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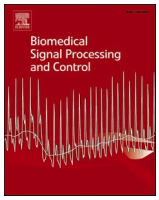



Motor imagery EEG signal classification using image processing technique over GoogLeNet deep learning algorithm for controlling the robot manipulator

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ABSTRACT

Controlling of a robotic arm using a brain-computer interface (BCI) is one of the most impressive applications. In this study, a novel method for the classification of motor imaging (MI) electroencephalography (EEG) signals are proposed for BCI. EEG signals are divided into three secondary tables, which were converted into spectrogram images. After applying the spectrogram method, the obtained images are divided into folder structures and deep learning is performed. In the deep learning stage, 400 images are obtained for each task as input to the GoogLeNet. After the deep learning completed, the presented system has been tested to imagine up, down, left and right movement to control the movement of the robot arm. It is observed that the robot arm performs the desired movement over 90% accuracy.

1. Introduction

BCI is a communication system that provides an alternative method for interacting with the world, where the messages or commands do not pass through the brain's normal output way out of the peripheral nerves and muscles [1]. BCI technology, a powerful communication tool between users and systems, records brain signals and sends them to the computer system to complete the desired task [2,3]. BCI is an area of research that has been extensively studied by researchers in recent years. Areas where BCI is used include neuroscience, control, industry, security, and smart home.

Nowadays, people who have lost their arms or due to various reasons or become unable to use them have difficulty in continuing their daily lives. Based on this problem, researches have shown that even if people have lost their arms, the brain continues to send signals for arm movement.

EEG is a non-invasive technique used to diagnose brain-related diseases and symptoms. It helps in diagnosing many neurological diseases, such as epilepsy, tumor, cerebrovascular lesions, depression, and problems associated with trauma. EEG signals are also widely used in BCI studies because of their high resolution compared to those obtained from other devices [4]. The EEG potentials measured from the surface of the scalp are bioelectric signals obtained as a result of the brain's neural activity [5]. In recent years, many researchers have been working on the basics of BCI through the interpretation of EEG-based commands and have focused on controlling a device with this method. These studies continue to contribute to the improvement of the quality of life of individuals who are disabled due to paralysis or have lost limbs such as arms and legs.

Do et al. performed the first successful application with the analysis of EEG signals by using the system called FESS which can manage the foot movements of patients who lost foot movements [6]. Mabrouk has developed an EEG-based BCI system that displays the user's EEG signals and classifies them as imaginary right and left hand movements with high accuracy [7]. C. Liu et al. classified the imagination of the right hand movement and the left hand movement with the Discrete Wavelet Transform and Fisher Linear Separation Analysis methods using the mean power of EEG data [8]. In their study, Robinson and Vinod classified the two-way movement of the person's dominant hand and the imagination of these movements [9]. Hajibabazadeh and Azimirad carried out the feature extraction process by Wavelet transform method by filtering the EEG data collected from 6 channels. They achieved 75% success using the Support Vector Machine method in classifying right hand and left hand movements [10].

In the literature, there are studies on robot control with EEG signals. Sunny et al. presented a study based on BCI with an objective of

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Table 1
Frequency bands of EEG and MI related tasks.

Band name	*Frequency band (Hz)*	*MI related frequency bands (Hz)*
Delta	1–3	–
Theta	4–7	–
Alpha	8–13	8–12
Beta	13–30	16–24
Gamma	>30	30–35

actuating a robotic arm with the help of device commands derived from EEG signals [11]. Sanchez-Fraire et al. proposed EEG-based BCI to decode commands to control a dynamic robot with low workload [12]. Xu et al. presented robot-assisted rehabilitation system based on motor imagery EEG for regular training of neurological rehabilitation for upper limb stroke patients [13]. John focuses on the classification of the user's thoughts using EEG signals with time–frequency analysis techniques [14]. Padfield et al. present a review about signal processing techniques for MI EEG-based BCIs [15]. Xu et al. design a BCI-based online robot control system based on linear discriminant analysis classifier, discrete wavelet transform and autoregressive model [16]. Izzuiddin et al. realized mental image classification with %92.09 accuracy using convolotuinal neural networks and proposed controlling a mobile robot [17]. Al-Saegh et al. presented a review about EEG based classification using deep learning. They conclude that deep convolutional neural networks architecture is the most effective architecture for the classification of motor imagery [18].

In Motor Imagery (MI) based BCI systems different filtering, wrapper or embedded methods are used for feature selection. Jin et al. proposed on feature selection for feature space using common spatial pattern algorithm [19]. Jin et al. suggested in their study a bispectrum channel selection method for BCI based on MI. The sum of logarithmic amplitudes and the first order spectral moment features extracted from bispectrum analysis are used to choice EEG channels [20]. Jin et al. in another study, they used the regularized common spatial pattern method to improve classification performance in MI-based BCI [21]. Another approach for this purpose is used to correlation based time window selection algorithm [22].

