A convolutional neural network and stacked autoencoders approach for motor imagery based brain-computer interface

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***Abstract*—In this research, we are investigating Convolutional Neural Networks (CNN) and Stacked Auto Encoders (SAE) to classify EEG Motor Imagery signals. Also, we use Cohen Class Distribution (CCD) to calculate time and frequency features derived from EEG signals to feed to our network. Using this combination of CNN and SAE decrease the data dimensions. the best accuracy percentage according to our method, in an average manner, is 82%. The proposed approach was applied to the dataset IVa from BCI Competition III, a multichannel 2-class motor-imagery dataset obtained from 5 healthy subjects**

***Keyword*— BCI, EEG, Motor Imagery, deep learning, convolutional neural networks, stacked autoencoders**

I. Introduction

The responsibility of the central nervous system (CNS) is to respond to environmental or body events by generating adequate outputs. The central nervous system's main function is to collect sensual inputs, process them and generate and transmit the outputs for adequate movement [2]. An alternate way between human brain and computers designed to assist people with disabilities to use their brain electrical activity is provided by a Brain Computer Interface (BCI) system [1],[2]. The aim of BCI's challenge is the realization of powerful modern assistive communication and management systems for people with neuromuscular disorders such as Amyotrophic Lateral Sclerosis (ALS), stroke, spinal cord injury, cerebral palsy, multiple sclerosis, and muscular dystrophies [3]. A BCI captures brain signals, extracts specific features from them, and translates features into new artificial outputs that operate upon the environment or the body itself. See Figure 1.

There are several invasive and non-invasive techniques for displaying brain signals such as Magnetic Encephalography (MEG), Electroencephalography (EEG), Functional Magnetic Resonance Imaging (FMRI) and Near Infrared Spectroscopy (NIRS), as well as Multielectrode arrays (MEA) and Electrocochleography (ECoG) methods [4]. In a BCI device the first step is the acquiring of signal. The next step is to pre-process the data to eliminate the noise caused by blinking, muscle activity, and background activity during the signal acquisition process.

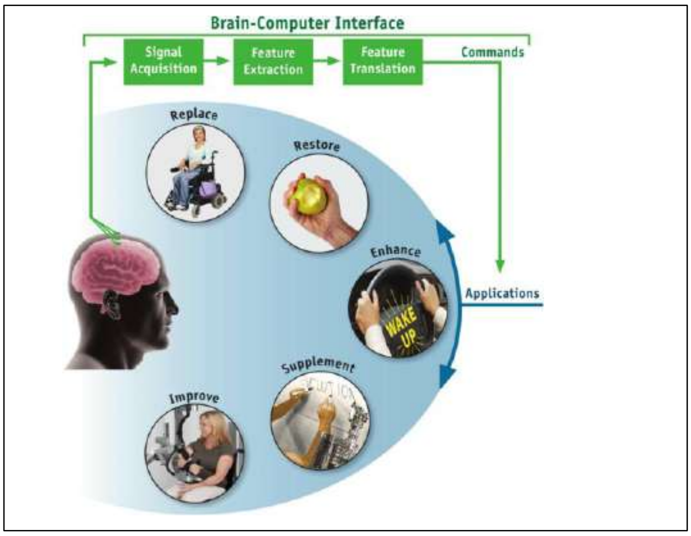

Fig. 1. Design of a brain–computer interface (BCI) system. Signals produced by brain activity are recorded from the scalp, from the cortical surface, or from within the brain. These signals are analyzed to measure signal features. extracted features are then translated into commands that control application devices that replace, restore, enhance, supplement, or improve natural CNS outputs [2].

One of the most critical steps is the extraction of the features from the obtained signal. The extracted characteristics are then graded and are eventually added as a command to the system. Figure 2 shows steps in BCI systems.

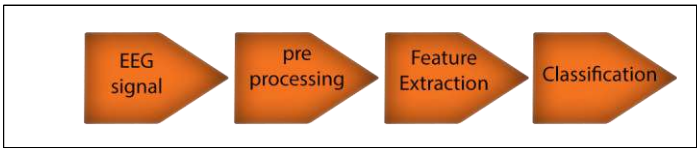

Fig. 2. diagram of a BCI system.

The Electroencephalography (EEG) technique provides a simple and inexpensive solution for BCI systems and is used in many non-invasive BCI studies [5]. Figure 3 Provides information on the human brain structure and also shows the locations of the 10–20 electrode positioning [6].

