Paper ID: 309

Classification of Motor Imagery EEG Signal by Convolutional Neural Network Utilizing Wavelet Transformed Based Mode Decomposition

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Abstract

Motor Imagery Electroencephalographic(MI-EEG) signal categorization is an intricate work in Brain-Computer Interface(BCI) system. The study generates a novel framework that categorizes MI-EEG signals utilizing pretrained Convolutional Neural Network (CNN) to optimize the classification accuracy. To classify two distinct types of MI-EEG signals (Left and Right-hand), the EEG signal of 1-Dimensional(D) time series data were preprocessed following conversion of 2-D images using Variable Mode Decomposition(VMD) and Continuous Wavelet Transform(CWT). Then, a CNN model was trained that achieved a strong classification with these images. Dataset from BCI Competition IV 2b was employed in the study. AlexNet, a pre-trained model was incorporated in the study for the classification. According to the experimental results, the model achieved 93.182% accuracy, the best result for subject-8 among all the subjects and produced average classification accuracy of 90.10±2.42%. The model can effectively classify MI-EEG signals in BCI systems in contrast to other methods.

Keywords: Brain-Computer Interface (BCI), Variational Mode Decomposition (VMD), Continuous Wavelet Transform (CWT), Convolutional Neural Network (CNN), Transfer Learning (TL).

1. Introduction

Brain-computer interface (BCI) applications frequently employ electroencephalography (EEG) which is a non-invasive mechanism for assessing brain functions, especially for motor imaging tasks [1]. Accurate classification of these signals are crucial for the advancement of reliable BCI systems. BCI allows direct communication, independent of the body's muscles and organs, between the brain and hardware, such as computers or other technological devices. This enables people to operate these gadgets solely with brain impulses. However, some issues are involved with EEG signals, such as their poor ratio of signals to noise, high dimensionality, and poor intensity. Furthermore, the signals produced by motor imagery EEG (MI-EEG) are unstable and non-linear, with mean and variance changing with time.

Motor imagery (MI) is a cognitive mechanism that allows a person to mentally mimic a physical motion without actually moving. This technique is pivotal in the field of BCIs due to its possible uses in prosthesis control, neurorehabilitation and communication assistance for those with motor disabilities. MI-EEG based BCI systems typically require accurate and reliable classification of EEG signals to translate mental intentions into control commands.

Traditional techniques to classify MI-EEG signals typically depend on manual extraction of features and conventional Machine Learning (ML) algorithms, like Support Vector Machine, Naïve Bayes and Logistic Regression comprising linear discriminant analysis [2]. These methods, however, might not adequately convey the complex patterns and temporal dynamics in EEG signals, as they often involve linear assumptions and manual feature extractions. As a result, their performance can be limited, especially with the existence of noise and variability in EEG data.

To avoid these problems, deep learning (DL) models have been generated where explicit feature extraction is not needed. Convolutional Neural Networks (CNNs), a sort of deep learning (DL) models, have shown higher performance in a number of signal processing applications because they are capable of extracting hierarchical features from unprocessed input [3].

In a study [4], Convolutional Block Attention Module (CBAM) based CNN model was suggested that extracts the details on the frequency dispersion and temporal location of MI-EEG signals and minimizes interference from unrelated noises. The mean accuracy of this work is 79.6%.

Another work [5], introduced CNN and long-term short-term memory (LSTM) classifier which took along the MI-EEG time series data and amplitude modulation properties to achieve accuracy of 83%.
In [6], combination of Continuous Wavelet Transform (CWT) and a Simplified Convolutional Neural Network (SCNN) was used which enhances average accuracy of categorizing MI-EEG signals to 83.2%.
In [7], converting MI-EEG signals to spectrogram images and training into CNN pre-trained models, 83.79±3.49% mean classification accuracy was achieved using InceptionV3 model. Furthermore, in [8], a better classification accuracy of 89.19% was acquired by implementing Short Time Fourier Transform (STFT) on EEG temporal domains, augmenting the images and training these images to multi-input CNN with feature concatenation.
In this paper, a novel approach to classify MI-EEG signals has been proposed using CNNs trained on Scalogram images. By transforming the raw MI-EEG data into Scalogram images applying Variational Mode Decomposition (VMD) & CWT, the potent feature extraction capabilities of CNN were fully utilized and mean classification accuracy of 90.10±2.42% was obtained. The outcomes show that our suggested method performs noticeably better than other traditional methods, demonstrating the potential of deep learning techniques in enhancing MI-EEG signal classification. Specifically, our method achieved higher classification accuracy, robustness to noise, and generalization across subjects.

