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Original Article

Brain Controlled Robotic Arm Using Motor Movements Using EEG Signals

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Abstract - *Brain-computer interface systems are a promising technology that allows individuals with physical disabilities to control various devices and applications through their brain activity. One of the vital challenges in developing effective BCI systems is the accurate classification of motor actual/imagery movements from electroencephalography signals. This study investigates the classification of actual motor and imagery-based BCI tasks identified using convolutional neural networks. Temporal features were extracted through spectrogram analysis, and the resulting images were fed to the CNN model to classify the data into four distinct classes. The model achieved an approximate prediction accuracy of 62% with a classification rate of 100% for Class 1, 50% for Classes 2 and 3, and 75% for Class 4. This model demonstrated a reasonably effective ability to detect the intended motor movements from Electroencephalography signals. Additionally, a robotic prototype is developed that is capable of performing specific functions, including moving backwards, moving forward, pinching in, and pinching out, based on the output of the classification model.*

Keywords - *Brain Computer Interface, Short-term fourier transforms, Spectrograms, CNN, EEG.*

1. Introduction

Brain-computer interface technology has emerged as a promising field offering a direct communication pathway between external devices and signals acquired from the brain. These systems enable people with disabilities such as limb paralysis or motor problems to operate assistive tools and perform daily tasks using their brain activity. The primary aim of a BCI system is to identify accurately the user's intentions from their Electroencephalography (EEG) [1, 2]. One of the most investigated applications in BCI is Motor-Imagery(MI) task classification, where subjects are trained to imagine the movement of a body part, and corresponding neural patterns are then employed in fulfilling tasks like controlling external devices [1, 3].

One major paradigm used in BCI systems includes detecting and classifying motor imagery tasks, which are tasks where the user imagines themselves performing certain body movements without actually performing them. MI-based BCI systems have successfully been applied to control robotic wheelchairs, prosthetic limbs and other assistive devices. Because the classification of motor imagery tasks well directly impacts the responsiveness of these systems and user control over a target device, See [4-8] for details. Various signal processing and machine learning tactics have been tested with the dataset to classify motor-imagery EEG signals [4].

In this respect, Convolutional Neural Networks (CNNs) have shown promising results, as these can learn discriminating features directly from raw EEG signals [1, 4]. BCI-based motor detection systems can be classified into 2 types: actual movement and imagery movement. Both these categories stem from different paradigms intended to elicit motor-related brain activity [9], and correct classification of both real and imagined movements is pivotal towards developing efficient BCI systems.

People with physical disabilities who use artificial devices (examples include prosthetics, computer cursors, wheelchairs or limbs) operate them through motor imagery. Furthermore, motor imagery has also been shown to be beneficial in stroke rehabilitation and motor learning therapy [4]. This paper uses the CNN method to perform the classification of the EEG-based motor movements, both real and imagery-based, for robotic arm control. This paper introduces a method that uses the Short-Term Fourier Transform (STFT) technique to convert 1-Dimensional EEG signals to 2-D images. Then, these images are used as input for a Google Net-based CNN model. The paper is structured as follows. Section I presents an overview of BCI, motor detection, and their various applications. Section II focuses on the work conducted by other scholars in the same domain. Section III examines the proposed framework, the signal processing methods involved, and the classifiers utilized, leading to Section IV, where the findings are deliberated. Section V presents the conclusions and potential future directions.

2. Related Work

The paper by Lomelin et al. [10] explores using Convolutional Neural Networks to classify MI signals from EEG data. The authors tested different spectrograms-based data and multi-dimensional raw data and achieved high accuracy (up to 93%) with transfer learning. However, they acknowledge that using spectrograms requires high computational resources. Therefore, they investigated alternative EEG representations for raw data in terms of 1D, 2D, and 3D, achieving promising results that still exceeded state-of-the-art ones, suggesting that these alternative methods could be valuable for improving MI classification with fewer preprocessing steps. Du et. al.'s [11], main contribution is proposing a new model for recognizing motor imagery electroencephalography signals. This model, a three-dimensional capsule network (3D-CapsNet), is designed to extract spatial and temporal features from MI-EEG signals, leading to more accurate identification of motor imagery. The authors Sartipi et al. [12] demonstrate the effectiveness of their model through experiments on a standard dataset, showing that it achieves high accuracy and outperforms other state-of-the-art methods, particularly in overcoming individual variability across subjects. Jain et al. [13] investigate the feasibility of predicting hand movement trajectories from pre-movement EEG signals during a grasp and lift task, with potential applications in brain-computer interfaces for motor control. EEG data were collected from 10 healthy participants performing the tasks, using a 64-channel EEG cap to record signals during the pre-movement phase. The researchers proposed a CNN-LSTM-based deep learning framework to decode the motor information encoded in the EEG. The results indicated that EEG signals can be utilized to predict movement trajectories, offering promising applications in BCIs for motor control tasks. Specifically, their method achieved an average prediction accuracy of 74.6% across all subjects, demonstrating the viability of using EEG signals for trajectory prediction in motor tasks.

