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Detection of amyotrophic lateral sclerosis disease by variational mode decomposition and convolution neural network methods from event-related potential signals

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Abstract: Amyotrophic lateral sclerosis (ALS), also known as motor neuron disease, is a neurological disease that occurs as a result of damage to the nerves in the brain and restriction of muscle movements. Electroencephalography (EEG) is the most common method used in brain imaging to study neurological disorders. Diagnosis of neurological disorders such as ALS, Parkinson's, attention deficit hyperactivity disorder is important in biomedical studies. In recent years, deep learning (DL) models have been started to be applied in the literature for the diagnosis of these diseases. In this study, event-related potentials (ERPs) were obtained from EEG signals obtained as a result of visual stimuli from ALS patients and healthy controls. As a new method, variational mode decomposition (VMD) is applied to the produced ERP signals and the signals are decomposed into subbands. In addition, empirical mode decomposition (EMD), one of the popular decomposition methods in the literature, was also analyzed, and ERP signals were divided into subbands and compared with the VMD method. Subband signals were classified in two stages with the one-dimensional convolutional neural network (1D CNN) model, which is one of the DL techniques proposed in the study. Accuracy, sensitivity, specificity, and F1-Score measurements were obtained using 5- and 10-fold cross-validation to evaluate classifier performance. In the first stage of classification, only VMD and EMD subband signals were used and 92.95% classification accuracy was obtained by the VMD method. In the second stage, VMD, EMD subband signals, and original ERP signals were all classified together with the VMD+ERP model achieving the maximum classification accuracy rate of 90.42%. It is thought that the results of the study will contribute to the diagnosis of similar neurological disorders such as ALS, attention studies based on visual stimuli, and the development of brain-computer interface (BCI) systems using the method applied to the proposed ERP signals.

Key words: Deep learning, amyotrophic lateral sclerosis, variational mode decomposition, empirical mode decomposition, electroencephalography, event-related potentials

1. Introduction

Many people around the world are dealing with neurological diseases such as amyotrophic lateral sclerosis (ALS), schizophrenia, autism spectrum disorders (ASD), which are caused by abnormal disorders in the brain. ALS, also known as motor neuron disease in some countries, is an advanced age disease that occurs as a result of damage to the nerves in the central nervous system and affects many parts of the brain [1–3]. Difficulties in hand and arm movements, weakness, difficulties in swallowing and speaking are shown as symptoms of ALS

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disease [3]. People with ALS disease can facilitate these difficulties with the designed brain computer interface (BCI) systems. Thanks to BCI technology, they can transmit the messages sent by the brain to the other party when the nerves and muscles are insufficient. Brain imaging methods are used in the design of the BCI system. Among these methods, the most widely used is electroencephalography (EEG) [4]. EEG is a noninvasive data collection method that is widely used in BCI studies designed to facilitate the lives of ALS patients and to examine the electrical activity of the brain [5]. EEG is also important for the diagnosis of neurological diseases such as ALS, Parkinson's, schizophrenia, ASD, attention deficit hyperactivity disorder (ADHD). Event-related potentials (ERPs) have been a widely used method in clinical studies in recent years with EEG signals for the diagnosis of these neurological diseases. ERP is small amplitude signals embedded in EEG signals that emerge as a result of stimuli that show a specific visual or auditory activity sent to individuals. These stimuli must be repeated many times to obtain ERP signals. As a result of repeated stimuli, ERP signals are formed as a result of taking the average of the signals belonging to these small amplitude target stimuli in the EEG signals. ERP signals have components such as P100, N200, P300, N400, and P600, but the most commonly used and the most informative component in studies is P300 [6, 7]. The P300 wave is approximately 250–500 after the stimulus is sent as a result of stimulation of the brain with a stimulus found by Sutton et al. [8], it is the component that occurs between milliseconds (ms). In this study, the sample ERP signal and P300 wave obtained from the occipital region from the ALS patient and a healthy controlled individual as a result of visual stimuli are shown in Figure 1.

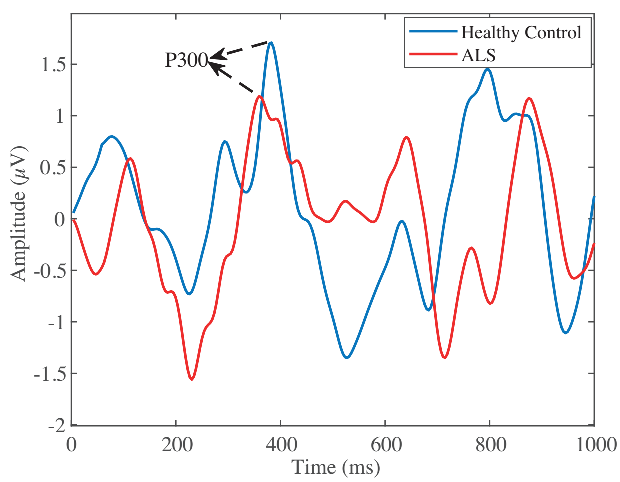

Figure 1. Healthy control and ALS sample ERP signal of the occipital region (Participant No: 3rd healthy control, 1st ALS).

