# Recognizing Hand Movements Using EEG-Signal Classification


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*Abstract*—Classifying various precise manual movements based on electroencephalogram (EEG) signals presents an important research obstacle, particularly in the field of motor rehabilitation within brain-computer interface (BCI) applications. This study focuses on classifying EEG signals into six hand movement classes (forward, backward, up, down, right, left) using machine learning and deep learning techniques. The goal is to detect the person's current thoughts and intentions, including motor imagery and real movements, to assist individuals with physical disabilities or limb loss in controlling their robotic arms. After data collection and preprocessing, feature extraction is performed on the EEG signals obtained from the five signal bands (alpha, beta, theta, delta, gamma). By employing classical classifiers such as Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA), as well as deep learning techniques like Convolutional Neural Networks (CNN) and Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM), an overall best accuracy 70% is achieved in detecting the 6 hand movements classes from one subject. DWT with Logistic Regression, also CSP using SVM (one vs rest) achieved the same accuracy 70%. EEG-Net also got 70% accuracy on the 6 classes. 93% accuracy is achieved for binary classification (2 classes) with CSP as a feature and Random Forest classifier also DWT using LSTM achieved the same accuracy 93% using a 60-channel EEG system, the results that overcome the results from literature review on the same dataset. Cross subjects is experimented also in this study. Using cross subjects' data from 4 classes, CSP using LSTM shows high accuracy of 61%. The use of a 60-channel EEG system and the adoption of deep learning techniques resulted in the best accuracy for hand movement recognition in this study.



***Keywords—EEG signal classification – Hand movement – signals – BCI system- Multi class Classification***


## I. Introduction

In recent years, the field of Brain-Computer Interface (BCI) has gained significant attention due to its potential to provide a direct communication pathway between the human brain and external devices. One of the key areas within BCI research is the recognition of hand movements based on Electroencephalography (EEG) signal classification [1]. By deciphering the brain's electrical activity, it becomes possible to interpret a person's intentions and enable them to control external devices, such as robotic arms, through their thoughts [2].

The objective of this paper is to present a project focused on recognizing hand movements using EEG signal classification [3]. The ultimate goal is to develop a system that can accurately classify EEG signals into six Multi-classes. This classification task serves as a crucial step in understanding the intentions and motor commands of individuals, particularly those with physical disabilities or those who have lost the ability to use their limbs[4].

To achieve this goal, machine learning and deep learning techniques are employed .These techniques have shown remarkable success in various domains, including computer vision [5], natural language processing, and pattern recognition. By harnessing their power, it is possible to analyze the complex patterns present in EEG signals and create models capable of recognizing and interpreting specific hand movements.

The project workflow begins with the collection of EEG data from individuals wearing EEG headbands, which capture the electrical signals generated by the brain during motor imagery or real movements (motor execution). The collected signals undergo preprocessing techniques to remove noise, artifacts, and any unwanted interference. Subsequently, a set of features is extracted from the EEG signals to capture their distinctive characteristics.

The next phase involves the utilization of various classifiers for the classification task. Classical classifiers, such as Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA), are employed to explore the effectiveness of traditional machine learning algorithms in recognizing hand movements from EEG signals. Additionally, deep learning techniques, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks with Long Short-

Term Memory (RNN-LSTM), are investigated due to their ability to automatically learn complex features and temporal dependencies from data.

While previous studies have achieved promising results in EEG signal classification [6] [7], there are challenges that need to be addressed. One such challenge is the decrease in classification accuracy as the number of classes increases. Recognizing six distinct hand movements introduces additional complexity, as the system needs to differentiate between a larger set of motor commands. Another challenge arises when attempting to train the classifier model on multiple subjects, known as cross-subject analysis.

The inter-subject variability in EEG signals and neural activation patterns poses a significant hurdle in achieving consistent and accurate classification results.

## II. Related Work And Dataset

The prior researches in the field of hand movement classification have primarily focused on distinguishing between two different hand movements due to the difficulty of this task. The following studies have tried to solve this task.

Boonme etal. [8] proposed a classification method on EEG signals data to develop a BCI in the future. By using deep learning approach and using High Gamma dataset[9] to classify arm movement into 2 classes (raising the right arm, raising the left arm ). with using DCNN, they achieved a prediction accuracy 90.86% of raising right arm and 94.71% of raising left arm . The high gamma dataset that was used is collected from 19 electrodes and obtained from 14 subjects, the duration for each signal was 4 seconds.

