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Research Article

Deep Learning Based Imaginary Finger Control Detection Algorithm

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ABSTRACT

Conventionally, the brain signals were analysed manually by the neuroscientists on how the brain signals reacts in proportion with the human body. However, this process is very time consuming and unreliable. Therefore, we have proposed a brain signal detection system based on deep learning algorithm in response to the output of EEG device on the imagery finger movements. These fingers include thumb, index, middle, ring and little of right hand. In this study, 4 Convolutional Neural Network (CNN) classification models were developed. These 4 CNN models are different in terms of the pre-processing requirements and the neural network architecture. The best results for offline classification obtained in this project are 69.07% and 82.83% respectively in terms of average accuracy from 6-class and 2-class tests. Moreover, this project has also developed a proof of concept for applying the trained models in online or real-time classification.

1. INTRODUCTION

Brain-computer Interface (BCI) is a device used to detect brain signals [1]. The device enables human brain activities to interact with the environment [1]. BCI is used widely in medical application, such as stroke rehabilitation, controlling smart devices, communication device for patients without motor abilities, mental disease diagnosis and many more. Generally, there are three types of BCI devices: invasive, partially invasive, and non-invasive.

Due to the clinical risks and impracticality of invasive and partially invasive BCI, this research will only focus on electroencephalogram (EEG) based non-invasive BCI device. According to [2], EEG are mostly used in other BCI research because of its reliability, ease of use and non-invasiveness. EEG functions by detecting the brain signals in terms of voltage fluctuations from the human scalp through the electrodes. Besides, EEG is high in temporal resolution and relatively low in cost.

In 2018, Samson et al. has developed an EEG-based Open BCI device for controlling home appliances for impaired individuals [3]. The EEG signals generated by eye-blinking movement and concentration levels are collected using four electrodes. The frontal and occipital lobes, which are located at FP1, FP2, F8, and CP6, are used to insert electrodes. The Mu waves created when the user blinks his eyes are read by the electrode implanted

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on the frontal love. The electrode on the occipital lobe reads the alpha impulses produced when the user placed his teeth against each other at the same moment. These signals will be utilised to operate home appliances as a command. However, the project is not fully EEG-based because it utilizes EMG signals as one of the inputs, which is generated by eye-blinking.

According to [4], there are six classes of brain signals: motor imagery (MI), sleep stage scoring, emotion recognition, mental workload, seizure detection and event-related potential detection. Since that this research is about imagery finger detection, therefore, it falls under the category of MI. MI refers to the mental's thought on motor movements [5]. This phenomenon can be detected by the EEG devices as the brain signals are induced in motor cortex during imagination of motor movements.

To classify these signals, deep learning approach are often being used. Deep learning is a subset of machine learning in which a computer model learns to perform certain tasks based on a set of data [6]. The deep learning architecture is inspired by the structure of human brain; hence, they are often called as artificial neural networks. When properly trained, deep learning models can achieve high accuracy for tasks like classification, regression, and text generation [7].

The research done by [8] [9] [10] do not implement any feature extraction technique to pre-process the training data. The raw EEG signals were used directly as the training data for the deep learning algorithm. Due to the nature of Convolutional Neural Network (CNN) architecture, the learnt parameters in this algorithm form layers of filters capable of producing the feature maps from the raw EEG signals. Therefore, by stacking more convolutional layers, the deep learning algorithm can produce higher order of feature maps automatically, increasing the classification accuracy. However, the increase in number of learnable parameters causes more computational power required to execute the algorithm.

The Common Spatial Pattern (CSP) and Fast Fourier Transform Energy Map (FFTEM) algorithms was used by [11] for feature computation and feature selection, respectively. The CSP algorithm works by applying spatial filters to obtain the distinctive features between two classes. The FFTEM algorithm then used these features to compute the energy maps. These energy maps are used as the training data. This method can reduce the computational power needed for running the deep learning algorithm as lesser neural network layers are required. However, some of the features from the signals might be discarded when applying the CSP algorithm which leads to lower classification accuracy.

