Short Communication

# Detection of ADHD From EOG Signals Using Approximate Entropy and Petrosain's Fractal Dimension

**Nasrin Sho'ouri**

*Faculty of Technology and Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran*

## Abstract

**Background:** Previous research has shown that eye movements are different in patients with attention deficit hyperactivity disorder (ADHD) and healthy people. As a result, electrooculogram (EOG) signals may also differ between the two groups. Therefore, the aim of this study was to investigate the recorded EOG signals of 30 ADHD children and 30 healthy children (control group) while performing an attention-related task. **Methods:** Two features of approximate entropy (ApEn) and Petrosian's fractal dimension (Pet's FD) of EOG signals were calculated for the two groups. Then, the two groups were classified using the vector derived from two features and two support vector machine (SVM) and neural gas (NG) classifiers. **Results:** Statistical analysis showed that the values of both features were significantly lower in the ADHD group compared to the control group. Moreover, the SVM classifier (accuracy: 84.6% ± 4.4%, sensitivity: 85.2% ± 4.9%, specificity: 78.8% ± 6.5%) was more successful in separating the two groups than the NG (78.1% ± 1.1%, sensitivity: 80.1% ± 6.2%, specificity: 72.2% ± 9.2%). **Conclusion:** The decrease in ApEn and Pet's FD values in the EOG signals of the ADHD group showed that their eye movements were slower than the control group and this difference was due to their attention deficit. The results of this study can be used to design an EOG biofeedback training course to reduce the symptoms of ADHD patients.

**Keywords:** *Approximate entropy, attention deficit hyperactivity disorder, electrooculogram, neural gas, Petrosian's fractal dimension, support vector machine*

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## Introduction

Attention deficit hyperactivity disorder (ADHD) is a common mental disorder in childhood and adolescence, commonly known as three symptoms of attention deficit, hyperactivity, and impulsivity and affects the quality of social life of children. This disorder causes antisocial behaviors, educational and emotional problems, learning disabilities in the affected person, and increases the risk of drug addiction, motor vehicle accidents, etc., in adulthood.[1-5] Accordingly, timely diagnosis, rehabilitation, and treatment of people with this disorder are important, and many researchers have focused on providing rehabilitation programs to treat ADHD patients.[3]

The ADHD is typically diagnosed using various versions of the ADHD criteria published in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) by the American Psychiatric Association.[6] The diagnostic accuracy of ADHD through these criteria is strongly influenced by the accuracy of the responses of the child's relatives and their understanding of psychological questions.[7] Therefore, some researchers have turned to finding strategies independent of child's responses, in the diagnosis of ADHD.[7-14]

In the meantime, Lubar examined the brain signals of healthy individuals and ADHD patients, and observed that there was a significant difference between the activities of theta and beta frequency bands in the ADHD patients.[11] This result led many researchers to diagnose ADHD using EEG signal processing. They extracted a variety of features such as power in different frequency bands, entropy, Lyapunov exponent, correlation dimension, and AR

***Address for correspondence:***
*Dr. Nasrin Sho'ouri, Faculty of Technology and Engineering Central Tehran Branch, Islamic Azad University, Tehran, Iran.*
*E-mail: Nas.shourie@iauctb.ac.ir*

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model coefficients from EEG signals of ADHD patients and healthy individuals and showed that the two groups were well separable using various combinations of these features.[7-10,12]

On the other hand, other researchers have shown that eye movements were influenced by the amount of attention, and thus monitoring eye movements may be useful in detecting attention-related disorders.[13-19] For this reason, to date, various studies have been conducted to evaluate the eye movements of ADHD patients in comparison with healthy individuals.[13-25]

