor movements by using the executed motor movement of EEG signals. This study classifies different movement tasks according to EEG signals. These tasks are eye state (open or closed). All steps are pre-processing, feature extraction, and classification for this study. The analysis is carried out for three levels of decomposition using Daubechies 4 wavelet (db4). The system performance is evaluated using Neural Networks.

2 Material and Method

Firstly, classification is made using Random Forest Classifier before proceeding to the signal processing stage. Recursive Feature Elimination with Cross-Validation (RFECV) technique is used. The channels with the best features from the dataset are selected using the RFECV technique. Among the 14 channels, 'AF3', 'F7', 'P', 'O1', 'FC6', 'F8', 'AF4' are selected as the best channels. 3-layer (input layer, hidden layer, output layer) Neural network model is created. The training is carried out with the best selected features. Training time lasted 42.287466 sec. and Test time lasted 0.059001 sec. Mean square error is obtained as

0.239 and accuracy is obtained as 0.55. The accuracy rate is too low. As a result, it is decided to use Wavelet transform to make the feature extraction process more effective in the EEG signals. The basic block diagram of the system is given in figure 1.

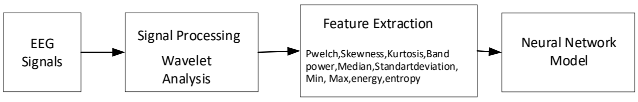

Fig.1. The basic block diagram of the system

2.1 Data Set

The dataset comprises occasions of EEG measurements. The measurement of the output is whether the eye is open or not. The eye state (either 0 for open, or 1 for closed) was identified by a camera during the EEG measurement. For the dataset, you can visit https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State [8]. The dataset was prepared which contains 14980 instances. EEG measurements from the headset, labeled AF3, F7, F3, FC5, T7, P, O1, O2, P8, T8, FC6, F4, F8, AF4. Figure 2 shows the distribution of the dataset for open eye and close eye.

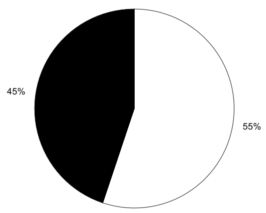

Fig.2. Distribution of the dataset for eye state classification

The number of examples with open eye class in the dataset is 8257, while the number of closed eye type examples is 6723. The data were normalized by using a min-max normalizer. The Equation 1 is given below. X is the original value and x' is its normalized value [9].

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

2.2 Signal Processing: Wavelet Transform

EEG signals have non-stationary and transient characteristics, so only time domain features are not enough for classification. For this aim, the Wavelet transform method is applied to EEG signals. It is suitable for the analysis of non-stationary signals [10]. In wavelet transform, the signal is passed through low and high-pass filters to produce approximate and detail coefficients, respectively [11]. Wavelet transform is used to examine the signal at a different scale. WT decomposes the signal into approximation and detail coefficients. Choosing the appropriate wavelet is important. Daubechies 4 (db4) is widely used in biomedical signal processing [12]. Hence, Daubechies 4 (db4) is used in this paper. Figure 3 shows the scaling function and mother wavelet for db4. The EEG signal is applied to a half-band high pass filter and low pass filter. The result of this stage produces an approximate coefficient for high pass and detail coefficient for low pass filters [12].

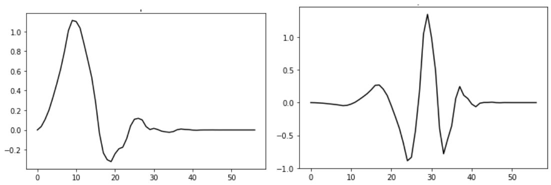

Fig.3. Scaling function and mother wavelet for db4

After the decomposition and reconstruction stage, low-pass filters and high-pass filters are shown in figure 4 for db4.