In the papers written by [12] [13], Short Time Fourier Transform (STFT) was applied to convert the EEG signals into 2D images. The resulting images contain 3 information: time, frequency, and intensity. This technique can greatly increase the classification accuracy of the algorithm since CNN architecture is very effective on image recognition. However, performing STFT for feature extraction increases the complexity of the classification algorithm because higher dimensions of data is being used.

Sakhavi et al. has extracted characteristics from EEG data using the Filter-Bank Common Spatial Pattern (FBCSP) approach [14]. The FBCSP algorithm is an improved variant of the CSP algorithm. To discover the patterns between each EEG channel, spatial filters are applied. This technique yields discriminative features that can be used to distinguish between two classes. The complexity of the classification algorithm can be reduced by using FBCSP to pre-process the EEG data, using less CPU power. However, when compared to using a deep learning approach to create trained filters for feature extraction, the FBCSP technique may disregard some characteristics in the EEG signals.

The combinations of artefact removal with bandpass filters, CSP feature extraction and random forest (RF) classifier to classify the imagery finger movements was done by [15]. This research has successfully obtained the best accuracy of 54% with 5 classes (thumb, index, middle, ring and little) of imagery finger movements.

The research done by [15] uses the combinations of artefact removal with bandpass filters, ERD/ERS feature extraction and Support Vector Machine (SVM) classifier. This research obtains average accuracy of 62.5% in classifying the 2 classes of imagery movements for left and right index fingers.

2. METHODS

3. Overall system

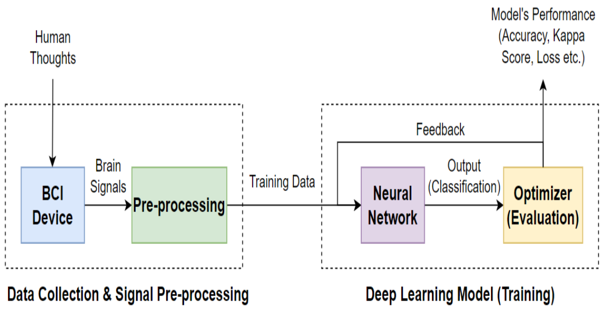

Fig 1: Block diagram for the system in training the deep learning based classification algorithm.

The system shown in Fig 1 can be separated into 2 sections: data collection and signal pre-processing as well as training and evaluation of the classification algorithm. The former prepares the MI dataset recorded from the EEG device. In this stage, artefacts removal, feature extraction and data conversion are performed at the raw EEG signals. These pre-processed signals are being used as the training data for the deep learning model. The deep learning model in turn trains the neural network to classify the MI tasks based on the pre-processed training data. The deep learning model's performance will be evaluated in terms of accuracy and loss.

2.1.1 Data Pre-processing Technique

Summarizing the outcomes obtained from literature review, there are 5 feature extraction techniques that can be applied in this research as shown in Table 1.

Table 1: Description of pre-processing techniques that can be applied in this research.

Pre-processing Technique	Description
No feature extraction	Raw EEG signals are used directly as the input to the deep learning algorithm.
EEG channels selection	Only certain EEG channels that contains the most MI related information are selected as the input to the deep learning algorithm.
Short-time Fourier transform (STFT)	This technique converts the time-based EEG signals into 2D images as the input to the deep learning algorithm.
Common spatial pattern (CSP)	CSP algorithm is applied on the EEG signals to obtain the distinctive features between each class. The extracted features are used as the input to the deep learning algorithm.
Cropped training	Each MI trials are cropped with a sliding window of smaller period. This technique increases the number of training data and improves the performance during online classification.

In this research, combinations of each of these data pre-processing techniques will be applied. The results are compared to obtain the classification algorithm with the highest performance.

2.1.2 Deep Learning Architecture

Summarizing the outcomes obtained from the literature review, there are 3 convolutional layer architectures that can be applied in this research as shown in Table 2.