The eye-tracking system or EOG signal processing is mainly used to monitor eye movements. Studies using the eye-tracking system showed that binocular coordination was weaker in ADHD patients than in healthy controls.[22] Compared to healthy individuals, the ADHD patients showed less ability to suppress unwanted saccades.[21] The mean micro-saccade rate in the ADHD patients was significantly higher when performing an attention-related cognitive task, especially near the onset of stimulation, than in healthy controls.[18] It has been shown that there was a significant relationship between attention-related eye vergence and orienting visuospatial attention.[26] Thus, there was a significant difference in attention-related eye vergence between the two groups.[17] In addition, the visual search pattern of ADHD patients was different from that of healthy individuals, and the ADHD patients revealed poorer performance in detecting a change than controls.[23] Moreover, during the Stroop test, there was a significant difference between the total time spent on the target stimulus and the distracter stimulus and the number of fixations on these stimuli in the two groups. In this test, the ADHD patients switch between the two stimuli more frequently than healthy controls and exhibit a poorer performance in ignoring the distracter stimuli.[24] In addition, it has been shown that the saccades were inhibited in healthy individuals before the onset of predictable stimulation, but not in the ADHD patients.[25]

The use of the eye-tracking system is more common in the monitoring of eye movements than the use of EOG signals. However, there are studies that also used the EOG signal to examine the differences in eye movements in ADHD patients and the healthy controls.[13,14,19,20] For example, poor ability of ADHD patients to suppress unwanted saccades using EOG signal analysis has also been concluded.[20] EOG analysis has also been shown that healthy people have performed better in image follow-up, compared to those with ADHD.[27] Decreased values of ApEn and SampEn entropies in the vertical EOG signal have shown a delay in attention or lack of desire to pay attention to the surrounding environment.[28] It has been found that standard deviation and energy of wavelet detail coefficients were significantly higher in ADHD children as compared to healthy controls.[13] The values of low-frequency (0.5–4.125 Hz) band power, fractal dimension, and entropy were also found significantly lower in the EOG signals of the ADHD children, compared to the healthy individuals.[19] Moreover, the scaling exponent detrended fluctuation analysis (DFA) was found significantly higher in ADHD children.[14,19] Petrosaian's fractals dimension (Pet's FD) and approximate entropy (ApEn) were found as the most effective features to separate the EOG signals of the groups. The two groups were also classified using scaling exponent and Growing Neural Gas (NG) classifier with an average detection accuracy of 72.22% ± 2.8%.

The present study focused to diagnose ADHD with a simpler and cheaper recording and processing steps. EOG signal recording is possible even only with a single channel and is more cost-effective than multi-channel EEG recording and eye-tracking system. However, there is insufficient research into the diagnosis of ADHD by the EOG signal. To date, only one study has been performed on the classification of the two groups' EOG signals using the scaling exponent.[14] In addition, it has been shown that the combination of Pet's FD and ApEn was more effective in separating the two groups' EOG as compared to the scaling exponent.[19] Moreover, ApEn can quantify the complexity, predictability, and irregularity of the signals.[29] The Pet's FD also shows the amount of complexity and self-similarity of a time series over a period of time.[30] Both features have been used successfully in goals such as diagnosing different diseases, quantifying the cognitive workload, separating skilled and unskilled people using the EEG signals.[31-34] Therefore, it is possible that the accuracy of EOG classification of the two groups will be improved by using these two features. Therefore, the present research has focused on calculation of the Pets' FD and ApEn values of EOG signals in two groups of ADHD and healthy children and to determine their differences by statistical tests. In addition, the two groups are classified by the calculated features and two classifiers (support vector machine [SVM] and NG). These classifiers have been selected based on the results of previous studies that have shown good results in classifying biological signals in different states.[35,36]

## Proposed approach

### *Constitute necessary data*

#### Participants

This study used the database of research by Mohammadi *et al*., including EEG and EOG signals of 30 healthy children (25 boys and 5 girls, with mean age of 9.85 ± 1.77 years) and 30 ADHD children (22 boys and 8 girls, with mean age of 9.62 ± 1.75 years). A psychiatrist diagnosed the ADHD children using the DSM-IV criteria, which consisted of 25 children with ADHD-C (hyperactive with attention deficit), three children with ADHD-I (with attention deficit), and two children with ADHD-HI (hyperactive). Raven`s Progressive Matrices