2. Methods

The suggested methodology has been presented in figure 1. Initially, the raw MI-EEG data were acquired from a publicly accessible database site and preprocessed by filtering and removing the baseline wandering noises. Then, based on the annotation given from the database, MI-EEG signals were sorted on an interval of 4 seconds according to the events mentioned in the dataset. Then, the sorted segmented signals were transformed into several intrinsic modes with Variational Mode Decomposition (VMD) technique. The several modes were added again to form EEG signals. Later, this reconstructed signal was transformed into Scalogram based images using Continuous Wavelet Transform (CWT) operation. Afterwards, the images were resized into 224 by 224 matrix which is the dimension of input layer of the Convolutional Neural Network (CNN) model. By carrying out this methodical process, eventually, the identification of two kinds of MI-EEG signals (Left and Right hand) was accomplished in this study.

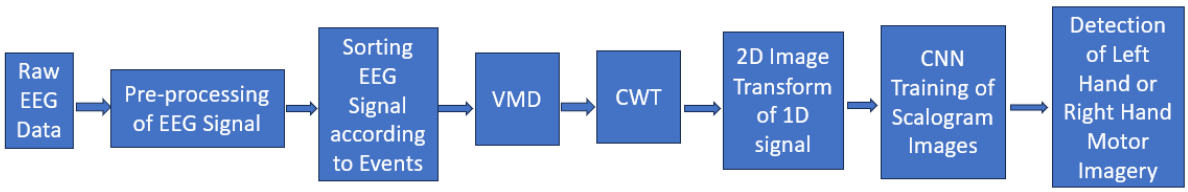


Fig. 1. Block schematic of the suggested methodology.

Dataset

BCI Competition IV dataset 2b were utilized for conducting this work. It includes EEG data from nine healthy people for the left and right hands in two classes of motor imagery activity. To record the EEG signals three channels (C3, Cz and C4 electrodes) were used which has a sampling rate of 250 Hz. For our work, C3 & C4 channels were comprised in order to minimize noise, redundancy in the input signals and to ensue experimental layout [4]. For every subject, 5 sessions are available. There are sixty trials for each MI class, for an overall of 120 trials of MI activities completed throughout each session. Further information on the dataset is available in [9]. Based on the annotation, the events of both classes are for a duration of 4 seconds and have been segmented for further work in order to classify.

Pre-processing

Various forms of noises frequently contaminate the original EEG signal during signal recording. Consequently, in order to eliminate undesired artifacts and ameliorate the signal-to-noise ratio (SNR), pre-processing techniques are crucial. In this study, a FIR bandpass filter was introduced which has a cut-off frequency with range of 8 to 32 Hz to filter the signal. For this, range of frequency bands mainly Alpha i.e., 8 to 13 Hz, Beta i.e., 13 to 30 Hz and Gamma for about 30 to 32 Hz of the MI-EEG signals passed into the filter and these bands are crucial for motor imagery (MI) classification. The signals below 8 Hz and above 32 Hz did not pass the filter. After filtering, to eradicate baseline wandering noise the function ‘detrend’ was applied. Later, the signals were sorted according to events with the help of MATLAB 2021a.

Variational Mode Decomposition (VMD)

A signal can be broken down into several intrinsic mode functions (IMFs) or modes using signal processing approach known as VMD. It is ideal for non-stationary and nonlinear signal analysis. VMD breaks down a signal into a set number of modes IMFs, each characterized by a unique central frequency and bandwidth. These modes

symbolize various parts of the initial signal, typically aligning with distinct physical events or origins. The breakdown was accomplished by tackling a problem that seeks to minimize the overall bandwidth of the modes. This task was executed through a variational method, aiming to discover the modes that most accurately reflect the initial signal, while also keeping their bandwidths as small as feasible. The modes derived from VMD have the extra benefit of being less noise-sensitive and more stable. Every mode obtained is a signal with a specific frequency center that is band limited [10]. To perform VMD method, at the beginning intrinsic modes u_k and central frequency ω_k was initialized including the Lagrange multiplier $\lambda(t)$ and the penalty parameter α. The mode u_k contains the envelope of the input signal and written as:

$$u_k(t) = A_k(t)\cos(\phi_k(t)) \tag{1}$$

Here, $\phi_k$is the phase function that is non-decreasing and A_k is the non-negative envelope function obtained from the original MI-EEG signal, $x(t)$. Then, each mode was updated as:

$$u_k^{n+1} = \arg\min_{u_k} \| x - \sum_{i \neq k} u_i - u_k \|_2^2 + \alpha \| \nabla u_k \|_2^2 \tag{2}$$