Table 2: Description of different convolutional layer architectures.

No.	Deep Learning Architecture
1	2 convolutional layers with one-dimensional filters. These filters are applied across the time and channel axis of EEG data, respectively. This architecture allows the filter parameters to be learnt separately and produce feature maps on the temporal and spatial information from the input signals.
2	2 convolutional layers with two-dimensional filters. This architecture is applicable only when the EEG signals are converted into 2D images via Short Time Fourier Transform (STFT). This technique can greatly reduce the number of learnable parameters in the deep learning algorithm, hence, reducing the computational power needed to run the algorithm.
3	The Channel-wise CNN architecture. This architecture consists of 2 convolution layers both with 1D filters applied across the time axis of the EEG signals. Higher order of feature maps can be obtained by applying more than one filters across the temporal axis of the signals. Therefore, this can improve the classification accuracy of the trained model.

In this research, each of CNN architectures will be applied and compared to obtain the technique that can yield to the highest performance.

2.1.3 Preliminary Design for Data Acquisition

The first step for acquiring the EEG dataset is to determine the timings where the subjects perform the imagery finger movement tasks. To ensure that the timings used are consistent across each subject, videos will be used as the guidance for collecting the dataset. To achieve this, a timing diagram is developed as the videos framework as shown in Fig 2.

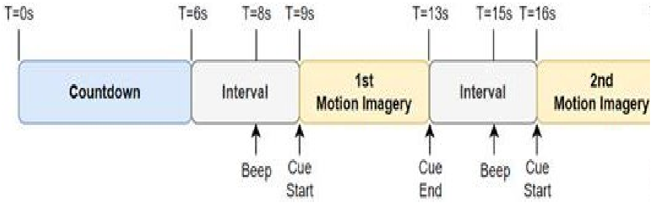

Fig 2: Timing diagram for data acquisition.

10 samples per class per session will be used in this research. The cue time or the period of MI task is 4 seconds. The time interval between each MI is 3 seconds to allow space for the subject in preparing the next MI task. A beeping sound will be played 1 second before the cue start to notify the subject for the next MI task. Therefore, combining the time required for initial countdown, 76 seconds are needed to record each MI class per subject.

2.1.4 Preliminary Design for Artefact Removal

Since that battery-based EEG device will be used in this research, the use of notch filter (bandstop filter) to remove the line noise is not required. This is because the battery power supply can provide perfect direct current (DC) to the device, hence, the line noise is not present in the EEG signals. Besides, 8-30Hz bandpass filter will be applied to the EEG signals to remove the noise in the signals due to muscle movements. This frequency range is chosen as it covers the mu (8-13Hz) and beta (13-30Hz) frequency bands of brain signals, consisting of the most optimal signal-to-noise ratio for MI related classification.

2.1.5 EEG Dataset Collection

In stage 1, the EEG headset is used to record the brain signals of the subjects. There are 6 subjects who participated in the EEG data collection for this project. Two recording sessions were conducted for each subject, with 10 MI trials per class per session. Therefore, there will be a total of 20 MI trials for each class per subject. The EEG signals are sampled at the rate of 250Hz and 16 channels. The electrode locations (based on 10-20 EEG electrode placement standard) and their respective channels were illustrated in Fig 3 and summarized in Table 3.

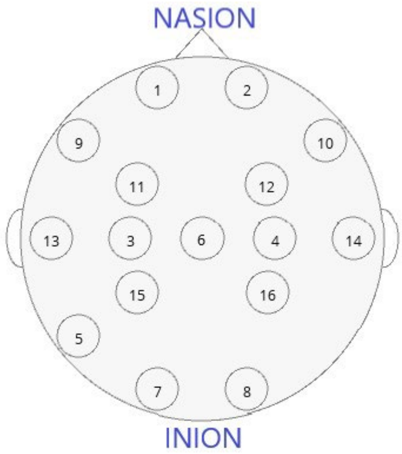

Fig 1: Illustration of electrode locations and their respective channel.