Looking at the work of Velu et al., which uses recurrent CNN and controls the robot by classifying the EEG data without converting them into images, it is seen that they achieved 84.69% and 79.2% accuracy [23]. In Li et al.'s study, motor imagery EEG signals were classified according to time and frequency domain features using convolutional neural network and stacked auto-encoder, co-spatial pattern, adaptive co-spatial patterns, deep belief network. They achieved an average accuracy of 83.2% [24].

Time or frequency information of EEG signals have been used in most of the classification studies conducted in this area. In recent studies on this subject, the characteristics of the signal are obtained from the EEG data converted into spectrogram images and these data are classified by deep learning methods. Unlike these studies, we propose a new approach to classify EEG signals in this paper. In this approach, considering all the EEG bands (alpha, beta ..) could be effective for the classification purpose, all EEG signals were wanted to be observed. For this purpose, firstly EEG signals are converted into spectrogram images which cover the visual representation of the spectrum of frequencies of a signal as it varies with time. Then these images are used for classification using the CNN type deep learning algorithm. Real-time robot control realized using these classified data. In addition, since the experiments were carried out in an electromagnetic noise-free environment and on a battery-powered EEG device, no additional filter was added to the system.

The rest of this paper is organized as follows. Methods used in this study are presented in Section 2. The system are explained in Section 3. Results are presented in Section 4. Finally, Section 5 concludes the study.

2. Methods

This section introduces information on Electroencephalography. Also, Convolutional Neural Network (CNN) and GoogLeNet networks and training strategy are explained.

2.1. Electroencephalography (EEG)

EEG signals are often used for BCIs because of their high time resolutions, easier to acquire brain signals compared to other methods, and lower cost. EEG-based BCIs can be divided into two types: evoked and spontaneous. External stimulation such as auditory, visual, or sensory is required in evoked systems. External stimulation is not necessary in spontaneous BCIs and control actions are performed according to the datas produced by mental activity [25]. This study is realized spontaneous way.

The electrical activity of a brain shows a complex behavior with nonlinear and dynamic properties. Communication in the brain cells occurs by electrical pulses. Since the brain waves are non-linear and nonstationary, it is impossible to define a general pattern in the EEG. Depending on the situation, different waves emerge. In normal subjects, EEG waves are classified as delta, theta, alphai beta and gamma activity. The frequency ranges in EEG signals and Motor Imagery (MI) frequency bands are shown in Table 1 [18]. The EEG signals are produced by cortical nerve cell inhibitory and stimulating postsynaptic potentials. The postsynaptic potentials are collected within the cortex and extend to the scalp surface where they are recorded as EEG. A characteristic EEG signal measured from the scalp will have a frequency in the range of 1 Hz to about 100 Hz and amplitude of about 10 μV to 100 μV.

There are different signal processing methods used to extract the hidden information from the EEG signal: linear, frequency domain, time - frequency and non-linear techniques like correlation dimension, higher order spectra, fractal dimension, largest Lyapunov exponent, different entropies, Hurst exponent. A detailed summary of the studies on the EEG signal can be found from the source provided in Subha et.al study [26].

2.2. Convolutional neural network (CNN)

An artificial neural network (ANN) is an information processing

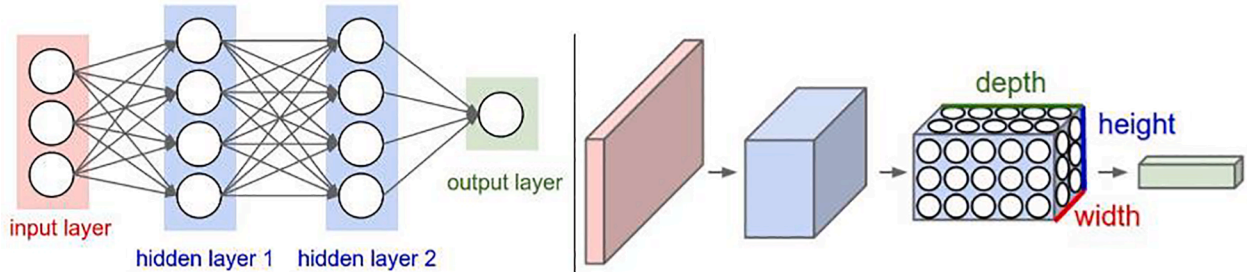


Fig. 1. Classical neural network versus CNN. Left: A regular 3-layer ANN. Right: CNN.

