Brain-Controlled Wheelchair through Deep Learning, Raspberry Pi, and Arduino

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Abstract

The brain is the most important part of our body. Brain controls both voluntary and involuntary activities. From blinking of the eyes to giving signals to muscles to thinking of any idea, feeling pain, etc., all is controlled by the brain. The brain sends signals to body parts through neurons. This research explores the development of a brain-controlled automatic wheelchair system using synthetic electroencephalogram (EEG) signals. This system is designed to help people with motor impairments by utilizing brain-computer interface (BCI) technology. Given the challenge of accessing a real-time EEG device, this study employs synthetic EEG signal generation that stimulates brain wave patterns associated with different movements. These signals are then preprocessed and sent into a deep learning model that predicts the movements of the wheelchair. Subsequently, the Arduino will receive the signals and then move the wheelchair. The system's efficiency is validated through real-time simulations that demonstrate its potential to provide reliable navigation commands based on an EEG device.

Introduction

The important problem in bioengineering is to use brain signals to control any activities, software, or devices. This problem can be solved through two stages. The first stage includes the development of computer and brain interface. Afterwards, the second stage includes the designing of brain-based control of devices.[1]

As the development of EEG devices is increasing, the design of brain-controlled devices is skyrocketing. These devices are usually expensive; thus, in this research, testing of the final prototype is purely based on synthetic signals (similar to the signals measured by EEG devices) generated by our model. An EEG (electroencephalogram) device works by measuring the electrical signals or impulses that travel between brain cells. These signals are tracked with the electrodes that are attached to the wires, which sense the electrical impulse and transmit them to the recording device.

The first research in the BCI field was published by Tanaka et al. in 2005.[2] For making brain-controlled wheelchairs. We have to be careful while working on the system so that the safety of the user is not in danger. We have to overcome some challenges in order to improve the safety of our system. Accordingly, we have to use reliable navigation systems in order to guarantee the safety of users and give a flexible displacement in the environment in order to provide free and comfortable movement to users.[3]

This research paper focuses on the development of a brain-controlled wheelchair using deep learning, Raspberry Pi (a microprocessor), and Arduino (a microcontroller). Synthetic signals are generated through Python using different libraries, and Neural Networks are used to classify the directions of wheelchair through brain signals. This deep learning model is then deployed into Raspberry Pi. Afterwards, Arduino is used to move the wheelchair. Section 1 contains details of previous research on brain-controlled wheelchair. Section 2 discusses the methodology on which the system works. Section 3 contains experimental results of the system. Section 4 contains discussions and analysis related to the system. Lastly, Section 5 contains the conclusion of this research. This research aims to help people with motor impairment and to develop an affordable solution for them.

1. Literature Review

SNo.	References	Year	WorkDone
1.	Rebsamen B. [4]	2010	Created a brain-controlled wheelchair system and focus on overcoming challenges. They had crated a system that constrains the motion of the wheelchair to a predefined path and used P300 EEG brain interface for selecting destinations.
2.	Khan MM. et al. [5]	2021	They had created a brain-controlled wheelchair for paralyzed patients. Brain signals are captured with the Neurosky MindWave headset, and then the movements are controlled by eye blinking.

3.	Awais MA. et al.[6]	2020	They focus on developing a model that is controlled by a joystick and an Android phone. In their model, eye blink and attention level were the most important features extracted and identified by the Android application.
4.	Xin L. et al.[7]	2018	They have created a system in which signals are taken by an EEG device and transmitted to the STM32 to control the movements of the wheelchair.
5.	Wang H. et al.[8]	2017	They have created a system that employs two-stage control strategies that combine sustained and brief motor imagery brain-controlled interfaces (SB-MI-BCIs) that allow users to navigate more effectively than existing single-modal BCI (S-BCI).
6.	Li Z. et al.[9]	2023	They have designed P300 brain-controlled wheelchair that uses Digital-to-Analog converter for transmission of signals. Subjects using this wheelchair have to control the direction by seeing randomly flickering white circles.

7.	Ghasemi S. et al. [10]	2024	They designed a non-invasive BCI system that uses EEG signals. They trained their users to produce specific brain activities that allow them to precisely control the wheelchair.
8.	Sharif MK. et al. [11]	2023	Designed a system that comprises an electric wheelchair, an electroencephalogram headset, a Bluetooth module (HC-05), a controller, and gear motors for quadriplegic persons.
9.	Qaysi AI. et al. [12]	2024	Created an EEG-MI brain-controlled interface based on a generic pattern recognition model (GPRM) for their wheelchair steering control.
10.	Hussain SAH. et al. [13]	2024	Focus on creating a BCI system that adaptively tunes toward the patient's psychological effects. They collect signals using an EEG device and do filtration or processing through frequency-based distribution of EEG signals.