Each frequency was updated as:

$$\omega_k^{n+1} = \frac{\int_0^\infty t \mid \hat{u}_k(t) \mid^2 dt}{\int_0^\infty \mid \hat{u}_k(t) \mid^2 dt} \tag{3}$$

And with a learning rate τ, Lagrange multiplier was updated as:

$$\lambda^{n+1} = \lambda^n + \tau(x - \sum_k u_k^{n+1}) \tag{4}$$

The changes of the modes and frequencies were evaluated by convergence method. If the change was below a certain threshold, the iteration stopped. Thus, when iteration stopped, the final modes $u_k(t)$ were represented as the decomposed components of the initial signal. In this work, the EEG signal was broken into five modes of IMFs using VMD with unique central frequency and bandwidth. Then, these five modes altogether were added to acquire the reconstructed EEG signals.

Continuous Wavelet Transformation (CWT) and Image Transformation

CWT is a well-known technique to analyze time-frequency based signal. By breaking down signals into wavelets at different scales, CWT offers a thorough time-frequency representation of signals. As functions that may capture several signal frequency components, these wavelets allow for a more comprehensive analysis that can be achieved with standard approaches providing only a single frequency representation at a certain moment. CWT is especially useful in analyzing EEG signals since it can show the temporal and frequency features of brain activity. The expression of the CWT, $X_\varphi^\Psi(s,\beta)$ is shown in Equation (5).

$$X_\varphi^\Psi(s,\beta) = \langle \varphi, \psi(s,\beta) \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} \varphi(t) \cdot \psi * (\frac{t-\beta}{s}) dt \tag{5}$$

where φ is termed as segmented input signal, $\psi(s,\beta)$ stated as the mother wavelet, β as the translator that shifts along time *t* with a scale *s*. By convolution process of the Morlet as mother wavelet with scale *s*, moving throughout the signal's duration *t*, the CWT operation was carried out with the processed EEG signal at predetermined intervals. After the convolution the output obtained was stated as wavelet co-efficient which remains as a 2-Dimensional sized matrices. Then, with the co-efficient in the matrices, RGB images were generated with a size of about 341×1000×3 using 'jet' as the color-map [11]. These images subsequently were rescaled to a dimension of 224×224×3. By taking these images as input, CNN model was trained.

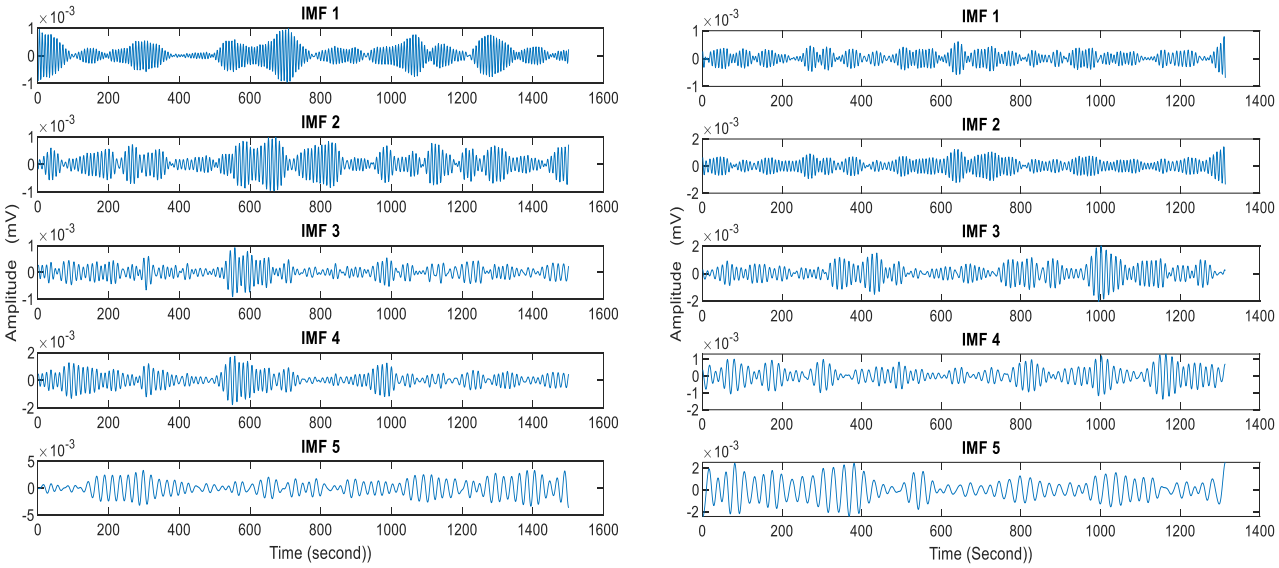
Pretrained Convolutional Neural Network (CNN)