Test was used to select the subjects, and children over moderate level were selected for the study. Children in both groups had no history of other mental disorders and brain injuries such as epilepsy, learning disabilities, and taking medications such as benzodiazepine and barbiturate.[7]

### How to record electrooculogram signals

The desired database has been recorded at the Psychiatric and Clinical Psychology Research Center, Roozbeh Psychiatric Hospital, Tehran University of Medical Sciences (TUMS), Tehran, Iran, using the SD-C24 device. The EEG signals were recorded using 20 electrodes in accordance with 10–20 international standard System, and electrodes A1 and A2 located in the earlobes were used as reference. The EOG signal was recorded using two electrodes located above and below the right eye. The sampling frequency was set to 256 Hz. During the recording, all signals were filtered with a band-pass filter with a frequency range of 0.3–30 Hz. To reduce noise and artifacts, the signal recording operation was performed in a conserved room and subjects were asked to avoid extra movement, especially in the head area.[7]

### Study methodology

A number of images, including some figures of animals or cartoon characters, were shown to each subject. The number of figures in each image ranged from 5 to 16, and the size was large enough for subjects to easily see and count. Some of these figures were at the top of the image and others at the bottom of the image. The subject must first count the number of figures at the top of the image and then count the number of figures at the bottom of the image, finally summing this number together and announcing the total. Immediately after the response, the next image was displayed to the child. This process was repeated for 17 different images and the subject's EEG and EOG signals were recorded while performing this process[7]; Figure 1 shows an example of these images. The study methodology was approved by the Ethical Committee of TUMS.

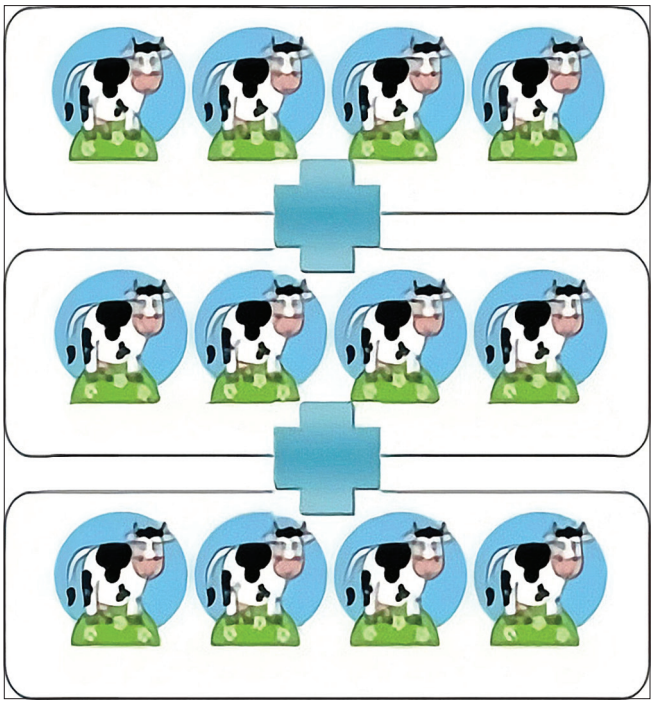

**Figure 1: An example of pictures shown to each child[7]**

#### *Data preprocessing*

In the present study, the EOG signals were examined visually and parts of the signal containing large artifacts such as blinking and muscle movement artifacts were excluded. Since there is an effect of brain activity on the EOG signal, we tried to remove the effect of the EEG signal from the EOG to observe the pure effect of the EOG signal. Independent component analysis method was used for this purpose. Thus, the matrix containing the 21-channel EEG of each subject (20 EEG channels, along with the A1, A2, and EOG signals) was subdivided into independent components, and all the components containing the effect of eye movement and EMG signal artifacts were excluded. The signals were then reconstructed. The reconstructed EOG signal was, in fact, the brain activity recorded through the EOG channel. This brain component was subtracted from the raw EOG signal to obtain a purer EOG. The resulting signal was then subdivided into fragments with a length of 20 s with 10 s of overlap for next processing and termed the cleaned EOG signal. Figure 2 shows an example of raw EOG signal, EEG component recorded at the EOG channel location and cleaned EOG for a healthy subject.