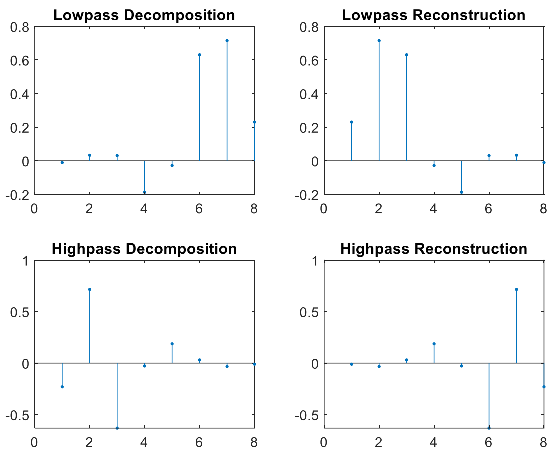

Fig.4. The four filter for db4

Equation 2 shows the detail and approximation equality [13]. Where Ø(t) and Ψ(t) are the basic scaling and mother wavelet respectively. Where $c_j(k)$ and $d_j(k)$ are the approximation and detail coefficients [13]. The low pass filter is called the approximation (A). it contains the low frequency. The high pass filter is called the detail (D) and contains the high frequency [13].

$$c_j(k) = \int_{-\infty}^{\infty} f(t)\Psi(2^j t - k)dt$$
$$d_j(k) = \int_{-\infty}^{\infty} f(t)\Psi(2^j t - k)dt \qquad (2)$$

The EEG signal decomposed by using the db4 mother wavelet up to 3th-level of the decomposition. Figure 5 shows the Discrete Wavelet Transform (DWT) Sub-band decomposition.

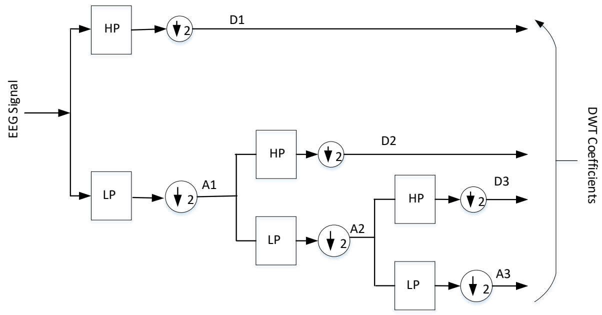

Fig.5.Discrete Wavelet Transform decomposition

Figure 6 shows the detail coefficients for states (0 for open,1 for closed). Figure 7 shows the approximation coefficients for states.

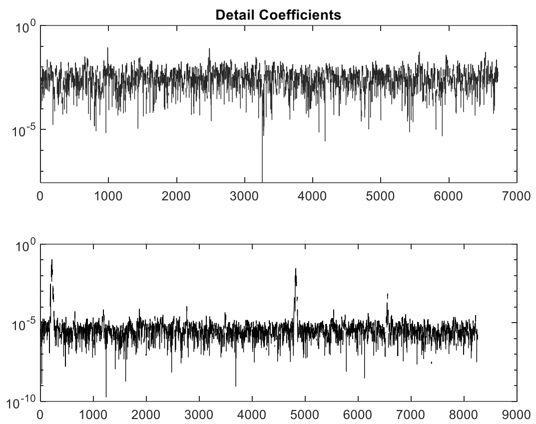

Fig.6. Detail coefficients for states (0 for open, 1 for closed)

Feature extraction is performed to obtain meaningful data from these details and approach coefficients. Pwelch, skewness, kurtosis, band power, median, standard deviation, min, max, energy, entropy are used for feature extraction.

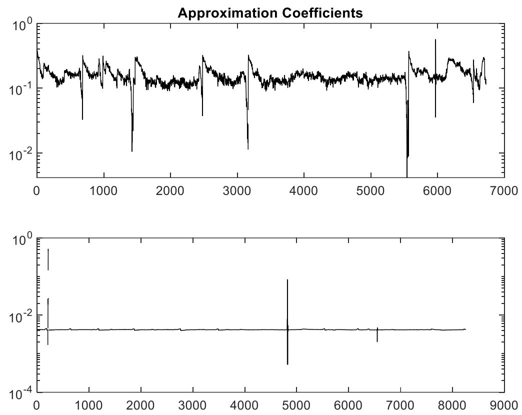

Fig.7. Approximation coefficients for states (0 for open, 1 for closed)