A 3D capsule network model to recognize MI EEG signals was suggested by Du et al. [11]. This model can extract spatial and temporal features directly from EEG data to improve motor imagery task identification. The proposed model used a multi-layer 3D convolution module for feature extraction and integrated a capsule network to learn the spatial relation of features, demonstrating an average accuracy rate of 84.028% and an average kappa of ~0.789 on the BCI competition IV dataset. These experimental results demonstrate the feasibility of patch-based fine-tuning in enhancing four-class classification accuracy while mitigating patient variability to a certain degree. Arpaia et al. [14] presented the wearable brain-computer interface system with 8 dry EEG sensors for detecting motor imagery. Integrating a multimodal feedforward system with the Extended Reality environment improves the online detection of neurological phenomena. The results showed that participants who underwent neurofeedback during the motor imagery tasks could achieve a higher mean classification accuracy (69%) compared to the control group (62%).

The work by Lomelin et al. [10] was proof of concept that advanced methods, such as Convolutional Neural Networks, could be used to detect MI movements from EEG signals. This paper studies classifying MI-based EEG signals using multiple data representations. The authors used the Physionet Motor Movement/Motor Imagery database, which contained EEG recordings from 109 subjects, and each subject provided 14 data files (2 baseline and 12 task-related). Collazos et al. [15], proposed a paper that studies MI and BCI systems, seeking to improve the interpretability of neural responses based on a study group formed by their motor imagination ability via a framework for connectivity using a convolutional neural network. The authors present a dedicated deep CNN framework to study MI patterns from rich high-dimensional frequency-domain electroencephalography dynamical data. EEG data from 50 subjects were gathered for MI, where each subject performed MI tasks involving finger movements while EEG signals were recorded. The proposed method involves extracting functional connectivity features and clustering subjects based on their achieved classifier accuracy. An extensive electroencephalography dataset for evaluating cross-session matching on an MI-based BCI was provided by Ma et al. [16]. The dataset covers five sessions by 25 subjects, and for either left-hand or right-hand motor imagery tasks, there are 100 trials. The average classification accuracy within a session was up to 68.8% (which degraded to 53.7% across sessions and increased significantly through cross-session adaptation techniques (e.g., an accuracy of 78.9%). For example, the detection of motor imagery movements from EEG signals in this dataset is one as it promotes fundamental research to solve cross-session and cross-subject problems in the BCI field. Indeed, the results showed that although the average within-session classification accuracy was 68.8%, the accuracy degrades to 53.7% with cross-session validation since variability exists between sessions.

Javed et al. [17] proposed a first logistic regression method to recognize four individual finger movements of the right-hand thumb, index finger and a combination of the middle (2nd of right) and ring fingers (4thof left), fist, with EEG signal. The method concentrates on active channels in alpha and beta bands with the most activity, usually high-frequency components. This method gave true accuracy at almost 65%. Nevertheless, this categorization only applies to finger gesture identification and cannot identify the movements of other body parts. The paper shows that using EEG signals makes it feasible to recognize individual finger movement for controlling upper limb prosthesis, and this novelty has great potential in improving the performance and dexterity of the devices. A study by Dhongade et al. [18] used MATLAB to extract features regarding EEG signals from the Physio bank database.

The K- nearest neighbour algorithm for signal detection and servo motor control. It will tell the difference between two states: eyes opened or closed. If the classification indicates that the eyes are open, the servo motor will rotate 90°, and it will also rotate back when the classification indicates the eye is closed state. Only 5 out of the 64 EEG channels were used in this analysis. While a larger complex disease category is expected to emerge over time, there are only two categories to choose from, and this binary classification approach limits the possibilities. In addition, signal processing, feature extraction, and classification can take time- ultimately resulting in it taking even longer before power can be applied to control the robotic hand.