#### *Calculation of features for the studied electrooculogram signals*

### Approxiamte entropy

Approxiamte entropy (ApEn) is a measure of irregularity and unpredictability (uncertainty) of a time series introduced by Richmann in 2000.[29,37] The higher the ApEn value, the greater the irregularity and the unpredictability of the time series; the ApEn is calculated for the x time series (x(1), x(2),…, x(N)) as follows:

$$ApEn(m,r,N) = \frac{1}{N-m+1}\sum_{i=1}^{N-m-1} logc_i^m(r) - \frac{1}{N-m}\sum_{i=1}^{N-m} logc_i^{m+1}(r) \quad (1)$$

Where, $m$ is embedding dimension, $r$ shows tolerance and N represents the number of time series data. $C^m(r)$ shows the correlation integral and indicates the probability that two sets of data points of an embedding dimension m having a distance less than $r$. Similarly, $C^m + 1(r)$ is defined for two sets of data points of an embedding dimension m + 1.[37] In the present study, m = 1 and r are considered to be 25% of the standard deviation of each signal.[33]

### Pet's fractal dimension

The fractal dimension is a criterion for quantifying complexity and self-similarity and is defined as a ratio of the change

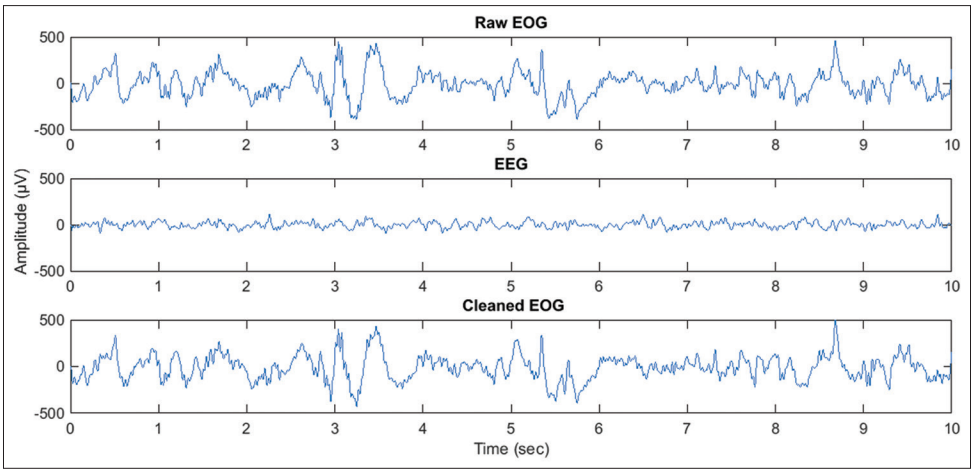


**Figure 2: An example of a raw electrooculogram signal, the recorded brain component in the place of electrooculogram channel and the cleaned electrooculogram for a healthy subject[13,14]**

in detail to the change in scale. There are several methods for calculating the fractal dimension, which was calculated by the Pet's method in this study. In this method, a binary sequence is generated by assigning + 1 or − 1 depending on whether the result of the subtraction is positive or negative, respectively. Then, Pet's FD was calculated as follows:

$$D = \frac{log(n)}{log(n) + log(\frac{n}{n + 0.4N_{\Delta}})} \quad (2)$$

Where, n is the number of time-series samples and $N^{\Delta}$ is the number of sign changes in the generated binary sequence.[38]

### *Statistical analysis of calculated features*

Kolmogorov–Smirnov test was used to assess the normal distribution of the features. According to the results of this test, the distribution of all features was nonnormal. Therefore, Mann–Whitney *U*-test was used to detect differences between the two groups.