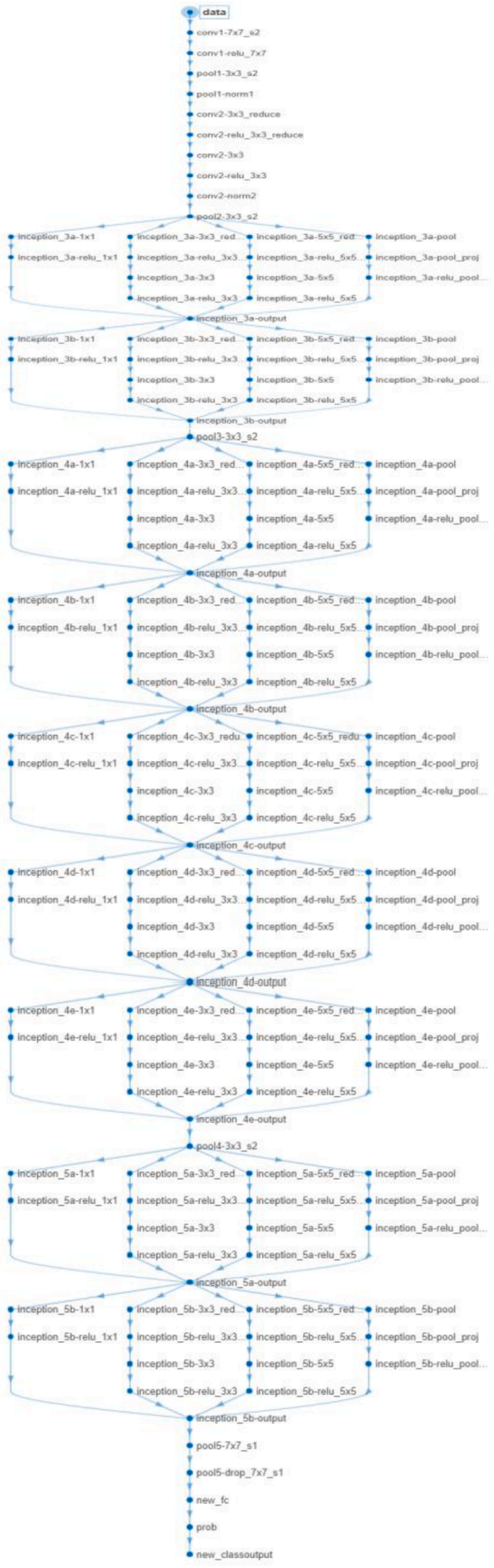


Fig. 2. CNN model used in the study.

technology based on the human brain's ability to work and learn. Many algorithms related to ANNs have been developed and used in many areas. Unlike a conventional ANN, CNN is an extremely deep ANN in which layers have neurons arranged in width, height, depth dimensions (Fig. 1) [27]. CNN are designed to recognize visual patterns directly from pixel images with minimal preprocessing.

Nowadays, different CNN algorithms are available such as LeNet-5, AlexNet, GoogLeNet/Inception and ResNet. GoogLeNet architecture was released in 2015. It includes 22 layers with specific functions. In general, this architecture is one of the first CNN architectures to move away from stacking the convolution and pooling layers in a consecutive structure. In addition, this new model has an important place on memory and power usage. Because stacking all layers, adding a large number of filters brings a calculation and memory cost. This increases the possibility of memorization. To overcome this situation, GoogLeNet has been used in parallel architectures [28].

A CNN contains convolution layers, pooling layers and dense layers components [29]. The task of the convolutional layers is to extract numerous features from the images and to make maps of the distribution of those features in the image. Deeper convolutional layers are able to determine more complex features.

The feature extraction process performed by a convolution layer typically consists of a combination of linear and nonlinear processes. These are the convolution process and the activation function. A kernel is applied to the input (tensor) in convolution process. Between each element of the kernel and the input tensor an element-wise product is calculated at each location of the tensor. It is then summed to obtain the corresponding position of the output tensor, called the feature map. To generate a random number of feature maps, this procedure is repeated by applying multiple kernels.

The outputs of a linear operation such as convolution are then passed through a nonlinear activation function. The most common nonlinear activation function rectified linear unit (ReLU) was used in this architecture. It has proven that ReLU function reduces the vanishing gradient problem providing better performance than other non-linear functions (such as the sigmoid function or the hyperbolic tangent) [30]. Hidden neurons output, when ReLU function is employed, can be written as:

$$f(x) = \begin{cases} 0, if wx + n \le 0 \\ wx + b, if wx + b > 0 \end{cases} \tag{1}$$

A feature map is obtained by convolution of the input image with a linear filter, adding a bias term and then applying a non-linear function. The k. feature map for *tanh* nonlinearity at a given layer h^k can be shown as follows:

$$h_{ij}^k = \tanh\left(\left(W^k * x\right)_{ij} + b_k\right)\mathrm{h}_{\mathrm{ij}}^{\mathrm{k}} \tag{2}$$

where W^k is the weights that determines the filters and b_k is the bias. Convolution for a 1D signal is defined as follows:

$$o[n] = f[n] * g[n] = \sum_{u=-\infty}^{\infty} f[u]g[n-u] = \sum_{u=-\infty}^{\infty} f[n-u]g[u] \tag{3}$$

This can be extended to 2D as follows:

$$o[m,n] = f[m,n] * g[m,n] = \sum_{u=-\infty}^{\infty}\sum_{u=-\infty}^{\infty} f[u,v]g[m-u,n-v] \tag{4}$$

Each hidden layer is composed of multiple feature maps to form a richer representation of the data, $\left\{h^{(k)}, k = 0 \cdots K\right\}$ [28].