Table 1: The list of electrode locations and their respective channel.

Channel	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Location	Fp1	Fp2	C3	C4	T5	Cz	O1	O2	F7	F8	F3	F4	T3	T4	P3	P4

Before the recording session, the subjects were asked to ensure the cleanliness of their hair and scalp. This is to prevent that the EEG signals obtained contains noises due to the poor conductivity of the electrodes caused by blockage of grease or dirt on the scalp. The subjects were briefed about the details and procedures of the recording session, while any enquiry from the subjects were answered. After that, they were asked to fill in a consent form as an agreement to participate in this research.

During the recording session, the subjects were asked to sit on a comfortable chair in a quiet room, with their right arm resting on a table and palm facing upwards. This is to help the subjects on focusing during the recording session. Then, the subjects were asked to wear the EEG headset. The electrodes were tuned such that they were touching the subjects' scalp. A video was played for each class and the subjects were asked to perform MI trial according to the instructions given in the video as shown in Fig 4. The subjects were requested not to do any muscle movements such as blinking when performing the MI trials. This is because the muscle movements will decrease the quality of the EEG dataset, as it confuses the deep learning algorithm during the training session.

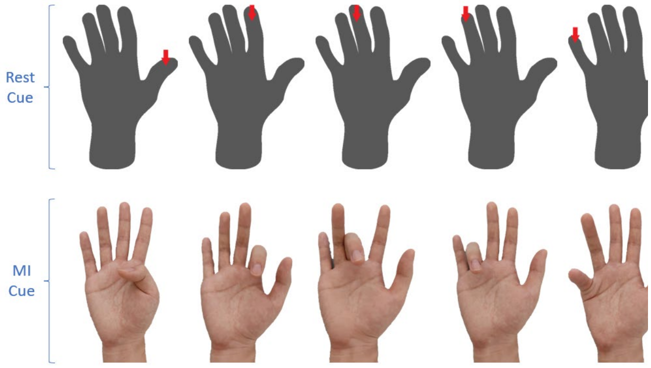

Fig 4: Image montage of the cues used in the video for recording EEG dataset.

After the first recording session was completed, the subjects were given 5 minutes of break before continuing with the second session. The total duration of recording sessions is estimated to be around 15 to 20 minutes per subject excluding the time taken for briefing.

2.2 Classification Model Development

Variable that can be measure are the EEG signals we get form the 16 electrodes from the BCI (Brain Computer Interface) Headset. The 16 electrodes will give 16 channels of reading. The signal for each channel is sampled at 250Hz. The BCI equipment is shown in Fig 5.

Fig 5: BCI Equipment

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In this stage, the EEG signals data was pre-processed before being used as the training and testing data for the CNN classification models. The EEG signals were passed through an 8-30Hz bandpass filter to remove the artefacts. After artefact removal, the EEG signals are trimmed according to the MI task for each class and the rest interval. Two recording sessions were conducted for each subject, with 10 MI trials per class per session. Therefore, there will be a total of 20 MI trials for each class per subject.

The EEG data was recorded for 1 minute for each class and the duration is for 20 minutes between the rest and IM finger movement class. Out of these 20 MI trails, two trials data set was set aside for testing and 18 trails were used for testing. Each class trial consists of 16 channel recording of EEG data for 20 minutes.

The trimmed dataset is then separated into testing and training data with the ratio of 9:1. After that, cropped training algorithm is applied on the dataset to further increase the number of testing and training data.

After trimming, the EEG dataset are down sampled from 250Hz to 125Hz. During dataset collection, the EEG signal values were stored directly into the SD card from the EEG headset. Using SD card as storage allows more consistent and higher sampling frequency (250Hz) as compared with streaming via Bluetooth connection and storing the data in computer. However, during online classification, the EEG signals are streamed directly into the computer via Bluetooth connection at the sampling frequency of 125Hz. Therefore, down sampling on the EEG dataset is required so that the trained CNN classification models can be used in online classification. The flow is shown in Fig 6.

