Hybrid CNN-RNN in Motor Imagery Identification of Brain-Computer Interface

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Abstract— **Brain-computer interface (BCI) is a technology that develops human and machine interactions. BCI allows the brain to move external devices without gestures, muscles, and sounds. This technology has great benefits, such as biomedical applications, neural rehabilitation, and entertainment applications. BCI depends on the ability of intermediate devices to translate brain commands, whether consciously or not, to select the appropriate action. The instrument most often used in BCI is the Electroencephalogram (EEG), so BCI-EEG seems inseparable. BCI actions can be Motor Imagery variables, emotions, or focus. Usually, the Motor Imagery variable is carried out in a conscious state, making it easier to control. The identifying Motor Imagery variables in the EEG signal needs to be improved continuously. First, an EEG signal needs to be extracted representing the variable under consideration, the Motor Imagery. Usually, the extraction of frequencies containing Beta and Mu waves is carried out. The next problem is that the multi-channel use of EEG recording resulted in data redundancy. Research with similar data has been discussed using Independent Component Analysis (ICA) but has not paid attention to the sequence. This study proposed the Hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) methods as a multi-channel identification and handling method that considers the sequences of EEG signal data to classify BCI into four classes. Experiments using Hybrid CNN and RNN resulted in an accuracy of 98.62% and resulted in the shortest computation time compared to previous studies with similar data. We also experiment with the use of wavelets and some optimization weight models.**

Keywords— Brain-Computer Interface, motor imagery, EEG signal, Wavelet, hybrid CNN and RNN

I. INTRODUCTION

Humans constantly do activities that involve the movement of limbs every day, and these movements occur at the behest of the brain. Even if a person loses his motor ability to perform actions, he can still imagine the motion [1]. Brain-Computer Interface (BCI) can identify the command for moving external devices by analyzing a brain signal without involving gestures, muscles, sounds other motor functions.

BCI consists of three components, particularly command input, intermediate devices, and command control. BCI is very much determined from the intermediate device used, the Electroencephalogram (EEG). EEG records neural activity by recording electrical signals from the brain, thus extracting information about brain activity [2]. BCI captured EEG signals related to specific user activity and then translated them into control commands for machines or other devices [3]. In previous studies, BCI was used for the rehabilitation of post-stroke patients [4], and people with disabilities could control computer applications by imagining hand and leg movements [5], as well as checking the consistency of mental state classification [6]. Also, BCI is used to move the robot arm as a rehabilitation effort [3].

Some of the variables of the EEG signal that are considered to drive external devices include motor imagery [7], concentration [8], and emotion [9]. Motor imagery represents a movement imagined in the brain without the need to move limbs. Motor imagery is represented in Mu and Beta waves [10], 8-30 Hz frequency range [11]. In previous research, motor imagery variables were used to identify left and right-hand movements on EEG signals [12] and BCI with the right foot, right, and left-hand classes [13].

EEG signals contain many components, but not all of them are used, so they need extraction. Previous research often used a frequency filter. Like previous studies that used Motor Imagery for BCI control, so it filtered 8-30 Hz frequency [14], Wavelet is often used for non-stationary signals such as EEG signals. In previous studies, wavelets obtained higher accuracy than other methods on BCI [8].

BCI is controlled by identifying the reviewed variables, such as Motor Imagery, emotion, and concentration. Continuing the problem of EEG signal identification often uses several methods such as Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN). The RNN is good at processing sequential data such as EEG signals, where information sequences can be retained. Previous research RNN was used to classify EEG signals of BCI into four classes [15]. Meanwhile, CNN contains a feed-forward network that can extract information in multiple data arrays such as signals [16] and constantly reduced data dimensions in multi-channel handling, increasing computational efficiency in BCI application[17].

EEG signal identification needs to pay attention to multi-channel handling because it can duplicate information between channels or data redundancy. Previous research used Correlation-Based Channel Selection (CCS) as a multi-channel treatment with correlated channel selection that can improve accuracy [18]. Another study used Independent Component Analysis (ICA), which produced better accuracy than without ICA [19] but ignored EEG signal sequences during the multi-channel handling process. Considered that the EEG signal is sequential data, it is necessary to pay attention to the handling of multi-channel without neglecting the sequence.

