Indonesian Journal of Electrical Engineering and Computer Science
Vol. 34, No. 1, April 2024, pp. 173~185
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v34.i1.pp173-185

Brain-computer interface-based hand exoskeleton with bidirectional long short-term memory methods

Osmalina Nur Rahma[1,2], Khusnul Ain[1,2], Alfian Pramudita Putra[1,2], Riries Rulaningtyas[1,2], Khouliya Zalda[1], Nita Lutfiyah[1], Nafisa Rahmatul Laili Alami[1], Rifai Chai[3]
[1]Biomedical Engineering, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
[2]Biomedical Signals and Systems Research Group, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
[3]Department of Engineering Technologies, School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Melbourne, Australia

Article Info

Article history:

Received Sep 11, 2023
Revised Jan 29, 2024
Accepted Feb 1, 2024

Keywords:

Bidirectional long short-term memory
Brain-computer interface
Exoskeleton
Rehabilitation
Stroke

ABSTRACT

It takes at least 3 months to restore hand and arm function to 70% of its original value. This condition certainly reduces the quality of life for stroke survivors. The effectiveness in restoring the motor function of stroke survivors can be improved through rehabilitation. Currently, rehabilitation methods for post-stroke patients focus on repetitive movements of the affected hand, but it is often stalled due to the lack of professional rehabilitation personnel. This research aims to design a brain-computer interface (BCI)-based exoskeleton hand motion control for rehabilitation devices. The Bidirectional long short-term memory (Bi-LSTM) method performs motion classification for the ESP32 microcontroller to control the movement of the DC motor on the exoskeleton hand in real-time. The statistical features, such as mean and standard deviation from the sliding windows process of electroencephalograph (EEG) signals, are used as the input for Bi-LSTM. The highest accuracy at the validation stage was obtained in the combination of mean and standard deviation features, with the highest accuracy of 91% at the offline testing stage and reaching an average of 90% in real-time (80%-100%). Overall, the control system design that has been made runs well to perform movements on the hand exoskeleton based on the classification of opening and grasping movements.

Corresponding Author:

Osmalina Nur Rahma
Biomedical Engineering Study Program, Faculty of Science and Technology, Universitas Airlangga Surabaya, Indonesia
Email: osmalina.n.rahma@fst.unair.ac.id

1. INTRODUCTION

Stroke is a condition of focal neurological dysfunction due to impaired blood supply to the brain caused by blockage or bleeding in the brain. Stroke symptoms are often also characterized by numbness in some areas of the face and limbs [1]. If not treated quickly, stroke can cause death in less than 24 hours. Stroke is the second leading cause of death worldwide, with 11% of total deaths. In Indonesia, stroke ranks as the top cause of death, with 131 deaths per 100,000 population [2]. Therefore, various methods have been developed in stroke management, such as antihypertensive therapy and intravenous thrombolytic drugs, to reduce the high mortality due to stroke so that life expectancy in stroke patients can increase [3].

Despite the increased life expectancy for stroke survivors, stroke survivors have difficulty performing activities of daily living (ADL) due to disabilities caused by a stroke. As many as 80% of stroke survivors experience motor impairment in the movement of one side of the hand. This motor impairment is characterized by low residual electromyography (EMG) activity and easy achievement of muscle fatigue conditions when the hand is moved [4]. It takes at least three months to restore hand and arm function to 70% of its original level. This certainly reduces the quality of life for stroke survivors [5].

The effectiveness in restoring the motor function of stroke survivors can be improved through rehabilitation. With rehabilitation, neuronal activity in the brain will increase so that the brain can make adjustments both structurally and functionally, such as regenerating neurons and forming new synapses. This adjustment in the brain is called neuroplasticity [6]. Currently, rehabilitation methods in post-stroke patients focus on repetitive movements of the affected hand or constraint-induced movement therapy (CIMT). In performing CIMT, the patient will be accompanied by a physiotherapist to perform a directed movement in a training session. Although effective, the CIMT method cannot be applied to patients with low hand movement ability [7]. CIMT also requires an intensive training process, which is difficult to obtain in Southeast Asia due to the lack of rehabilitation professionals. As a result, the rehabilitation process is often stopped before the patient reaches the optimal recovery process [8], [9].

Motor imagery (MI) is an individual's mental process when simulating specific movements. MI has received significant attention as an alternative post-rehabilitation for post-stroke patients because it can reorganize sensorimotor-related brain parts. This is shown by an increase in activity in the sensorimotor segment in the corpus callosum, primary motor cortex (M1), and supplementary motor area (SMA) areas when MI is performed [10], [11]. This opinion is reinforced by the discovery of increased activity in the same parts of the brain in post-stroke patients. Qualitatively, patients also feel more motivated to do MI therapy than conventional therapy [12].

Brain activity that appears when post-stroke patients perform MI can be tapped as input for the brain-computer interface (BCI). BCI is a device that can be a direct channel of control and communication from the central nervous system to a computer or other electronic device, either invasively or non-invasively. In invasive techniques, brain signals are obtained from electrodes implanted directly in the cortex. In one of the non-invasive techniques, electrodes are placed on the scalp's surface to intercept signals as an electroencephalograph (EEG) [13]. Research conducted [14] shows that EEG signals can be used as a wheelchair motion control system to assist movement for people with disabilities. Researchers use discrete wavelet transform on EEG signals to obtain the energy value of the signal on the mu and beta waves that correlate with the brain's sensorimotor output. This energy value is used as the input of hidden neurons in the extreme learning machine (ELM) algorithm for brain wave classification into forward, backward, and stop movements in a wheelchair. Researchers obtained a classification accuracy of 86.7%-93.3%, with the test's success on the subject range of 84%-88%.

BCI can also be used as an upper limb exoskeleton control system. An exoskeleton is a rehabilitation robot with a link and joint structure similar to the anatomical structure of the human body [15]. The BCI-based exoskeleton control system has advantages over CIMT-based rehabilitation therapy and conventional exoskeletons because its control comes directly from the central nervous system, so post-stroke patients with low hand movement abilities can use it. The use of BCI as a control system on the exoskeleton can also provide visual and kinesthetic feedback when patients perform MI, which impacts the effectiveness of therapy. This is shown by the Fugl Meyer motor assessment (FMMA), and Action Research Arm Test (ARAT) scores of post-stroke patients treated using BCI-based exoskeletons higher than patients using exoskeletons without BCI [16]. The study also found a correlation between the classification accuracy of BCI and the improvement of upper limb motor function. Researchers used a Bayesian classifier with a low computational cost even though the classification accuracy is also low, with a maximum accuracy of 51.9%. Thus, the most optimal MI motion classification method is needed so that users can accurately control movements on the exoskeleton.