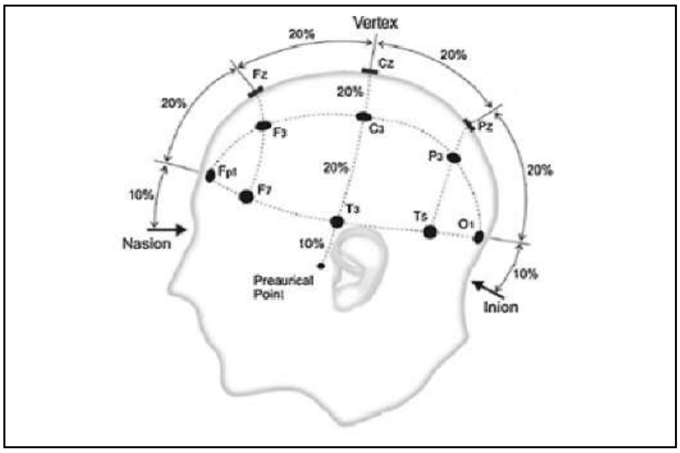

Fig. 3. The international 10-20 electrode placement sysytem[6]

In BCI research, different types of EEG signals were used to work as control signals. Among these signals, the most common signals are P300 evoked potential, steady-state visual evoked potentials (SSVEP), and motor imagery (MI). In this paper, we consider brain potentials related to motor imagery tasks. Motor imagery (MI), a visual method of imagining movement without actual movement, is helpful for disabled people in therapy for muscle recovery [7] and also for healthy individuals in gaining new mental abilities in sports [8]. Motor imagery (MI) is a mechanism of mind in which subject imagines that she/he is performing a specific motor action such as a hand or foot movement without otherwise performing it in reality [9].

Several researches studied various methods of extracting features and classifying MI tasks for Motor Imagery based Brain-Computer Interface. Common spatial patterns (CSP) [6,9] are a common method for extracting features in MI studies. In several MI activity recognition studies, CSP has been successfully applied [10]-[15]. Researchers are also implementing multiple machine-learning methods for MI discrimination, e.g. Independent Component Analysis (ICA) [16],[17]. Other well-known methods for extracting or selecting features, such as Principal Component Analysis (PCA) [18], Empirical mode function (EMD) that is an time-frequency based method thus efficient for time frequency analysis of non-stationary signals [19], Common Bayesian network (CBN) [20] and wavelet packet transformation (WPT)[21] are commonly used to improve the classification accuracy. Several conventional algorithms such as Support Vector Machine (SVM) [22],[23], Linear Discriminant Analysis (LDA) [22],[24] and the Bayesian classifier [25] have been used in various studies for classification.

Among current methods for feature extraction of EEG, some relay on a single channel resulting in information loss, some use multichannel, but fail to ensure the location of the channel. Continuous data gathering in BCI systems produces a large amount of data which can be used to train classifiers. On the other hand, by increasing the size of training data, the deep learning approaches are known to provide better classification efficiency. Which makes deep learning methods a great choice for BCI systems. In study [26] a Deep convolutional neural networks (CNNs) model was applied for two class MI classification. This paper introduces a method that uses CNN to examine the EEG signals generated by motor imagery tasks of the left and right hand and CNN proved more efficient than SVM method. In [27], On average, CNN performs slightly better than FBCSP approach using both the 2D and the 3D kernels. In [28] Arnold et al, presented a class of deep learning techniques such as deep belief networks, stacked auto associators, deep kernel machines and deep convolutional networks.

In our study, the input data is used by the CNN to learn the activation patterns of different MI signals. Next, a stacked autoencoder (SAE) with six layers enhances classification across a deep network. Several studies used various methods to convert EEG signal to images before feeding them to a CNN. In [29] Short time Transform Fourier (STFT) approach used to transform EEG signals to images. Filter bank common spatial pattern (FBCSP) features were developed in [30], focused on a pairwise projection matrix. It can be found by extracting CSP features from a multi-level decomposition of various frequency ranges. Time-frequency quadratic representations (TFR's) are widely used for analyzing non-stationary signals, for example speech and bio-acoustical signals. Shift-invariant TFR's belong to Cohen's class of distributions.

