Electroencephalography-based wheelchair navigation control using convolutional neural network method

Khairul Anam[1,2], Satrio Marta Wicaksono[1,2], Muchamad Arif Hana Sasono[1,2], Bima Wahyu Maulana[1,2], Fatkhul Mubarok[1,2], Ananta Pinsentius Rahmat Pamungkas[1,2], Moch. Rijal Fatoni[1,2]
[1]Department of Electrical Engineering, Faculty of Engineering, University of Jember, Jember, Indonesia
[2]Center for Development of Advanced Science and Technology, University of Jember, Jember, Indonesia

Article Info

Article history:

Received Jan 22, 2024
Revised Nov 10, 2024
Accepted Nov 26, 2024

Keywords:

Classification
Convolutional neural network
Deep learning
Electroencephalograph
Wheelchair

ABSTRACT

Artificial intelligence refers to a computer-based system capable of learning human activities. For instance, in medical technology, AI can be used for a thought-controlled wheelchair. This study discusses the use of deep learning, specifically convolutional neural network (CNN), in predictiong of the user intention to navigate a wheelchair. The training data was collected from an EEG sensor and included the wheelchair's movements - turning right, turning left, moving forward, moving backward, and idle. The signals were then sampled and feature-extracted using root mean square (RMS). In CNN classification, both raw and RMS data were used. This study compared two different CNN architectures. The first architecture has three convolutional layers and three pooling layers, while the second has two of each. The research compares the accuracy and loss values of CNN predictions using architecture 1 and 2 on both raw and RMS data. The experimental results indicate that when using raw data, the first CNN architecture achieved an accuracy of 85.12%, and the second model achieved 91.04%. However, when using RMS data, the first architecture achieved an accuracy of 76.47%, and the second achieved 73.74%. The study concludes that the movement of the wheelchair is better in real-time when using raw data compared to using RMS data.

Corresponding Author:

Khairul Anam
Department of Electrical Engineering, Faculty of Engineering, University of Jember
Jember, Indonesia
Email: khairul@unej.ac.id

1. INTRODUCTION

Disease, a condition of abnormality in the body or mind, causes discomfort, dysfunction, or difficulty for the affected individual [1], [2]. Various diseases have afflicted humans for centuries, and Indonesia is no exception. Degenerative diseases are among the health issues present in Indonesia. According to the World Health Organization (WHO) report, deaths due to degenerative diseases are expected to continue increasing worldwide. The most significant increase is projected to occur in developing and impoverished countries. Stroke remains a leading cause of death and disability globally, with a substantial increase in burden over the past three decades. Recent estimates indicate there were 12.2 million new stroke cases, 6.6 million deaths, and 143 million disability-adjusted life-years lost in 2019 [3]. Degenerative diseases result from changes in the body's cells, which subsequently affect organ functions due to aging, leading to a decline in the functioning of human tissues. Currently, technological developments such as artificial intelligence have been widely used to help work in the health sector, such as predicting dementia [4], health monitoring [5], detecting pneumonia disease [6], and diagnosing COVID-19 [7], cancer detection [8], automated surgical systems [9], risk prediction for cardiology and neuroscience [10]. One of the degenerative diseases is stroke. It is a major cause of death and chronic disability, particularly among individuals aged 45 and above, in Indonesia [11], [12]. Artificial intelligence technology can help the needs of stroke patients with treatment [13], [14] stroke disease prediction [15], and stroke rehabilitation [16], [17]. This study aims to develop a control system for wheelchairs for patients who are completely paralyzed due to stroke. The system operates based on the user's intention, utilizing an electroencephalograph (EEG) sensor that detects brain activity. With EEG technology, patients can control the movement of the wheelchair using their brain signals [18]. It is a device that records the electrical activity in the brain by placing electrodes on the scalp.

Recent studies have demonstrated the potential of EEG-based classification for wheelchair control using deep learning techniques. Abdulghani *et al.* [19] achieved a 95% classification accuracy for wheelchair navigation commands using a combination of wavelet scattering and deep learning. Similarly, Ngo and Nguyen [20] proposed a semi-automatic wheelchair system combining EEG control with virtual-real 2D grid maps and deep Q-Networks for path planning. Zubair [21] developed an optimized multi-layer perceptron model for motor imagery-based wheelchair control, improving performance by 3% through grid search optimization. Aswin *et al*. [22] compared artificial neural networks and deep neural networks for classifying EEG signals to control wheelchair direction, evaluating performance using precision, recall, and F1-score. Zgallai *et al.* [23] this paper presents a prototype smart wheelchair using an Emotive EPOC headset to assist blind and paralyzed individuals. It employs a convolutional neural network (CNN) to recognize four movements: left, right, forward, and stop. Testing with ten volunteers showed a success rate of 70% with raw EEG and 96% with spectrum data, demonstrating the potential of deep learning for EEG-based wheelchair control.