Pooling layers are used to decrease data volume and to reduce the size of feature maps while maintaining the most important information. The max pooling is the most popular form of pooling operation. It extracts patches from the input feature maps and removes the other values [31]. A max pooling with a filter of size 2 × 2 with a stride of 2 is commonly used in practice. The down-samples the in-plane dimension of feature maps by a factor of 2. Unlike height and width, the depth

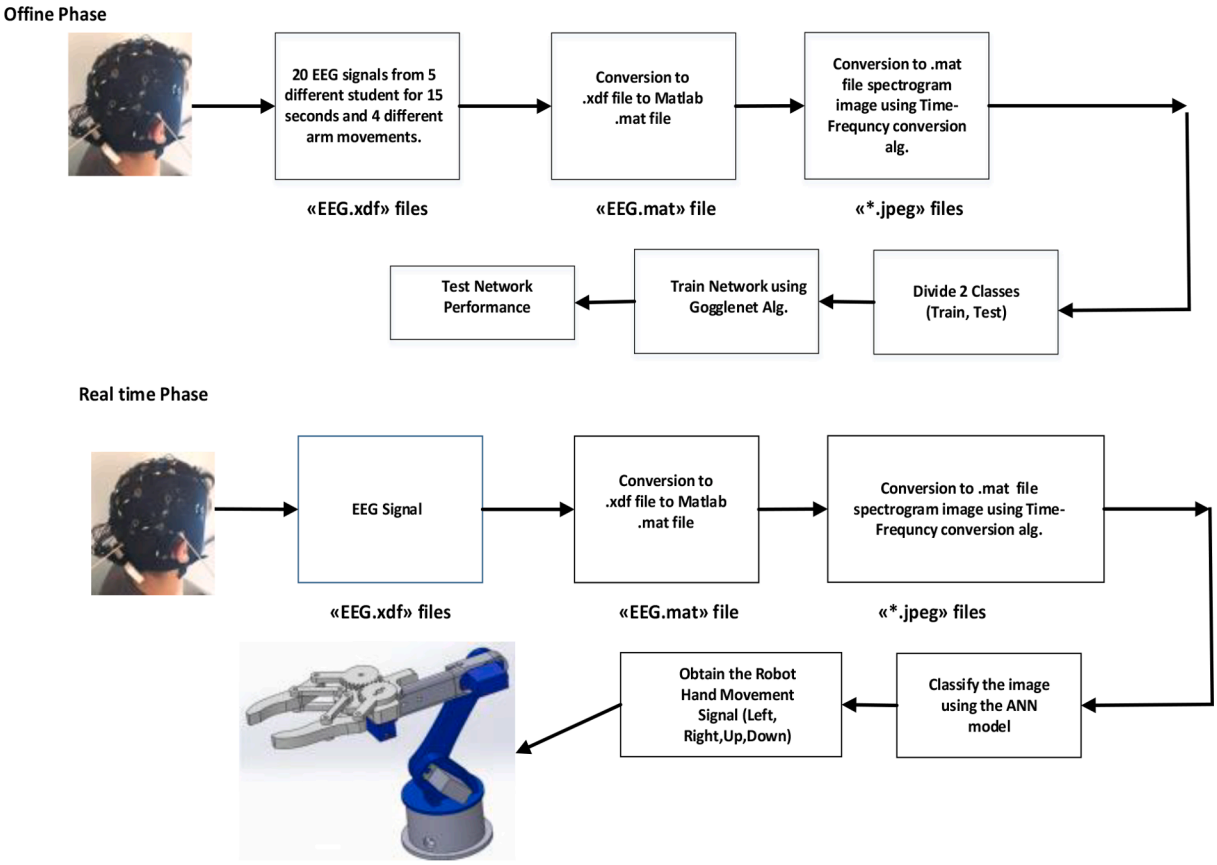


Fig. 3. Process of the study.

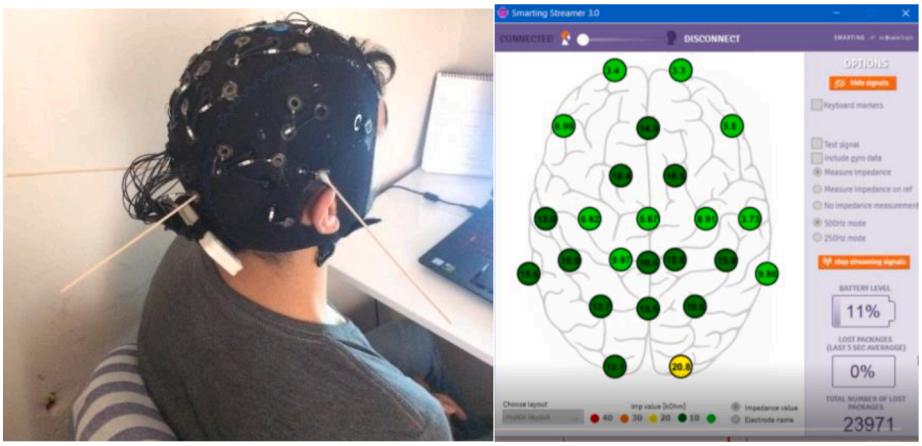


Fig. 4. EEG recording system.