CNN is a type of deep neural network model that comprises an input layer receiving the input image, multiple convolution and pooling layers, fully connected (FC) layer and finally an output layer. Input image of N×N matrix afterwards was convoluted with f×f matrix-based filters (or kernels) in the convolutional layer to create a number of feature maps; the overall dimension of these maps was then decreased in the pooling layer. To extract characteristics from the input image, these layers were combined in many ways. The FC layer received the extracted features following flattening and sending to feedforward network to classify. The model gained learning by using the back-propagation process for adjusting the filter weights. In the field of ML, transfer learning (TL) is a process by employing a trained-model which was created for categorizing a certain task to categorize different task by putting the acquired information that had been learned. A pretrained CNN model encompasses many network factors. These factors were used for TL for a new dataset in order to get a better classification accuracy with less training data points. In our study, AlexNet was used as a pretrained model for the detection of both hands MI-EEG signals. The AlexNet model has five convolutional layers and three FC layers. Also, Rectified Linear Units (ReLU) was taken which is a non-linear function that receives the output acquired from each convolutional and FC layer [7].

In this work, the input layer received a 224 x 224 x 3 input image. After that, 9216 input features were generated from final convolutional layer with AlexNet that was minimized into 256 output features by the means of FC layer. Another FC layer converted the 256 input features into the two output features needed for the binary classification of two MI-EEG classes. A 40% dropout rate was incorporated into our model to avoid overfitting of the data. Out of all the MI-EEG experiments, for each subject arbitrarily 80% data were utilized for training purposes, while the remaining 20% were reserved for testing in CNN.