Based on this background, research is proposed to design a BCI-based hand exoskeleton motion control system with the Bidirectional LSTM (Bi-LSTM) method. The designed exoskeleton hand will translate grasping and opening motion commands on the fingers of the hand based on EEG signals from MI performed by the user. EEG signals are obtained from the EMOTIV EPOC+headset EEG device, which uses 14 channel surface electrodes. Researchers use deep learning methods of the Bi-LSTM type to classify movements. Bi-LSTM has an advantage in classifying EEG signals from MI because of its ability to maintain and extract features in temporal sequences. Bi-LSTM can see the signal correlation in the current sequence with the previous one and has two types of forward and backward layers. Thus, the classification method using Bi-LSTM is more accurate than other deep learning methods, such as recurrent neural network (RNN) or extreme learning machine (ELM) [17].

EEG signal processing is done digitally using OpenViBE software. The information obtained from the preprocessing results will be the input for the Bi-LSTM to distinguish the types of opening and closing movements. This movement was chosen because it indicates improving the quality of ADL in post-stroke patients [18]. Furthermore, the classification results will be used as input for the ESP32 microcontroller to control the DC motor motion on the exoskeleton hand. Thus, the user can move the exoskeleton hand in opening and closing movements according to the given MI command. The main contributions of the study are summarized as follows: i) real-time model for post-stroke therapy based on Bi-LSTM algorithms, ii) achieving good performance and minimal delay, and iv) improving the performance of traditional CIMT techniques by combining them with DC controller and deep learning techniques. Hopefully, the exoskeleton control design can make it easier for stroke survivors to carry out rehabilitation therapy independently so that hand motor function can be done quickly and optimally.

2. MATERIALS AND METHODS

2.1. Data collection

The data collection process in the study will use the EMOTIV EPOC+device from 4 narcotics in the age range of 19-22 years, male gender, and no history of the disease. This is related to MI, which can be generated in post-stroke patients and normal subjects with no history of disease [10]. Gender selection is done so that the EEG signal is of good quality without noise due to electrodes that are less attached to the scalp.

In the data collection stage, the participants were asked to sit facing the screen relaxedly. In the first stage, the screen will display instructions to relax. After that, the screen will display instructions for the subject to imagine the movement of grasping or closing the hand, accompanied by visual feedback for 10 seconds and a relaxation session for 10 seconds. This aims to avoid fatigue to obtain good-quality recording results. This process is repeated in one recording session for up to 40 seconds [16]. Thus, 2 data were obtained: the recording results when grasping for 10 seconds and 3 when opening the hand for 10 seconds. The data collection stage was carried out for ten sessions. Each person's ability to control the BCI is different, so there is a possibility that they cannot produce EEG signals with significant differences between opening and closing movements [19]. To handle this case, the opening movement can be replaced by recording a relaxed state because the opening and closing movements in the hand are mutually antagonistic [20].

2.2. Feature extraction

The EEG signal feature extraction stage is carried out using statistical methods. In this research, three features are extracted from the signal: mean, variance, and a combination of mean and variance features. The feature extraction stage is carried out by applying the sliding window technique, which takes a small segment of the signal with a certain length of time with an overlap between windows. The signal will be extracted and evaluated for each feature for 1 second (128 data points) with a shift in the windows every 1 data point (1/128 seconds) [16], [21], [22].

The data obtained from the feature extraction stage is labeled with the data obtained when the opening movement is labeled as 'open' and the data obtained when the closing movement is labeled 'close'. Because there were 10 recording sessions lasting 50 seconds with a sampling frequency of 128 Hz, the total number of data points labeled was 64,000 data points with 38,400 data points labeled open and another 25,600 labeled closed. The training process is divided into 70% training data (44,800 data points) and 30% testing data (19,200 data points).

For data to be trained on the Bi-LSTM model, the data needs to be processed first so that it is in the form of a time series dataset consisting of data input dimensions, timesteps, and batch size. The input data dimension states the number of features used as input for the Bi-LSTM. The batch size dimension states the amount of data that will be processed simultaneously in one training process, or it can also be said as the segment size. The timesteps dimension states the number of data points required for classification to take place. A signal can be represented as a sequence of values sampled over time. Each value in the sequence represents a specific point in time or a specific interval. Timesteps determine the duration of each sequence in the signal.

The converting process is illustrated in Figure 1, where the 2^{nd} and 3^{rd} data points contained in the timesteps 1 data segment are generated from the 51^{st} and 101^{st} data points. The 1st and 2nd data points in the timesteps 2 data segment are generated from the 2^{nd} and 52^{nd} data points in the same table. This process happens repeatedly until the 50^{th} timestep. So, the size of the training data becomes (896×50×14) and the test data becomes (384×50×14). Thus, 896 data segments will be obtained as Bi-LSTM input and 384 segments to evaluate Bi-LSTM classification results on the confusion matrix.

2.3. Bidirectional LSTM (Bi-LSTM)

The classification method used in this research is bidirectional LSTM (Bi-LSTM). Classification stages of EEG signals can be grouped into training and testing processes. The training process is carried out so that the model can generalize from the training data in the form of EEG signal features to predict the class into closing or opening movements. The description of the algorithm in the LSTM cell is as follows:

- At the forget gate (f_t), the information to be stored and discarded is selected from the previous hidden layer state (h_{t-1}) and the current input (x_t) by passing it through a sigmoid function and adding it to the previous output state (c_{t-1}) as in (1).

$$f_t = \sigma\left(W_{X_f} x_t + W_{H_f} h_{t-1} + W_{c_0} c_{t-1} + b_f\right) \tag{1}$$

- At the input gate (i_t), the previous hidden layer condition (h_{t-1}) and the current input (x_t) are passed to the sigmoid and tanh functions. The results obtained from the two functions are then multiplied as in (2).

$$i_t = \sigma\left(W_{X_i} x_t + W_{H_i} h_{t-1} + W_{c_i} c_{t-1} + b_i\right) \tag{2}$$