2.3 Feature Extraction

Extraction of features plays an important role in the training of the classifier. One should be careful in selecting the prominent features as they affect the accuracy of the classifier. In this study, features are extracted for every class. There are numerous statistical and nonstatistical features suggested in the literature, but we have computed the following most prominent features: pwelch, skewness, kurtosis, band power, median, standard deviation, min, max, energy, entropy. These extracted features are used to classify the different classes of EEG signals [14]. Energy for approximately and detailed coefficients are computed by using equation 3 [15].

$$E_{D_i} = \sum_{j=1}^{N} |D_{ij}|^2$$
$$E_{A_i} = \sum_{j=1}^{N} |A_{ij}|^2 \qquad i=1,2,3...l \qquad (3)$$

The total energy can be defined as equation 4 [15].

$$E_{total} = (\sum_{i=1}^{l} E_{D_i} + E_{A_i}) \qquad (4)$$

Max and min values are obtained for detail coefficients. Mathematical representations are shown in Equations 5 and 6 [10].

$$M = max_{ij}(D_{ij}) \qquad (5)$$

$$m = min_{ij}(D_{ij}) \qquad (6)$$

X is a signal with a mean μ, N is the number of samples for standard deviation [16]. The standard deviation formula is given in equation 7 [10].

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{7}$$

The skewness shows the symmetry of the probability density function of the amplitude of a time series [16]. The skewness formula is given in equation 8 [10].

$$S = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)}{\sigma^3} \tag{8}$$

The kurtosis measures the summit of the probability density function of a time series [16]. The kurtosis formula is given in equation (9) [10].

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^4}{\sigma^4} \tag{9}$$

The median shows the central tendency [16]. The median formula is given in equation 10 [10].

$$Median = \begin{cases} \left(\frac{n+1}{2}\right)^{th}, if\ N\ is\ odd \\ \frac{\left(\frac{n}{2}\right)^{th}+\left(\frac{n}{2}+1\right)^{th}}{2}, if\ N\ is\ even \end{cases} \tag{10}$$

Entropy shows the randomness of a signal in wavelet space. Entropy measurement is given in equation 11 [1].

$$H = -\sum_{i=1}^{K} p(cA_i)logp(cA_i) \tag{11}$$

Where K is the number of samples, cA is the approximation coefficients and p(cAi) symbolize the probability measure associated with the approximation.

Pwelch computes the power spectral density with Welch's technique [17]. The results of Pwelch analysis applied to the approximation coefficient are given in figure 8 for classes (1,0). The properties obtained as a result of Wavelet analysis are given below.

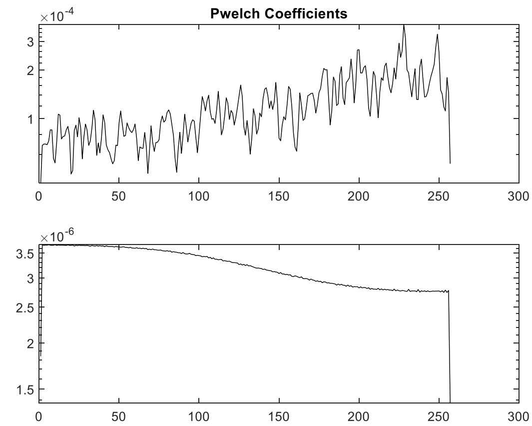

Fig.8. Pwelch results for approximation coefficients (1,0)

Figure 9 and Figure 10 shows the Skewness results for approximation and detail coefficients results. Figure 11 and Figure 12 show the kurtosis results for approximation coefficients and detail coefficients, respectively. Figure 13 and Figure 14 show the band power results for approximation and detail coefficients, respectively. Figure 15 shows the median results for detail coefficients. Figure 16 shows the Maximum results for detail coefficients, Figure 17 shows the minimum results for detail coefficients. Figure 18 shows the standard deviation results for detail coefficients. Figure 19 shows the entropy results for approximation and detail coefficients.