In this research, Cohen's Class Distribution (CCD) method is applied to convert EEG time series to 2D images. Then the converted images are fed to a CNN followed by SAE and a SoftMax classifier. CNN and SAE are first pre-trained separately and then the whole network is fine-tuned. The proposed approach is analyzed and evaluated using BCI Competition III dataset Iva [31]. the results are presented considering classification accuracy metrics. The rest of the paper is as follows: Input data, STFT and networks (CNN, SAE) is described in section II. Preprocess and experiments are presented and discussed in section III. And finally, the report is concluded under section IV.

II. METHODS

A. Dataset and preprocessing

The proposed method consists of three principal parts shown in Figure 4. First, Pre-processing step: It is important to use a sufficient amount of data to provide more reliable information and analysis to transfer to the machine learning model. Second, using convolutional neural network and stacked autoencoders: this step is important because in this part the signal pattern is taught and classified. Finally, in the last step the trained stacked autoencoders is used to classify the data set.

1) Dataset

The BCI competition III public benchmark Dataset IVa given by Fraunhofer FIRST (Intelligent Data Analysis Group) was used to evaluate the performance of the proposed method. Dataset IVa from BCI competition III [31] was recorded from five healthy subjects. Signals from 118 EEG channels of the extended international 10/20 system were captured and then band-passed filtered between 0.05 and 200 Hz. Although the sampling frequency used was 1000 Hz, EEG signals that are down-sampled at 100 Hz were also provided and used in this paper. Visual clues display the type of motor imaging for 3.5 seconds: (R) right hand, or (F) right foot. Periods of length around 2 seconds have been introduced to allow subjects to take a short break. For each of the five subjects, continuous signals with 118 EEG-channels and time-point markers with 280 cues are available. The five subjects are labeled aa, al, av, aw, and ay. The data set consists of 280 trials for each subject (140 for each class). Table 1 shows the number of training trials and test trials for all subjects. More details about the dataset can be found in the following website: http://www.bbci.de/competition/iii/

TABLE I. THE NUMBER OF TRAINING AND TEST TRIALS FOR SUBJECTS

Subjects	*Training Trials*	*Test Trials*
"aa"	168	112
"al"	224	56
"av"	84	196
"aw"	56	224
"ay"	28	252

In addition, feature vector 324×1 was used. As mentioned in the study [32] the feature vector is derived from 49 channels. We decrease the number of channels to a maximum of 18 because we couldn't manage datasets with a larger number of channels. These 18 channels have been selected based on studies on useful channels in motor imagery.

2) Preprocessing

The EEG segments which only account for part of the motor imagery were extracted from the database. For all 118 channels, however, further processing was not done, but on the following six channels: C3, Cz, C4, CP3, CPz and CP4. These six channels have been chosen because they contain the most discriminative knowledge about hands and feet motor imagery activities. The motor cortex on both the right and left sides affects EEG signals at C4 and Electrodes with a C3. Czis also influenced by the MI task of hand movement. [33]. We used the marker location for that reason, which indicated the beginning of 280 clues and the fact that each movement was 3 seconds long from 0.5 to 3.5. At the conclusion of this phase, we had 280 EEG segments (with 6 channels) for each patient pertaining to two classes right hand and right foot.

3) Butterworth Distribution

One of the techniques used for a non-stationary signal analysis is to decompose a signal into a series of blocks that can extract the signal properties both in time and frequency. In consideration of information mentioned, we developed our input network to take advantage of the data's time and frequency properties. Cohen's class of distributions can be interpreted as the inverse Fourier transform (FT) of the product of the representation dependent kernel $\varphi(\varepsilon,\tau)$ with the Ambiguity Function (AF) $A_x(\varepsilon,\tau)$ of a signal x(t). The Butterworth Distribution (BUD) is a member of Cohen's class given in (1) with the kernel $\varphi_{BUD}(\varepsilon,\tau)$ given in (2).

$$C_x(t,\omega;\varphi) = \frac{1}{2\pi}\iint e^{j(\varepsilon t-\tau\omega)}\,\varphi(\varepsilon,\tau)A_x(\varepsilon,\tau)d\tau d\varepsilon \tag{1}$$

$$\varphi_{BUD}(\varepsilon,\tau) = \frac{1}{1+(\frac{\varepsilon}{\varepsilon_i})^{2N}(\frac{\tau}{\tau_i})^{2M}} \tag{2}$$

With positive order parameters N and M, and positive spectral and temporal scaling constants ε_1 and τ_1. Note that $\varphi_{BUD}(\varepsilon_1,\tau_1)$ =1/2 for any τ_1, ε_1, N, or M.