Ahmed et al. [19] proposed an algorithm that can control an automated arm by focusing on finger movements. A 16-channel device was used to capture and analyze the brain activity of 2 subjects aged 25-35 years. This work used the simple classification approach with too little data. Arshad et al. [20] employed various machine learning algorithms, such as Random Forest, Gradient Boosting, Logistic Regression, Support Vector Machine, and Decision Tree, to classify the EEG data collected from four participants. Using a servo motor, they acquired data corresponding to the left arm and right arm, which showed no movement. Random Forest conducted the best classification accuracy of ~76%, while it was Decision Tree at almost 74%. Hayta et al. [21] focused on a three-class Motor Imagery-based BCI system to control robotic arms with six Degrees of Freedom. EEG signals were recorded from 64 electrodes involving 12-time windows for spatial filtering and classifier calculation. They obtained an accuracy of 70%.

The inferences drawn from the literature review are as follows: Our work can focus on improving the analysis of one-dimensional, two-dimensional, and three-dimensional representations of EEG signals. In addition, we can explore and incorporate further machine learning algorithms or techniques to enhance the accuracy and interpretability of neural responses in individuals with varying motor movement abilities.

Our proposed work aims to contribute to the literature in the following ways:

- Extracting temporal correlations between EEG signals using the spectrogram technique.
- Developing a CNN algorithm based on Google Net to classify the EEG data into four distinct classes.
- A robotic arm capable of executing four distinct tasks based on the classified output is constructed.

3. Materials and Methods

This section describes the study's dataset and how the spectrogram technique extracted features. The details of the classification models employed are presented. The proposed approach is illustrated in Figure 1.

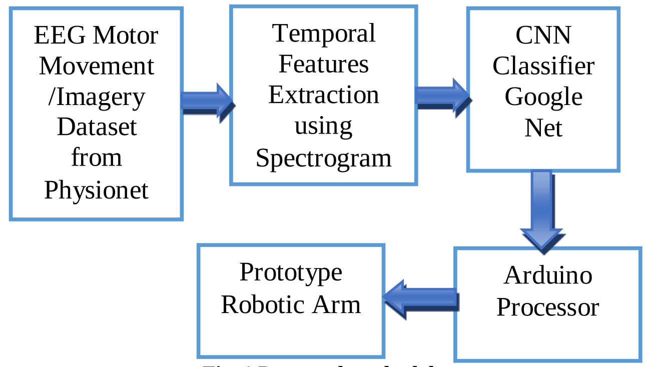

Fig. 1 Proposed methodology

3.1. Data Set

The study utilized a publicly available EEG database containing 1500 recordings, each lasting one or two minutes, collected from 109 participants [15]. The data was acquired from 106 volunteers using 64-channel EEG signals on the BCI2000 platform. Each participant underwent 14 sessions, including two one-minute baseline sessions for eyes open and eyes closed and three two-minute sessions for each of the four designated tasks:

Task 1: When a target appeared on the right or left side of the screen, the subject was instructed to close and open the respective fist until the target disappeared.

Task 2: When a target appeared on the right or left side of the screen, the subject was asked to imagine closing and opening the respective fist until the target disappeared.

Task 3: When a target appeared on the top or bottom of the screen, the subject was instructed to close and open both fists when the target was at the top and their feet when the target was at the bottom until the target disappeared.

Task 4: Again, when a target appeared on the top or bottom of the screen, the subject was asked to imagine closing and opening both fists when the target was at the top and their feet when the target was at the bottom until the target disappeared.

We considered data from 10 subjects and the trials corresponding to the above-mentioned tasks for further analysis.

3.2. Feature Extraction

Spectrograms often extract meaningful information to analyze raw EEG signals directly and improve classification accuracy. A spectrogram shows how the frequencies in a signal (such as an EEG) change over time. This gives a behavioral model of how the signal behaves in the frequency domain and reveals hidden patterns and features that will not be recognized only from the time domain representation. Motor imagery and execution activate different areas of the brain, inducing frequency-specific modifications in EEG bands (e.g., alpha, beta, and mu). Spectrograms are vital for motor movement detection since the power distribution across different frequency bands is visualized clearly, and this helps to identify specific features for a particular movement. STFT uses temporal information, which is addressed in several studies [22]. So, the approach was better for extracting the required features and converting 1-D signals to 2-D images.