11.	Glavas K. et al. [14]	2024	They used an Emotiv Epoc headset to record raw EEG data, and for feature extraction from the data, the Common Spatial Patterns (CSP) algorithm was used. Subsequently, an ML model was used to classify the brain commands.

2. Methodology

2.1 Dataset

Used wheelchair EEG detection dataset provided on Kaggle by Muneeb Ahmed containing EEG (electroencephalogram) signals collected from subjects visualizing backward, right, left, and forward.

2.2 Model Architecture

The model architecture is divided into three parts: EEG signal generation, direction classification model, and controlling the movement of the wheelchair. EEG signals are generated synthetically because of the absence of an EEG device due to financial problems.

2.2.1 Direction Classification Model

This part of the architecture is most important. This layer classifies the direction by receiving the signals from the brain. The model is made by using Artificial Neural Networks (ANN). Initially, the model is trained on the Kaggle dataset containing numerous features like Alpha Power, Beta Power, etc. These features are then split into train and test variables. Then these variables are preprocessed from the Standard Scaler function of the scikit-learn library. Standard Scaler transforms the data to have a mean of zero and a standard deviation of 1.[15] It is useful for algorithms that assume data is normally distributed or sensitive to the scale of features.[16]

$$Z = x - \mu\sigma$$

Eq.1

Eq.1 is the formula of the Standard Scaler, where ‘ z’ denotes the standardized value, ‘ x’ is the original value, ‘ μ’ is the mean of the feature, and ‘ σ’ denotes the standard deviation of the feature.

After the preprocessing of data, the neural network model is made. The first layer of the model is an Artificial Neural Network (ANN) with 80 neurons and a relu activation function. The second layer is a dropout layer with a value of 0.2, which means 20% of neurons will drop automatically. Subsequently, the third layer is an ANN layer with 30 neurons and a relu activation function. The fourth layer is a dropout layer with a value of 0.2. The fifth layer is an ANN layer with 80 neurons and a relu function. The sixth layer is a dropout layer with a value of 0.1. The last layer (or an output layer) is an ANN layer with 4 neurons and a softmax activation layer. Each of the 4 neurons will predict the probability of the direction of the wheelchair. The direction with the highest predicted probability will be considered as an output. Moreover, the model is compiled with 'sparse_categorical_crossentropy' loss' and ' adam' as an optimizer. The model is trained on 60 epochs with 50 batchsize.

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_20 (Dense)	(None, 80)	1,120
dropout_15 (Dropout)	(None, 80)	0
dense_21 (Dense)	(None, 30)	2,430
dropout_16 (Dropout)	(None, 30)	0
dense_22 (Dense)	(None, 80)	2,480
dropout_17 (Dropout)	(None, 80)	0
dense_23 (Dense)	(None, 4)	324

Total params: 6,354 (24.82 KB)
Trainable params: 6,354 (24.82 KB)
Non-trainable params: 0 (0.00 B)

Figure 1: *Summary of Neural Network Model.*

(Figure 1) shows the summary of the neural network model. It displays the type and output shape of the layer along with the trainable and non-trainable parameters for each layer.