Cohen's class distribution with BUD kernel was applied on the time series for each 3 seconds long trial. The size of the extracted image for each of 280 trials was 301×301. For 3 electrodes which are C4, Cz, and C3, this process was repeated. The findings were combined in a way that the output was obtained as a 4D matrix 280×150×301×6 for each subject.

B. Convolutional neural network (CNN)

CNNs are multi-layer neural networks, with multiple convolutional-pooling layer pairs and a fully connected layer. Standard CNN is intended to identify shapes in images and is partly invariant to the shape position. Input image is convolved with several 2D filters. And in the pooling layers, it is subsampled to a smaller size. In order to reduce the classification error, network weights and filters in the convolution layer are learned through the Back Propagation (BP) algorithm[34]. We used a CNN that has 7 convolutional layers with 5 batch normalization layers and 3 max pooling layers. The proposed CNN structure is presented in figure 4. The input image is convolved with trainable filters on the convolution layer and generated via the output function f from a map of the output. The k^{th} feature map is obtained at a given layer as:

$$h_{ij}^k = f(a) = f\left((W^k * x)_{ij}\right) + b_k \tag{3}$$

The output function f is chosen as the rectified linear unit (ReLU) function. ReLU is approximated by the function shown as below [34]:

$$f(x) = \begin{Bmatrix} x, x>0 \\ 0, x\leq 0 \end{Bmatrix} \tag{4}$$

Where x is the input image, W^K is the weight matrix for filter k and b_k is the bias value, for k= 1, 2, …

Using back propagation algorithm [35], the CNN parameters are learnt. The labeled training set is fed to the network in this process and the error E is determined evaluating the difference between the network output and the desired output. The gradient descent method is then employed to minimize this error E by changing the network parameters as shown in equations (5), (6).

$$W^K = W^K - \eta \frac{\partial E}{\partial W^K} \tag{5}$$

$$b_k = b_k - \eta \frac{\partial E}{\partial b_k} \tag{6}$$

Here η denotes the learning rate of the algorithm, while W^K is the weight matrix for filter k and b_k is the bias value as defined previously. Finally, the trained network shown in figure 4, is used for classification of the new samples in the test set.

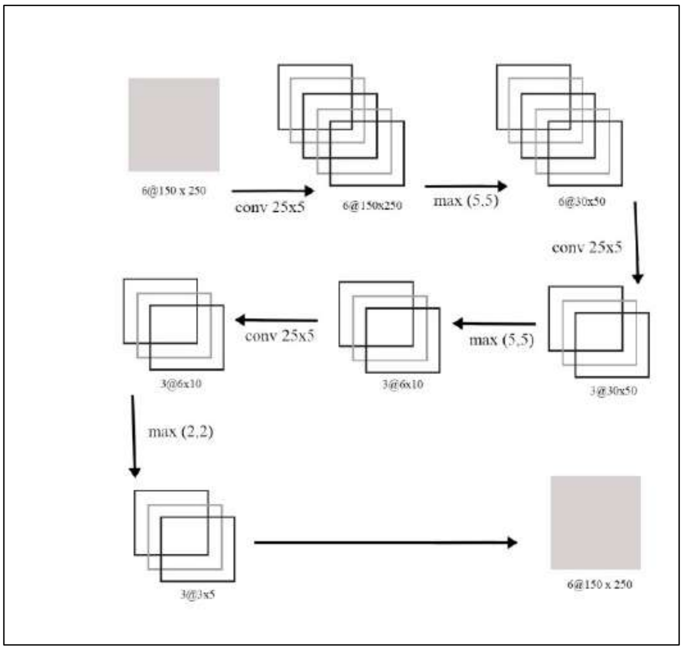

Fig. 4. Proposed CNN structure

C. *Stacked autoencoder (SAE)*

Autoencoder is a type of neural feed-forward network that can be used to reduce the dimension of the images. The input data is compressed into an unexpressed space representation and then reconstruct the output of this representation in These networks. In the output layer the number of neurons is equal to the number of neurons in the input layer. The training method for an autoencoder consists of two parts: encoder and decoder. The encoder is used to map the input data to hidden representation, and the decoder is used to recreate input data from hidden representation. The Stacked autoencoder (SAE) structure stacks n autoencoders into n hidden layers with an unsupervised layer wise learning algorithm and then fine-tuned with a supervised approach [36]. The SAE based approach can be broken down into three steps:

- Train the first auto encoder by input data and get the feature vector that has been learned.
- The previous layer's feature vector is used as the input to the next layer, and this process is repeated until the training is complete.
- Backpropagation algorithm (BP) is used after all the hidden layers are trained to reduce the cost function and change the weights with the labeled training set to achieve finetuning.