### *Classification of electrooculogram signals in two groups*

#### Neural gas

In this study, NG method was used to classify the EOG signals in two groups. The NG is one of the competitive artificial neural networks introduced by Martinetz and Schulten in 1991.[39] The number of neurons in this network remains constant during training and all neurons are updated based on their similarity to the input pattern. The training algorithm of this network is as follows:

1. At the beginning of the task, the number of neurons ($N$) is specified and a random weight is assigned to each
2. An input vector ($\xi$) is exhibited to the network and its similarity is computed relative to each neuron
3. The weights are updated using the following equations:

$$\Delta w_i = \varepsilon(t).h_{\lambda}(k_i).(\xi - w_i) \quad (3)$$

$$h_{\lambda}(k) = \exp(-k/\lambda(t)) \quad (4)$$

$$\varepsilon(t) = \varepsilon_i(\varepsilon_f/\varepsilon_i)^{t/t_{max}} \quad (5)$$

$$\lambda(t) = \lambda_i(\lambda_f/\lambda_i)^{t/t_{max}} \quad (6)$$

Where, $w_i$ is the weight of $i^{th}$ neurons, $\varepsilon(t)$ and $\lambda(t)$ represents the time-dependent training coefficients, and k is the order of the neurons.

1. The time parameter is increased (t = t + 1)
2. If t <$t_{max}$, it will move to step (2), and the previous process will be repeated.

To classify using the NG network, the coordinates of the neurons are first determined, as stated. Then, an input vector is selected, and its distance to each neuron is independently measured. Next, the closest neuron to the target input vector is designated, and this vector is placed in the cluster corresponding to the winning neuron. This process is also repeated for the rest of the training vectors. Finally, the members of all clusters are identified. To determine the label of each cluster, the number of members of each group is counted among the cluster members, and the cluster label is determined according to the most labels among the cluster members. After labeling the neurons, they are used in the network test phase. Thus, a feature vector is measured from the selected test data, and its distance to each neuron is measured. The winning neuron is then selected with the least distance and the label of the test feature vector is determined by the label of the winning neuron.[35,36]

In the present study, learning coefficients $\varepsilon_i$, $\varepsilon_f$, $\lambda_i$ and $\lambda_f$ were set to 0.5, 0.005, 10 and 0.01, respectively.[35,36,40]

#### Support vector machine network

SVMs are networks whose training is supervised and used for data classification and regression analysis purposes. Vapnik in 1963 for the first time proposed the SVM as a linear classifier. Later in 1992, Boser *et al*. proposed a nonlinear SVM in which a nonlinear classifier was constructed using a nonlinear

kernel. The standard soft-margin SVM model was also proposed by Cortes and Vapnik in 1993.[41,42] In the present study, nonlinear SVM with radial basis function (RBF) kernel was applied to classify the data.

## Analysis of experimental results

### *Statistical analysis*

The mean values of ApEn and Pet's FD of raw and cleaned EOG signals were calculated in two groups [Figure 3].

As can be seen, the mean ApEn value of the EOG signals in the control group (1.028 ± 0.20) was significantly higher than in the ADHD group (0.84 ± 0.25) ($P < 0.001$). In addition, the control group (1.16 ± 0.05) had a higher mean Pet's FD of EOG signals than the ADHD group (1.12 ± 0.06) ($P < 0.001$). According to the results, no considerable difference was observed between the results of the raw and cleaned EOG signals.

### *Classification of the electrooculogram signals in two groups*

The EOG signals of the two groups were classified using two-dimensional feature vector consisted of ApEn and Pet's FD values and two separate classifiers (NG network and SVM algorithm).