- At the output gate (o_t), important information that will be forwarded as output is calculated according to the (3).

$$o_t = \sigma\left(W_{X_0} x_t + W_{H_0} h_{t-1} + W_{c_0} c_{t-1} + b_0\right) \tag{3}$$

- The new output layer condition (c_t) is obtained through the result of the forget gate and input gate found in (4).

$$c_t = f_t * c_{t-1} + i_t \, tanh\left(W_{X_c} x_t + W_{H_c} h_{t-1} + b_c\right) \tag{4}$$

- The new hidden layer condition (h_t) is obtained by multiplying the gate output with the $tanh$ function of the new output layer condition (c_t) in (5).

$$h_t = c_t * \tanh(c_t) \tag{5}$$

Bi-LSTM extends the LSTM system so that it can extract information from EEG signal sequences bi-directionally in forward and reverse sequences such as combining two Bi-LSTMs. Thus, all inputs from the forward and backward sequences will be calculated for the output (ht) as per (6), with the arrow representing the sequence direction.

$$h_t = \sigma(W_h[h_\tau, h_\tau] + b_h) \tag{6}$$

Bi-LSTM is implemented by creating 2 LSTM layers that run in 2 opposite sequences, so that each LSTM cell receives both inputs as found in (6). The data sequences will enter the Bi-LSTM layers sequentially with the output being the final classification result.

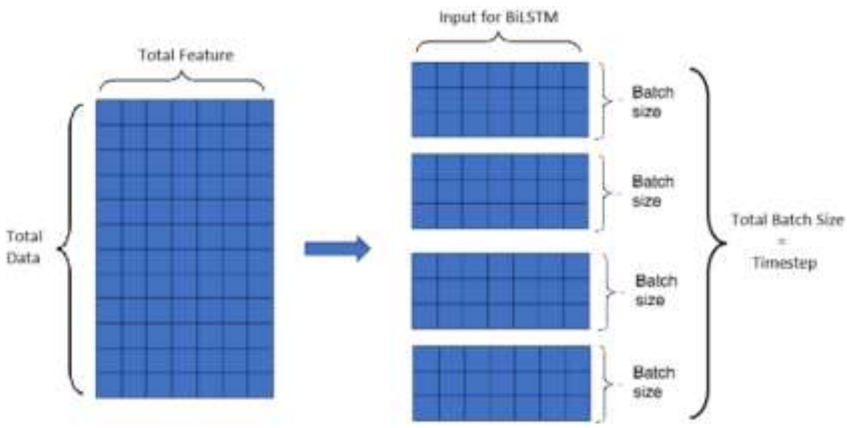

Figure 1. Process in converting data from 2D to 3D for bi-LSTM's input

3. RESULTS AND DISCUSSION

3.1. EEG signal processing

Raw EEG data were collected from 4 male subjects. Data collection on all subjects was carried out in a sitting position. The recording was carried out in 10 recording sessions, with each session consisting of 3 opening movements and 2 grasping movements so that a total of 50 raw data were obtained, with 30 raw data for opening movements and 20 raw data for grasping movements for each subject. Before the data collection process was carried out, the subjects received training first using EMOTIV BCI, a built-in software from EMOTIV to simulate cube movement through mental commands from motor imagery (MI). The training was conducted so that the participants were familiar with performing mental commands through MI.

After they were accustomed to controlling the movement of the cube, data collection was conducted. To make it easier for them to perform MI, a video instructing them to relax and clasp their hands was shown to them. Providing visual stimulation is done because alpha wave suppression is more easily detected in narcotics who perform MI when stimulation is given [11]. This opinion is supported by research [13] which found that many BCI-based stroke therapies use visual-type stimuli.

The data recording process uses the CyKit module in Python programming software connected to the OpenViBE software. OpenViBE software is used because this software is an alternative to retrieve raw EEG data without having to pay a subscription fee provided by EMOTIV. In the software, the 'acquisition client' block is connected, to the 'csv file writer' block so that the information obtained can be stored in .csv form for processing. The recording file produces information in the form of values from 14 sensors on the EMOTIV EEG with as many data points as the sampling frequency during recording multiplied by the length of time in one recording session.

The results of the EEG recording on each channel are shown in Figure 2. Furthermore, the EEG signal will be extracted using 3 types of statistical features, namely mean (μ), standard deviation (σ) and a combination of both features that are compared in accuracy. Features are extracted with the sliding windows method using windows length of 128 data points with a shift of 1 data point, which generated an input feature for Bi-LSTM. The sliding windows process and its result are illustrated in Figure 3. The difference between the mean data extraction results and the raw data is shown in Figure 4. It can be observed that the data extracted from the mean feature shows a wave pattern with high-frequency noise that is dampened while maintaining data variation at low frequencies, as stated [23].

The data points obtained from the feature extraction process are then segmented to have inputs that match the Bi-LSTM input (converting from 2D to 3D). It can be observed that the data points that originally had a 2D shape (64,000×14) changed their size to (1280×50×14). This is because the raw data totaling 50 data points is segmented into 1280 segments, or 128 segments per 1 recording (50 seconds) with a segment length of 50 data points.