Zhang etal. [10] proposed a method for classifying left/right hand movement by using Long Short-Term Memory (LSTM) network with attention mechanism with Time/Frequency domain features to learn EEG Signals. They achieved a prediction accuracy of 83.7% for cross subject and 94.7% for Intra subject. The dataset used was collected from 64 EEG channels Motor Movement/Imagery [11]. The dataset was obtained using BCI 2000 system from 109 subjects, with sampling frequency 160 samples per second. The participants were asked to perform three actions (Rest, Left-hand movement, and Right-hand movement).

Bressan etal. [12] applied a new Deep learning-based model using CNN on two datasets of the EU Horizon 2020 project “MoreGrasp"[13]. The classes of movements are touch, grasp, palmar, lateral and rest. Dataset 1 includes touch, grasp and rest classes, while dataset 2 includes palmar, lateral, and rest classes, both recorded are collected from 58 electrodes for brain activity and 6 electrodes for EOG, with sampling frequency 256 samples per second. There were 11 volunteers for touch-and-grasp, and 15 volunteers for palmar-lateral movements. CNN Model achieved an average accuracy of 70% for Dataset1 and 65% for Dataset2 across all participants.

Ofner etal. [14] proposed a classification method for single upper limb movements using shrinkage regularized linear discriminant analysis (sLDA) classifier [16][17] with discriminative spatial pattern (DSP) [18] using BNCI Horizon 2020 database [15]. The used dataset measures EEG signal from 61 electrodes and four 16-channel amplifiers. and collected from 15 subjects. Each subject did 6 different imagined and executed hand movements (elbow flexion, elbow extension, supination, pronation, hand close, and hand open) and the rest. The duration was 3 seconds, with a sampling frequency of 512 samples per second. sLDA achieved average accuracies of 55% (movement vs movement) and 87% (movement vs rest) for executed movements, and 27% and 73%, respectively, for imagined movement.

## III. System Architicture

This section contains the pipeline and the proposed method to solve the problem system architecture as shown in figure 3 consists of 3 main steps on the recorded EEG signal (dataset): preprocessing, feature extraction and finally the classification step.

### A. Dataset

In this work, we decided to use Giga Science dataset[19], which contains 6 movements for Arm reaching task motor execution ME and motor imagery MI for 25 subjects on one session. Throughout the experiments, every participant was seated in a chair equipped with armrests to ensure comfort. Each participant had an EEG cap, consisting of 60 channels, positioned on their head. (See fig.1).

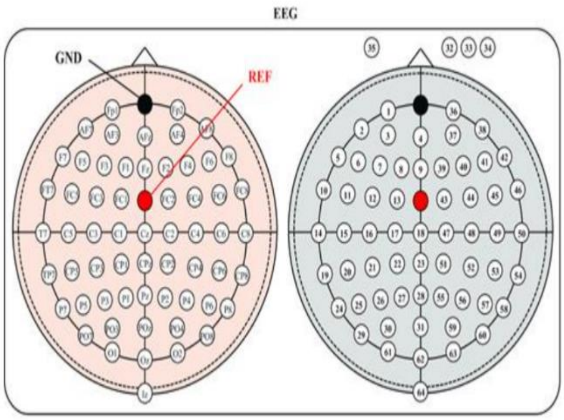


Fig. 1. Data configuration for EEG, EMG and EOG Channels

The EEG data was captured using an EEG signal amplifier (Brain Amp, Brain Product GmbH, Germany) at a sampling rate of 2,500 Hz. To mitigate the impact of external electrical interferences (e.g., DC noise from the power supply, scan rate of the monitor, and fluorescent lamp frequency) on the raw signals, a notch filter at 60 Hz was applied [23]. The Brain Vision software (Brain Product GmbH, Germany) in conjunction with MATLAB 2019a (MathWorks Inc., USA) was used to record the raw data. In total, 60 EEG electrodes were chosen following the 10-20 international configuration, encompassing specific locations such as (Fp1-2, AF5-6, AF7-8, AFz, F1-8, Fz, FT7-8, FC1-6, T7-8, C1-6, Cz, TP7-8, CP1-6, CPz, P1-8, Pz, PO3-4, PO7-8, POz, O1-2, Oz, and Iz).