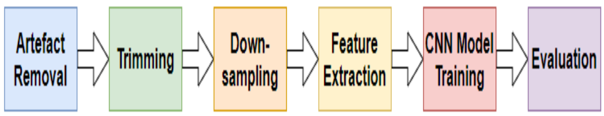

Fig 6: Block diagram of classification development

Feature extraction is applied to the EEG dataset before training and testing the CNN classification model. 4 types of CNN classification model are developed in this project to classify the EEG signals. These models differ with each other in terms of feature extraction requirement and the neural network architecture as summarized in Table 4.

Table 4: Summary of 4 types of CNN classification model. The abbreviations used are power spectral density (PSD), short-time Fourier transform (STFT), frequency band splitting (FBS), standard deviation (STD), convolutional (Conv) and fully connected (Fc).

Model	Feature Extraction					Number of CNN Layers	
	PSD	STFT	FBS	Mean	STD	Conv	Fc
A						2	2
B	x					2	1
C		x				2	3
D			x	x	x	2	2

Each of the CNN classification model was trained with 6 different sets of classes. The first set contains 6 classes including thumb, index, middle, ring, little and rest MI. The other 5 sets (2 classes) contain the combination of thumb, index, middle, ring and little MI each with respect to the rest MI. The data from 6 subject will be averaged to get the accuracy and the standard deviation of each model. Details about the CNN classification models and the test results will be discussed in section 3.

2.2.1 Models

Model A

Model A uses the raw EEG signals, which contain the sampled voltage values per unit time for each channel, as the input to the CNN architecture. Therefore, feature extraction is not required in this model. Instead, these features are produced by the filters in the convolutional layers during the training process as shown in Fig 7.

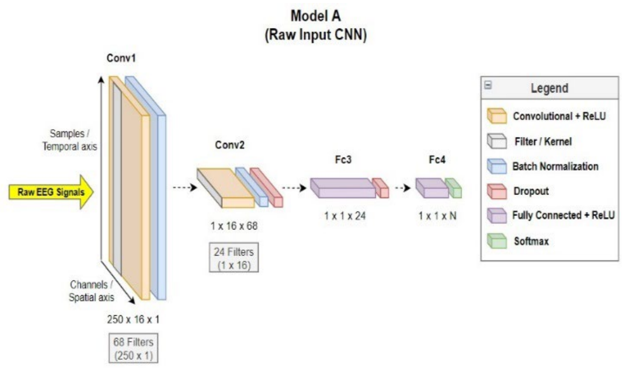

Fig 7: Block diagram of Model A.

The CNN architecture of Model A consists of 9 layers of neural network components as illustrated in Fig 7. The first convolutional layer Conv1 consists of 68 one-dimensional filters applied across the temporal axis of the EEG signals. This allows the neural network to learn and extract the features on the temporal axis for each channel on the EEG signals. The feature maps produced by Conv1 layer are fed into the second convolutional layer Conv2. As shown in Fig 8, this layer consists of 24 one-dimensional filters applied across the spatial axis on the EEG signals. This allows the neural network to learn and extract the features related to the spatial information from the EEG signals. The fully connected layer Fc3 is added to allow the neural network in recognizing more complex features. The layers labelled as Fc4 act as the classification layer of Model A, with the number of output classes as the number of nodes (N).

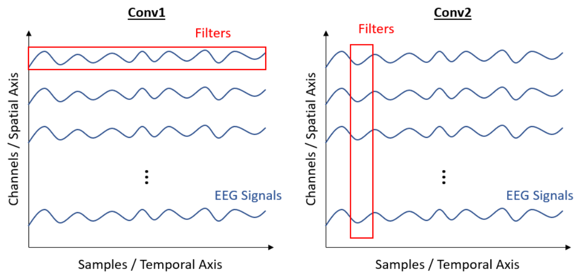

Fig 8: Illustration on the filter size with respect to EEG signals for each convolutional layer in Model A.