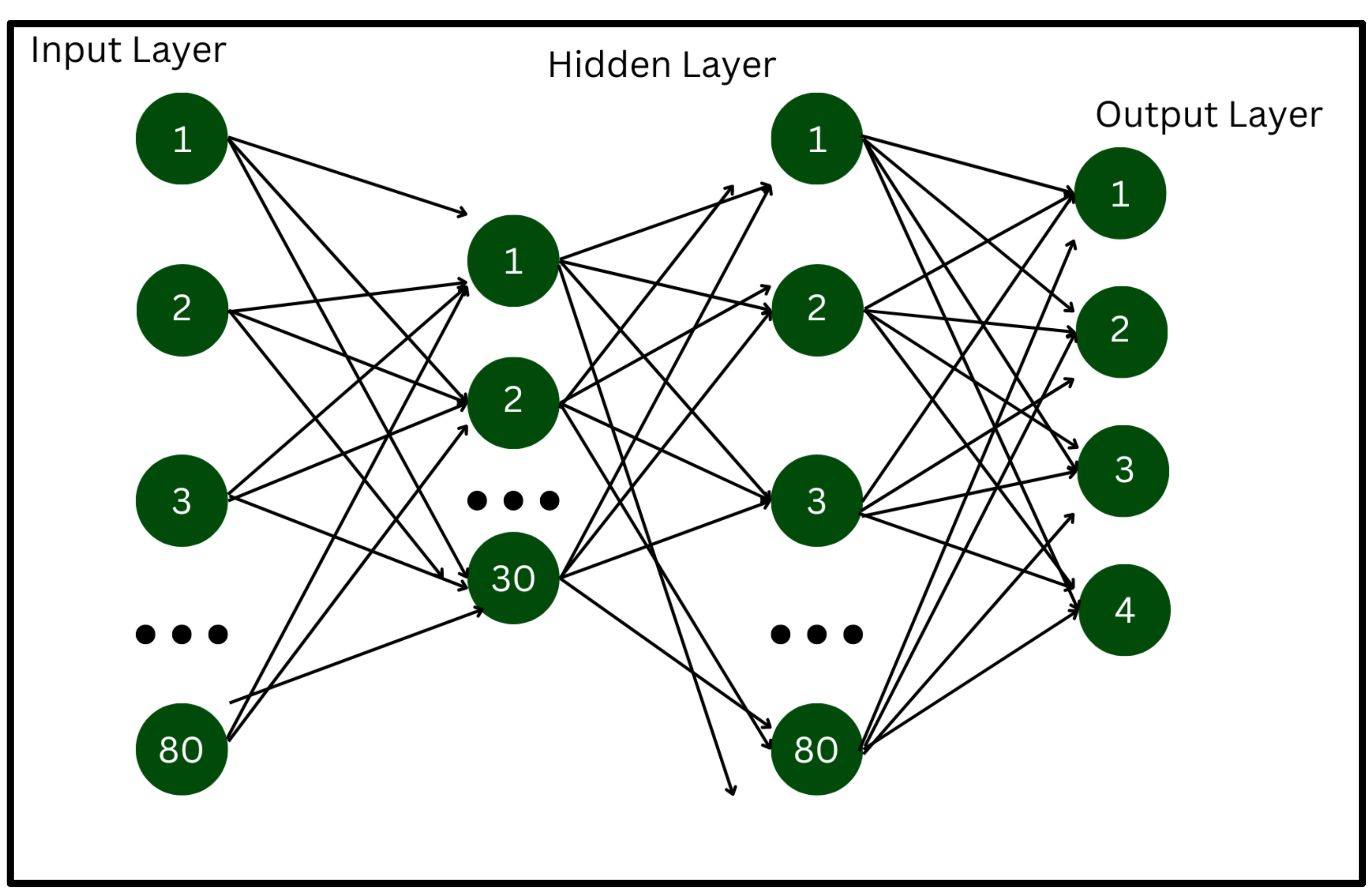

Figure 2. *Dense Network Architecture.*

(Figure 2) shows the input, hidden, and output layers. From the image, it can be inferred that the input layer of the model contains 80 neurons, one hidden layer contains 30 neurons, and the other hidden layer contains 80 neurons. Lastly, the output layer contains 4 neurons.

2.2.2 EEG signal generation

Synthetic EEG signals are generated to test the accuracy of the model and simulate the control of a wheelchair based on brain signals. This process is necessary due to the unavailability of physical EEG devices for real-time data collection because of financial constraints.

i). Synthetic Signal Creation: The synthetic EEG signals were generated by combining random noise with specific frequency components that represent different wave patterns. Characteristics of real EEG signals observed during mental tasks associated with movement commands is simulated by these components.

- **Alpha Waves (8– 13 Hz):** These waves are associated with relaxation. These waves were introduced with moderate amplitude to stimulate a calm state.[17]
- **Beta Waves (13-30 Hz):** These waves represent focused mental activity as they are linked to active thinking.[18]
- **Gamma Waves (30-50 Hz):** These waves are associated with higher cognitive function, representing intense focus.[19]
- **Delta Waves (0.5– 4 Hz) and Theta Waves (4– 8 Hz):** These are lower frequency waves that are generally present during drowsiness or light sleep. These are included to add realism.[20]

ii). **Combination of Frequency Bands:** To stimulate the variability seen in real EEG data, different frequency bands with random noise are combined with generated signals.
This was achieved by summing sine waves at the respective frequencies and adding Gaussian noise through Python. [21]

iii). **Feature Extraction:** Features such as Fast Fourier Transform (FFT), mean, standard variation, kurtosis, skewness, and band powers (alpha, beta, gamma, delta, theta) are extracted from the generated signals. (Figure 3) shows the different features extracted from the synthetically generated signals.
These features are similar to the real EEG data that help the model to learn and predict movements effectively.

iv). **Standardisation:** The synthetic signals are standardised using a Standard Scaler. This ensures that the data has a mean of zero and a standard deviation of one. This step is done to improve the model's generalisation during testing and real-time prediction.[22]