CNN has an advantage in spatial pattern recognition, and RNN excels at handling temporal information [3], allow it to be applied in this research. Spatial to handle information on multi-channels, while temporal for sequences of EEG signal after channel handling by CNN. Previous research showed the advantages of CNN-RNN over other classification methods in the BCI based on motor imagery and mental arithmetic [20]. The CNN-RNN also provided great accuracy in emotion recognition for the multi-channel EEG [21]. CNN-RNN also produced an accuracy of 73.9% in motor imagery classification in two classes, especially right hand and left-hand movements [3]. Based on previous research, Hybrid CNN and RNN can be applied to identify motor imagery on multi-channel EEG.

This research proposed Hybrid CNN and RNN methods to identify motor imagery of EEG signals as BCI command with multi-channel handling without losing the sequence. The EEG signal was filtered using a Wavelet to get a frequency range of 8-30 Hz containing Mu and Beta waves represented motor imagery variable and identify one of four classes.

II. Methods

The identification of motor imagery for BCI is shown in Fig. 1. First, preprocessing the EEG signal used a Wavelet filter to obtain the frequency range under review. Then Hybrid CNN and RNN identified one of four classes, particularly forward, right, left, and stop.

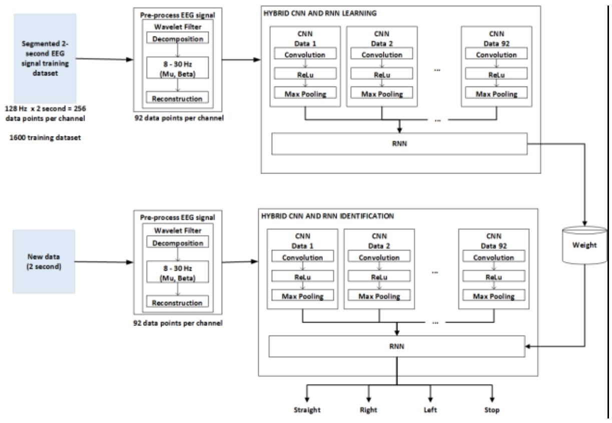

Fig. 1. BCI of motor imagery using Hybrid CNN and RNN

A. Dataset

This study used EEG signal data for BCI with motor imagery variables from previous studies [19]. Data were recorded on 20 subjects who were asked to imagine moving forward, right, left, and stop with repetition five times, as shown in Fig. 1. The subject is in good health, not under the influence of drugs, and in a neutral emotional state. The recording used Emotiv Epoch + wireless EEG, which has 14 channels with a sampling frequency of 128 Hz, with 60 seconds for each recording. The data was segmented every two seconds, so that gave five segments for each recording. Each class is 15 seconds. The first five seconds are pauses for switching commands and are not used. So the recording duration used is 40 seconds. There are 2000 sets of data, 80% for training and 20% for testing.

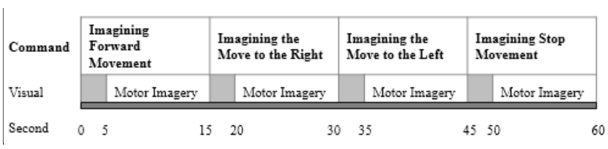

Fig. 2. Recording scenario

B. Wavelet Filters

EEG signals contain some frequency components representing brain activity. Mu wave (8–13 Hz) is a wave component in the central motor cortex and Beta (14–30 Hz) when thinking and concentrating. Although the Mu and Alpha waves are in the same frequency, they are different. Apart from their location, Mu waves are found in the motor cortex, while Alpha waves are found in the visual cortex. Mu dan Beta waves represent the motor imagery and provide important information in the BCI classification [10].

Wavelet can represent the time and frequency information of a signal well to analyze EEG signals. In a Wavelet filter, there are two main processes, namely decomposition and reconstruction. The technique of extracting a signal into a specific frequency is called decomposition, and the process of recombining the extracted signal into the time domain is called reconstruction. Approximation and Detail are two types of signals created by the Wavelet filter process. Convolution between signals with a low-pass filter is known as the Approximation. Detail is the signal obtained from the convolution process to the high-pass filter at the same time. An Approximation can be obtained from (1), and a Detail can be obtained from (2).

$$Aproximation = y_{low}(k) = \sum_n x(n).g(n-k) \quad (1)$$

$$Detil = y_{high}(k) = \sum_n x(n).h(n-k) \quad (2)$$

Where k is the index of the data, n is the number of features of each training data, $x(n)$ is the nth feature, $g(n-k)$ is the Approximation coefficient, and $h(n-k)$ is the Detail coefficient. The Wavelet was obtained from the frequency component in the wave range under review, namely 8-30 Hz, as shown in Fig. 3.