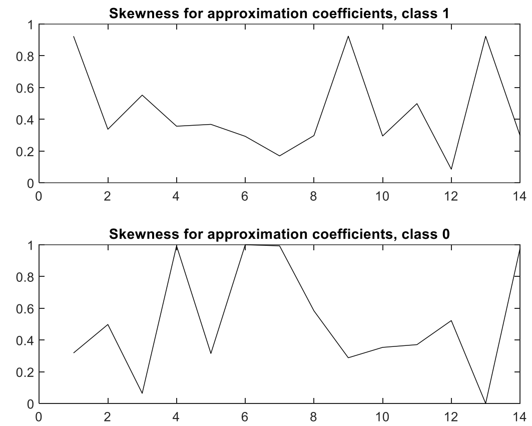

Fig.9. Skewness results for approximation coefficients

Fig.10. Skewness results for detail coefficients

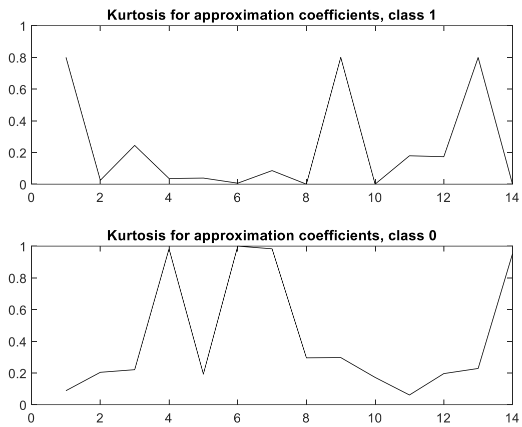

Fig.11. Kurtosis results for approximation coefficients

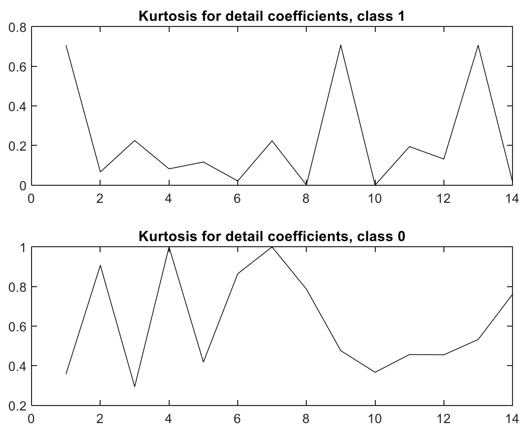

Fig.12. Kurtosis results for detail coefficients

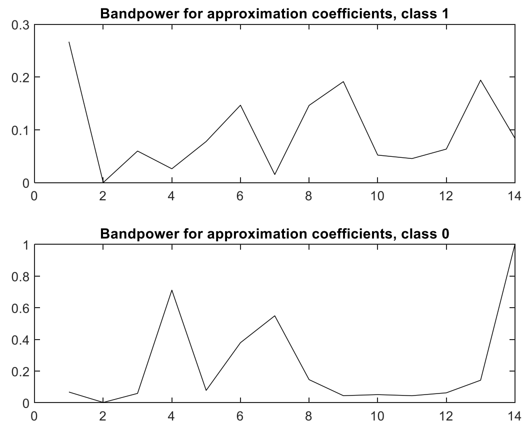

Fig.13. Band power results for approximation coefficients

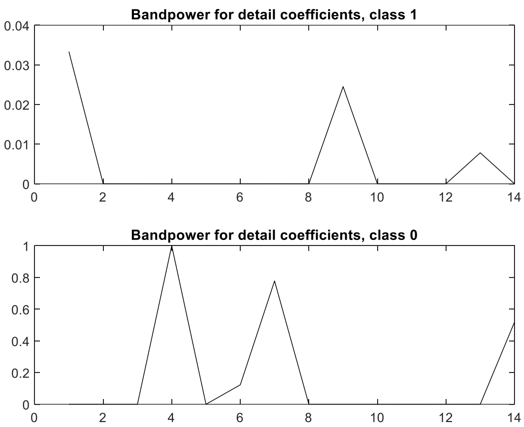

Fig.14. Band power results for detail coefficients

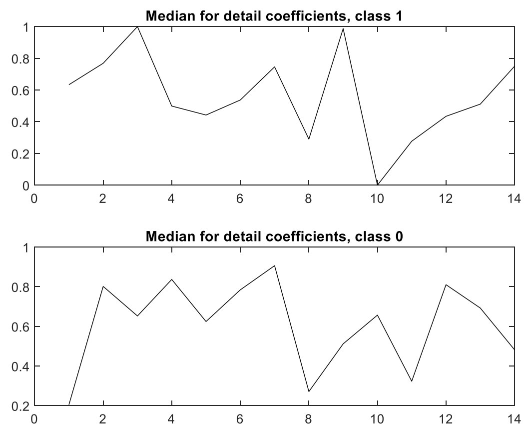

Fig.15. Median results for detail coefficients

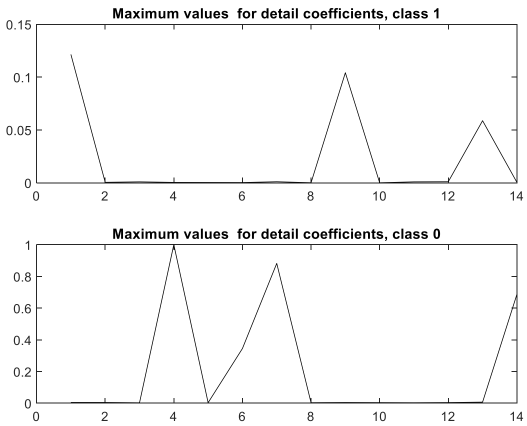

Fig.16. Maximum results for detail coefficients

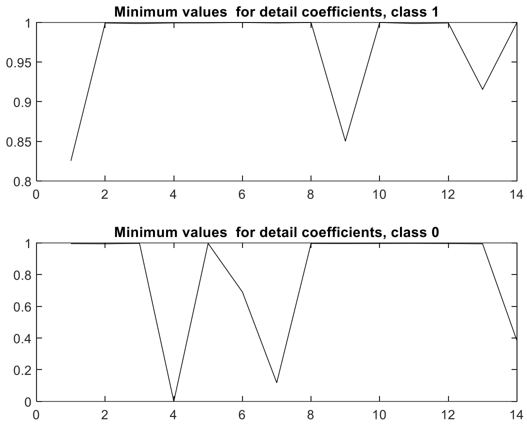

Fig.17. Minimum results for detail coefficients

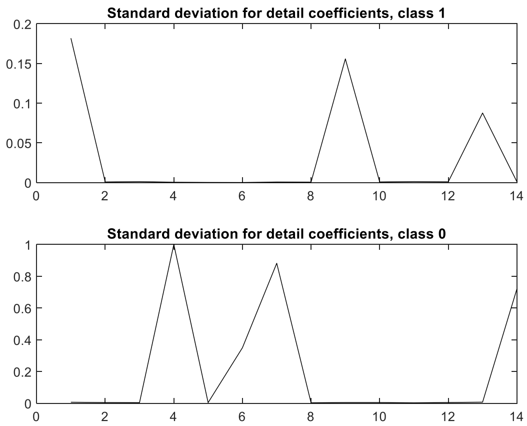

Fig.18. Standard deviation results for detail coefficients