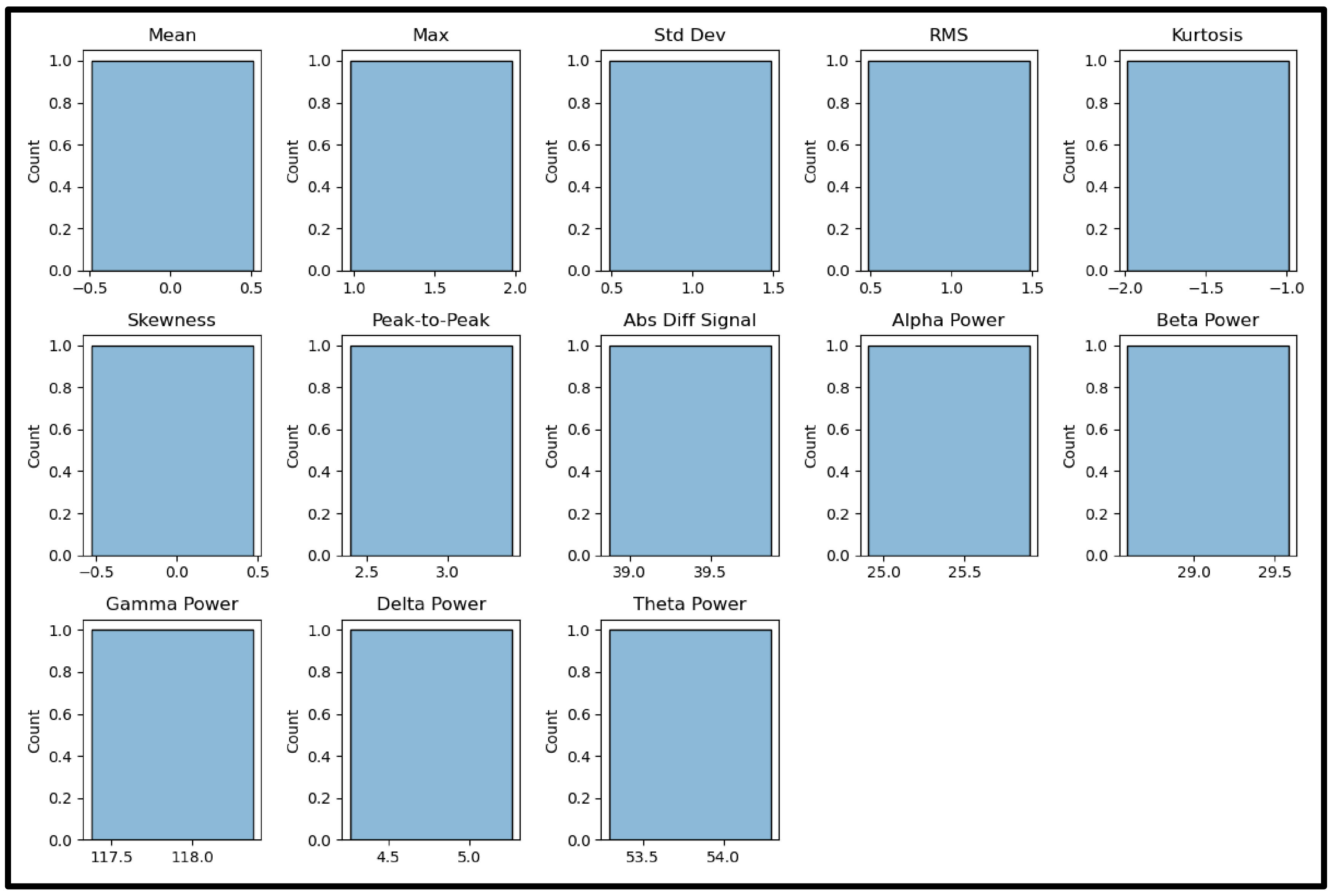

Figure 3. *Synthetically generated features*.

2.2.3 Controlling movement of wheelchair through Arduino

The simplicity and effectiveness of Arduino make it an ideal choice for this application. It provides a reliable and effective way to control the wheelchair. Additionally, a deep learning model is deployed on the Raspberry Pi to setup communication between the model and Arduino.

2.2.3.1 Model Deployment on Raspberry Pi

The Arduino microcontroller receives the labels (0, 1, 2, 3) through serial communication from the Raspberry Pi. The deep learning model that is trained to predict wheelchair movements based on EEG signals is converted into TensorFlow Lite format for efficient performance on a Raspberry Pi. This conversion is essential to reduce the model' s size and make it optimize for limited computational resources available on Raspberry Pi.

2.2.3.2 Communication Protocol

Serial communication is established between Raspberry Pi and Arduino to facilitate real-time control of wheelchair. After preprocessing the EEG signals and predicting movement, the Raspberry Pi sends the corresponding command to the Arduino via a serial interface.

2.2.3.3 Control Logic

The Arduino receives the movement commands in the form of integers (0 for forward, 1 for left, 2 for right, and 3 for backward). On receiving a command, the Arduino adjusts the motors controlling the wheelchair to move in a desired direction.