This study proposes an unsupervised method for motor imagery detection based on self-attention mechanisms applied to EEG spectrograms, further emphasizing the significance of spectrograms in this domain [23]. Spectrogram images were generated using STFT in MATLAB. A Hamming window with 1 second overlapping was used to generate 2-D images, and the images were cropped to provide input to the CNN model. Sample spectrogram images of the four classes are shown in Figures 2-5.

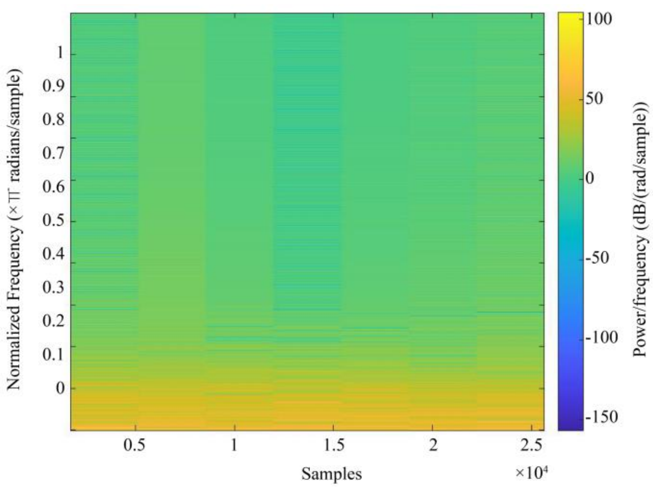

Fig. 2 Spectrogram image for class1

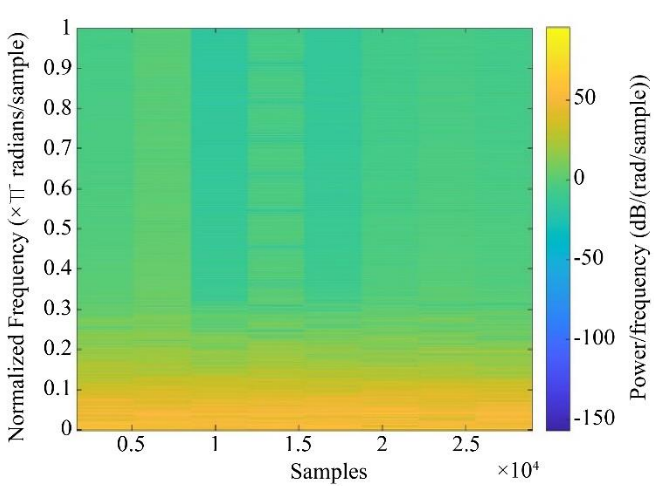

Fig. 3 Spectrogram image for class2

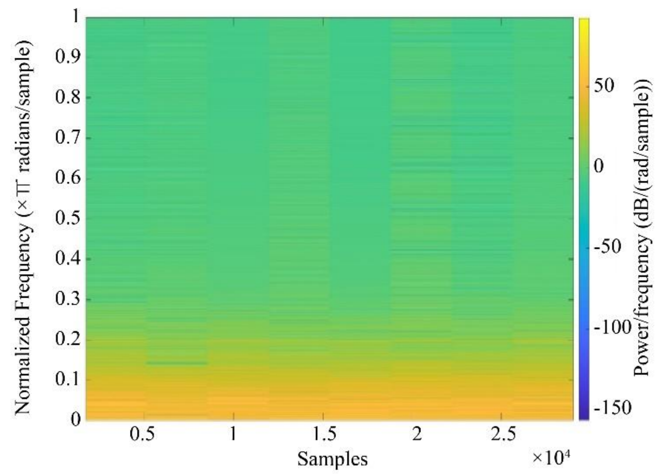

Fig. 4 Spectrogram image for class3

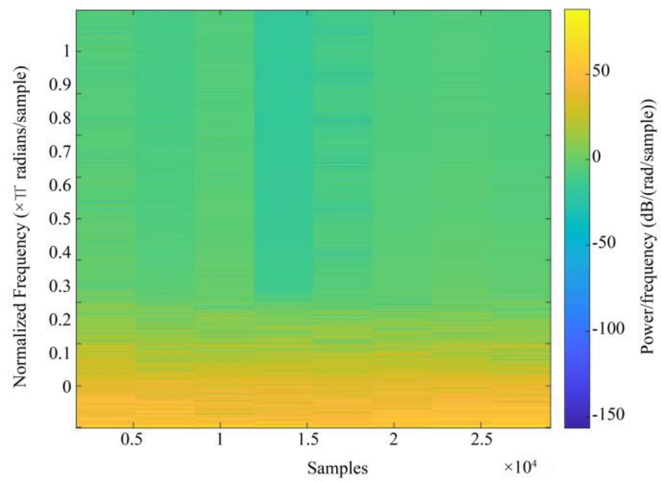

Fig. 5 Spectrogram image for class4

3.3. Classifier

In the current work, the Google Net model is employed to train and classify the data into four classes based on the tasks outlined in Section A. The input layer holds the raw pixel values of the image, such as a 531x601x3 RGB image. The Google Net model with the "no weights" algorithm is implemented using MATLAB 2024A.

The images are reshaped to 224x224x3, and the output layer is modified to have four nodes, as the data corresponds to four distinct tasks. The CNN model comprises a 22-layer deep architecture renowned for its inception modules, which enable effective image classification tasks with relatively low computational costs. The maximum batch size of 32 with a maximum epoch of 15 is used with a learning rate 0.001. The key components of Google Net are discussed as follows:

- Input Layer: It receives the initial image data, typically 224x224 pixels with three colour channels, enabling the network to handle various image classification tasks.
- Initial Convolutional Layer: It employs a 7x7

convolutional filter with a stride of 2, extracting preliminary features whilst reducing spatial dimensions.

- Max Pooling: Uses a 3x3 kernel with a stride of 2 to further downsample spatial dimensions, thereby reducing the computational burden and capturing salient features from the previous layer.