In this study, proposed model consists of one input layer, 3 hidden layers, and one output layer.

D. *Proposed Combination of CNN and SAE*

The amplitude of the EEG signal being reported is very low. The signal is therefore extremely sensitive to external and internal noises. Another source of disturbance is artifacts such as eye blinking and muscle movement, which cause irrelevant effects which corrupt the desired brain pattern. Additionally, in some trials some subjects are unable to perform successful MI tasks. These problems allow the input data to differ slightly among trials. We are proposing a new deep structure, which includes a CNN followed by a SAE, to solve those problems. The proposed model found in figure 5.

III. Results and Experiments

First, we used the proposed re-presentation of the data which are listed in table II and then CNN models to analyze our datasets. Next step was using AE to detect two MI classes. The suggested approach is comparable to the state-of-the-art algorithms which were worked on in Motor Imagery based Brain-Computer Interface field. The Accuracy is used to evaluate the proposed method related to MI classification. However, the accuracy of the classification which is the key focus of this task, is based in this paper. The proposed model has been compared to LDA classifier used in study [37], Also Compared to some of the recorded results by Ryota Tomioka et al [32]. in addition, compared to some other approaches like CSP\AM-BA-SVM approach proposed in [38], combination of common spatial pattern algorithm with SVM classifier [39]. Some studies work on channel selection methods like [40]. In this study First pick the channels from the motor cortex region and then decompose EEG signals into many bands of real and imaginary coefficients using wavelet energy function. After that, the extracted features are tested by three popular machine learning methods such as LDA, SVM and K-Nearest Neighbor (KNN). Root Mean Square (RMS) with LS-SVM, SVM, LS and LDA classifiers [41] compared to our purposed method. A comparison is stated in Table III between the proposed method and earlier methods. According to Table III the method proposed is equivalent to the state-of-the-art methods.

TABLE II. Dataset descriptions

Dataset	*Subjects*	*Num. Channels*	*Features*
Competition III dataset IVa	5	6	(150,301)
Competition III dataset IVa	5	18	(324)

IV. Conclusion

A method for the field of Motor Imagery based BCI is described in this paper. A deep neural network and SAE is used in this approach to classify MI task. In detection of two classes right hand and right foot which is equivalent to state-of-the-art and other contemporary approaches, an accuracy of 82 per cent was achieved. First, the suggested approach was tested and it was discovered that this module may be superior to others.

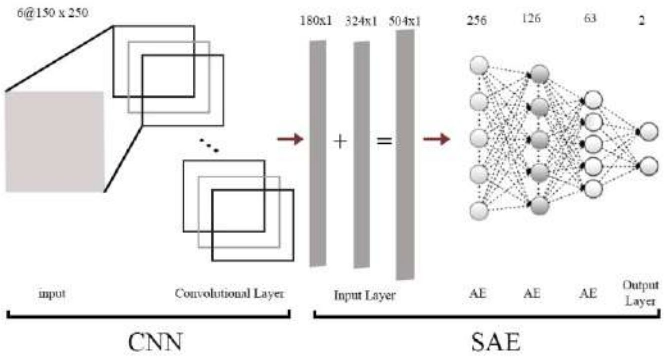

Fig. 5. Proposed network CNN-SAE. Number of neurons in each layer is shown at the top of the layer and at the bottom is the form of each layer.

TABLE III. Comparison of the Proposed Method with Other Techniques

Methods	*Accuracy (%)*
Wavelet + CSP, SVM [39]	75.55
MAV +α-BP-PSD+ AR , LDA [37]	75
CSP\SVM [38]	76.16
spectral regularization [32]	81
ICA , SVM [40]	76
RMS , LDA/ LS[41]	78.77
Proposed CNN-SAE	**82**

References

[1] Yousef Rezaei Tabar, Ugur Halici “A novel deep learning approach for classification of EEG motor imagery signals” Journal of Neural Engineering ,2016.