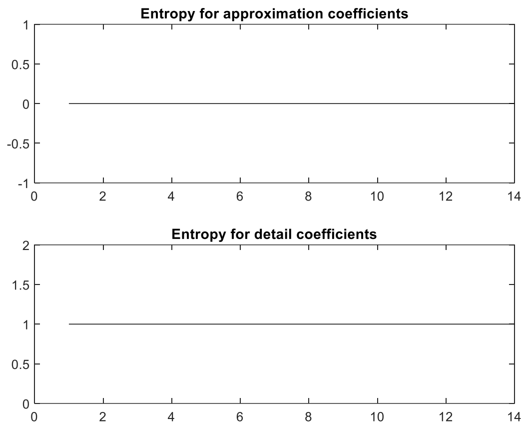

Fig.19. Entropy results for approximation and detail coefficients

3. RESULTS

A Neural Network is used for classification of EEG signals. The neural network model for the study is shown in Figure 20. Feature vector is applied to the model for training. The Mean Squared Error (MSE) graph is given in figure 21. Figure 22 shows the performance results for the model. The dashed line in each plot denotes *perfect result – outputs = targets*. The solid line denotes the best fit linear regression line between outputs and targets. The R-value shows the association between the outputs and targets. If R = 1, this shows that there is a linear association between outputs and targets. Figure 23 shows the performance for the running time. When the study is evaluated in terms of running time, it seems quite suitable for real-time applications.