dimension of feature maps remains unchanged. If generalized, the pooling layer accepts a volume with size $W_1 x H_1 x D_1$. Spatial extent F and stride S hyper-parameters are required. A volume with size $W_2 x H_2 x D_2$ is produced. Where [21]:

$$W_2 = \frac{(W_1 - F)}{S} + 1 \tag{5}$$

$$H_2 = \frac{(H_1 - F)}{s} + 1 \tag{6}$$

$$D_2 = D_1 \tag{7}$$

Dense layers also known as fully connected layers. Classification layers are dense layers, and dense layers are equivalent to conventional artificial neural networks. In this layer, a set of interconnected neurons analyze an input and generate an output to make predictions on new data. Every input is connected to every output by a learnable weight. After the properties are extracted by the convolution layers and they are down-sampled by the pooling layers, they are mapped to a subset of layers that are fully connected to the final outputs of the network. Finally, the fully connected layer has the same number of output nodes as the number of classes. Each fully connected layer is followed by a nonlinear function [32]. The convolutional neural network model used is shown in Fig. 2.

The accuracy criterion was used to determine the classification performance of the model. Accuracy is defined as the ratio of the number



Fig. 5. Robotic Arm.

of successful tests to the total number of tests as follows;

$$Accuracy(\%) = \frac{\sum_i^N (Labelled_output_i - Real_output_i)}{N} \quad (8)$$

where N is total test data number.

3. System

In this study, an MBrainTrain EEG System was used to obtain EEG data. The study consists of two different phases which as given in Fig. 3. The first part is the Offline Phase which is comprised of data collection, data transferring the time–frequency domain (spectrogram image), classification of the data using the Gogglenet deep learning algorithm. The second Phase, which called the Online or Real-Time Phase comprises data collection and transferring the time–frequency domain in real-time and Robotic arm control using the trained neural model.

3.1. Obtaining data set

EEG signals are extremely complex and signal quality is highly dependent on the mental state of the user. In this study, EEG data of a right-handed 20-year-old man without disease were used. For this reason, EEG signals were recorded in a quiet environment and free from distractions. EEG data were recorded with eyes closed. EEG recordings were taken from FP1, FP2, AFz, T7, F3, F4, C3, C4, T8, M1, CPz, M2, P7, P8, POz P3, P4, O1, O2, F7, F8, Fz, Cz, Pz electrodes. MBrainTrain EEG The EEG data can be streamed with 500 Hz sampling frequency (Fig. 4).

3.5-minute data were taken from the 24 electrode holder. EEG data of 27x100000 were obtained. The data was then converted from xdf format to mat format. For each movement of the robot arm up, down, left and right, 100 trials were made with 4 people and the data was recorded, thus a database consisting of 400 data was obtained. The obtained data sets were visualized by spectrogram method. The spectrogram method is a graphical representation with a time–frequency axis by calculating the frequency spectrum for each moment of a signal [33]. The time is on the horizontal axis and the frequency is on the vertical axis. The visualized data sets were applied to the GoogLeNet network.

3.2. Robotic control

A robot arm with four degrees of freedom is used (Fig. 5). Robot arm can perform right, left, up, down, forward, back and gripper open, close functions. Since the right, left, up, and down functions of the arm are sufficient to test the method, these functions have been utilized. The robot arm moves between 0 and 180 degrees.

4. Results

First, spectrograms of the data from each channel of the MBrainTrain EEG System were obtained. In line with the given task, the person was asked to think about moving his arm up, down, right and left. Considering that the data of the recordings from the F electrode of the frontal lobe responsible for motor movement are important, spectral power density and spectrogram images of those data are presented here. For the F4 channel, the spectral power density and spectrogram images of the data obtained from the left arm imagery are shown in Fig. 6a, Fig. 6b, Fig. 6c and Fig. 6d for arm up, arm down, arm right and arm left imaregy, respectively.

A single spectrogram image was obtained by combining the spectrograms obtained for each channel. The combined spectrogram images obtained for the arm up, down, right and left imagery are shown in Fig. 7.

Deep learning is provided using the GoogleNet network model of the Matlab DeepLearning Toolbox. Small changes that are not visible in the signals become distinctive in the classification process with GoogLeNet. After 90% of the EEG images obtained for each movement were allocated randomly for training and 10% for validation, they were trained for 50 epochs in the network using the GoogLeNet CNN architecture. At the end of the training process, 92.59% validation accuracy was achieved as shown in the Fig. 8.