It has been seen in several studies in the literature that the EEG or ERP signals of diseases that occur as a result of neurological disorders such as ALS, ADHD, and ASD are statistically analyzed by signal processing methods or machine learning methods [9–13]. It has been stated in the literature that the application of decomposition methods of EEG signals and the analysis of subbands is a promising approach in the detection of diseases resulting from neurological disorders [14]. When the studies using EEG and ERP signals are examined, it is seen that empirical mode decomposition (EMD), discrete wavelet transform (DWT), and recently variational mode decomposition (VMD) are widely used by researchers [14–18]. VMD is said to have advantages over the other two approaches because it is more noise-resistant than EMD, and nonidentifying waves that can be detected in EMD are unlikely to be observed in VMD. Despite the problems of ringing, shift variance, aliasing, and a lack of directionality found in DWT, VMD has an advantage [15, 17]. It has been observed that studies conducted in recent years on nonstationary and high-dimensional complex signals such as EEG use deep learning (DL) methods. The DL techniques have yielded successful results especially in the diagnosis of diseases caused by neurological disorders, and the use of these techniques to classify and identify psychiatric or neurological disorders has been an important research subject in the literature. Moreover, it has been observed that the results of the studies conducted with these techniques are superior to machine learning methods [19, 20].

In their study, Sengur et al. [21] obtained the spectrogram image of the signal by applying continuous wavelet transform (CWT) and smoothed pseudo wigner-ville distribution methods to the electromyogram (EMG) signals obtained from ALS patients and a healthy control group. The ALS patients and the healthy group were classified with an accuracy rate of 96.80% using the CNN method. Rusiya and Chaudhari [22] applied discrete wavelet transform (DWT) and proposed the teacher learning-based optimization algorithm to the EEG signals obtained from ALS patients to diagnose ALS disease and feature extraction for BCI systems. When the proposed algorithm with deep neural network (DNN), ensembled machine learning, and Bayesian networks methods are compared, the most successful result was obtained using the DNN method with a rate of 99%. In their study, Pandey and Seeja [23] proposed a new technique on emotion recognition by applying the combination of VMD and DNN to EEG signals. In another study, for the correct detection of the P300 component to increase the performance of BCI systems, which are important for ALS patients, the P300 component was correctly detected from the ERP signal at a rate of 94.18% using a deep convolutional neural network (DCNN) [24]. Cecotti et al. [25] used the CNN model and achieved a 95.5% success rate for the detection of the P300 wave. DL techniques in EEG signals have also been applied in studies aimed at detecting neurological disorders such as ADHD, Parkinson's, and schizophrenia, as well as detecting ALS diseases [26–28]. When the studies were examined, it was stated that the most preferred DL model in EEG and especially ERP studies and with the highest accuracy rate was CNN [29].

Several studies in the literature have been cited using DL techniques for the detection of diseases that occur as a result of neurological disorders such as ALS, ADHD, Parkinson's, schizophrenia, and the development of BCI systems, which are important for ALS patients. In this study, a DL technique that supports the literature, the CNN model was preferred.

Generally, DWT and EMD methods are popularly used in studies to decompose signals such as EEG and EMG into their subbands. However, it has been stated in the studies that the VMD method has emerged as a very powerful method especially for analyzing biomedical signals, and is a more advanced and new technique than the EMD method [14, 18]. For this reason, in this study, the VMD method was applied to decompose the ERP signals obtained from the EEG signals into their subbands. In addition, the EMD method, which is another decomposition method, was also tested in the study to compare with the VMD method. Signals decomposed into subbands were analyzed with 1D CNN from DL models.

This study aims to detect ALS disease with the 1D CNN method, where one of the subband signals is created by applying VMD as a new approach to the ERP signals generated from the EEG signals obtained from the ALS patients and healthy control group because of visual stimuli. The classification results obtained in this study were evaluated in terms of accuracy, sensitivity, specificity, and F1-score metric values. It was emphasized that the studies to be done for the prediction and detection of ALS disease are also important for the development of BCI systems [22].

The main contributions of the proposed approach are as follows:

(1) The signal processing and DL techniques utilized in this study may contribute to the detection of ALS and the development of BCI systems.

(2) A new method has been proposed for the detection of ALS disease by applying the VMD method and one-dimensional convolutional neural network (1D CNN) method, which is one of the DL techniques, to ERP signals.

(3) The findings were evaluated by comparing the EMD approach, which is one of the signal decomposition methods used in the literature frequently, to the VMD method. Both EMD and VMD methods were applied to ERP signals in this way, and the results were evaluated using a 1D CNN model.

Section 2 gives information about the data set and the method and model applied in the study are given. The obtained results in the study conducted in Section 3 are given. In the last section, the obtained results and information on similar studies in the literature are given and discussed.