- Inception Modules: this allows for multi-scale processing and uses various convolutional filter sizes and pooling operations simultaneously to extract a range of features. Each module incorporates multiple branches of 1x1 Convolution for efficient computing and dimensionality reduction. The network employs several iterations of Inception modules (A, B, and C), each refining feature extraction at a different stage.
- Reduction Layers are positioned between Inception modules to decrease the spatial dimensions, reduce computational load, and increase network depth.
- Intermediate Layers: Multiple Inception modules are stacked sequentially, each processing the output from the previous layer, thereby progressively extracting more complex features.
- Connected Layers: After the chain of Inception modules, the network contains a final Global Average Pooling layer, followed by a Fully Connected layer and a Softmax layer. The choice of Google Net is justified due to its state-of-the-art performance in image classification tasks and its efficient use of computational resources, making it suitable for real-time applications like robotic control.

3.4. Prototype Robotic Model

The trained model is tested on new data, and the classified output controls the robotic arm in four directions. The prototype robotic model is developed using an Arduino processor, which is connected to the serial port -COM 6 of the PC. Based on the classifier's output, the movement with the highest probability is selected for the robotic arm operation. The decision-making logic implementation based on the classifier's output is as follows: If the predicted class is 1, move the robotic arm backward. If the predicted class is 2, move the robotic arm forward. If the predicted class is 3, move the robotic arm to perform a pinch-in action. If the predicted class is 4, move the robotic arm to perform a pinch-out action. If the classification output does not match any of the above, terminate the process.

4. Results and Discussion

For initial analysis purposes, 10 subject's data is considered. For each subject, 4 tasks are considered in each of the three trials. So, 768 images per subject are generated. Each class has generated 2560 images and is given as input to the CNN model.

The model is trained using 70% of the data, 15 % of the data for testing, and the remaining 15% for validation. The minimum batch size is 32, and the training is carried out for 15 epochs. The training process is illustrated in Figure 6.