At the beginning of the experiment, participants were presented with visual instructions on the monitor. These instructions consisted of a black cross symbol displayed. on a gray background. Participants were instructed to focus their gaze on these visual instructions for a duration of 4 seconds while resting. Following the resting period, a visual cue appeared on the monitor in the form of a text sign, which remained visible for 3 seconds. Subsequently, either participants began preparing themselves to perform the actual movement tasks or the Motor Imagery (MI) tasks based on the provided visual cue (refer to Fig. 2 for details). The visual cue changed to display the text signs "Movement Execution" and "Movement Imagery," prompting participants to carry out the corresponding tasks within a timeframe of 4 seconds. For the real-movement tasks, participants were instructed to concentrate on the sensations associated with each motion and to remember those sensations for the MI tasks.

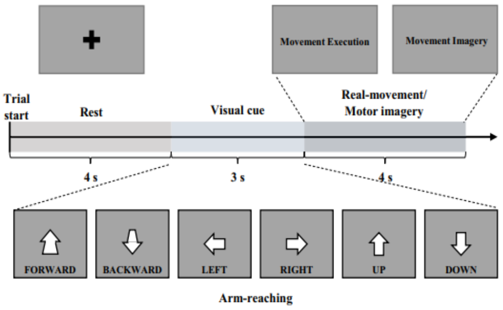


Fig. 2. Trial Sequence

In [30] Various conventional machine learning techniques have been utilized with this dataset such as LDA and SVM to classify the 6 movements (forward, backward, up, down, right, and left). The accuracies ranging between 0.23 for RM and 0.22 for IM in Average for all participant (see table 1)

*TABLE 1. results for real movement and imagery movement [30]*

| Participant No. | RM | IM | Participant No. | RM | IM |
|---|---|---|---|---|---|
| 1 | 0.21 ±0.01 | 0.21 ±0.02 | 4 | 0.17 ±0.02 | 0.21 ±0.02 |
| 2 | 0.24 ±0.01 | 0.22 ±0.01 | 5 | 0.21 ±0.01 | 0.2 ±0.01 |
| 3 | 0.18 | 0.2 | 6 | 0.19 | 0.19 |

## B. Preprocessing

As shown in figure (3), in the proposed methodology, the EEG Raw Signal goes through several steps to end up with our classification. Preprocessing step starts with Segmentation where we read the Raw Signals with baseline -0.5, 0 and segment it to trials , each trail 4 seconds, these trials are normalized [24] or standardized, based on the used feature extraction technique. Then a Butterworth bandpass filter of order 4 is applied with band frequencies 8 and 30 for Artifacts (Noise) removal and to target the two dominant EEG bands (Alpha and Beta) which emits during real movement or movement intention.

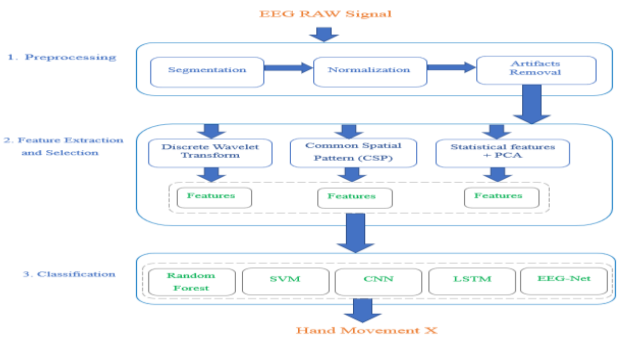


*Fig. 3. EEG Signal proposed system architecture*

## C. Feature Extraction

In the next step we applied three different types of feature extraction.

1- Discrete Wavelet Transform (DWT) is used to decompose the signal into levels of band frequencies, were we applied DWT with level 5 and mother wavelet “db4” to reach the frequencies [0-30 HZ][27].

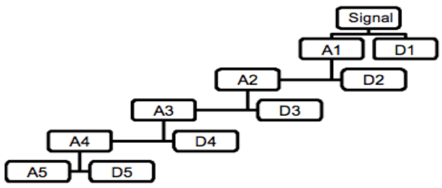


*Fig. 4. Decomposition of 5 levels of Discrete wavelet transform.*

2- Common spatial pattern (CSP): is a mathematical procedure used in signal processing for separating multivariate signal into additive subcomponents which have a maximum difference in variance between two windows. CSP is applied on two- classes classification and we select the first and last eigen vectors of the output components [20,21]. But in Multi-classes classification, CSP is joint with approximate diagonalization (JAD) [22], that is equivalent to independent component analysis (ICA)[23], where we choose components that maximize mutual information of ICs and class labels. The resulting data shape is 2d array (trials x components). Standardization is a preceding step for both DWT and CSP.