[2] Rabie A. Ramadan, S. Refat, Marwa A. Elshahed and Rasha A. Ali “Basics of Brain Computer Interface” chapter2, p.31-33, Springer International Publishing Switzerland 2015.

[3] Bin He, Shangkai Gao, Han Yuan, and Jonathan R. Wolpaw “Brain–Computer Interfaces” chapter2, p.88, Neural Engineering, Springer Science+Business Media New York 2013.

[4] Han-Jeong Hwang , Soyoun Kim , Soobeom Choi and Chang-Hwan Im “eeg-Based Brain-Computer Interfaces: A Thorough Literature Survey”, Intl. Journal of Human–Computer Interaction, 29: 814–826, 2013.

[5] Nicolas-Alonso L F and Gomez-Gil J,” Brain computer interfaces, a review ” , Sensors 2012.

[6] Siuly, YanLi , Peng(Paul) Wen “Modified CC-LR algorithm with three diverse feature sets for motor imagery tasks classification in EEG based brain–computer interface” Volume 113, Issue 3, , Pages 767-780 - March 2014

[7] N. Sharma, V. M. Pomeroy, and J.-C. Baron, "Motor Imagery: A Backdoor to the Motor System After Stroke " Stroke, vol. 37, no. 7, pp.1941-1952, Jul. 2006.

[8] Kai Keng Ang, Cuntai Guan “EEG-based Strategies to Detect Motor Imagery for Control and Rehabilitation”, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Volume: 25, Issue:4, April 2017.

[9] Nischal K. Verma,Senior Member, IEEE, L.S.Vishnu Sai Rao and Suresh K. Sharma, “Motor Imagery EEG signal Classification on DWT and Crosscorrelated signal features”, 9th International Conference on Industrial and Information Systems (ICIIS), 2014.

[10] Rui Zhang, Peng Xu, Tiejun Liu, “Local Temporal Correlation Common Spatial Patterns for Single Trial EEG Classificationduring Motor Imagery”, Hindawi Publishing Corporation Computational and Mathematical Methods in Medicine, Volume 2013.

[11] Yijun wang , shangkai Gao , Xiaorong Gao “Common Spatial Pattern methods for channel selection in motor imagery based brain computer interface” Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005.

[12] G. Cuntai, T. H. Dat, and X. Ping Q. Novi, "Sub-band Common Spatial Pattern (SBCSP) for Brain-Computer Interface," International IEEE/EMBS Conference on Neural Engineering, pp. pp. 204-207, 2007

[13] Grosse-Wentrup M and Buss M 2008 Multiclass common spatial patterns and information theoretic feature extraction, IEEE Trans. Biomed. Eng. 55 1991–2000

[14] Ang K K, Chin Z Y, Wang C, Guan C and Zhang H, “Filter Bank Common Spatial Pattern algorithm on BCI competition IV datasets 2a and 2b” , Front. Neurosci, 2012.

[15] Ramoser H, Muller-Gerking J and Pfurtscheller G 2000 Optimal spatial filtering of single trial EEG during imagined hand movement IEEE Trans. Rehabil. Eng. 8 441–6

[16] Comon P, “ Independent component analysis, a new concept?”, Signal Process. 36 287–314, 1994.

[17] Izabela Rejer, Paweł Górski “Independent component analysis in a motor imagery brain computer interface”, IEEE EUROCON 2017.

[18] Liwei Cheng, Duanling Li, Gongjing Yu, Zhonghai Zhang, Xiang Li, Shuyue Yu, “A Motor Imagery EEG Feature Extraction Method Based on Energy Principal Component Analysis and Deep Belief Networks”, IEEE Access (Volume: 8), 2020.

[19] Rijuta V. Wankar, Payal Shah, Rajendra Sutar, “Feature Extraction and Selection Methods for Motor Imagery EEG Signals”, Intelligent Computing and Control (I2C2) , 2017.

[20] Liaghua He, Die Hu, Meng Wan, Ying Wen, Karen M. von Deneen, MengChu Zhou, “Common Bayesian Network for Classification of EEG-Based Multiclass Motor Imagery BCI”, IEEE Transactions on Systems, Man, and Cybernetics: Systems (Volume: 46 , Issue: 6), June 2016.