This research aims to control the forward, backward, and stop movements of a wheelchair, ultimately enabling individuals with severe strokes to achieve independent mobility without assistance. The goal is to create a real-world application that allows for movement akin to walking. The methodology employed is the CNN, a type of deep feedforward neural network frequently utilized in computer vision tasks, including image classification [24]. CNN uses convolution by sliding a kernel over an image to extract features by multiplying different regions. Neurons are organized into a filter of specific dimensions. The pooling layer then reduces the feature map's size while preserving critical information [25].

Zgallai *et al.* [23] developed a smart wheelchair prototype for blind and paralyzed individuals using the Emotive EPOC headset for EEG signal recognition. The system utilizes deep learning to identify four movements left, right, forward, and stop with a CNN achieving 96% accuracy after ten epochs. A Raspberry Pi handles signal processing, while an Arduino Mega controls movement. Ultrasonic and Lidar sensors are included for collision avoidance, demonstrating superior performance with spectrum data over raw EEG data. Previous research shows CNN enhances EEG signal processing accuracy, but real-time testing remains unexplored, impacting flexibility and security. This study advances prior work by applying CNN in real-time EEG signal classification to optimize wheelchair control. CNN's parameters in image processing and feature extraction make it ideal for this purpose.

2. METHOD

2.1. Overall system design

The system starts by collecting EEG data from respondents, followed by pre-processing and classification using CNN. The classification results are sent to the Arduino Mega 2560 via serial communication to control the wheelchair's movement, as shown in Figure 1.

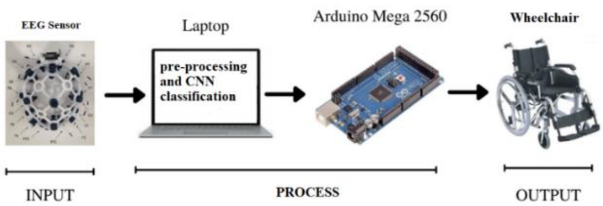


Figure 1. The block diagram of the proposed system

In Figure 1, the system's first stage involves collecting raw data from respondents using the Electrode Ultra Cortex Mark IV EEG sensor connected via Bluetooth. Once the data collection process is completed, it proceeds to the second stage, i.e., pre-processing. This stage occurs on a laptop and includes filtering, windowing, and feature extraction processes. The Bandpass filter is used for filtering, followed by windowing the data in segments of 200 data points per second, and root mean square (RMS), is employed as the feature extraction method. After completing the second stage, the process moves to the CNN classification. The classification comprises three categories: idle, right or forward movement, and left or backward movement. The output from the CNN is then connected to the Arduino Mega 2560 using serial communication to control the wheelchair's movement

2.2. Electroencephalograph signal acquisition

EEG data were collected using the UltraCortex Mark IV headset with eight dry electrode channels on the respondent's scalp. Brain activity signals were recorded as respondents imagined five motor actions: right, left, forward, backward, and stop, as shown in Figures 2(a) to (d). Data collection was facilitated through OpenBCI GUI connected to an Arduino Mega 2560 and adhered to ethical guidelines approved by the Medical Research Ethics Committee, Universitas Jember (No. 1278/UN25.8/KEPK/DL/2021). The EEG Electrode UltraCortex Mark IV in size M (for head circumferences 54-58 cm) was employed in two scenarios: the first involved imagining right-hand, left-hand movements, and idle states; the second included both hands, both legs, and idle states. Acquired EEG data were saved in CSV format and processed in Excel for analysis.