- **Label 0 (Forward)**: The Arduino sends signals to both motors to move the wheelchair forward.
- **Label 1 (Left Turn)**: The Arduino commands the right motor to move forward and the left motor to move backward, which results in turning the wheelchair left.
- **Label 2 (Right Turn)**: The Arduino commands the left motor to move forward and the right motor to move

backward, which results in turning the wheelchair right.

- **Label 3 (Backward)**: The Arduino sends signals to both motors to move the wheelchair backward.

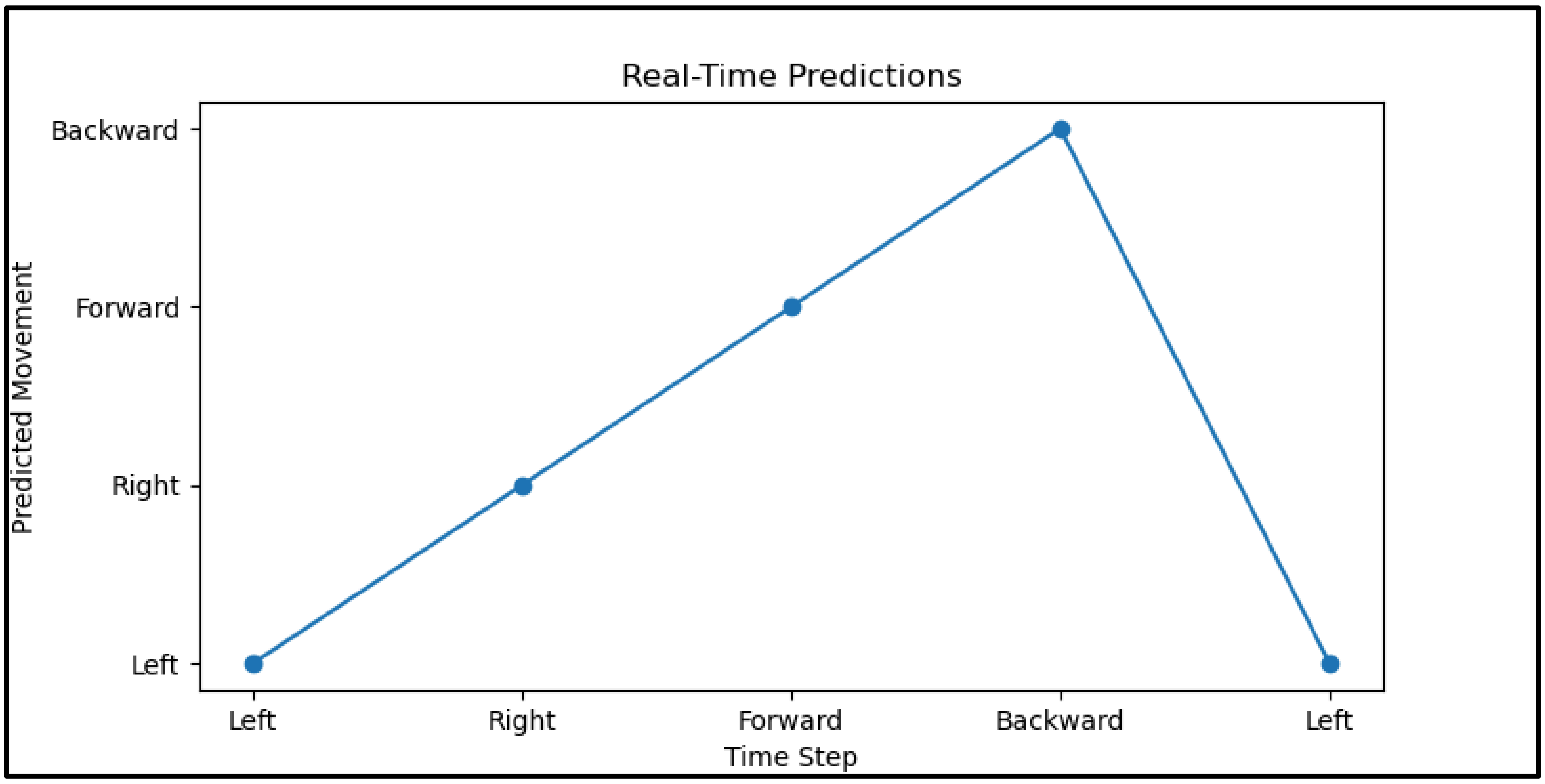

Figure 4. *Realtime prediction of the model.*

(Figure 4) displays the real-time predictions done by the deep learning model for specific intervals of time. This prediction is done on the synthetic EEG signals that is displayed in (Figure 3).

2.2.3.4 Autonomous Operation

This system allows the Raspberry Pi to work independently of external devices. It eliminated the need for a constant connection of a laptop or a mobile. The setup ensures that users are able to control the wheelchair in realtime using Raspberry Pi and Arduino only, which makes the system portable and user-friendly.