2. Methods

2.1. Data set and experiment phase

The EEG signals of the ALS patients and the healthy group used in the study were obtained in the IRCCS Fondazione Santa Lucia University, Neuroelectric Imaging, and BCI Laboratory in homogeneity conditions for both groups and were made available for open access by Francesca Schettini on the "bnci horizon 2020" website[1]. EEG signals were obtained from eight ALS patients (mean age = 58 ± 12, four = bulbar type, four = spinal type) and ten healthy individuals (mean age = 26.8 ± 5.6). The sampling frequency of the EEG signals was set to 256 Hz and the data set was created with the EEG signals obtained from the "Fz, Cz, Pz, Oz, P3, P4, PO7, PO8" channels according to the 10-10 electrode system [30]. During the experimental stage, while creating the data set, it was presented to the subjects in the study as a 6 × 6 type matrix training set designed by Farwell and Donchin [31], which contains characters such as letters, special signs, and numbers as visual stimuli. The presented matrix consists of letters [A–Z], numbers [1–9], and certain signs that are commonly used in everyday life. While visual stimuli were sent to the subjects, interstimulus interval (ISI) and stimulus onset asynchrony (SOA) times were set to be 125 ms and 250 ms. The target-to-target interval (TTI) time is set to be at least 500 ms so that the target visual stimuli that may come consecutively are prevented from mixing with each other [32]. Before each trial, the subjects were introduced to the target characters and asked to focus on the target character. Target and nontarget characters were shown to the subjects as stimuli in the row or column of the matrix. The target characters light up in a row or column at a random stimulus, and by doing this process many times, EEG signals were obtained by adjusting the total number of target stimuli sent to the subjects to be five hundred. An example image of the visual interface experiment set used to obtain EEG signals is given in Figure 2.

2.2. Data preprocessing

Especially in ERP signals, it was stated that the P300 component is seen clearly in the range of 0.1–20 Hz [33]. In the study, the EEG signals were filtered using a 0.1–20 Hz band-pass filter. After filtering, EEG signals of target stimuli were taken by discarding empty moments and nontarget stimuli from the EEG signals, and ERP

[1]BNCI Horizon 2020. Data sets [online]. Website: http://bnci-horizon 2020.eu/database/data-sets [accessed 05.01.2020].

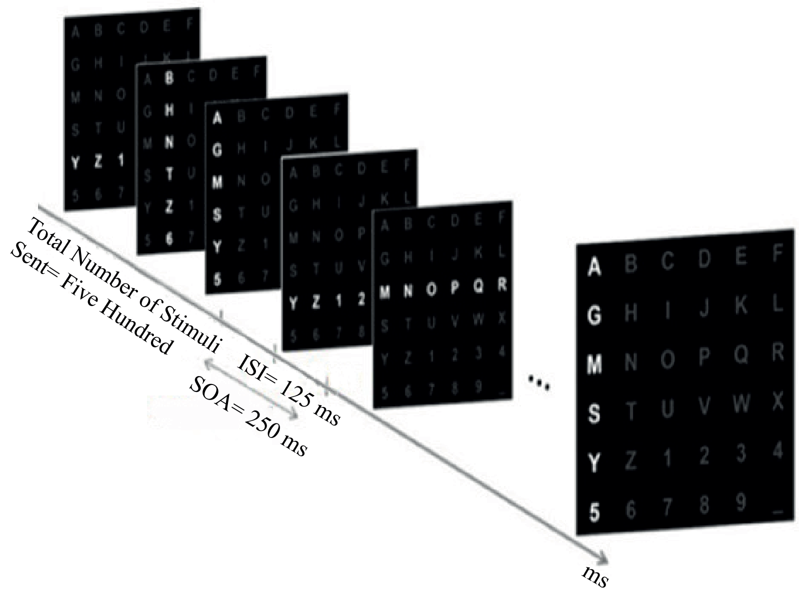

Figure 2. Visual interface used in the experiment.

signals were created by taking the average of these signals. VMD, which has recently been presented to the literature as a new method, has been applied to ERP signals and ERP signals are divided into three subbands.

2.3. Empirical mode decomposition (EMD)

The EMD method, also known as the Huang transform, transforms any linear or nonstationary signal s(t) into an intrinsic mode function (IMF) [34]. Obtaining an IMF in this method using an iterative process depends on two basic conditions [23]:

(1) The extreme number must be the same as the zero-crossing number or the difference between them must be at most one.

(2) The mean envelope value must be zero at all local maximum and minimum points.

Any s(t) signal is decomposed into IMF components with the formula given in Equation 1 with the EMD method. In the given formula, 'k' represents the number of IMFs, while 'IMF_i(t)' is the i'th IMF. 'X_k(t)' is the last residue. Detailed information about the EMD method is given in Ref [23, 34].

$$s\left(t\right)=\sum_{i=1}^{k}IMF_i\left(t\right)+X_k\ \left(t\right) \tag{1}$$

In the study, ERP signals were separated into three subbands using the EMD method, as seen in Figure 3. Decomposition was made according to the stopping criterion, so the number of decomposition levels was defined as three.