(a) (b) (c) (d)

Figure 2. Signal acquisition of: (a) imagining the right hand turning right, (b) imagining the left hand turning left, (c) imagining both hands moving forward, and (d) imagining both legs moving backward

2.3. Electroencephalograph signal processing

Signal processing is carried out after the signal acquisition stage. The whole system is depicted in Figure 3. As shown in Figure 3, the process includes filtering, EEG signal windowing, and feature extraction, leading to CNN classification output. Preprocessing starts with a bandpass filter (7-13 Hz), followed by windowing with a size of 200 over eight channels using 1-second time segments. The data is then processed for feature extraction using the RMS, which averages the squared values of the EEG signals from the eight channels and takes the square root. It is calculated using (1):

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|Xn|} \quad (1)$$

Where *N* is the coefficient of the sum of the nth values, and *Xn* is the sum of the data. The research employs RMS for feature extraction, segmenting the EEG data into parts after visual artifact inspection. The study aims to enable the wheelchair to turn right, left, move forward, move backward, and stop based on the user's intentions.

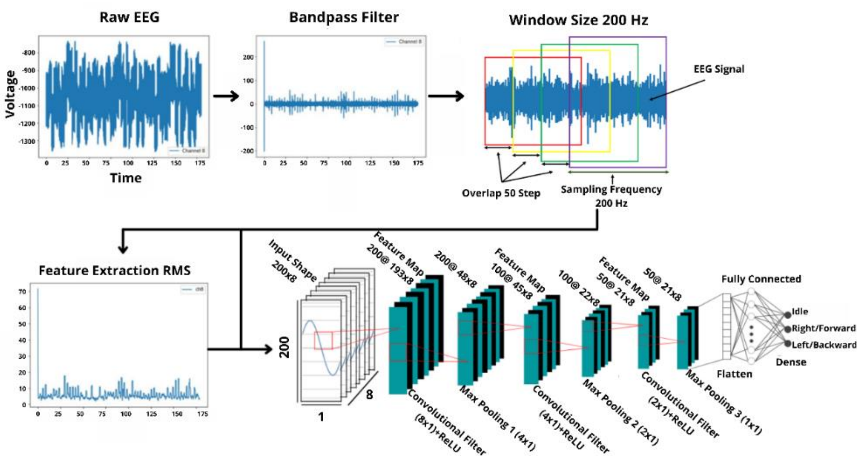


Figure 3. Schematic representation and methodology with processing using the CNN method

2.3.1. Designing convolutional neural network architecture

CNN is a type of neural network designed for image data. It is a deep-learning algorithm specifically crafted for two-dimensional data [25]. The CNN architecture consists of two main parts: the feature extraction layer, which includes convolution and pooling layers, and the fully connected layer. The convolution layer applies filters of specific dimensions to create feature maps, while the pooling layer scans these maps with a filter and stride to reduce dimensionality. Finally, the fully connected layer reshapes the resulting feature map into a vector for further processing. The proposed architectures are depicted in Figures 4 and 5.