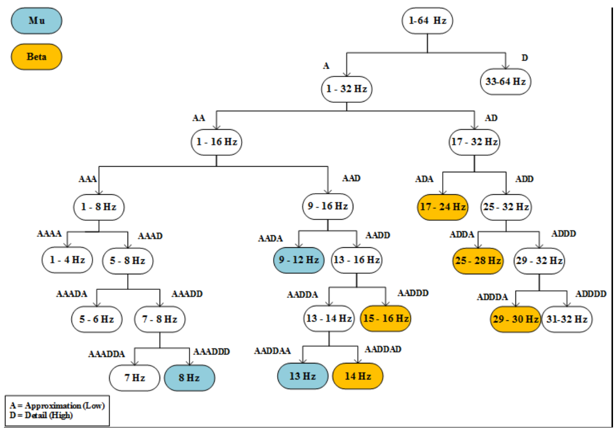

Fig. 3. Wavelet Filter

Blue and orange are the features that are used. The blue color shows the frequency range of the Mu wave, while the orange color shows the frequency range of the Beta wave. There are six decompositions stepped and several Approximation and Detail processes to obtain the frequency range used.

C. Hybrid Convolutional Neural Network dan Recurrent Neural Networks

Hybrid CNN and RNN is an integration of the CNN and RNN methods. The hybrid improved the accuracy of emotion identification compared to the CNN only [22], also in EMG signal processing to estimate limb movement results in better accuracy and good resistance to time variation [16]. The Hybrid CNN and RNN architectures used in this study are shown in Fig. 4.

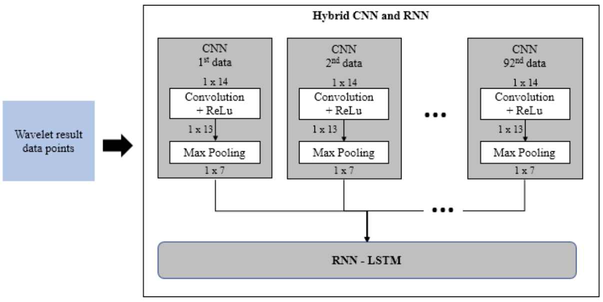

Fig. 4. Hybrid CNN dan RNN architectures

1) *Convolutional Neural Network (CNN)*

Convolutional Neural Network (CNN) is part of a deep learning algorithm that can analyze one, two, or three-dimensional. CNN has a layer to extract features by convolution to make it more effective at the classification or identification layer. However, this study only used an extraction layer for vertical or spatial directions that handle information from multiple channels. CNN is used to extract wavelet signals on 14 channels using convolution layers and Max Pooling, as shown in Fig. 4.

The convolution is the layer that processes the dot product matrix multiplication between the input data and the kernel. The kernel is used as a filter for input data that produces a feature map as output. The filter kernel shifts to the right according to the stride or step value during the convolution process. This stride is a value that determines how many shifts the filter has over the input data. The convolutional operation can be shown in (3).

$$s(t) = \sum_a I(a) \cdot K(t-a) \quad (3)$$

Where $I(a)$ is the input, and $K(a)$ is the kernel. The result of the convolution can produce an output that is always smaller than the input data so that information is not drastically lost in the output dimension, or the feature map can be manipulated using padding, which is adding a value of 0 to the pixel on each side of the input. Feature map can be calculated using (4). Where N is the input width, F is the filter width (kernel), P is Padding dan S is stride.

$$output = (N - F + 2P)/S + 1 \quad (4)$$

After the convolution process, the next step is to use Rectified Linear Units (ReLU) (5) to normalize all negative values to zero. The pooling layer functions to reduce the spatial size and number of parameters in the network, speed up computation, and control overfitting and generating feature patterns. Max Pooling can take the more significant value from the result of the convolution layer and activation function.

$$ReLU(x) = \max(0, x) \quad (5)$$

2) *Recurrent Neural Networks (RNN)*

Recurrent Neural Networks (RNN) is a neural network architecture whose processing is called repeatedly to process input, usually sequential data. RNN works to store information from previous data by looping it so that the last data is stored. Previous research used a variation of RNN Long Short-Term Memory (LSTM) because it can overcome the problem of RNN, namely, old data information be overwritten or replaced with new memory [19]. LSTM architecture can be seen in Fig. 5.