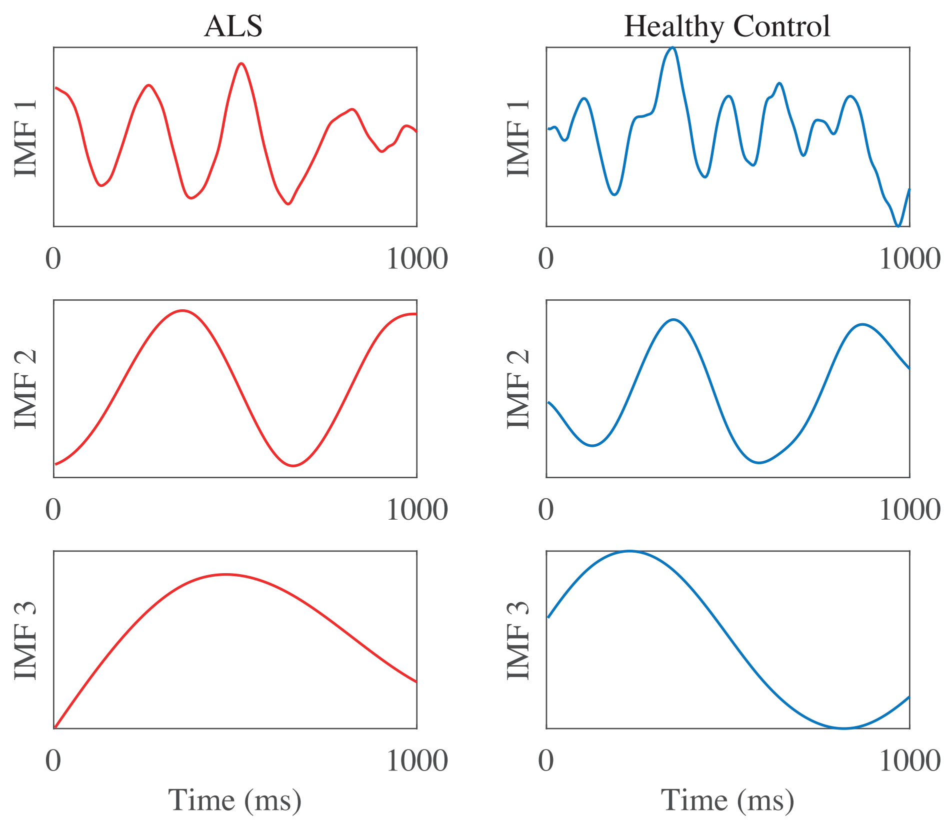

Figure 3. ALS and healthy control sample EMD subband signals of the Cz channel (Participant No: 4th ALS, 2nd healthy control).

2.4. Variational mode decomposition (VMD)

The VMD method is a technique recently introduced by Dragomiretskiy et al. [35], which can perform a robust adaptive signal decomposition against noise, detect sudden power changes, and give more successful results compared to the EMD method. VMD has been developed as a new technique to overcome some of the disadvantages of EMD. Because EMD is recursive, it does not allow backward error correction. However, VMD is a method that can simultaneously adaptively determine each mode and its associated frequency band. Therefore, if an error occurs in one of the iterations while calculating the frequency bands, the modes can be quickly balanced while calculating. It has been observed that VMD is more resistant to noise than EMD and does not leave any residual noise [18, 35]. One of the disadvantages of EMD is that it lacks the mathematical theory of the algorithm. Therefore, the results of the algorithm depend heavily on the endpoints and stopping criteria [18].

With the VMD method, the input signal is decomposed into basic subbands as variational mode functions (VMFs). VMD method is expressed with the formulas given in equations 2 and 3.

$$\min_{(u_k,w_k)} \left(\sum_{k=1}^{n} \left\| (\partial t[\delta(t) + \frac{j}{\pi t}) * u_k(t)]e^{-jw_k t} \right\|_2^2 \right) \tag{2}$$

$$\sum_{k=1}^{n} u_k(t) = f \tag{3}$$

When Equations 2 and 3 are examined, a certain f signal in the time domain is decomposed into n number of subbands (u_k) with the VMD method. In the frequency components of the signal, the first u_k modes contain low frequency components, while the subsequent modes contain higher frequency components. In the VMD method, each node of the signal is assumed to be close to the central frequency (w_k) and also each node is considered to have a compact frequency. In the given equations, 't' refers to the time domain, 'δ' refers to the Dirac distribution, while '*' indicates the convolution process [35, 36]. Detailed information about the VMD method is given in [35]. In this study, the ERP signals were decomposed into three subbands using the VMD method as seen in Figure 4. ERP signals are decomposed into three subbands with VMD, as in the EMD approach, to produce comparable conditions for the classification produce.