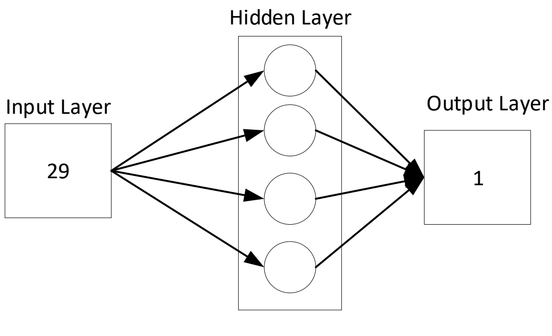

Fig.20. Neural network model for the study

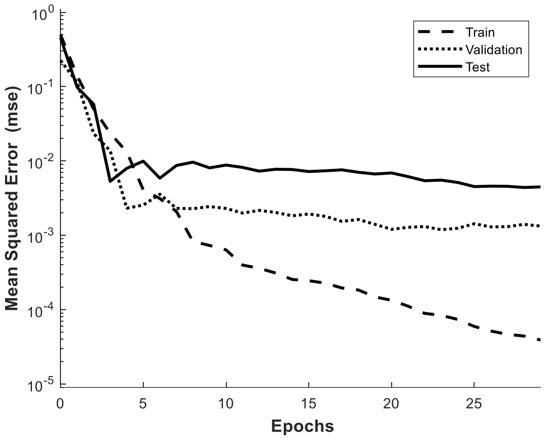

Fig.21. MSE results for neural network model

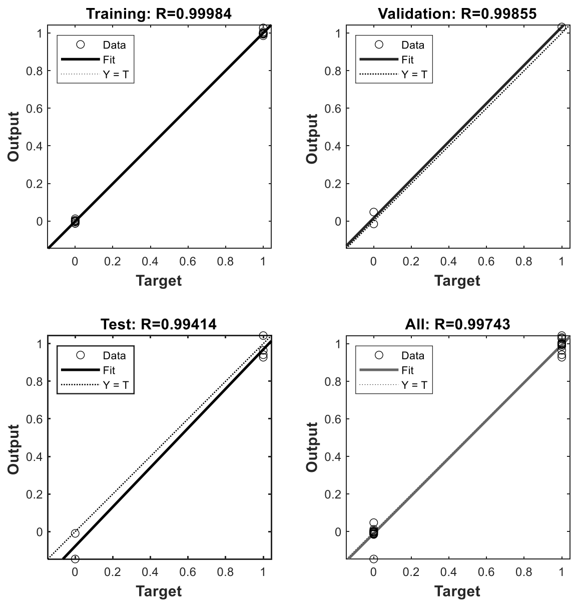

Fig.22. Performance results for the model

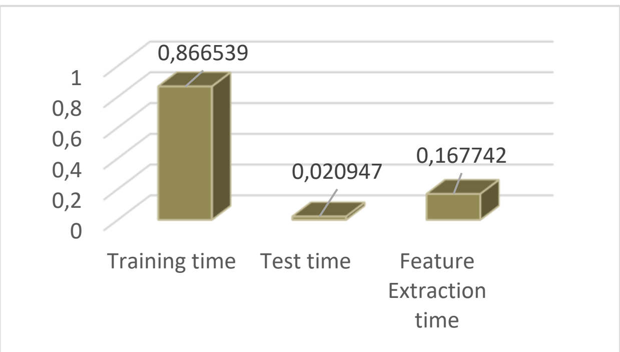

Fig.23. The performance for the duration

4. CONLCUSIONS

A study has been done on the EEG signals. The EEG signals contain two conditions; situations in which the eye is closed and open. These movements can be easily used in BCI systems by detecting them through EEG signals. Thus, control systems can be developed by using EEG signals. Wavelet transform has been used. Db4 wavelet is selected. The obtained detail and approximation coefficients are analyzed with statistical properties. Pwelch, skewness, kurtosis, band power, median, standard deviation, min, max, energy, entropy are used. Then, training is realized for the feature vector on the 3-layer neural network. The performance is achieved 99,414%. As a result, this study has revealed quite distinctive features for the classification process. Besides, running times are examined. Duration is important for real-time implementations. For this study, the running time has obtained as 0.0209 seconds.

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