Taking EEG data based on 3 s, it was determined that the conversion of the data to mat format, visualization, taking the test results of the system, transmitting the results to the arm and moving the arm in an average of one second. Although the accuracy of the test data varies according to the direction of the movement, an average of 85% accuracy is achieved (Fig. 9). It is expected that the accuracy rates will increase even more as the training process is chosen longer.

5. Conclusion

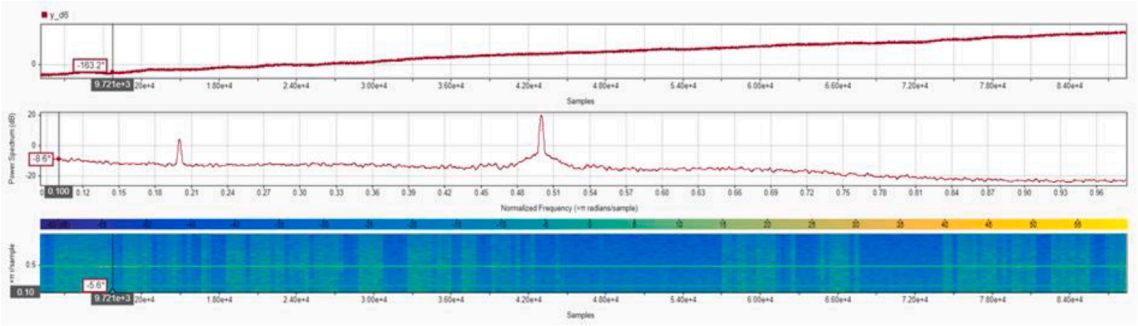
In this study, a new method was proposed for BCI using EEG captured with the MBrainTrain EEG System. EEG data were taken from mBrainTrain cap, the data were converted from xdf format to mat format and then visualized by spectrogram method. These converted signals are applied to the Convolutional Neural Network. GoogLeNet network was chosen as the network structure. The visualized data were taught to the system with deep learning algorithm. Thus, EEG data was classified by performing deep learning process. Unlike other studies carried out to date, the classification process was performed after the EEG signals were converted into images.

When the data set that imagines up, down, left and right movements is applied to the artificial neural network, the network classified with 92.59% accuracy for training data and 85% accuracy for test data. Thus, real-time movement of the robot arm in the desired directions is also provided with high accuracy. Higher accuracy can be achieved by increasing the number of data used for training or by changing the network structure.

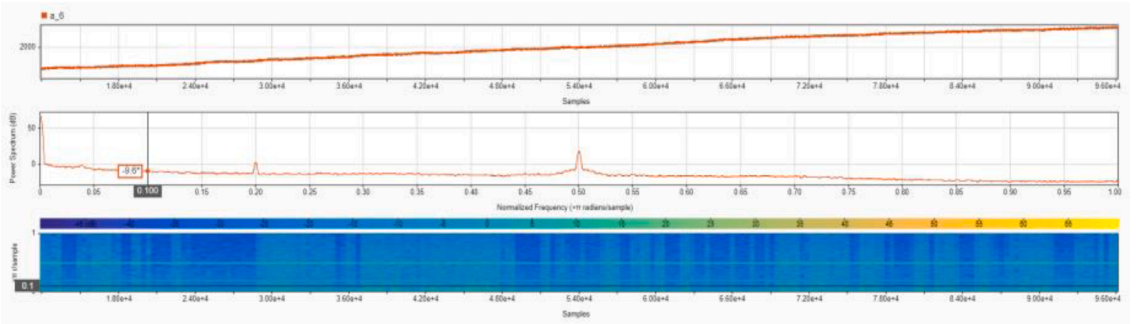
In future studies, it is planned to classify the movement of the right and left hand and the movement of the right and left foot, using the data of many more people of different ages, male or female. Not only individuals who cannot use their arms, but also individuals with different physical disabilities will be able to benefit from the studies. The positive results obtained in this study were promising for the applicability of the study to patients who had diseases such as stroke.

CRediT authorship contribution statement

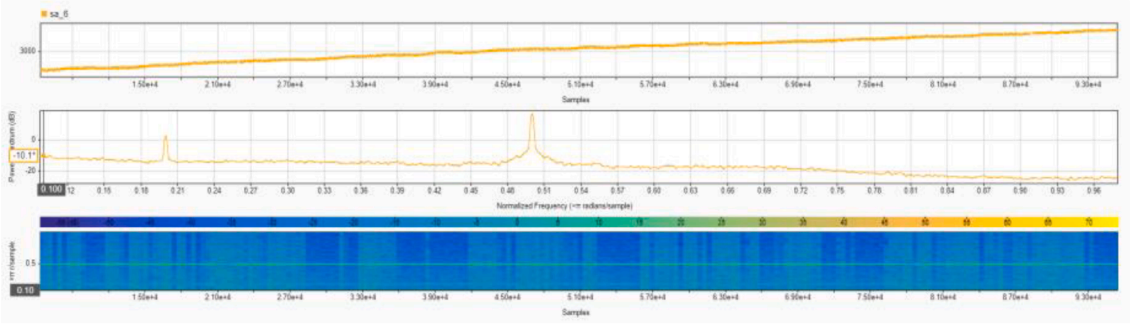
Ayca Ak: Conceptualization, Methodology, Writing – review & editing. **Vedat Topuz:** Software, Writing – review & editing. **Ipek Midi:** Supervision.