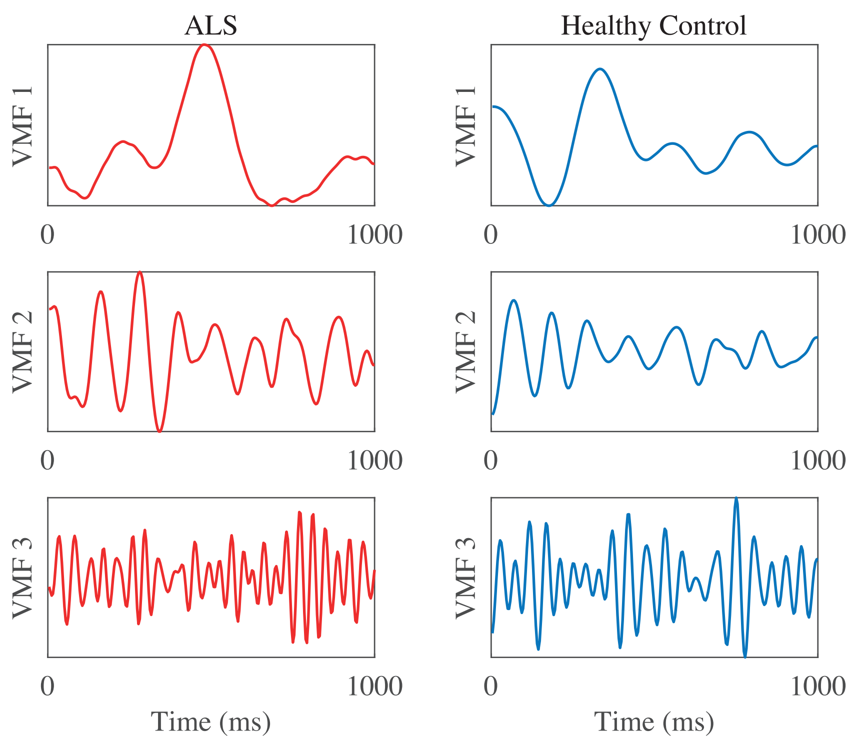

Figure 4. ALS and healthy control sample VMD subband signals of the Cz channel (Participant No: 7th ALS, 1st healthy control).

2.5. One-dimensional convolutional neural network (1D CNN)

CNN is a recommended method used for supervised learning tasks and object detection [21, 37]. In the CNN method, one-dimensional or multidimensional data can be processed. In CNN model, the spatial or temporal relationships between neighboring data are used to determine which features will be useful or not in machine learning. CNN model generally consists of three layers: convolution, pooling, and fully connected. Properties are created in the convolution layer and classification processes are made according to the properties created in this layer. In the pooling layer, the parameters in the created network, the amount of information in the properties, and the number of calculations is greatly reduced. In this way, in the pooling layer, incompatibility in the network is controlled and deeper and more efficient networks are created. In the fully connected layer, the classification process is carried out so that the neurons in this layer are completely connected with the previous layers [21, 37, 38]. Detailed information about the CNN method is reviewed in [40]. It has been stated that the CNN model can extract properties from brain signals such as EEG and ERP and has a high success rate in studies such as the design of EEG, ERP, and BCI systems [29, 38]. In the study, one of the DL techniques that supports the literature, the CNN model was preferred.

2.6. Training and testing of network

In this study 1D CNN method was used. The 1D CNN structure proposed in the study was designed for the classification of ALS patients and healthy individuals without requiring any manual feature selection and extraction. The proposed 1D-CNN architecture is shown in Figure 5. This architecture consists of three convolution layers, one max-pooling layer, three RELU layers, two fully connected layers, one dropout layer, and one Softmax layer. The kernel of each convolution layer is 36, 18, and 9, respectively. Moreover, there are 500 exits in the first fully connected layer section and 2 exits as much as the number of classes in the second fully connected layer section. In the last layer of the proposed architecture, the Softmax activation function was used.

In the proposed model, the learning rate for the training of the network was set at 0.001, and dropout was set as 0.5. The data applied at the input layer has a 256x1 sample length. In the classification process, 5-fold cross-validation and 10-fold cross-validation was used when testing the network. In this process, for 5-fold cross-validation, the data set was randomly divided into five pieces of the same length, each of the separated pieces was used for testing at a rate of 20%, and 80% was used in the training phase. This process was repeated five times to determine the overall performance of the network, and the metric values to be used in the study were obtained by taking the arithmetic mean of the values resulting from the repeated operation. Similar procedures were performed for 10-fold cross-validation.

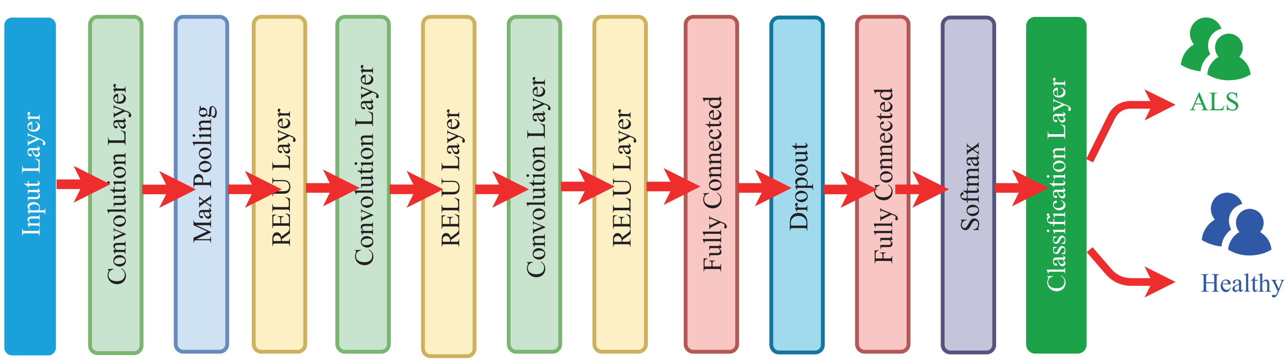

Figure 5. Proposed 1D-CNN architecture.