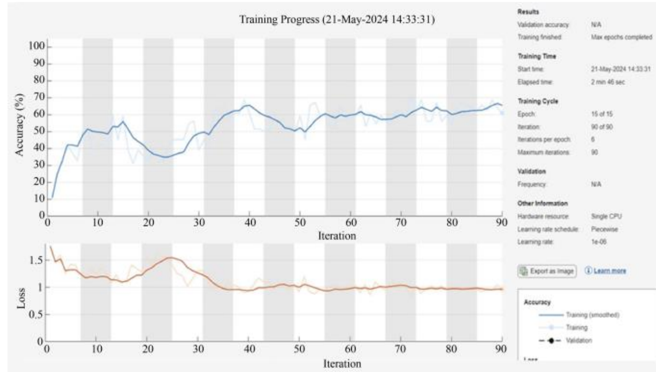

Fig. 6 Training process of CNN algorithm

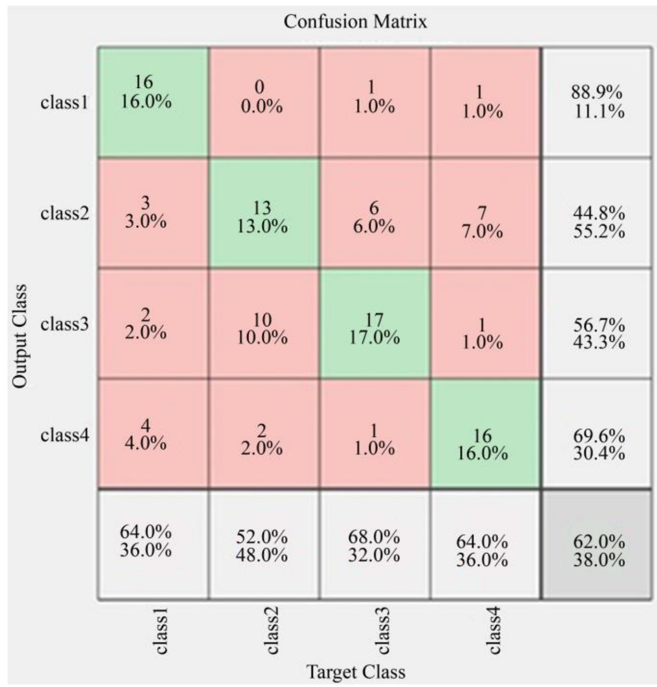

Fig. 7 Confusion matrix of CNN model

The confusion matrix of the CNN model is shown in Figure 7. The overall accuracy for the proposed CNN model is 62%. From the confusion matrix, it is seen that the model can obtain 88.9% for class 1, 44.8% for class 2, 56.7% for class 3 and 69.6% for class 4. The precision rate of class 1 is 64%, class 2 is 52%, class 3 is 68%, and class 4 is 62%, which shows that classes 1 and 4 have higher precision and recall rates. The F1-crore for Class1 is 0.74, class 2 is 0.58, class 3 is 0.61, and Class 4 is 0.57, indicating that Class 2 and 4 need further improvement. The kappa value is ~0.50, which indicates a moderate agreement between the predicted and actual values.

The output of the prediction model is connected to the Arduino processor, and based on the classified output, the robotic arm is developed to carry out specific functions like moving backward, moving forward, pinching in, and pinching out. Around 16 test data, four test cases for each class were given as input for the trained model, out of which all 4 test data for class 1 were predicted correctly, 2 test data were predicted correctly as class 2 and class 3, 3 test data were predicted correctly as class4. The prediction rate of the classifier is 100 % for class 1, 50% for classes 2 and 3, and 75% for class 4.

4.1. Case 1

The test data that belongs to class 1 is applied, and the predicted output is a 1*4 vector, which gives the probability of the classes, and the result obtained is Y= 0.3464, 0.3321, 0.1174, 0.2042 out of the four values the maximum value is 0.3464, and it belongs to class 1. The robotic arm moves backwards, as shown in Figure 8.

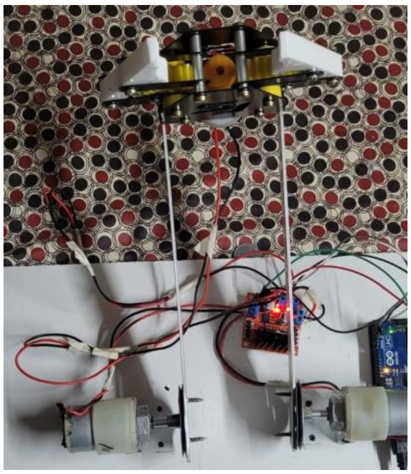

Fig. 8 Backward movement of the robotic arm

4.2. Case 2

The test data that belongs to class 2 is applied, and the predicted output is 1*4 vector, which gives the probability of the classes, and the result obtained is Y= 0.2317, 0.4624, 0.11227. 0.1832, out of the four values, the maximum value is 0.4624; it belongs to class 2. The robotic arm moves in the forward direction, as shown in Figure 9.