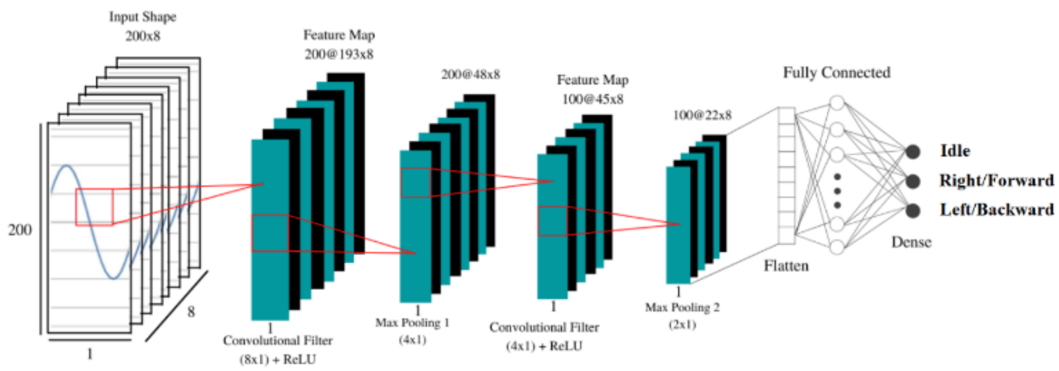


Figure 4. The CNN architecture 1

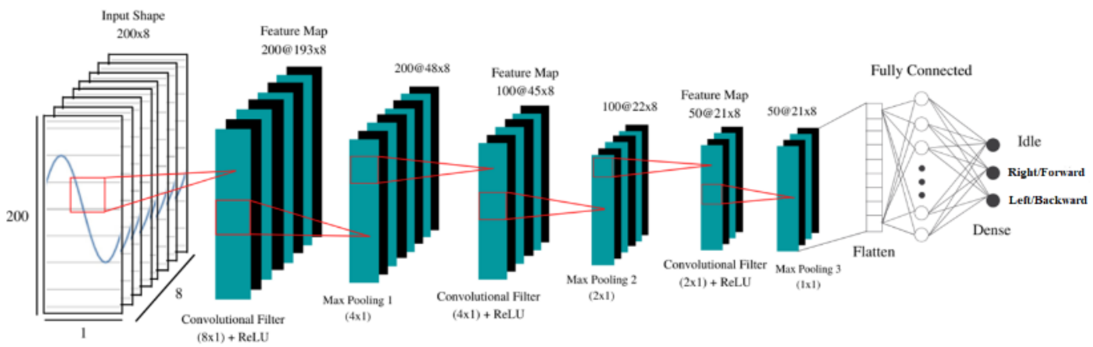


Figure 5. The CNN architecture 2

The CNN architecture consists of crucial components in its success, including feature learning and classification. Feature learning comprises several layers, starting with the input layer and continuing with the convolution process and pooling. Meanwhile, the classification phase consists of the flattened, fully connected, and dense layers. The following is a table detailing the configuration parameters of the CNN architecture.

Table 1 highlights key differences in CNN architecture configurations for raw and RMS data. The ‘input_shape’ for raw data is (200, 8), while for RMS data, it is (8, 1) due to reshaping during feature extraction, which averages out the sequential structure of the raw data. Each data type from the two scenarios is tested across both architectures, resulting in two distinct CNN models: model 1 and model 2.

Table 1. CNN architecture parameter configuration

Parameter	Raw data						RMS data					
	Architecture 1			Architecture 2			Architecture 1			Architecture 2		
Input_shape	200,8			200,8			8,1			8,1		
Filter	200	100	-	200	100	50	200	100	-	200	100	50
Kernel_size	8	4	-	8	4	2	4	2	-	4	2	1
Pool_size	4	2	-	4	2	1	2	1	-	2	1	1
Dense	3			3			3			3		
Pat	5			5			5			5		
n-fold	5			5			5			5		
Epoch	10			10			10			10		
Batch_size	100			100			4			4		

3. RESULTS AND DISCUSSION

In this section, we evaluate the findings from the EEG signal processing, which involves several essential phases. We began with raw data, applying filtering techniques to reduce noise and enhance the quality of the signal. Next, we used windowing to divide the data into manageable segments for analysis. After that, we extracted features to identify important patterns, which were later analyzed using a CNN model. The results were further validated through extensive testing, which included collecting EEG data under controlled conditions to ensure reliability and accuracy.

3.1. Result

3.1.1. Offline testing of convolutional neural network architecture

After setting the CNN parameters and architecture, performance testing evaluates prediction accuracy to identify the optimal setup. Each architecture is trained and tested on data from 5 respondents with a 7:3 train-test split. Results are shown in Tables 2 to 4, which compare testing outcomes for raw and RMS data across CNN architectures 1 and 2, as well as models 1 and 2.

– Testing of raw data for CNN architecture 1 and 2

This testing involves raw data with CNN architecture 1 that has been designed. It is conducted to evaluate the accuracy values for raw data using CNN architecture 1, as presented in Table 2.

Table 2. Experimental results of the CNN architecture 1 and 2 with raw data

No	Subject	Raw data for CNN architecture 1				Raw data for CNN architecture 2			
		Model 1		Model 2		Model 1		Model 2	
		Loss	Accuracy (%)	Loss	Accuracy (%)	Loss	Accuracy (%)	Loss	Accuracy (%)
1.	R1	0.3804	61.96	0.0944	90.56	0.3562	64.38	0.0816	91.84
2.	R2	0.0144	98.56	0.0271	97.29	0.0013	99.87	0.0137	98.63
3.	R3	0.0079	99.21	0.0133	98.67	0.0058	99.42	0.0062	99.38
4.	R4	0.0098	99.02	0.0121	98.79	0.0037	99.63	0.0059	99.41
5.	R5	0.3132	68.68	0.3033	69.67	0.3769	62.31	0.3402	65.98
Average		0.14514	85.486	0.09004	90.996	0.14878	85.122	0.08952	91.048