Accuracy, sensitivity, specificity, and F1-Score metrics were used to evaluate the classifier performance. Formulas related to these metrics are given in equations (4−7), respectively. Accuracy is one of the basic metrics used to measure the success of the model used. Accuracy value is obtained by the ratio of correctly classified measurements to all measurements evaluated in the study. The sensitivity value is calculated by the ratio of correctly classified positive measurement values to all positive measurements used in the study and refers to the patient (positive) class correctly classified in the study. Specificity metric value refers to the healthy (negative) class that is correctly classified. F1-Score is interpreted as a measure of accuracy. While finding the F1-Score metric value, the sensitivity and precision criteria are evaluated together, and the harmonic averages of these criteria are obtained [39].

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \times 100 \tag{4}$$

$$Sensitivity = \frac{tp}{tp + fn} \times 100 \tag{5}$$

$$Specificity = \frac{tn}{tn + fp} \times 100 \tag{6}$$

$$F1 - Score = \frac{2 \times Sensitivity \times Precision}{Sensitivity + Precision} \times 100 \tag{7}$$

3. Results

The present study was performed in two stages. In the first stage, only VMD and EMD subbands were applied as input to the 1D CNN model proposed in the study. In the data set, there are ERP signals (described in Section 2.1) received from eight different channels belonging to eight ALS patients in total. The ERP signals belonging to eight different channels are divided into 3 subbands using the VMD and EMD method. Thus, there are 192 (8 patients × 8 channels × 3 subbands) input data in total for ALS patients. By following the same method, input data were arranged within the healthy group and a total of 240 input data were obtained. However, 192 pieces of data were randomly selected out of 240 input data in terms of balanced distribution of the data set. As a result, 192 input data were obtained in both groups. The classification results obtained by 5- and 10-fold cross-validation using only the VMD and EMD subbands are given in Table 1.

As seen in Table 1, the most successful classification result was obtained in VMD with 92.95% classification accuracy using 10-fold cross-validation with the 1D CNN model applied when only VMD and EMD subbands are used. Sensitivity, specificity, and F1-Score values of other classification criteria were 91.33%, 94.78%, and 92.73%, respectively.

In the second stage of the classification studies, both ERP signals and VMD, EMD subband signals were applied as input to the classifier input. At this stage, as described above, there were a total of 192 VMD and EMD subband signals input data for ALS patients. Sixty-four ERP signals (8 patients × 8 channels) were added to these data and a total of 256 signals belonging to ALS patients were obtained as input data. In the healthy control group, there were 240 VMD and EMD subband signals data in total. By adding 80 ERP signals (10 healthy × 8 channels) to these data, a total of 320 signals belonging to the healthy control group were obtained as input data. However, in terms of the balanced distribution of the data set, as in the first stage, 256 pieces of data among 320 input data were randomly selected. As a result, 256 signals in both groups were obtained as input data. The classification results obtained for 5- and 10-fold cross-validation when ERP signals and signals belonging to VMD and EMD subbands are used together are given in Table 1.

As seen in Table 1, when ERP signals and VMD, EMD subbands were used together, the most successful classification accuracy was obtained at similar rates using 5- and 10-fold cross-validations. The highest classification accuracy of 90.42% was achieved, while the other classification criteria were sensitivity, specificity, and F1-Score of 97.12%, 83.53%, and 90.85%, respectively. When Table 1 is examined, it is seen that the VMD method is superior to EMD in the classification results obtained by using only the lower bands and adding ERP, and applying 5- and 10-fold cross-validation processes.

The confusion matrix (CM) created for the classification results is given in Figure 6. Since the most successful classification results were obtained with 10-fold cross-validation, only 10-fold cross-validation results were given as CM. In Figure 7, the classification results of all the processes applied in the study are shown in detail.

Table 1. Classification results.

Method-CV		Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
EMD-5	(Mean±SD)	76.8079 ± 6.1821	80.7408 ± 18.7965	70.9549 ± 20.2366	76.5528 ± 9.3815
VMD-5	(Mean±SD)	90.3315 ± 6.8113	87.8342 ± 15.0493	93.3148 ± 4.572	89.3981 ± 8.2408
EMD-10	(Mean±SD)	77.0985 ± 7.15	75.4491 ± 16.1187	80.1846 ± 13.1503	75.8958 ± 8.6131
VMD-10	(Mean±SD)	92.9555 ± 3.4981	91.3371 ± 7.8015	94.7832 ± 5.6075	92.73 ± 3.6860
EMD+ERP-5	(Mean±SD)	81.0508 ± 2.0398	74.2278 ± 11.8446	89.8446 ± 7.8079	79.3873 ± 2.2823
VMD+ERP-5	(Mean±SD)	90.4264 ± 1.9078	97.1225 ± 2.087	83.5302 ± 4.1002	90.8546 ± 2.3438
EMD+ERP-10	(Mean±SD)	83.405 ± 3.3850	82.1328 ± 8.1046	84.429 ± 7.1725	82.779 ± 4.5236
VMD+ERP-10	(Mean±SD)	90.0415 ± 3.1966	88.6846 ± 8.9074	92.2249 ± 7.5542	89.7116 ± 3.6756