To select the kernel type for SVM, the ROC curves were plotted for SVMs with linear, RBF, and polynomial (order 3) kernels [see Figure 4]. Accordingly, the SVM model with RBF kernel showed a higher diagnostic performance in terms of area under the ROC curve.

A 10-fold cross-validation structure was used to classify and evaluate the calculated features. Thus, 90% of the ADHD's feature vectors were used for training and 10% for classifiers testing. It was observed that if 90% of the control group's samples were used for training in the training of the SVM, the sensitivity of the algorithm was considerably lower compared to its specificity. Therefore, the number of control group's samples was varied from 10 to 127 (total control group's samples) and for each set of samples in the control group, sensitivity, specificity (detection accuracy for the remaining samples in the control group) and total classification accuracy averages were measured. For example, if 10 samples from the control group were considered for network training and evaluation, the remaining samples in the control group were 117. It was observed that if the control group samples used in the SVM training increase, its sensitivity decreases. Therefore, only 10 samples from the control group were used to train the SVM and 117 samples were used to calculate the specificity.

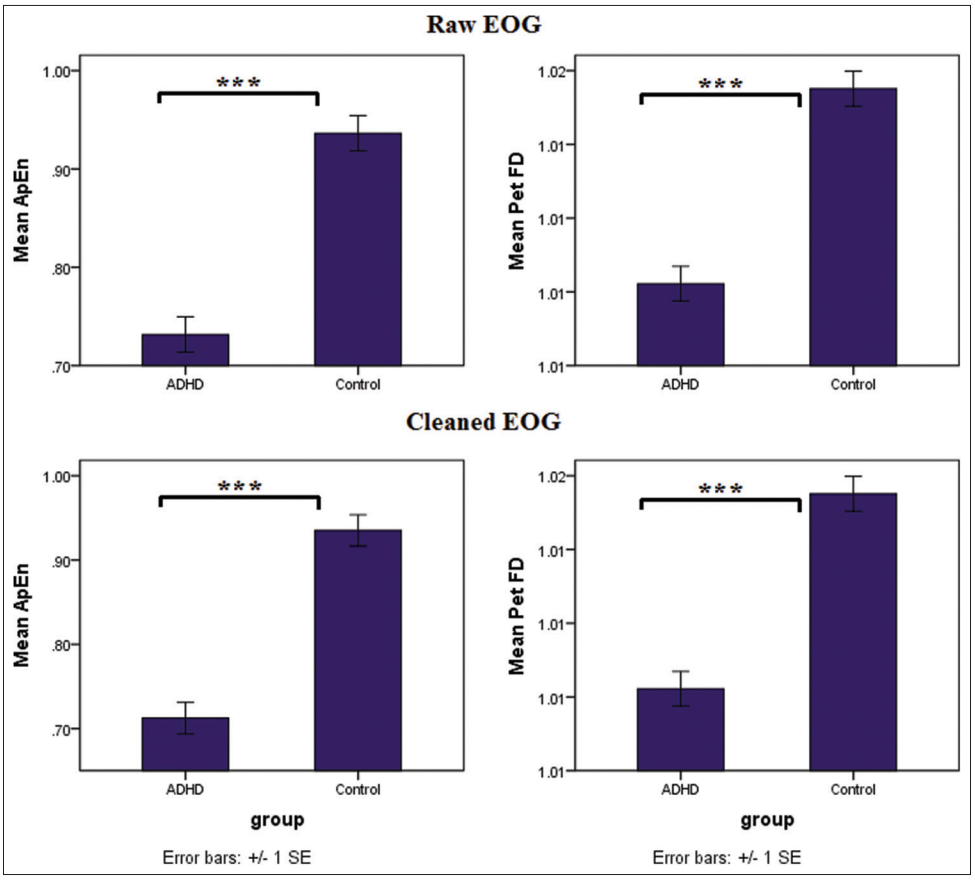


**Figure 3: The mean approximate entropy and Petrosian's fractal dimension values of both raw and cleaned electrooculogram signals of the two groups (***: $P < 0.001$)**