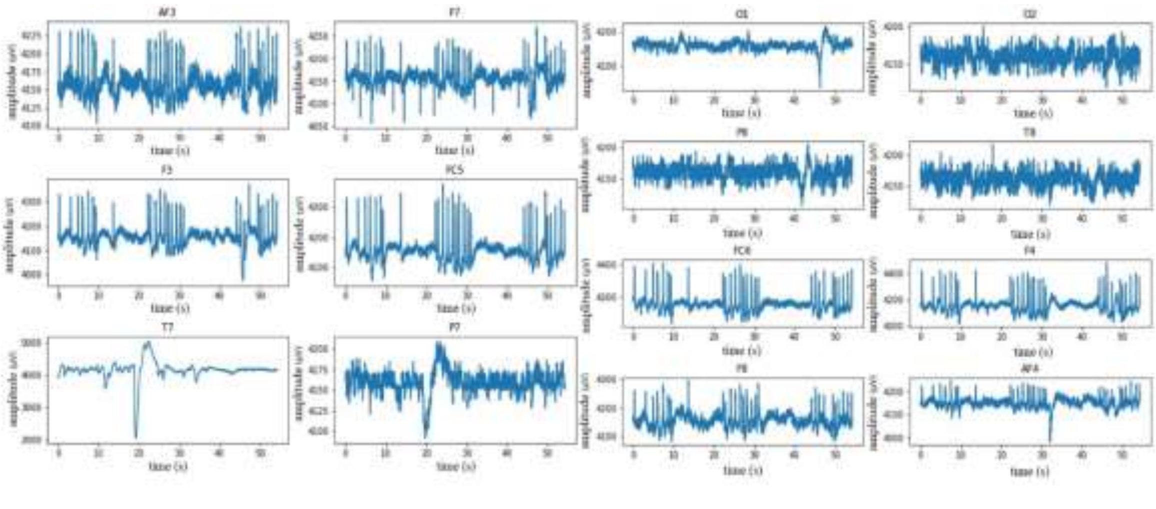

Figure 2. EEG signal from each channel

3.2. Classification result

In the initial training stage, the first feature used is raw data sourced from 14 EEG channels without going through the preprocessing stage. Machine learning (ML) training using raw data is done to find out how good ML accuracy is in classifying data without a specific pattern. The model is evaluated based on its validation accuracy and validation loss. Validation loss is evaluated using binary cross-entropy to compare the discrepancy between predicted results and actual results on binary output data. The graph of learning accuracy results using raw data features can be observed in Figure 5.

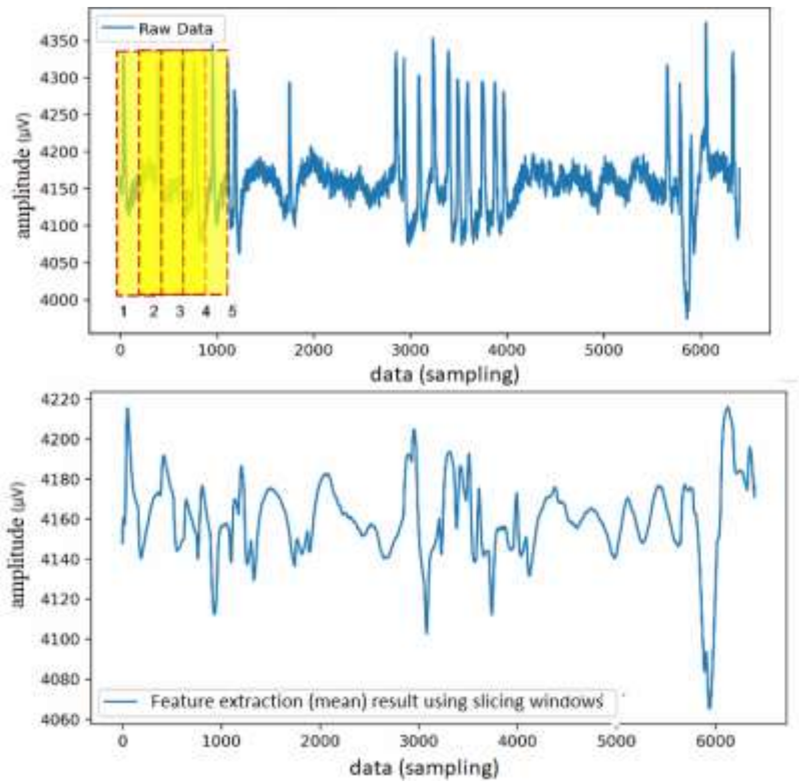

Figure 3. Feature extraction ‘mean’ using slicing windows

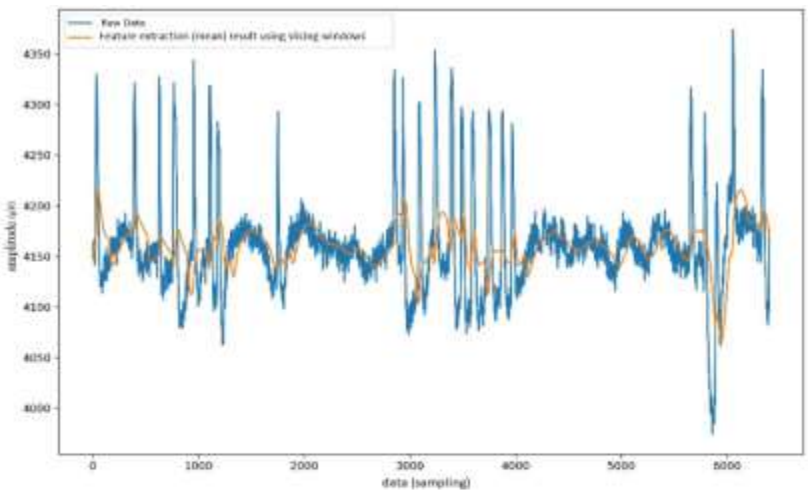

Figure 4. Comparison between raw data and data after extracting the mean feature on channel AF3

The graph of training results using raw data shows an increasing loss value. Accuracy had decreased when entering the 10th to 20th epoch range before finally increasing and stagnating at an average validation accuracy of 0.68. This shows that the raw data from EEG is still not good enough to be used as input for the Bi-LSTM model for motor imagery classification. The training stage then continued by comparing the accuracy between 3 types of statistical features, namely mean (μ), standard deviation (σ) and a combination of the two features. The effect of data normalization is also seen by comparing the accuracy and loss resulting from the training process between input features that are normalized first and those that are not normalized. The training results on the ML model can be observed in Figure 6. Training and validation performance using standard deviation (Figure 6(a)) and mean (Figure 6(c)) as a feature compare to its normalized features (Figure 6(b) and Figure 6(d)). It can be seen that features that go through the data normalization stage first have increased classification accuracy. When the standard deviation feature is used, the model validation accuracy only reaches 71%. However, the value increased to 76% after undergoing normalization.

Figure 5. Loss and accuracy of training from raw data

The same thing happens when the mean feature is used. The mean feature accuracy, which is worth 80%, has increased to 83% after the data normalization stage is carried out. The resulting loss also tends to experience a more stable decline before finally stagnating. Loss is a parameter used to measure how good the ML model is in distinguishing between the predicted output produced by the model and the actual output. Validation loss can be calculated by applying the training model to the test data.