*SD: standard deviation

4. Conclusion and discussion

In this study, the 1D-CNN model was proposed for the detection of ALS disease. Before applying this model, ERP signals were obtained from the ALS patients and the healthy control group, depending on the visual target stimuli. By applying VMD as a new method to the obtained signals, the signals were decomposed into four subbands. At the last stage, ALS patients and healthy control groups were classified by applying the 1D-CNN technique to these signals. Information about the classification stage is explained in Section 3.

ALS is a neurological disorder that occurs because of damage to the nerves in the brain, limiting people's mobility and causing fatal consequences in the advanced stages. For this reason, early diagnosis of ALS disease is important. Early diagnosis of ALS disease will help individuals solve the problems they will encounter in their daily life. When diseases that occur as a result of neurological disorders such as ALS are not diagnosed early, individuals who suffer from these diseases face some difficulties in their daily lives. These people need BCI systems to reduce the difficulties they face. In this sense, it is thought that the study will contribute to the development of BCI systems with the methods applied as well as the detection of ALS disease. When the studies on the detection of ALS disease and the development of BCI systems were examined, it was seen that analyses were made with signals such as EEG, ERP, and EMG [10, 13, 21, 22, 42, 43]. It has been stated in the studies that the CNN model, which is one of the DL techniques, gives successful results in the selection of properties from these signals and disease detection in the biomedical field [29, 38, 41]. Using this model will be advantageous in studies because it is possible to obtain high classification accuracy without applying any feature selection process and without requiring an extra calculation load. In the proposed study, when the signals that