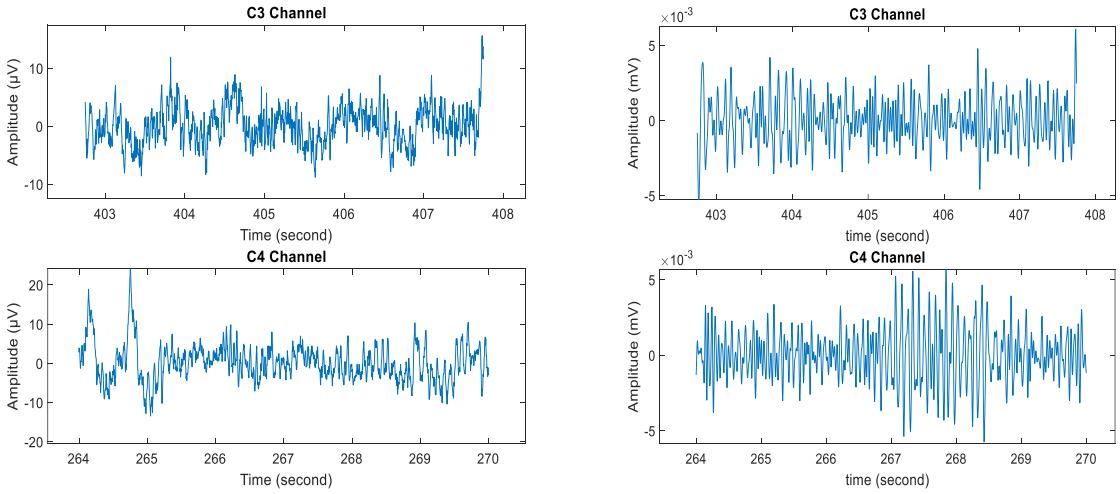
3. Results and Discussion

Samples of raw noisy EEG signals of C3 and C4 electrodes collected from the dataset have been shown in the figure 3(c). In the dataset, all the MI-EEG signals of the nine subjects were utilized for classification. These signals proceeded through a bandpass filter of 8-32 Hz and baseline wandering noise was removed. Later, the signals were structured into five intrinsic modes with VMD technique, where samples of intrinsic modes of C3 and C4 has been depicted in figure 2 (a) & (b). Each mode was characterized by a unique central frequency and bandwidth. Then, all the modes were added to make the signal less noise sensitive and more stable as shown in the figure 3 (d). On these signals, CWT operation were performed which were converted eventually into 224 x 224 dimensioned RGB images exhibited in figure 5 (e) & (f). Finally, from each respective subject, 80% images were trained into CNN model rest 20% were used for testing to extract the features and obtain the classification results of the work as exhibited in table 1.



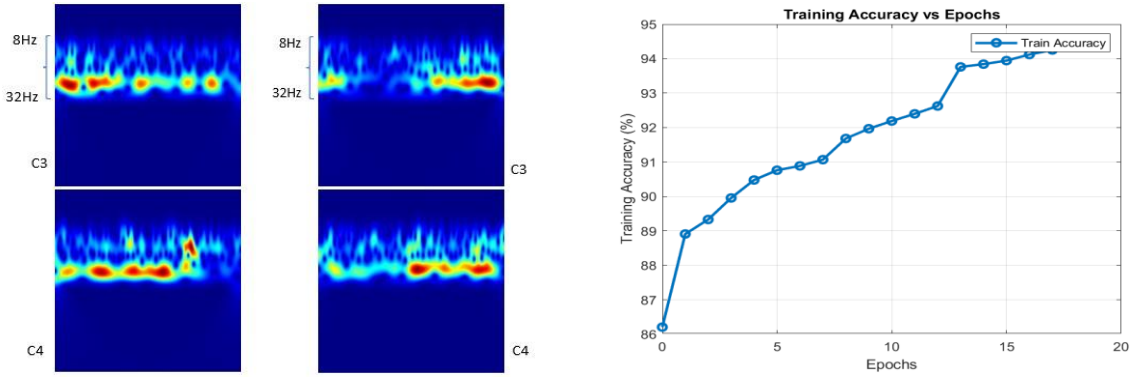
(a) (b)

Fig.2. Samples of Variational Mode decomposition of MI-EEG signal (a) C4 channel & (b) C3 channel



(c) (d)

Fig. 3. (c)Samples of noisy raw MI-EEG signal for C3 & C4 channel
(d)Reconstructed and Processed MI-EEG signals for C3 & C4 channel



(e) (f) (g)

Fig. 5. Samples of Scalogram representation of reconstructed MI-EEG Signal (e) C3-C4 Channel (left hand) (f) C3-C4 Channel (right hand). (g) Training accuracy vs Epoch curve for subject 8.

Table 1. Results of classification accuracy for BCI competition dataset and accuracy comparison table

Subject	CBAM-CNN [4]	CWT-SCNN [6]	InceptionV3 [7]	**Proposed Method**
S1	80.3 ±1.5	74.7	83.93	88.125
S2	75.0 ±1.8	81.3	78.18	86.875
S3	67.7±2.6	68.1	90.9	87.342
S4	95.4±0.6	96.3	78.85	91.071
S5	88.3±1.5	92.5	80.39	91.975
S6	80.0±1.7	86.9	81.44	90.506
S7	73.7±2.2	73.4	77.36	88.750
S8	77.4±2.0	91.3	82.69	93.182
S9	78.6±2.1	84.4	91.3	93.125
Mean	79.6±1.8	83.2	82.78 ± 4.87	**90.10±2.42%**