Table 2 presents the test results of raw data using CNN architecture 1, showing variations in loss and accuracy across respondents. For respondent 1, model 1 yielded a loss of 0.3804 with 61.96% accuracy, whereas model 2 achieved a loss of 0.0944 with 90.56% accuracy. In contrast, respondent 4’s results showed a loss of 0.0098 and 99.02% accuracy for model 1 and 0.0121 loss with 98.79% accuracy for model 2. These accuracy variations directly impact the prediction reliability for wheelchair movement in real-time tests. Higher accuracy values, nearing 1, indicate greater prediction reliability, while loss values inversely relate to accuracy; as accuracy improves, loss decreases. CNN architecture 2 shows variation in loss and accuracy for different respondents. For respondent 3, model 1 recorded a loss of 0.0058 and an accuracy of 99.42%, while model 2 had a loss of 0.0062 with 99.38% accuracy. In contrast, respondent 5’s results showed a loss of 0.3769 with 62.31% accuracy for model 1 and 0.3402 with 65.98% accuracy for model 2. These accuracy differences influence the reliability of wheelchair movement predictions in real-time testing. An accuracy value closer to 1 enhances prediction reliability, while an inverse relationship is observed between accuracy and loss-higher accuracy corresponds with lower loss.

– Testing of root mean square data for CNN architecture 1 and 2

This testing involves RMS data with CNN architecture 1 and CNN architecture 2 to evaluate the performance of the models on RMS inputs. Table 3 displays results for RMS data using CNN architecture 1, with respondent 1’s model 1 showing a loss of 0.4219 and 57.81% accuracy, while model 2 had a loss of 0.3694 and 63.06% accuracy. Respondent 4’s model 1 achieved 82.82% accuracy with a loss of 0.1718, while model 2 recorded 75.70% accuracy with a loss of 0.243. Table 3 shows outcomes for RMS data with CNN architecture 2. Respondent 2’s model 1 achieved an accuracy of 83.68% (loss: 0.1632), and model 2 had an accuracy of 82.01% (loss: 0.1799). For respondent 5, model 1 recorded 68.45% accuracy (loss: 0.3155), while model 2 achieved an accuracy of 67.80% (loss: 0.322). Higher accuracy improves directional prediction reliability. Comparing architectures with raw and RMS data, raw data showed better accuracy due to its sequential structure. In CNN architecture 1, model 1 achieved an accuracy of 85.486% (loss: 0.14514), while model 2 reached 90.996% (loss: 0.09004). CNN architecture 2 performed best overall, with accuracy affected by factors like alertness and hair thickness impacting EEG quality. An ANOVA p-value calculation will analyze the mean differences between model 1 and model 2. Table 4 compares p-values.

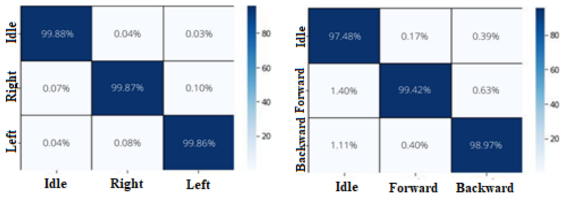
Table 3. Results of testing RMS data with CNN architecture 1 and 2

No	Subject	Raw data for CNN architecture 1				Raw data for CNN architecture 2			
		Model 1		Model 2		Model 1		Model 2	
		Loss	Accuracy (%)	Loss	Accuracy (%)	Loss	Accuracy (%)	Loss	Accuracy (%)
1.	R1	0.4219	57.81	0.3694	63.06	0.3949	60.51	0.3647	63.53
2.	R2	0.1873	81.27	0.1903	80.97	0.1632	83.68	0.1799	82.01
3.	R3	0.1393	86.07	0.2376	76.24	0.1291	87.09	0.202	79.80
4.	R4	0.1718	82.82	0.243	75.70	0.1737	82.63	0.244	75.60
5.	R5	0.338	66.20	0.346	65.40	0.3155	68.45	0.322	67.80
Average		0.25166	74.834	0.27726	72.274	0.23528	76.472	0.26252	73.748