Similar method was applied for the other 3 models. Model B, Model C and Model D as describe in Table 4.

2.2.2 Testing of the Proposed Design

There are 6 subjects participated in the EEG data collection for this project. The test for online classification requires the participation of the same subject in separate session after CNN classification models were trained. Therefore, this test could only be conducted on one subject due to the limitation of time for the subject's participation.

4. RESULTS AND DISCUSSIONS

As shown in Table 5 and Fig 9, model A has the average accuracies of 55.46% and 74.17% on the 6-class and 2-class tests, respectively. Although the accuracy in 2-class test is 18.71% higher than the 6-class test.

Table 5: Test results of offline classification for Model A.

Subject	6-Class Model	2-Class Model
	Accuracy (%)	**Accuracy (%)**
1	62.22	84.00
2	51.67	65.00
3	51.67	67.00
4	54.45	71.00
5	71.11	89.00
6	41.67	69.00
Avg	**55.46**	**74.17**

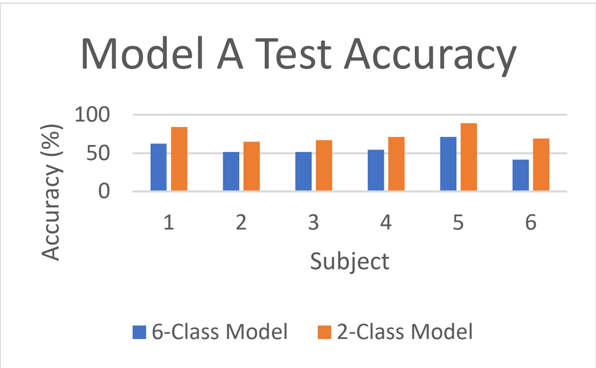

Fig 9: Bar chart showing test results of offline classification for Model A.

Model B has the average accuracies of 55.64% and 81.83% on the 6-class and 2-class tests respectively as shown in Table 6 and Fig 10. This result indicates that Model B is better in performance when classifying lower number of classes.

Table 6: Test results of offline classification for Model B
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Subject	6-Class Model	2-Class Model
	Accuracy (%)	**Accuracy (%)**
1	73.33	98.00
2	52.22	77.00
3	53.33	83.00
4	54.45	79.00
5	53.89	83.00
6	46.60	71.00
Avg	**55.64**	**81.83**

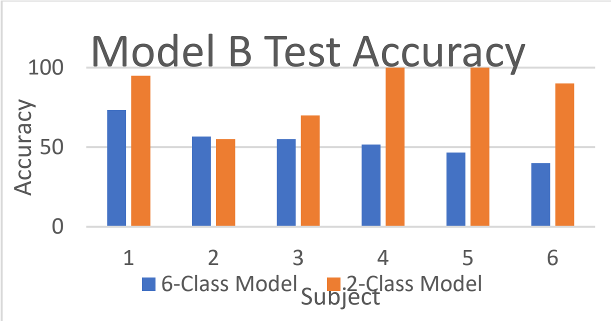

Fig 10: Bar chart showing test results of offline classification for Model B.

Model C has the average accuracies of 46.48% and 70% on the 6-class and 2-class tests respectively. Although the accuracy in 2-class test is 23.52% higher than the 6-class test as shown in Table 7 and Fig 11.

Table 7: Test results of offline classification for Model C.