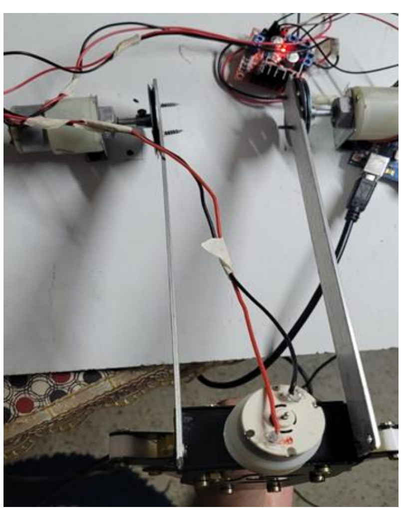

Fig. 9 Forward movement of the robotic arm

Fig. 10 Pinching in of robotic arm

4.3. Case 3

The test data that belongs to class 3 is applied, and the predicted output is a 1*4 vector, which gives the probability of the classes and the result obtained Y= 0.1079, 0.1798, 0.4803, 0.2320. Of the four values, the maximum value is 0.4803, which belongs to class 3. The robotic arm is pinched in, as shown in Figure 10.

4.4. Case 4

The test data that belongs to class 4 is applied, and the predicted output is a 1*4 vector, which gives the probability of the classes and the result obtained Y= 0.2516, 0.1318, 0.0612,0.553 out of the four values the maximum value is 0.553 it belongs to class 4. The robotic arm is pinched out, as shown in Figure 11.

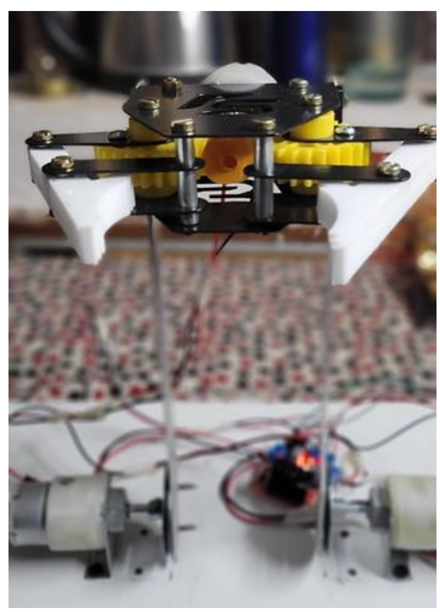

Fig. 11 Pinching out of robotic arm

The proposed model focuses on classification for four tasks, which include actual and imaginary movements and the implementation of the robotic arm was carried out for 4 operations, which seems to be better than the other related works. The performance rate was increased to a better level and is focused on temporal features of the signals, which seems to be a vital factor in detecting movement-related tasks.

5. Conclusion

Detecting motor movements using EEG signals is a promising research area that can significantly benefit individuals with motor disabilities. Researchers are employing sophisticated algorithms to develop systems capable of decoding motor intentions precisely and in virtually real time. Integration of EEG and neural networks has promised to improve communication, controllability, and therapies for people with motor disabilities. The spectrogram is analysed to extract temporal features and fed these images into a CNN model to classify into four states. The model achieved a prediction accuracy of approximately 62%, with a performance rate of 100% for Class 1, 50% for Classes 2 and 3, and 75% for Class 4. This model has a modest performance in decoding the desired motor movements from the EEG signals. To test the framework, a robotic prototype is developed that could carry out distinct tasks— e.g., move in reverse, go forward, pinch in and pinch out— as they collected data to run through the classification model.

For better performance, further study might be considered by integrating more biomedical signals (such as EMG and fNIRS) to improve feature extraction and classification. Subject size can be further increased to achieve a higher prediction rate and F1 score. The prototype can be further implemented using a high processor to match the real-time application. Moreover, the real world testing should be expanded to see how reliable the algorithm is and how robust it will be for practical applications.

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