Some of the activation functions in the model consist of sigmoid and tanh functions that are sensitive to large input values and prone to saturation from input features with extreme inputs. This can lead to stagnation in model training [17]. By normalizing, the possibility of the activation function accepting too large or small inputs is reduced. After normalizing each feature, the features derived from the 14 channels that underwent mean feature extraction and the 14 channels that underwent standard deviation feature extraction were combined for a total of 28 features.

The comparison result of the variation feature was summed up in Table 1. When both features are combined, much better training results are obtained than when each feature is used as a separate input, with the highest training accuracy reaching 91%. In this model, the specificity, sensitivity, and precision values were obtained at 91% specificity, 87% precision, and 89% sensitivity. Table 1 shows that the combined features have the highest accuracy compared to when each feature is used separately. Therefore, this combination feature is used in training because it has the highest accuracy, sensitivity, specificity, and precision parameters. Configurations on ML models, such as the type of layer in the model, the number of Bi-LSTM units in the layer, and the weight of the training results on each person, are then saved in a file with the .h5 format.

Table 1. Summary of Bi-LSTM training accuracy comparison results on each statistical feature

No.	Features	Accuracy
1.	Raw data	68%
2.	Standard deviation	71%
3.	Normalized standard deviation	76%
4.	Mean	80%
5.	Normalized mean	83%
6.	A combination of normalized standard deviation and normalized mean	91%

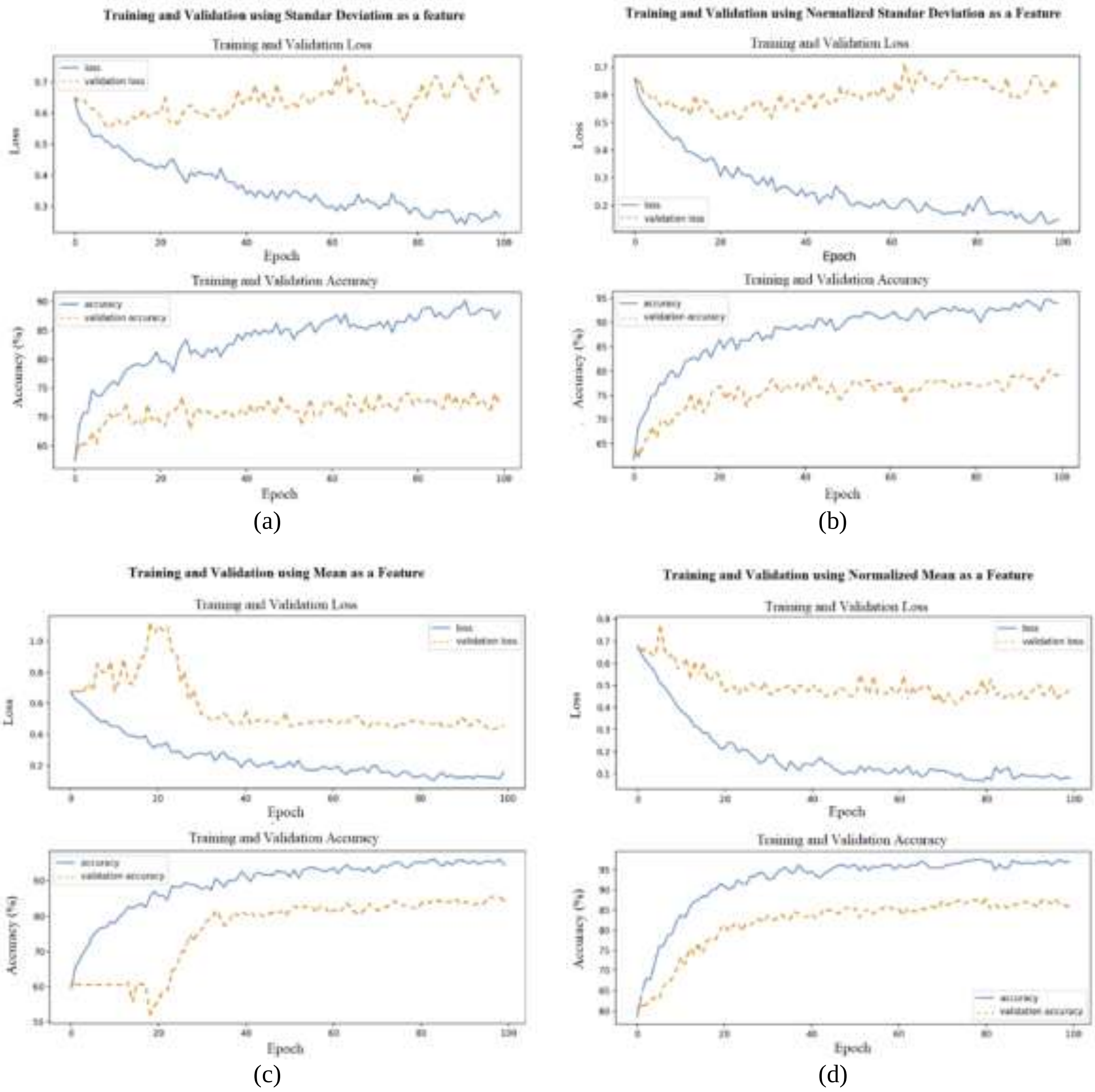

Figure 6. Training and validation accuracy and loss results using feature: (a) standard deviation, (b) normalization of standard deviation, (c) mean, and (d) normalization of mean

3.3. Real-time implementation on exoskeleton

The final stage of the research is to determine the ability of the exoskeleton control system that has been designed to perform grasping and opening movements according to the EEG wave input given. However, before it was implemented in real-time on exoskeleton, we tested the accuracy of the offline process. Offline testing is done by using the saved weights and ML architecture and testing it with datasets that are not included in the training. It can be observed that the accuracy of the movement test has different values for each person, with the highest accuracy being 100% and the lowest being 80%. This may occur because each person's ability to control the BCI is different, so there is a possibility that the EEG signals produced by the trials do not produce features that machine learning recognizes as significant differences between recordings during relaxed and focused conditions [19].

Furthermore, during the real-time testing, the subjects were again given a visual stimulus in the form of a video of grasping movements to make it easier for them to focus on performing MI grasping movements and black display videos to make it easier for them to return to a relaxed state so that data collection could take place accurately. The real-time testing process looks like Figure 7 by connecting a servo motor to the exoskeleton prototype controlled by an ESP32 that receives commands from the computer via 'serial' communication. The computer receives data in the form of EEG signals from the EMOTIV device via a dongle. For the data to be processed using Python, the data must first enter the OpenViBE software through the 'Acquisition Client' block connected to the 'LSL Export' block as a method of communication with Python.