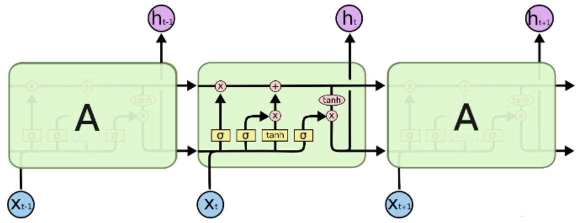

Fig. 5. LSTM architectures

There are four activation functions for each input to the next neuron, referred to as gate units. The gate unit is Forget gates, input gates, cell gates, and output gates.

In the forget gates, the information on each input data is processed. Data be selected to be stored or discarded in memory cells using the sigmoid activation function by (6).

$$f_t = \sigma\,(W_f.[h_{t-1}, x_t] + b_f) \quad (6)$$

Which this sigmoid function accepts h_t, x_t, W_f (weight), b_f (bias) Moreover, it produces an output of 0 or 1 for each cell state. The number 1 means "remember/keep completely", and 0 means "forget this completely". Next, on the second sigmoid and tanh layers, decide which new information be saved to the cell state.

In the input gates, there are two gates. First, it is decided which value is updated using the sigmoid activation function, as seen in (7). Furthermore, the tanh activation function created a new value vector (8) stored in the memory cell.

$$i_t = \sigma\,(W_i.[h_{t-1}, x_t] + b_i) \quad (7)$$

$$\check{c}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (8)$$

In cell gates, it replaced the value in the previous memory cell (c_{t-1}) with the new memory cell value (c_t), by multiplying the old state by f_t then adding it by $i_t\ x\ \check{c}_t$ use (9).

$$c_t = f_t \times c_{t-1} + i_t\, x\, \check{c}_t \quad (9)$$

At the output gate, there are two gates. First, the value of the memory cell is decided using the sigmoid activation function. Furthermore, the value is placed in the memory cell using the tanh activation function. Then the gate is multiplied so that the value to be issued can be seen in (10) and (11).

$$o_t = \sigma\,(W_o.[h_{t-1}, x_t] + b_o) \quad (10)$$

$$h_t = o_t \tanh(c_t) \quad (11)$$

Previous research used LSTM to adjust memory at each input to solve the RNN problem, namely that old data information is overwritten or replaced with new memory [12].

This research used two LSTM layers. The first LSTM layer is four gates with the Relu activation function, followed by the dropout layer, then the second LSTM layer is followed by the sigmoid activation function. After that, enter the dense layer as an identification layer using the Softmax activation function.

In machine learning, there is a process to compare the value of the computational output with the actual output called Loss to measure convergence in the learning process [23]. One of the Loss functions that can be used is Cross-entropy, as shown in (12). Where Loss is the distance, t_i is the actual value, s_i is the predicted value, and C is the number of class labels.

$$Loss = -\sum_{i}^{C} t_i \log(s_i) \tag{12}$$

D. Evaluation of Identification Methods

The built method needs to be tested to determine the performance in identification. Confusion Matrix makes it possible to provide information from the distribution of data that is predicted to be correct and which is predicted to be wrong. Measurements often used in the Confusion Matrix include Precision, Recall, and F1-Score using (13) to (15).

$$Precision = \frac{TP}{TP+FP} \tag{13}$$

$$Recall = \frac{TP}{TP+FN} \tag{14}$$

$$F1-\text{Score} = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{15}$$

Consider a class. We call it positive while the other class we call negative. True Positive (TN) is the number of data from the class under review predicted to be correct, while False Positive (FP) is the number of data predicted to be false. True Negative (TN) is the number of data from other classes predicted correctly, while False Negative (FN) is the number of incorrectly predicted data from other classes. Precision describes the variation of data of each class. Recall shows the success of the model in retrieving information. At the same time, the F1-Score is the harmonic mean of Precision and Recall.

III. Result And Discussion

This study conducted several experiments with test data, including testing the effects of using Wavelets, comparing the multi-channel identification and handling method of Hybrid CNN RNN with only the RNN method. The proposed method was compared with previous literature using similar data.

Learning used 80% parts or 1600 datasets. The built model was examined used data that had not been trained before, as much as 20%, or validation data. Therefore, as shown in Table I-V, the experiment used validation data. The experiment is compared CNN-RNN with RNN only, the effect of Wavelet, and the evaluation model.