Table 4. Comparison of p-value values

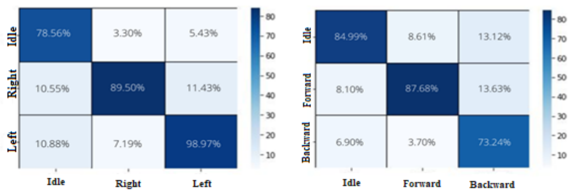
Group1	Group2	p-value
Model 1 raw arsitektur 1	Model 2 raw arsitektur 1	0.60707
Model 1 rms arsitektur 1	Model 2 rms arsitektur 1	0.714501
Model 1 raw arsitektur 2	Model 2 raw arsitektur 2	0.615433
Model 1 rms arsitektur 2	Model 2 rms arsitektur 2	0.68543

The p-value analysis in Table 4 indicates no significant difference between the models, as the p-value is greater than 0.05. This allows flexibility in choosing any architecture. However, selecting the architecture with the highest accuracy or referring to the confusion matrices in Figures 6(a) and (b), as well as Figures 7(a) and (b), can provide additional guidance for selecting the most effective model. Figures 6 and 7 show discrepancies in the confusion matrix, where some commands-idle, turn right, turn left, move forward, and move backward-are misclassified. This impacts movement accuracy, but the proposed model successfully captures brain patterns for these commands.



(a) (b)

Figure 6. Confusion matrix of the: (a) model 1 and (b) model 2 using raw input



(a) (b)

Figure 7. Confusion matrix of the: (a) model 1 and (b) model 2 using RMS input

– The best CNN architecture

Based on previous results, the second architecture is the optimal choice for the model, utilizing input dimensions of 200×8 with a batch size of 50 for raw data and 4 for RMS data. This configuration effectively reduces the GPU workload during training. The architecture incorporates two-dimensional CNN input shapes, with the first input shape of (200, 8) representing EEG channels and the second input shape of (8, 1) derived from RMS feature extraction. The architecture begins with a first convolution using 200 filters of size 8×8, producing a feature map of dimensions 193×8 after applying the ReLU activation function. This is followed by a pooling layer that reduces the feature map to 48×8 using max pooling. The second convolution uses 100 filters and a kernel size of 4×4, yielding a 45×8 matrix, also processed with the ReLU activation function. A second max pooling layer further reduces this to a 22×8 matrix. The third convolution employs 50 filters with a 2×2 kernel, resulting in a 21×8 matrix, and the subsequent pooling layer maintains this size. The data is then flattened into a new matrix with 1050 weights, leading to a fully connected layer comprising three dense layers corresponding to the classes of idle, right/forward, and left/backward, using the sigmoid activation function for classification. Finally, the CNN output is transmitted to an Arduino Mega 2560 via serial communication for further processing.

3.1.2. Online data testing

During the online testing phase, the respondent was in a wheelchair using an EEG sensor. This testing was conducted to determine the accuracy of predicting real-time wheelchair movements. Table 5 shows the results of the online testing. Table 5 shows that the anticipated wheelchair movements for respondents 1 and 5 did not occur as expected, with both achieving low accuracy rates of 50%. In contrast, respondents 2 and 3 reached 85% accuracy, attributed to their better physical condition and focused brain activity during data acquisition. The less focused states of respondents 1 and 5 contributed to their lower accuracy. Factors like physical condition and brain resting state are crucial for optimal data acquisition results, and hair thickness can also affect EEG signal quality, with thinner or bald hair yielding better data. Both online and offline testing yielded higher accuracy during offline sessions due to the consistency of brain signal data, while online testing faced fluctuations in the real-time signal collection.

Table 5. Results of online testing

Respondent	Accuracy (%)
Respondent 1	50
Respondent 2	85
Respondent 3	85
Respondent 4	80
Respondent 5	50
Average	70

3.2. Discussion

This study achieved high accuracy in predicting four wheelchair control motions using a CNN model, with an average real-time accuracy of 70% across five respondents. However, improvements are needed for real-time performance, a common challenge in EEG-based applications. Advanced methods in the field are exploring recurrent neural networks (RNNs) and hybrid systems that combine EEG with other biosignals to address the variability and instability in EEG data, a well-known limitation. Additionally, while this research focuses on four basic motions, more complex state-of-the-art systems offer finer control options, like variable speeds or multidimensional commands, to enhance user interaction. Thus, while the CNN model shows strong predictive capabilities, further work in improving real-time accuracy, adapting to signal dynamics, and achieving greater control flexibility is necessary to make EEG-based wheelchair systems feasible for broader, real-world use.