Figure 7. Real-time implementation connected the EEG and the exoskeleton

The feature extraction steps are performed after the Python program receives data via LSL communication from OpenViBE. The incoming data will first be collected until it reaches 1500, then the program will extract the mean and standard deviation features and store them into an empty array. Each time data comes in, and the computer will perform the feature extraction and store it in the array until the collected data has met the size requirements needed by Bi-LSTM. Considering the sampling frequency of EMOTIV, the control system design can perform classification every 0.4 seconds. The classified data will then be emptied from the array so that the array is ready to receive the latest feature input. The process will continue as long as the computer still receives the latest data from EMOTIV.

Data that has gone through the classification process will produce output in the form of the letter '*h*' for grasping movements or '*l*' for opening movements. The output is then sent to the ESP32 device using serial communication by adjusting the 'port' and 'baud rate' of the device. In testing, the ESP32 device is connected to 'COM5' with a baud rate of 115,200. In real-time testing, it is necessary to pay attention to the surrounding conditions to avoid distraction to the experimenter so that the recording results in the focus condition become inaccurate and the exoskeleton cannot perform grasping movements for too long. The real-time test results are shown in Table 2.

By calculating the correspondence between the type of command and the actual movement of the exoskeleton, the classification accuracy of each subject 1 to subject 4 is 100%, 90%, 90%, and 80%, respectively. In Table 2, it can be observed that the designed control system can perform classification quite well on all four subjects. EEG is a subject-dependent device, so the success rate of classification for each person may vary depending on the ability of the ML Bi-LSTM to identify differences in the input EEG data within the specified time window.

There are some discrepancies in this test, such as misclassification of data in a short period, moving to another movement classification result too quickly, or delay. These discrepancies may arise due to the nature of the Bi-LSTM, which classifies movements based on a specific time window. Therefore, if the ML identifies a pattern within that time window, it will misclassify the data within that time window before classifying it correctly. Moving too quickly could also be due to the trials losing focus during the grasping movement and ML identifying the loss of focus as a transition to the opening movement.

Table 2 shows a low-value movement delay of 0.5 to 1 second. Delay can occur because ML still identifies a movement within a time window as the same as the previous one. Delay can also occur due to latency in processing incoming data, resulting in a delay in displaying classification results. This opinion is reinforced by a statement submitted which states that in the design of the BCI system, the occurrence of delay cannot be avoided because the latency of the system built, the process when acquiring EEG data, and the latency when the output is displayed will always appear [24]. This latency can only be minimized by improving the efficiency of the BCI system so that the bottleneck of processing time caused by inefficiency in each BCI process block can be reduced.

Table 2. Realtime data testing results

Subject	Desired hand movement	Exoskeleton movement	Movement compliance (Yes/No)	Delay time
1	Open	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	0 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay 1 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
2	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Open hand	No	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay <1 s
	Open hand	Open hand	Yes	Delay<0.5 s
3	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Open hand	No	Delay 1 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
4	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Close hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Open hand	No	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Open hand	Yes	Delay 1 s
	Open hand	Open hand	Yes	Delay<0.5 s
	Close hand	Open hand	No	Delay<0.5 s
	Open hand	Open hand	Yes	Delay<0.5 s

EMOTIV EPOC+ has a delay range of 60 ms in data acquisition (EMOTIV, 2014). The delay range does not affect the reading of the Mu wave, which has a frequency range of 7-11 Hz in both the amplitude measurement and the resulting feedback update [24]. According to Wu, the human reaction time in response to a stimulus is 200-500 ms. In the design of the control system, the hand exoskeleton has also been set to move slowly so that sudden movements in a short period do not drastically change the angle at the joints of the fingers [25]. Thus, any delay or misclassification in a short period does not harm the experimenter and can be tolerated in non-emergency situations. It can be concluded that the system that has been created has run quite well despite the insignificant delay.

In the testing process, the subjects complained about using the exoskeleton and EEG device, which took quite a long time because they had to attach each strap to the fingers. In addition, the exoskeleton also causes discomfort when used for too long because the design is too flat at the connection between the upper arm and hand. Therefore, a more ergonomic design is needed in further research in the hope that users can carry out the therapy process comfortably. A reduction in the number of EEG channels is also expected so that the subject feels more comfortable using the EEG device without affecting the accuracy of the classification results from the EEG. In research conducted by Sarasola-sanz *et al*. [4], it is mentioned that EEG signals can be incorporated together with EMG signals that have undergone a reduction process to obtain better classification results and a smoother BCI control process [4]. Reducing the number of channels can be done by looking at the correlation between signals and reducing the dimensionality of the data using methods such as PCA, ICA, or CSP [26].

Overall, the design of the BCI-based hand exoskeleton control system using the EEG EMOTIV EPOC+headset as an EEG signal acquisition device, Bi-LSTM as a signal classification method as a movement on a PC, and ESP32 as a motor control device for the exoskeleton based on the classification results sent from the computer still runs well to classify grasping and opening movements. Additionally, Bi-LSTM models perform better than traditional ML models since they can handle lengthy sentence sequences and have a bidirectional memory that allows them to retain words from the past and present [27]. Thus, the features extracted from Bi-LSTM significantly enhance ML performance [28]. Hopefully, the BCI system that has been made can be developed for other movement variations, such as pinching or wrist flexion, so that the therapy process for patients is not limited to grasping and opening the fingers.

4. CONCLUSION

The design of the control system is carried out using the EEG EMOTIV EPOC+headset for the EEG signal acquisition device using a dongle connected to a PC to process data using mean and standard deviation feature extraction as input for the Bi-LSTM classification method. The classification results are then sent using 'serial' communication to an ESP32 device connected to 5 servo motors placed on the exoskeleton device. Thus, the servo motors will rotate and make the exoskeleton perform closing/opening movements when the device receives the classification results. The Bi-LSTM classification system can classify the input EEG signal into two movements, namely opening and grasping movements, with a success rate in 4 trials with an accuracy value in subject 1 of 100%, subject 2 of 90%, subject 3 of 90%, and in subject 4 of 80%. The best feature of the MI EEG signal as input training data for classifying opening and closing movements in the Bi-LSTM model is the mean and standard deviation combination feature for opening and grasping movements, with the highest offline training accuracy of 91% and a loss of 0.29.