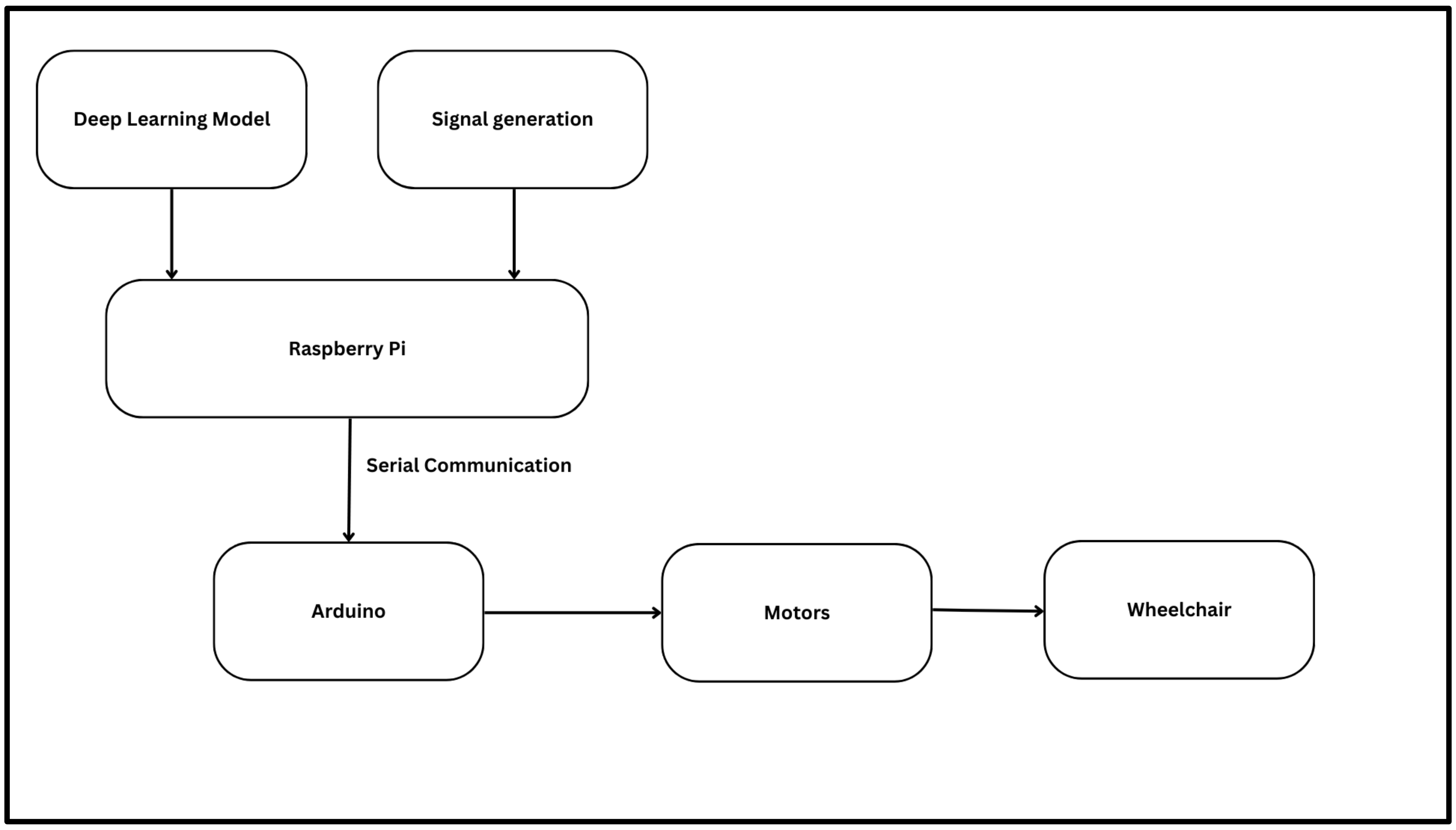

Figure 5. *Control logic of the system.*

(Figure 5) shows the control logic of the system. It shows that signal generation model and deep learning model is deployed on Raspberry Pi, and then Arduino is connected to Raspberry Pi through serial communication. Subsequently, the motors of the wheelchair are controlled by Arduino.

3. Results

The data is split into train, test, and valid sets. 80% of data is split into train sets, and 10% of data is split into test and valid sets each. It is considered a normal test_train_valid split ratio. Before sending to training, data is preprocessed.