3- Statistical features[25,26]: twelve statistical features is used as follows

- Power of the signal x defined as follows:

$$p(X) = \frac{1}{N}\sum_{i=1}^{n} x_i^2 \qquad (1)$$

- Peak of the signal: Calculate the maximum peak of the signal, and calculated as follows:

$$P_m = \max(|x_i|) \qquad (2)$$

- Peak to Peak: Calculates the distance between the maximum peak and the minimum peak, and calculated as followis:

$$P_k = \max(x_i) - \min(x_i) \qquad (3)$$

- RMS of the signal: which calculated as follows:

$$\text{RMS}=\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (4)$$

- Crest Factor: Calculates the ratio of the peak value to the RMS (Root Mean Square) value, which describes the waveform, and calculated as follows:

$$\text{C}= \frac{P_m}{RMS} \qquad (5)$$

- Form Factor: Calculates the ratio of the RMS value to the Average Value, which measures the perfectness of the waveform, and calculated as follows:

$$FF = \frac{RMS}{\bar{X}} \qquad (6)$$

- Pulse Indicator: Calculates the ratio of the peak value to the Average Value, calculated using the following equation:

$$PI=\frac{P_m}{\bar{X}} \quad (7)$$

- Mean of the signal E(x): calculated as follows:

$$Mean(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (8)$$

- Variance of the signal: calculated as following:

$$Var = \frac{\sum_{i=1}^{N}(x_i-\bar{X})^2}{N-1} \quad (9)$$

- Standard Deviation of the signal: calculated as following:

$$STD = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\mu)^2}{n-1}} \quad (10)$$

- Kurtosis of the signal: calculated as follows:

$$Kurtosis(x) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\bar{X}}{\sigma}\right)^4 \quad (11)$$

- Skewness of the signal: calculated as follows:

$$Skewness(x) = \frac{N\sum(x_i-\bar{X})^3}{(N-1)(N-2)\sigma^3} \quad (12)$$

We extract these 12 statistical features from each channel of the signal. As the number of channels is 60, then we end up having about 720 features. Then, we apply PCA (principle component analysis) algorithm and select the first 30 components that have most of the variance of the data to reduce the dimensionality of the data and enhance the performance. The resulting data shape is 2d array (trails x Components).

*D. classification*

In classification step, We applied several machine learning algorithms on the extracted features such as:

1- K-nearest neighbors (KNN): is one of the simplest Machine Learning algorithms based on Supervised Learning technique. That assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.[27]
2- Support vector machines (SVM): a supervised machine learning algorithm used for both classification and regression tasks. It is a powerful and versatile algorithm that can effectively handle complex data and achieve high accuracy. By get the max margins between different classes, [28]
3- Logistic Regression (LR): a Machine Learning classification algorithm that is used to predict the probability of certain classes based on some dependent variables.
4- Linear discriminant Analysis (LDA): is a statistical method used for dimensionality reduction and classification tasks. It is a supervised learning algorithm commonly used in machine learning and pattern recognition.
5- Decision tree (DT): a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks.
6- Ensemble methods and Random Forest (RF): is a popular machine learning algorithm that is used for both classification and regression tasks. It is an ensemble method that combines multiple decision trees to make predictions.
7- AdaBoost: short for Adaptive Boosting, is a machine learning algorithm that is used for binary classification tasks. It is a boosting algorithm, which means it combines multiple weak learners (typically decision trees) to create a strong classifier.

Also some deep learning architectures are applied to select:

1- Convolution Neural Network (CNN): a type of deep learning neural network architecture commonly used in computer vision.
2- Long Short-Term Memory (LSTM): LSTM is a type of recurrent neural network (RNN) architecture. LSTMs were designed to address the limitations of traditional RNNs in capturing long-term dependencies in sequential data.
3- EEG-Net: an architecture proposed by Lawhern etal. [29]. is a compact convolutional neural network (CNN) designed for EEG-based brain-computer interfaces (BCI). It consists of convolutional layers, batch normalization, activation functions, max pooling, and classification layers. The network employs depth-wise separable convolutions to reduce parameter count while maintaining performance. EEG-Net captures spatial dependencies in EEG signals and uses a global average pooling layer and fully connected layer for classification. The architecture is optimized for efficient processing of EEG data and accurate classification in brain-computer interface (Figure 5).