A. Compared With Non-Multi-Channel Handling

The experiment conducted by this study was to compare Hybrid CNN and RNN as a method of identification and multi-channel handling with the RNN method that only performs identification. The experimental result is shown in Table I—the transient state's accuracy in Fig. 6 and Loss value in Fig. 7.

TABLE I. Comparison With RNN Only

Method	Accuracy (%)		Loss	
	Adam	*AdaMax*	*Adam*	*AdaMax*
CNN + RNN	98.62	98.62	0.167	0.110
RNN	84.81	85.44	0.848	1.031

Table I shows that combining CNN and RNN has a better accuracy reaching 98.62% with the AdaMax optimization in 100 epochs. In comparison, the RNN method alone produced an accuracy of 85.44%. RNN produced a drastically improved accuracy at the beginning but only reached 85.44%. In contrast, CNN-RNN produced an accuracy of 98.62% even though the increase was slower at the beginning of the epoch. The transient state can be seen in Fig. 6. Therefore, identification of EEG signal needs multi-channel handling to improve accuracy. In the weight correction process, the CNN and RNN method decreased the loss value quickly at the beginning of the epoch and is stable as the epoch increases. While the RNN method decreased drastically, but increased later, as in Fig. 7.

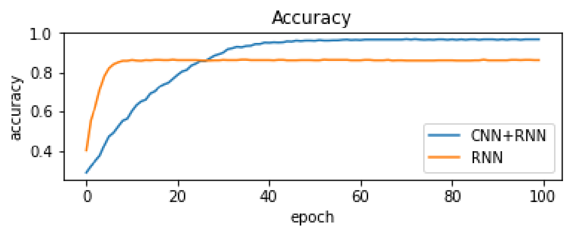

Fig. 6. Accuracy of CNN+RNN and RNN

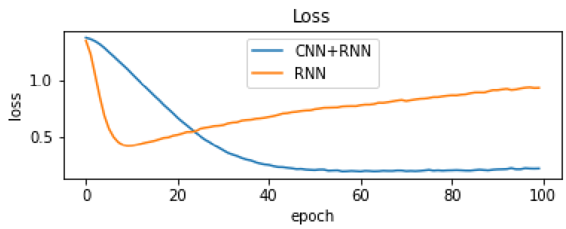

Fig. 7. Loss of CNN+RNN and RNN

B. Wavelet with Optimization Model

The EEG signal is filtered using Wavelet Symlet 3 in the 8-30 Hz range. The method reduces data points from 256 to 92 of each channel. This experiment compared the Hybrid CNN and RNN computational models between Wavelets and those without Wavelets for identification, accuracy, and response time. Both use Adam and AdaMax optimizers. The accuracy obtained by both models is the same, namely 98.62%. However, AdaMax has a slightly smaller disadvantage than Adam. It showed that hybrid CNN-RNN is robust.

The accuracy obtained with the use of wavelets is better, although the difference is less significant. This result shows that channel handling in identification using CNN and RNN is more dominant in improving performance so that the use of extraction only slightly increases accuracy. However, the use of extraction will undoubtedly reduce the computation time. However, Wavelets are still recommended because of the focus on extracting the required frequency ranges to help improve performance. Comparison of accuracy, Loss, and computation time from wavelet extraction can be seen in Table II.

TABLE II. ACCURACY OF WAVELET USING OPTIMIZATION MODEL

Wavelet	Accuracy		Loss		Identification Time (s)	
	Adam	*AdaMax*	*Adam*	*AdaMax*	*Adam*	*AdaMax*
With	98.62	**98.62**	0.167	0.110	0.72	0.72
Without	96.37	97.00	0.294	0.257	0.96	0.96

Based on Fig. 8 and Fig. 9, the accuracy of the Wavelet with the AdaMax optimization model tends to be more stable. However, in the beginning, the epoch is somewhat slower in reaching its maximum accuracy. Besides that, the Loss value generated by AdaMax tended to be stable. With Wavelet, the Loss value was much smaller than those that do not use Wavelet. Unlike Adam, along with the increasing epoch, the use of this model looks more fluctuating compared to AdaMax.