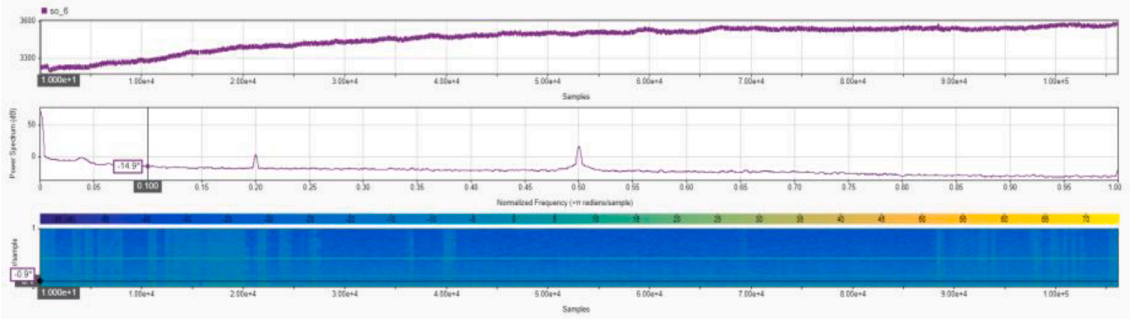
a. Spectral power density and spectrogram images from the arm up imagery.



b. Spectral power density and spectrogram images from the arm down imagery.



c. Spectral power density and spectrogram images from the arm right imagery.



d. Spectral power density and spectrogram images from the arm left imagery.

Fig. 6. EEG Data.