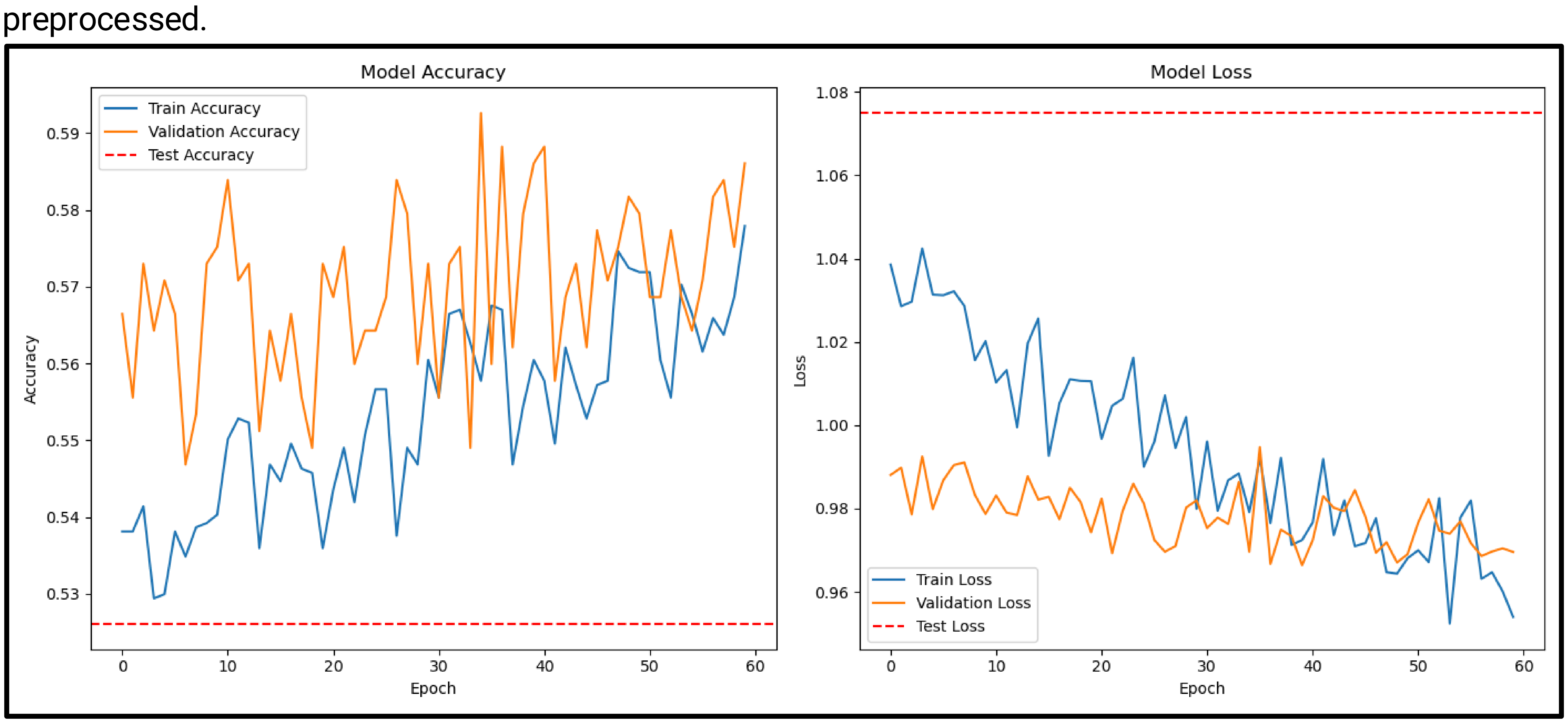

Figure 6. *Comparison of Accuracy and Loss.*

(Figure 6) displays the comparison of the accuracy and loss of model with training, testing, and validation sets.

The training set had an accuracy of 58.64% and a loss of 0.92. The validation set had an accuracy of 58.61% and a loss of 0.96. Afterwards, we tested the data, and it got an accuracy of 52.61% and a loss of 1.07.