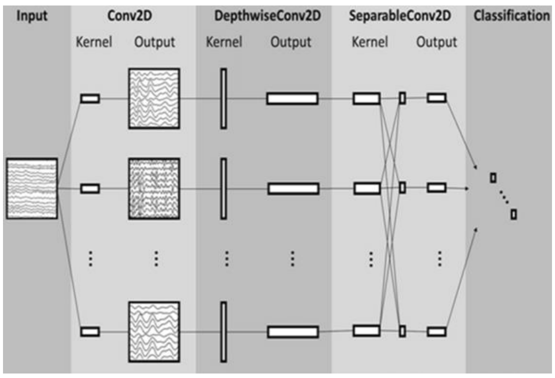


*Fig. 5. EEG-Net Architecture*

TABLE . Binary Classification results for subject 11 where Classes Codes are :(forward,11), (Backward,21), (Left,31), (Right,41), (UP,51), (Down, 61).

## IV. RESULTS AND DISCUSSION

This section shows the achieved results after applying the preprocessing and features extraction techniques and fed these distinctive features to different classifiers. First of all, we tried to classify between two discriminative classes only to test the effectiveness of our features and models, then we try four and six classes.

Table 2 shows the best results from real movement (RM) and imagery movement (IM). For each feature extraction pipeline for binary classification for subject 11.

It is obvious that CSP using Random Forest and DWT using LSTM both got the highest Accuracy about 93% accuracy for up and down cases and for left and right classes, consecutively. Also, statistical features and PCA using Random Forest got great performance 86% for forward and Down classes.

TABLE 3: Multi Classification results for subject 11

| Sub 11 - Binary Classification | | | | | |
|---|---|---|---|---|---|
| **Pre-process** | **Feature-extraction** | **Classification technique** | **Accuracy** | **RM/IM** | **N0- classes** |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | Random Forest | 0.86 | RM | 2 (11,61) |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | Random Forest | 0.83 | IM | 2 (51,61) |
| Standardization + (8,30) butter filter | CSP | SVM | 0.76 | RM | 2 (11,61) |
| Standardization + (8,30) butter filter | CSP | Random Forest | 0.93 | IM | 2 (51,61) |
| Standardization + (8,30) butter filter | DWT + Log-var | AdaBoost | 0.7 | RM | 2 (11,61) |
| Standardization + (8,30) butter filter | DWT + Log-var | LSTM | 0.93 | IM | 2 (31,41) |

Table 3 shows the best results from imagery movement (IM). For each feature extraction with Multi classification for subject 11. For Four classes (Forward, Backward, Up, and Down), DWT using SVM (one vs one) is achieved 65% accuracy and CSP using Random Forest got 63%, where statistical features and PCA using MLP got 40 %. For six classes, DWT using Logistic Regression is achieved the best accuracy 70% and CSP using SVM (one vs rest) achieved 70%, where statistical features and PCA using LSTM got 42%. Also, EEG-Net got 70% accuracy.

TABLE 4: Multi class results for some subjects in comparison to other research results

| No-record | Subject | [30] IM Accuracy | Our Accuracy | [30] RM Accuracy | Our Accuracy |
|---|---|---|---|---|---|
| 1 | 11 | 0.35 | 0.7 | 0.25 | 0.33 |
| 2 | 22 | 0.23 | 0.5 | 0.29 | 0.5 |
| 3 | 21 | 0.2 | 0.3 | 0.28 | 0.5 |
| 4 | 6 | 0.19 | 0.4 | 0.19 | 0.4 |
| 5 | 12 | 0.21 | 0.5 | 0.21 | 0.56 |
| 6 | 4 | 0.21 | 0.3 | 0.17 | 0.36 |
| 7 | 2 | 0.22 | 0.26 | 0.24 | 0.5 |
| 8 | 7 | 0.24 | 0.46 | 0.22 | 0.36 |

Table 4 shows the results after applying the EEG-Net architecture on 8 subjects and compare our results to the results mentioned in [30]. As shown on the table, we achieved higher accuracy than [30], especially accuracy achieved by subject 11.