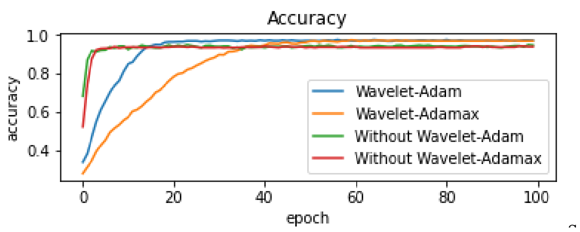

Fig. 8. Accuracy of using Wavelet

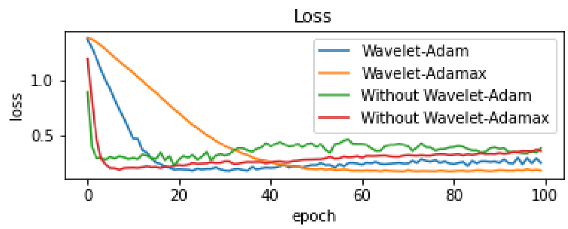

Fig. 9. Loss of using Wavelet

C. *Evaluation Identification*

The next step is to measure the performance of the Hybrid CNN RNN method using the Confusion Matrix. Table III shows the number of errors and the accuracy of the test data at the time of identification for each class.

TABLE III. CONFUSION MATRIX

True Label	Predicted			
	Forward	*Right*	*Left*	*Stop*
Forward	99	0	1	0
Right	1	98	1	0
Left	0	0	99	1
Stop	0	2	0	98

From a total of 400 data, six data were identified as incorrect. One data is incorrectly identified in the Forward class, two data are identified incorrectly in the Right class, two are incorrectly identified in the Left class, and one is incorrectly identified in the Stop class.

Table IV showed that the evaluation metrics gave a high score. The lowest Precision value is in the Left class. Considering that the class has more varied training data, the model can call non-training data well. However, the Precision generated from each class is good, which means the model built has a good level of prediction accuracy. F1-Score itself gets high results which indicate that the value of Precision and Recall is also high. Also, the average produced a relatively similar value as the accuracy of the computational model.

TABLE IV. EVALUATION METRICS

Class	Precision (%)	Recall (%)	F1-Score (%)
Forward	99	99	99
Right	99	98	98
Left	98	99	99
Stop	99	98	99
Average	98.75	98.5	98.75

D. *Compared with Previous Methods*

Furthermore, the performance of the computational model made is compared with several studies with BCI cases. The results are shown in Table V.

TABLE V. COMPARISON WITH OTHER METHODS

Method	Accuracy (%)	Loss	Learning Time (m)
RNN [23]	79.81	1.356	8.6
CNN [24]	90.00	0.5611	4.4
ICA + RNN [19]	99.06	0.006	30.3
CNN + RNN (proposed method)	98.62	0.111	3.3

Research [23] used RNN to identify focus and motor imagery variables, obtained an accuracy of 79.81%. Research [24] also used emotional variables and motor imagery to identify BCI, with the CNN method resulting accuracy of 90.00%. Both studies have not used multi-channel handling methods. Meanwhile, research [19] used the same data as this research, carried out multi-channel handling with Independent Component Analysis (ICA) for dimension reduction, and RNN as identification obtained an accuracy of 99.06%. The proposed method, namely Hybrid CNN and RNN for multi-channel identification and handling that maintains the sequence during the process, produces almost the same accuracy, 98.62%. This slight difference is sometimes affected by the architecture used or the random number generation. In terms of learning time, the proposed method is much faster because CNN handles signals from multiple channels, so that generalizing involves much less data which also affects learning time without sacrificing accuracy.

IV. CONCLUSION

This study proposed Hybrid CNN-RNN as an imagery motor identification method based on multi-channel EEG signals. CNN can extract spatial information on multiple channels, and RNN can learn information from sequential data. Thus, Hybrid CNN-RNN is used to identify and multi-channel handling that can retain sequence information. The Hybrid CNN-RNN provided an accuracy of 98.62%, with the shortest learning time than other comparable methods.

In addition to selecting the right method of identification and handling of canals, the combination of feature extraction methods and optimization models is also important to explore. Wavelet used for feature extraction provides significant results because it can help the machine recognize patterns in the EEG signal. In addition, it can improve the performance of the computational model because it focuses on extracting the required wave range only. However, in this research, Adam and Adamax optimization model did not provide significant results because both AdaMax and Adam use dynamic techniques. The difference lies in how the learning parameters adapt, with Adam moving on an infinite scale. Meanwhile, AdaMax limits its scale to avoid fluctuations in learning parameters.

Hybrid CNN and RNN show good results in identified BCI Motor Imagery, so it will be interesting if applied to multi-variable data using the 2D CNN method as the channel extraction method.

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