In this study, to optimize the functionality of BCI systems, VMD-CWT-CNN algorithm has been proposed that identifies MI-EEG signals of left and right hand. From table 1, it can be understood that the mentioned framework achieved higher classification accuracies i.e. 90.10±2.42%. in terms of subjects compared to all other mentioned works done for sorting both hand fist of MI-EEG signals. Also, our method obtained better average categorization accuracy in contrast. With the help of VMD, the signal was decomposed into five modes containing different frequency oscillations. By summation of all the modes a clean reconstructed MI-EEG segmented signal was obtained where the high frequency noise was discarded to make the signal more robust and stable. Moreover, by breaking down the raw signal and delivering a time-dependent window having a prominent temporal resolution, CWT operation reconciled simultaneously global aspects like overall structure, low frequency components with long term patterns and local aspects like fine details, high frequency components with short term events of the reconstructed signal. And lastly, AlexNet as a pretrained CNN model, made use of the categorization and feature extraction. The model was customized by modifying some parameters. After performing convolution and max pooling operation, flattening layer was included which has input features of 9216. This was minimized to 256 and finally using 'Softmax' as activation function the output layers was two that basically classify the left and right fist. To get better accuracy result, 'Cross Entropy' a loss function was set with an optimizer 'Adam' to minimize the loss function at an automated learning rate. Figure 5 (g) depicts the training accuracy of subject 8, at which the model learnt the 2-D images obtained from 1-D MI-EEG signals. From all the subjects the training accuracy were obtained. But subject 8 since showed best test classification accuracy i.e. 93.182% among all subjects so, the training accuracy curve has been exhibited in figure 5 (g), where the model was trained and learned the two types with a highest of 94.438% accuracy. In general, when compared to conventional or DL classification techniques, the VMD-CWT-CNN approach often enhanced the system's overall performance in addition to its classification performance.

4. Conclusion

In this work, a novel framework has been presented to classify MI-EEG signals in BCI systems, utilizing pretrained CNN model in order to improve categorization efficiency. By converting the 1-D EEG time series data into 2-D images using VMD and CWT operation, and subsequently training a CNN model on these images, the proposed approach demonstrates a robust ability to categorize between motor imagery tasks using the left and right hands. The utilization of the AlexNet pretrained model further underscores the effectiveness of this method in achieving reliable classification outcomes across different subjects. The outcomes imply that this strategy offers a promising alternative for the classification of MI-EEG signals, potentially enhancing the performance of BCI systems compared to traditional methods.

5. References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," Clinical Neurophysiology, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[2] N. E. Binti Md Isa, A. Amir, M. Z. Ilyas, and M. S. Razalli, "Motor imagery classification in brain computer interface (BCI) based on EEG signal by using machine learning technique," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 1, pp. 269–275, Mar., 2019.

[3] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," Journal of Neural Engineering, vol. 4, no. 2, pp. R1–R13, Jan. 2007.

[4] Z. Chen, Y. Wang, and Z. Song, "Classification of motor imagery electroencephalography signals based on image processing method," *Sensors*, vol. 21, no. 14, Jul. 2021.

[5] R. Zhang, Q. Zong, L. Dou, and X. Zhao, "A novel hybrid deep learning scheme for four-class motor imagery classification," *J Neural Eng*, vol. 16, no. 6, Oct. 2019.

[6] F. Li, F. He, F. Wang, D. Zhang, Y. Xia, and X. Li, "A novel simplified convolutional neural network classification algorithm of motor imagery EEG signals based on deep learning," *Applied Sciences (Switzerland)*, vol. 10, no. 5, Mar., 2020.

[7] N. Shajil, M. Sasikala, and A. M. Arunnagiri, "Deep Learning Classification of two-class Motor Imagery EEG signals using Transfer Learning," Institute of Electrical and Electronics Engineers (IEEE), pp. 1–4, Dec., 2020.

[8] T. H. Shovon, Z. Al Nazi, S. Dash, and M. F. Hossain, "Classification of motor imagery EEG signals with multi-input convolutional neural network by augmenting STFT," in *2019 5th International Conference on Advances in Electrical Engineering, ICAEE 2019*, Institute of Electrical and Electronics Engineers Inc., pp. 398–403, Sep., 2019.

[9] C. Brunner, R. Leeb, G. R. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI Competition 2008-Graz data set A Experimental paradigm."

[10] Y. Seo, S. Kim, and V. P. Singh, "Machine learning models coupled with variational mode decomposition: A new approach for modeling daily rainfall-runoff," *Atmosphere (Basel)*, vol. 9, no. 7, Jul., 2018.

[11] Md. F. Mina, A. D. Roy, and Md. B. Uddin, "Detection of Ventricular Fibrillation from ECG Signal Using Hybrid Scalogram-Based Convolutional Neural Network," Proceedings of International Conference on Information and Communication Technology for Development, pp. 483–495, 2023.