4. CONCLUSION

The impact of CNN on EEG-based wheelchair performance is considered effective in accurately predicting the direction of the wheelchair. This is done using raw data and the second CNN architecture during online or real-time testing. The offline data test was based on raw and RMS data with both CNN architecture 1 and CNN architecture 2, as well as model 1 and model 2. In CNN testing with raw data using CNN architecture 1, the highest results obtained were 85.486% in model 1 and 90.996% in model 2. In the online testing phase, it was observed that the wheelchair cannot be said to move according to the desired command. Several influencing factors, such as hair thickness and the physical condition of the respondent, were identified as possible causes.

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BIOGRAPHIES OF AUTHORS

Khairul Anam is a Lecturer at the Department of Electrical Engineering, Faculty of Engineering, University of Jember, Indonesia. He holds a Ph.D. in Electrical Engineering with specialization in Rehabilitation Robot at Faculty of Engineering and IT, University of Technology Sydney, Australia. His research areas are intelligent control system, robot learning, bio-signal processing, artificial neural network, and deep learning. He is the head of Intelligent System and Robotics Laboratory-CDAST Research Lab of Jember University. He is the recipient of various awards such as the best paper award at the 3rd International Conference on Soft Computing in Data Science 2017 (SCDS2017), awards satyalancana karya satya of the year x. He can be contacted at email: khairul@unej.ac.id.

Satrio Marta Wicaksono born on March 8, 1999, in Kendal, Central Java, he is a Bachelor of Electrical Engineering from the University of Jember, specializing in Control Systems and Electronics (2017). He joined the Intelligent System and Robotics Lab, served as a Control System Lab Assistant, and actively participated in student activity units. He is prepared to contribute to industry 4.0 through AI system development. He can be contacted at email: satriomarta08@gmail.com.

Muchamad Arif Hana Sasono born on November 23, 1999, in Mojokerto, East Java, is a dedicated Master's student in Electrical Engineering at the University of Jember. He serves as a research assistant at the Intelligent Systems and Robotics Lab, with a focus on developing intelligent systems and robotics. Holding a Bachelor's degree in Electrical Engineering (2018-2022) from the same university, he has consistently excelled in his studies. Driven by a passion for AI and its potential to enhance daily life, he is prepared to make impactful contributions to electrical engineering and AI fields. He can be contacted at email: arifhana04@gmail.com.

Bima Wahyu Maulana is a Master's student in Electrical Engineering and researcher in the Intelligent Systems and Robotics Lab at the University of Jember. He holds a Bachelor's in Physics, focused on Electronics and Instrumentation. Born in Jember on May 8, 1999, he is currently researching EEG-based motor imagery with CNN systems, aiming to apply intelligent robotics solutions across Indonesia. He can be contacted at email: bimawahyumaulana@gmail.com.

Fatkhul Mubarok is an undergraduate student in Electrical Engineering at the University of Jember, where he began his studies in 2021. He is a research assistant in the Intelligent Systems and Robotics Laboratory at CDAST. Born on January 24, 2003, in Kediri, East Java, he is passionate about electrical engineering and robotics. His current research focuses on developing intelligent systems and robotics, driven by a desire to explore the potential of artificial intelligence to enhance daily life. He can be contacted at email: fatkhulmubarok08@gmail.com.

Ananta Pinsentius Rahmat Pamungkas an Electrical Engineering student at the University of Jember, focused on robotics, automation, and AI. With experience in robotics competitions, he contributes as a research assistant in the Intelligent System and Robotics Lab. As team leader of the university's soccer robot Team, he works on advancing autonomous soccer robots through AI integration. He can be contacted at email: anantavincent1@gmail.com.

Moch. Rijal Fatoni Bachelor's degree in Electrical Engineering, specializing in Control Systems and Electronics, from the University of Jember. Born on August 10, 2001, in Probolinggo, East Java, Rijal joined in 2020 and has been an active member of the Robotics Team, representing the university nationally. As a research assistant in the Intelligent System and Robotics Lab, he focuses on intelligent control systems and robotics to enhance human activity. With a commitment to AI development, he is prepared to contribute to the future of Industry 4.0. He can be contacted at email: rijalfatooni@gmail.com.