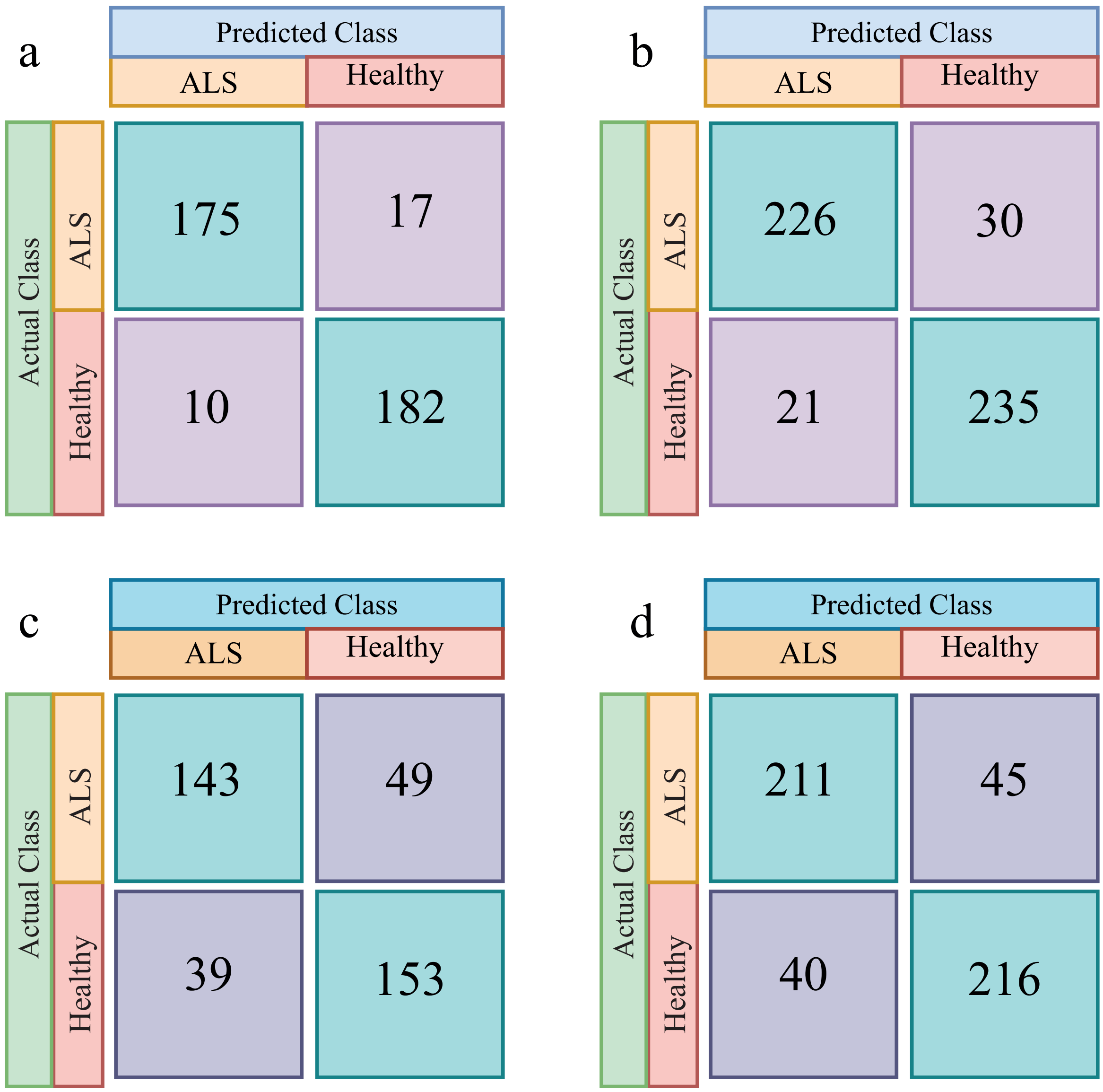

Figure 6. Confusion matrix created using 10-fold cross validation. (a) Only VMD, (b) VMD+ERP, (c) only EMD, (d) EMD+ERP.

were decomposed into subbands by VMD and EMD method in the first part of the classification phase were evaluated with the 1D CNN model alone, ALS patients and the control group were classified correctly at a rate of 92.95% using 10-fold cross-validation with VMD method. In the second part of the classification phase, in addition to VMD and EMD signals, ERP signals were added and the highest success rate was obtained in the VMD method with 90.42%. Table 2 compares the methods proposed in this study with similar studies in the literature with signals such as EEG and EMG for the detection of ALS with machine learning and DL techniques. In the study, the classification performance of ERP signals was analyzed using EMD-CNN and VMD-CNN models. The results obtained in the study show that ALS disease can be detected successfully with the proposed method and model.

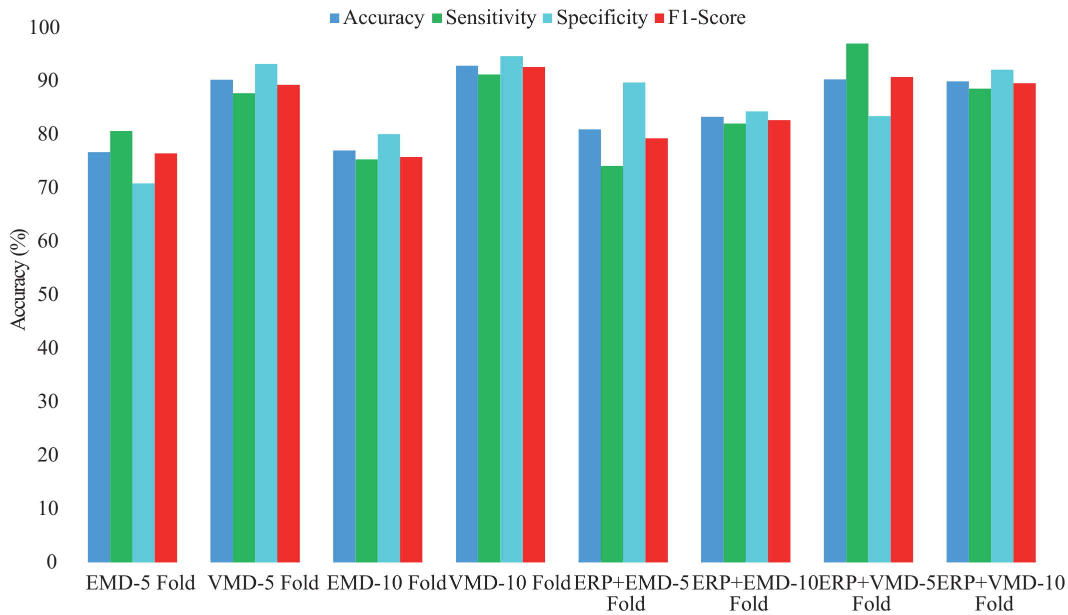

Figure 7. Detailed classification results.

Table 2. Comparison of classification performances with different studies in the literature.

Study	Data	Method	Classifier	Accuracy (%)
Sengur et al. [21]	EMG	CWT	CNN	96.8
Rusiya and Chaudhari [22]	EEG	DWT	DNN	99
Mishra et al. [42]	EMG	Feature extraction	ELM	88
Mishra et al. [43]	EMG	EMD	LS-SVM	95
Proposed	ERP	VMD	CNN	92.95

The findings of the study and its contributions to the literature can be summarized as follows:

(1) In the proposed study, VMD and EMD methods were applied to ERP signals for the first time in the literature and analyzed. The classification performance of the ERP signals was produced using EMD-CNN and VMD-CNN models. The results obtained in this study show that ALS disease can be successfully be detected with the VMD-CNN model.

(2) It has been stated that the VMD method is used in EEG signals and can also be used in other biological signals such as EMG [17]. In addition to these, the applicability of decomposition methods such as VMD and EMD for ERP signals and the usability with the CNN model have been demonstrated in the proposed study.

(3) The novelty of this study is that the VMD-CNN and EMD-CNN models are applied to ERP signals for the first time in the literature in this study for the detection of ALS disease via visual stimulation.

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