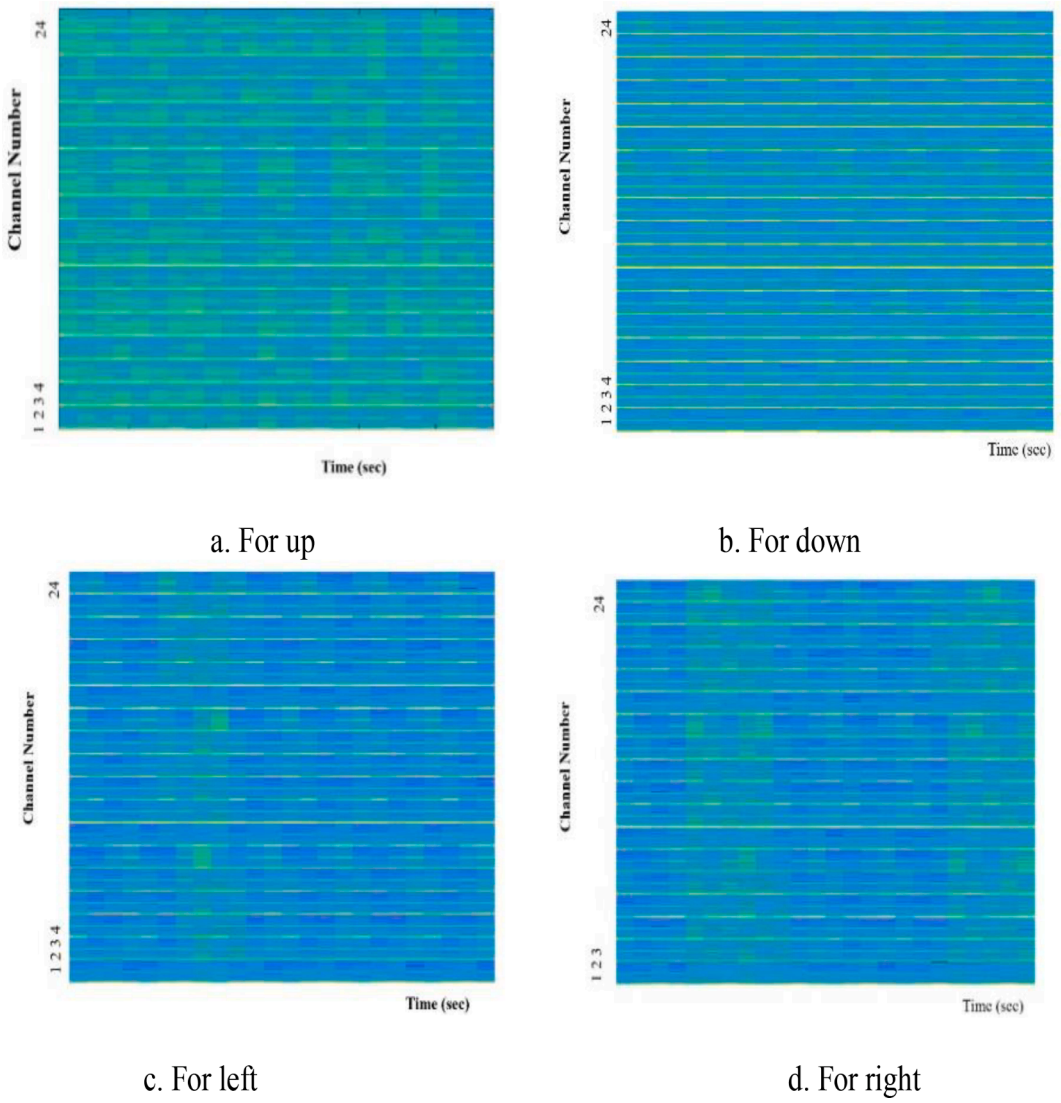


Fig. 7. Combined spectrogram images.

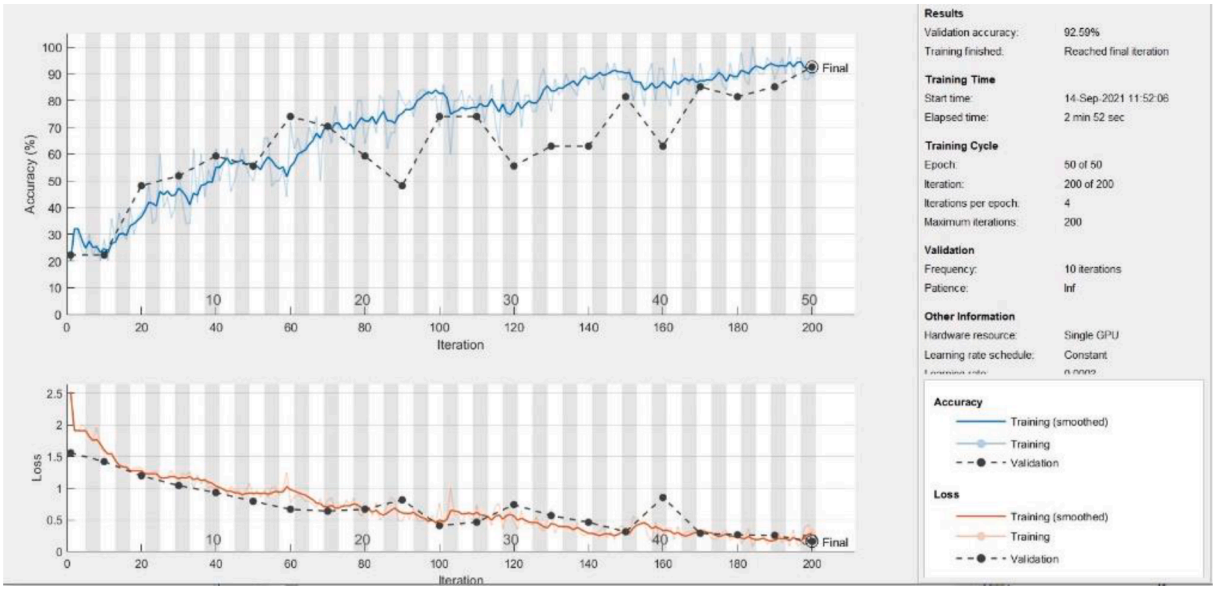


Fig. 8. Training Result.

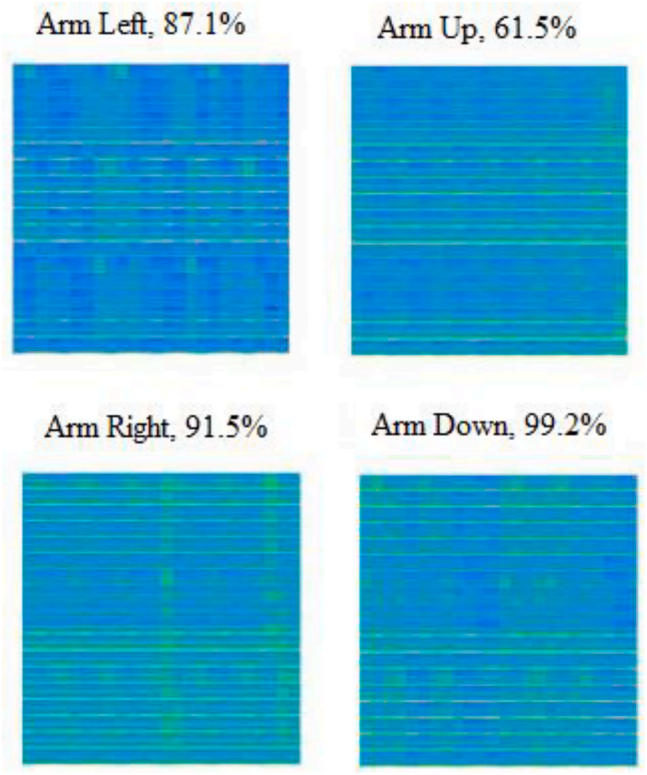


Fig. 9. Test data success rates.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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