[21] I. T. Hettiarachchi, T. T. Nguyen, S. Nahavandi, “Motor imagery data classifcation for BCI application using wavelet packet feature extraction” in Proc. Int. Conf. Neural Inf. Process. Cham, Switzerland: Springer, 2014.

[22] Tomas Uktveris, Vacius Jusas, ”Comparison of Feature Extraction Methods for eeg BCI Classification“, Information and Software Technologies pp 81-92, 2015.

[23] Nischal K. Verma, L.S.Vishnu Sai Rao, Suresh K. Sharma “Motor Imagery EEG signal Classification on DWT and Crosscorrelated signal features” IEEE-ICIIS 2014

[24] Le Quoc Thang, Chivalai temi yasathit “Increase performance of four-class classification for Motor-Imagery based Brain-Computer Interface” CITS -2014

[25] Liang-hua He, Bin Liu, “Motor Imagery EEG Signals Analysis Based on Bayesian Network with Gaussian Distribution”, Springer International Publishing Switzerland, 2014.

[26] Jin Zhang, Chungang Yan, Xiaoliang Gong, “Deep Convolutional Neural Network for Decoding Motor Imagery based Brain Computer Interface”, IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC),2017.

[27] Tao Yang, Kok Soon Phua, Juanhong Yu, Thevapriya Selvaratnam, Valerie Toh, Wai Hoe Ng, Kai Keng Ang, Rosa Q. So, “Image-based Motor Imagery EEG Classification using Convolutional Neural Networ”, IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), 2019.

[28] L. Arnold, S. Rebecchi, S. Chevallier, and H. Paugam-Moisy, “An Introduction to Deep Learning”, European Symposium on Artificial Neural Networks (ESANN), Bruges, Belgium, apr 2011.

[29] Yousef Rezaei Tabar, Ugur Halici, “A novel deep learning approach for classification of EEG motor imagery signals” , Journal of Neural Engineering, 2017.

[30] Mengxi Dai, Dezhi Zheng, Rui Na, Shuai Wang, Shuailei Zhang, “EEG Classification of Motor Imagery Using a Novel Deep Learning Framework”, sensors, January 2019.

[31] Guido Dornhege, Benjamin Blankertz, Gabriel Curio, and Klaus-Robert Müller. Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms. IEEE Trans. Biomed. Eng., 51(6):993-1002, June 2004

[32] Ryota Tomioka, Kazuyuki Aihara, “Classifying Matrices with a Spectral Regularization”, Machine Learning, Proceedings of the Twenty-Fourth International Conference ICML, 2007.

[33] J.A. Wilson, G. Schalk, L.M. Walton, J.C. Williams, Using an EEG-Basedbrain-computer interface for virtual cursor movement with BCI2000, J.Visualized Exp. 29 (2009).

[34] Jin Zhang, Chungang Yan, Xiaoliang Gong, “Deep Convolutional Neural Network for Decoding Motor Imagery based Brain Computer Interface”, IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2017.

[35] LeCun Y A, Bottou L, Orr G B and Müller K-R 2012 Müller K-R 2012 Efficient BackProp Neural Networks: Tricks of the Trade (Berlin: Springer) pp 9–48

[36] Guifang Liu, Huaiqian Bao, Baokun Han, “A Stacked Autoencoder-Based Deep Neural Network for Achieving Gearbox Fault Diagnosis”, Hindawi Mathematical Problems in EngineeringVolume 2018.

[37] Seyed Navid Resalat 1, Valiallah Saba, “A Study of Various Feature Extraction Methods on a Motor Imagery Based Brain Computer Interface System”, 2016.

[38] Sahar Selim, Manal Tantawi, Howida A. Shedeed, Amr Badr, “A CSP\AM-BA-SVM Approach for Motor Imagery BCI System’.2017.

[39] Ayad G. Baziyad, and Ridha Djemal, “A Study and Performance Analysis of Three Paradigms of Wavelet Coefficients Combinations in Three-class motor imagery based BCI”, 2014.

[40] Md. A. Mannan Joadder, Siuly Siuly, Enamul Kabir, “A New Way of Channel Selection in the Motor Imagery Classification for BCI Applications”, Springer Nature Switzerland AG, 2018.

[41] Sahar Selim1, Manal Tantawi, Howida Shedeed, Amr Badr, “Reducing Execution Time for Real-Time Motor Imagery Based BCI Systems”, Springer International Publishing AG, 2017.