ACKNOWLEDGEMENTS

The authors thank the Faculty of Science and Technology, Universitas Airlangga, for funding this research under the Airlangga Research Fund with grant number 2417/UN3.1.8/LT/2019.

REFERENCES

[1] S. J. Murphy and D. J. Werring, “Stroke: causes and clinical features,” *Medicine*, vol. 48, no. 9, pp. 561–566, Sep. 2020, doi: 10.1016/j.mpmed.2020.06.002.
[2] “Top 10 causes of death in Indonesia for both sexes aged all ages.” [Online]. Available: https://www.who.int/data/gho/data/themes/mortality-and-global-health- estimates/ghe-leading-causes-of-death.
[3] D. Kuriakose and Z. Xiao, “Pathophysiology and Treatment of Stroke: Present Status and Future Perspectives,” *International Journal of Molecular Sciences*, vol. 21, no. 20, p. 7609, Oct. 2020, doi: 10.3390/ijms21207609.
[4] A. Sarasola-Sanz *et al.*, “A hybrid brain-machine interface based on EEG and EMG activity for the motor rehabilitation of stroke patients,” in *2017 International Conference on Rehabilitation Robotics (ICORR)*, IEEE, Jul. 2017, pp. 895–900, doi: 10.1109/ICORR.2017.8009362.
[5] J. M. Rondina, C. Park, and N. S. Ward, “Brain regions important for recovery after severe post-stroke upper limb paresis,” *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 88, no. 9, pp. 737–743, Sep. 2017, doi: 10.1136/jnnp-2016-315030.
[6] Y. Xing and Y. Bai, “A Review of Exercise-Induced Neuroplasticity in Ischemic Stroke: Pathology and Mechanisms,” *Molecular Neurobiology*, vol. 57, no. 10, pp. 4218–4231, Oct. 2020, doi: 10.1007/s12035-020-02021-1.
[7] G. Kwakkel, J. M. Veerbeek, E. E. H. van Wegen, and S. L. Wolf, “Constraint-induced movement therapy after stroke,” *The Lancet Neurology*, vol. 14, no. 2, pp. 224–234, Feb. 2015, doi: 10.1016/S1474-4422(14)70160-7.
[8] A. F. Abdul Aziz, N. A. Mohd Nordin, N. Abd Aziz, S. Abdullah, S. Sulong, and S. M. Aljunid, “Care for post-stroke patients at Malaysian public health centres: self-reported practices of family medicine specialists,” *BMC Family Practice*, vol. 15, no. 1, p. 40, Dec. 2014, doi: 10.1186/1471-2296-15-40.
[9] C. M. Stinear, C. E. Lang, S. Zeiler, and W. D. Byblow, “Advances and challenges in stroke rehabilitation,” *The Lancet Neurology*, vol. 19, no. 4, pp. 348–360, Apr. 2020, doi: 10.1016/S1474-4422(19)30415-6.
[10] T. Marins, E. C. Rodrigues, T. Bortolini, B. Melo, J. Moll, and F. Tovar-Moll, “Structural and functional connectivity changes in response to short-term neurofeedback training with motor imagery,” *NeuroImage*, vol. 194, pp. 283–290, Jul. 2019, doi: 10.1016/j.neuroimage.2019.03.027.
[11] K. Yuan, C. Chen, X. Wang, W. C. Chu, and R. K. Tong, “BCI Training Effects on Chronic Stroke Correlate with Functional Reorganization in Motor-Related Regions: A Concurrent EEG and fMRI Study,” *Brain Sciences*, vol. 11, no. 1, p. 56, Jan. 2021, doi: 10.3390/brainsci11010056.
[12] G. Lioi *et al.*, “A Multi-Target Motor Imagery Training Using Bimodal EEG-fMRI Neurofeedback: A Pilot Study in Chronic Stroke Patients,” *Frontiers in Human Neuroscience*, vol. 14, Feb. 2020, doi: 10.3389/fnhum.2020.00037.
[13] S. R. Soekadar, N. Birbaumer, M. W. Slutzky, and L. G. Cohen, “Brain–machine interfaces in neurorehabilitation of stroke,” *Neurobiology of Disease*, vol. 83, pp. 172–179, Nov. 2015, doi: 10.1016/j.nbd.2014.11.025.
[14] O. N. Rahma, M. N. Kurniawati, A. Rahmatillah, and K. Ain, “Human-computer-interface for controlling the assistive technology device,” in *AIP Conference Proceedings*, 2020, p. 060001, doi: 10.1063/5.0034256.
[15] F. Aggogeri, T. Mikolajczyk, and J. O’Kane, “Robotics for rehabilitation of hand movement in stroke survivors,” *Advances in Mechanical Engineering*, vol. 11, no. 4, p. 168781401984192, Apr. 2019, doi: 10.1177/1687814019841921.
[16] A. A. Frolov *et al.*, “Post-stroke Rehabilitation Training with a Motor-Imagery-Based Brain-Computer Interface (BCI)-Controlled Hand Exoskeleton: A Randomized Controlled Multicenter Trial,” *Frontiers in Neuroscience*, vol. 11, Jul. 2017, doi: 10.3389/fnins.2017.00400.
[17] X. Zheng and W. Chen, “An Attention-based Bi-LSTM Method for Visual Object Classification via EEG,” *Biomedical Signal Processing and Control*, vol. 63, p. 102174, Jan. 2021, doi: 10.1016/j.bspc.2020.102174.

[18] S. H. Kim and J. H. Park, "The Effect of Occupation-Based Bilateral Upper Extremity Training in a Medical Setting for Stroke Patients: A Single-Blinded, Pilot Randomized Controlled Trial," *Journal of Stroke and Cerebrovascular Diseases*, vol. 28, no. 12, p. 104335, Dec. 2019, doi: 10.1016/j.jstrokecerebrovasdis.2019.104335.

[19] N. Padfield, J. Zabalza, H. Zhao, V. Masero, and J. Ren, "EEG-Based Brain-Computer Interfaces Using Motor-Imagery: Techniques and Challenges," *Sensors*, vol. 19, no. 6, p. 1423, Mar. 2019, doi: 10.3390/s19061423.