TABLE 5. classes result for the subjects in table 4.

| No-record | Forward | Backward | Left | Right | UP | Down |
|---|---|---|---|---|---|---|
| 1 | 0.6 | 0.6 | 0.8 | 0.4 | 0.8 | 0.6 |
| 2 | 0.2 | 0.6 | 0.4 | 0.6 | 0.4 | 0.8 |
| 3 | 0.4 | 0.4 | 0.4 | 0.8 | 0.8 | 0.3 |
| 4 | 0.6 | 0.8 | 0.2 | 0.8 | 0.2 | 0.2 |
| 5 | 0.2 | 0.6 | 1 | 0.6 | 0.2 | 0.4 |
| 6 | 0.2 | 0.4 | 0.4 | 0.4 | 0.4 | 0.2 |
| 7 | 0.4 | 0.4 | 0.6 | 0.2 | 0.6 | 1 |
| 8 | 0.2 | 0.2 | 0.8 | 0.6 | 1 | 0.2 |

Table 5 shows the accuracies achieved by 8 subjects using EEG-Net to classify between our 6 classes.

TABLE 6. cross subject results across four subjects.

| Cross subject Classification | | | | | | |
|---|---|---|---|---|---|---|
| **Pre-process** | **Feature-extraction** | **Classification technique** | **Accuracy** | **RM/IM** | **N0- classes** | **Subjects** |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | LSTM | 0.7 | IM | 2 (31,41) | subs 11,12,4,7 |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | LSTM | 0.68 | IM | 2 (51,61) | subs 11,12,4,7 |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | SVM | 0.42 | IM | 4 (31,41,51,61) | subs 11,12,4,7 |
| Standardization + (8,30) butter filter | CSP | LSTM | 0.61 | IM | 4 (31,41,51,61) | subs 11,12,4,7 |
| Standardization + (8,30) butter filter | DWT + Log-var | LSTM | 0.58 | IM | 4 (31,41,51,61) | subs 11,12,4,7 |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | LSTM | 0.36 | IM | 4 (11,21,51,61) | subs 11,12,4,7 |
| Min Max normalization + moving average | statistical features +PCA (feature selection) | LSTM | 0.31 | IM | 6 | subs 11,12,4,7 |
| Standardization + (8,30) butter filter | CSP | LSTM | 0.36 | IM | 6 | subs 11,12,4,7 |

In table 6, we experimented cross subject classification with subjects 11, 12, 4 and 7. For cross subject with 2 Classes, Statistical features using LSTM show high performance of about 70% accuracy for 2 different pairs of classes. As we know from table 1 and table 2 CSP and DWT always show a higher performance than statistical features, so we didn't experiment them. For cross subject with 4 Classes, CSP using LSTM shows high accuracy of 61%, And DWT using LSTM shows near result equals 58%, Statistical features show low performance of 42% accuracy. For cross subject with 6 Classes, CSP using LSTM shows accuracy of 36% accuracy Where Statistical features show lower performance of 31% accuracy.

## V. CONCLUSION AND FUTURE WORK

This study demonstrates the potential of machine learning and deep learning techniques in recognizing hand movements using EEG signal classification. By classifying EEG signals into six classes representing different hand movement directions, such as forward, backward, up, down, right, and left, the system aims to decode the person's intentions and assist individuals with physical disabilities or limb loss. Through data collection, proposed preprocessing, and feature extraction from the five EEG signal bands (alpha, beta, theta, delta, and gamma), combined with classical classifiers (SVM, Random Forest and LDA) and deep learning techniques (CNN and RNN-LSTM), the highest achieved accuracy is 93% for 2 classes by using two approaches Common spatial pattern (CSP) with Random Forest Classifier and DWT with LSTM. However, our study reveals that accuracy decreases when the number of classes exceeds two, and the highest achieved accuracy is 70% on 6 classes by using three approaches CSP with SVM, DWT with Logistic Regression and EEG-Net. And when the classifier model is trained on multiple subjects, highlighting the challenges of multi-class classification and cross-subject analysis, Thus the highest achieved accuracy for 6 classes across 4 subjects is 36% and for 4 classes is 61% using cross subjects using CSP with LSTM using our limited hardware and memory. These classification results that, overcome the results from other research work on the same dataset, highlights the proposed contribution in this study. Even with limited hardware, the proposed methodology in this study enhanced the classification accuracy for one subject and cross subjects.

The use of a 60-channel EEG system and the adoption of deep learning techniques yield the highest accuracy in hand movement recognition. These findings provide insights into the potential and limitations of EEG signal classification for assisting individuals in regaining control over robotic arms and underscore the need for further advancements in addressing the challenges of multi-class classification and cross-subject analysis.

We intend to improve our proposed accuracy by applying HCI techniques and make a flexible and fast application.

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