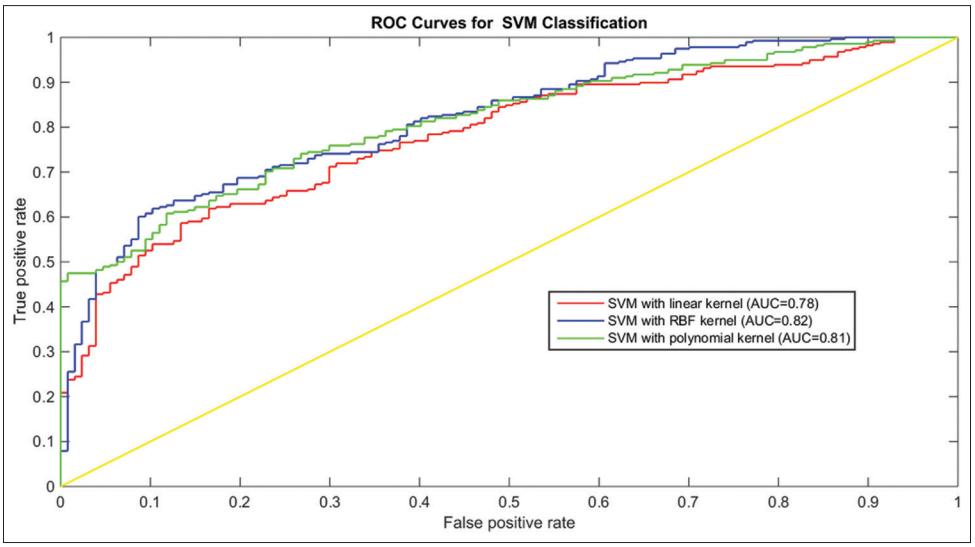


**Figure 4: The ROC curves were plotted for SVMs with linear, radial basis function (RBF) and polynomial (order 3) kernels**

The appropriate size for the NG network was also set to 20 neurons and training was obtained at 50 epochs. 90% of the feature vectors of the two groups were used for training and 10% for classifiers testing. Table 1 presents the mean detection accuracy of 10-time classification of EOG signals using the both classifiers.

As can be seen in Table 1, the SVM classifier was more successful in classifying the two groups than the NG network.

**Table 1: The mean detection accuracy of classification of electrooculogram signals using support vector machine and neural gas classifier**

| | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|---|---|---|---|
| SVM | 85.2±4.9 | 72.2±9.2 | 84.6±4.4 |
| NG | 76.2±5.8 | 78.4±10.2 | 78.1±1.1 |

SVM - Support vector machine; NG - Neural gas

## Discussion

### Statistical analysis of the calculated features

In this study, we examined the differences in EOG signals between ADHD and healthy children. The results showed that the ApEn values of the EOG signals were significantly higher in the control group than in the ADHD group while performing an attention-related task. The decrease in ApEn values of the vertical EOG signal indicates slower eye movements and unwillingness to pay attention or delay in attention to the surroundings of the subject.[28] Therefore, the eye movements of ADHD group were slower than control group and this difference was due to their attention deficit. The results of a previous study showed that the relative power of the low-frequency range (0.5–7.5 Hz) of the EOG signals in the ADHD group was significantly higher than in the control group, and the relative power of the high-frequency range (7.5–15 Hz) of their EOG signals was lower compared to the control group. The higher relative power of the low-frequency range and the lower relative power of the high-frequency range in the EOG signals of ADHD group also indicate slower eye movements compared to the control group.[19] Therefore, this result is consistent with the finding in the present study.[19]