[20] S. Paszkiel, *Analysis and Classification of EEG Signals for Brain–Computer Interfaces*, vol. 852. in Studies in Computational Intelligence, vol. 852. Cham: Springer International Publishing, 2020. doi: 10.1007/978-3-030-30581-9.

[21] J. J. Bird, D. R. Faria, L. J. Manso, A. Ekárt, and C. D. Buckingham, "A Deep Evolutionary Approach to Bioinspired Classifier Optimisation for Brain-Machine Interaction," *Complexity*, vol. 2019, pp. 1–14, Mar. 2019, doi: 10.1155/2019/4316548.

[22] G. Zhang, V. Davoodnia, A. Sepas-Moghaddam, Y. Zhang, and A. Etemad, "Classification of Hand Movements From EEG Using a Deep Attention-Based LSTM Network," *IEEE Sensors Journal*, vol. 20, no. 6, pp. 3113–3122, Mar. 2020, doi: 10.1109/JSEN.2019.2956998.

[23] K. Chang and F. Claude, "Workshop on Utilizing EEG Input in Intelligent Tutoring Systems," *Intelligent Tutoring Systems*, 2014.

[24] J. A. Wilson, J. Mellinger, G. Schalk, and J. Williams, "A Procedure for Measuring Latencies in Brain–Computer Interfaces," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1785–1797, Jul. 2010, doi: 10.1109/TBME.2010.2047259.

[25] D. Wu, J. Li, Z. Pan, Y. Kim, and J. S. Miguel, "uBrain: A Unary Brain Computer Interface," in *Proceedings of the 49th Annual International Symposium on Computer Architecture*, New York, NY, USA: ACM, Jun. 2022, pp. 468–481, doi: 10.1145/3470496.3527401.

[26] S. Aggarwal and N. Chugh, "Signal processing techniques for motor imagery brain computer interface: A review," *Array*, vol. 1–2, p. 100003, Jan. 2019, doi: 10.1016/j.array.2019.100003.

[27] D. E. Cahyani, A. D. Hariadi, F. F. Setyawan, L. Gumilar, and S. Setumin, "COVID-19 classification using CNN-BiLSTM based on chest X-ray images," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 1773–1782, Jun. 2023, doi: 10.11591/eei.v12i3.4848.

[28] R. Kamil and A. R. Abbas, "Predicating depression on Twitter using hybrid model BiLSTM-XGBOOST," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 6, pp. 3620–3627, Dec. 2023, doi: 10.11591/eei.v12i6.5416.

BIOGRAPHIES OF AUTHORS

Osmalina Nur Rahma received the S.T. degree in biomedical engineering from Universitas Airlangga, Indonesia, in 2013 and the M.Si. degree in biomedical engineering from the University of Indonesia, Indonesia, in 2016. Currently, she is a lecturer at the Biomedical Engineering Study Program, the Department of Physics, Faculty of Science of Technology, Universitas Airlangga, Indonesia. Her research interests include biomedical instrumentation, signal processing, and rehabilitation engineering. She can be contacted at email: osmalina.n.rahma@fst.unair.ac.id.

Khusnul Ain received the S.T. degree in nuclear engineering from Gadjah Mada University, Indonesia, in 1995, an M.Si. degree in Physical Sciences from Gadjah Mada University, Indonesia, in 2002, and a Doctoral degree in Engineering Physics from Bandung Institute of Technology, Indonesia, in 2014. Currently, he is a senior lecturer at the Biomedical Engineering Study Program, Department of Physics, Faculty of Science of Technology, Universitas Airlangga, Indonesia. His research interests include biomeasurement, electrical impedance, computational modeling, and bioinstrumentation. He can be contacted at email: k_ain@fst.unair.ac.id.

Alfian Pramudita Putra received the S.T. degree in biomedical engineering from Universitas Airlangga, Indonesia, in 2014 and the M.Sc. degree in biomedical engineering from the University of Groningen, The Netherlands, in 2017. Currently, he is a lecturer at the Biomedical Engineering Study Program, Department of Physics, Faculty of Science of Technology, Universitas Airlangga, Indonesia. His research interests include biomechanics, biomedical instrumentation, rehabilitation engineering, biomedical signal processing, and biomedical product development. He can be contacted at email: alfian.pramudita@fst.unair.ac.id.

Riries Rulaningtyas received the S.T. and M.T. degree in Electrical engineering from Institut Teknologi Sepuluh Nopember, Indonesia and a Doctoral degree in Electrical Engineering from Bandung Institute of Technology, Indonesia. Her research interests include biomedical image and signal processing, machine learning and artificial intelligence. She can be contacted at email: riries-r@fst.unair.ac.id.

Khouliya Zalda received the S.T. degree in biomedical engineering from Universitas Airlangga, Indonesia in 2023 and currently became a master student in biomedical engineering from Universitas Airlangga. His research interests include biomedical instrumentation and signal processing. He can be contacted at email: khouliya.zalda-2023@fst.unair.ac.id.

Nita Lutfiyah received the S.T. degree in biomedical engineering from Universitas Airlangga, Indonesia in 2023. Her research interests include biomedical instrumentation and signal processing. She can be contacted at email: nita.lutfiyah-2019@fst.unair.ac.id.

Nafisa Rahmatul Laili Alami received the S.T. degree in biomedical engineering from Universitas Airlangga, Indonesia in 2023. Her research interests include biomedical instrumentation and signal processing. She can be contacted at email: nafisa.rahmatul.laili-2019@fst.unair.ac.id.

Rifai Chai received the B.Eng. degree from Krida Wacana Christian University (UKRIDA) Jakarta, Indonesia in 2000 and the Ph.D. degree in Biomedical Engineering from the University of Technology Sydney (UTS), Sydney, Australia in 2014. From 2000 to 2011 he has worked as electronic-product development engineer with companies in Indonesia and Australia. Currently, he is working as Senior Lecturer with Faculty of Science, Engineering & Technology, Swinburne University of Technology, Melbourne, Australia. His research interests are brain-computer interfaces, rehabilitation, medical technologies, and artificial intelligence. Currently, he is a senior member of IEEE and serves as Associate Editor for Electronics Letters. He can be contacted at email: rchai@swin.edu.au.