Subject	6-Class Model	2-Class Model
	Accuracy (%)	**Accuracy (%)**
1	61.11	86.00
2	30.00	61.00
3	34.45	63.00
4	50.56	70.00
5	66.67	87.00
6	36.11	53.00
Avg	**46.48**	**70.00**

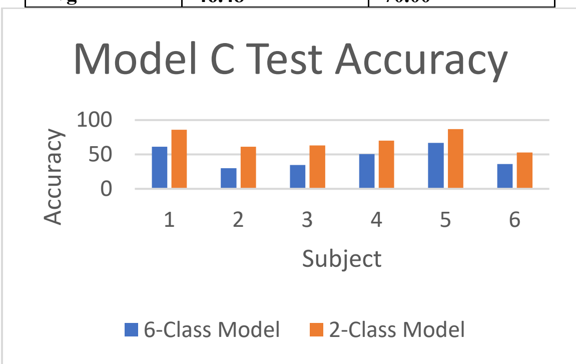

Fig 11: Bar chart showing test results of offline classification for Model C.

Model D has the average accuracies of 69.07% and 82.83% on the 6-class and 2-class tests respectively as shown in Table 8 and Fig 12. The overall result shows that Model D has the highest accuracy both 6-class and 2-class tests. This indicates that the combinations of feature extraction techniques with frequency band splitting, mean and standard deviation are most optimized for MI related EEG classification by using CNN architecture as shown in Table 9.

Table 8: Test results of offline classification for Model D.

Subject	6-Class Model	2-Class Model
	Accuracy (%)	Accuracy (%)
1	78.33	97.00
2	56.11	75.00
3	69.45	79.00
4	71.67	84.00
5	73.89	88.00
6	65.00	74.00
Avg	**69.07**	**82.83**

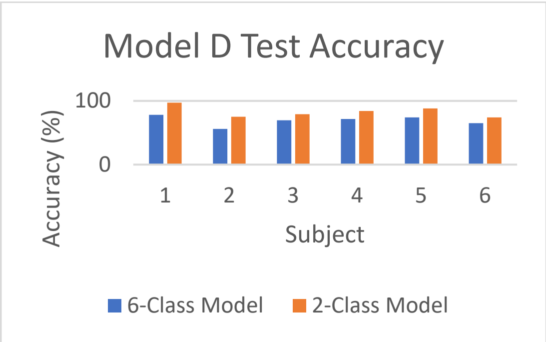

Fig 12: Bar chart showing test results of offline classification for Model D.

Table 9: Summary of test results for all models in offline classification.

Model	6-Class Model	2-Class Model
	Accuracy (%)	Accuracy (%)
A	55.46	74.17
B	55.64	81.83
C	46.48	70.00
D	**69.07**	**82.83**

The consistency of the CNN classification model to be implemented across different individuals can be indicated by calculating the standard deviation on the classification accuracy across each subject as shown in Table 10.

Table 10: Standard deviations of classification accuracy for each subject.

Model	Standard Deviation		
	6-Class Model	2-Class Model	Average
A	10.11	9.89	10.00
B	11.29	18.44	14.86
C	15.25	13.89	14.57
D	7.75	8.75	8.25

The lower the value of standard deviation, the more consistent is the CNN model. This is because lower standard deviation indicates that the difference in accuracies across each subject is low. Therefore, Model D has the highest consistency among the other CNN classification models.

4. CONCLUSIONS

This project contributes to the creation of 4 techniques to classify the imagery finger movements on EEG signals by using the state-of-the-art deep learning technology. The best results achieved was 82.83% and 69.07% in terms of accuracy on classifying the MI of 2 classes and 6 classes respectively. In addition, this project also contributes to the development of EEG classification algorithm that is both lightweight and accurate. The training, testing and online classification could be run entirely on CPU without the need for discrete graphics. Hence, the low computational power requirement contributes to reducing the cost of BCI solutions and making it affordable to more people. Moreover, the low computational power requirement also indicates that it is possible to integrate the BCI device and classification algorithm as a battery-based standalone system, which can be useful when being used as the controller for other devices. This project has successfully achieved all the research objectives. 4 types of CNN based deep learning algorithm were developed for classifying the imagery finger movement consisting of 6 classes and 2 classes. The best results obtained are 69.07% and 82.83% in model D, respectively in terms of average accuracy for 6 classes and 2 classes. It is suggested deep learning method with better features and classifiers will further improve the accuracy of the results.

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