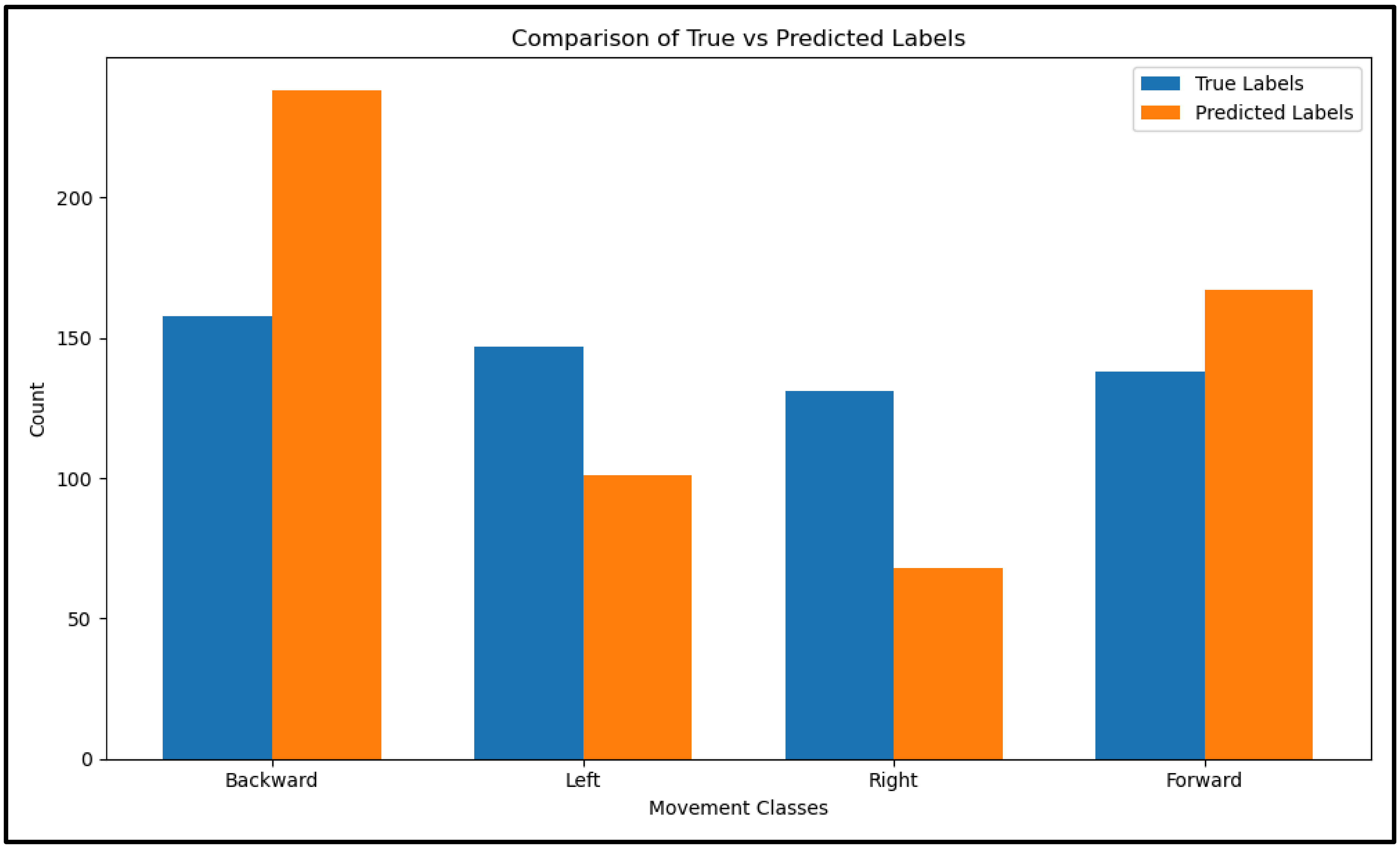

Figure 7. *Comparison of True vs Predicted labels*

(Figure 7) contains the count of predicted and true labels. Predicted labels are the labels predicted by the model on the test dataset, while true labels are the actual labels from the test dataset.

4. Discussion and Result Analysis

The results of the research have provided important insights into the effectiveness and limitations of the proposed approach. Below are the key points of discussion based on the findings:

4.1 Context of Errors and Results Interpretation

The accuracy of the model was 58.64% for the training set and 52.61% for the test set, which indicates a moderate performance level. The loss values were high, with a training loss of 0.92 and a test loss of 1.07. The difference between the model' s accuracy on training and test sets may be because of the issue of overfitting. Overfitting may happen in the model due to the synthetic nature of EEG signals because it may not fully capture the variability present in real EEG data.

4.2 Use of Results

Although this model can classify the movements based on synthetic EEG signals, the results indicate that further improvement is needed for more effective practical applications. The current model serves as the foundation step to increasing the accessibility and portability of users.

The accuracy of the model was lower than expected, which suggests the necessity of using real EEG data in future research. The result supports the hypothesis that we can control wheelchair by brain using deep learning; however, some further exploration is needed to increase the accuracy of the model. Comparing the model with other researchers' models emphasizes the importance of using actual EEG signals and expanding the dataset. Therefore, the research provides a foundation for developing affordable helping technologies.

Conclusion

This research provides an overview of the development of a brain-controlled wheelchair through deep learning, Raspberry Pi, and Arduino. Deep learning model was used to classify the directions of wheelchairs, and Raspberry Pi was used to deploy the deep learning model, synthetic-generated EEG signal mode, and establish communication with Arduino to control real-time wheelchairs. Moreover, the result highlights the limitation of relying solely on synthetic EEG signals and emphasizes the need for real EEG signals. The current study shows that improvements are needed to realize the full potential of brain-controlled wheelchairs. By solving the limitations identified in the paper and increasing advancements in BCI technology, future studies can contribute to the development of robust and user-friendly systems that result in increasing the quality of life of people with motor impairments.

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