The results obtained in the present study also indicate a significant decrease in the value of the Pet's FD of the EOG signals in the ADHD group. The fractal dimension indicates the complexity of the signal. If only a small number of low frequencies dominate a signal, the fractal dimension value of that signal will decrease. Conversely, the wider the signal spectrum, the higher the fractal dimension;[43,44] previous research has shown that the major activity of EOG signals in the ADHD group and the control group was in the range of 0.5–4.125 Hz and 4.125–15 Hz, respectively.[19] As a result, the lower fractal dimension of the EOG signals in the ADHD group is consistent with a narrower frequency range and less dominant frequencies. This result also confirms slower eye movements due to attention deficit disorder in the ADHD group.

In the present study, the raw EOG signal and the EOG signal after exclusion of the component related to the EEG signal were investigated, separately. The results show that there was no significant difference between the two raw and cleaned EOG signals in the separation of the two groups. Therefore, there is no need to remove the EEG component from the EOG and that extracting a feature from the raw EOG signal can determine the difference between the two groups.[19]

### Classification of the electrooculogram signals using the calculated features

The EOG signals were classified in the ADHD and control groups using feature vector consisted of ApEn and Pet's FD values. The results showed that the SVM classifier was

more successful in separating the EOG signals than the NG classifier in two groups.

The detection accuracies of two groups' EOG signals using SVM and NG classifiers were obtained as 84.6 ± 4.4% and 78.1 ± 1.1%, respectively. There is insufficient research to compare the classification accuracy of eye movements in the two groups (with both methods of EOG processing and eye-tracking system). In a previous study, the scaling exponents of the EOG signals in the two groups were classified by Growing NG classifier with a detection accuracy of 72.2% ± 2.1%. As a result, the obtained detection accuracy of the EOG signals in the two groups using feature vector consisted of ApEn and Pet's FD values was improved as compared to the previous research.

### The importance of processing ocular signals of the two groups

Most research on eye movements in ADHD patients and healthy individuals has used eye-tracking systems, while the EOG signal is an appropriate indicator of one's mental activity and is commonly referred to as an external reflection of unconscious behaviors. In fact, the EOG signal is considered to be an information-rich signal and can indicate a level of fatigue or even attention.[28,45-47] If the same results can be obtained with eye-tracking system by processing EOG signals, it will be possible to distinguish between the two groups with a simpler and cheaper system. The present study investigated the EOG signals of ADHD patients and controls without the need to extract signal peaks and calculate the degree of deviation. There is hope for a cheap, simple, and reliable system to differentiate ADHD patients and healthy individuals by extracting diverse features from the entire EOG signal.

Moreover, one of the nonpharmacological treatments for ADHD is EEG signal biofeedback or neurofeedback. In this way, the EEG signals of the subjects are recorded and their brain activity is feedbacked in the form of an audio or video feedback to try to modify or alter their brain activity.[48-50] Given the differences observed between the ApEn and Pet's FD values of the two groups, it is likely that EOG biofeedback alone or in combination with neurofeedback may be effective in treating or reducing the symptoms of ADHD people. Some types of neurofeedback training methods require the classification or clustering of data related to the initial group (ADHD people) and the target group (healthy people).[51-54] In conclusion, the results of this study could be useful in designing an EOG biofeedback course for the treatment of ADHD disorder.

## Conclusion

The current study investigated the differences in ApEn and Pet's FD values of EOG signals between the ADHD and control groups. According to the results, a significant decrease was observed in the values of ApEn and Pet's FD of EOG signals in the ADHD group. Moreover, the two groups were classified using the vector derived from ApEn and Pet's FD and two SVM and NG classifiers. The two groups were separated using the SVM and NG classifiers with detection accuracy of 84.6% ± 4.4% and 78.1% ± 1.1%, respectively. Therefore, the SVM classifier was more successful in separating the two groups than the NG.

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### Conflicts of interest

There are no conflicts of interest

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