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Brain-Computer Interface for Smart Home Design Based on Machine Learning and Deep Learning Techniques

Mariam W. Al-Mohammadi [*1] Auns Q. Al-Neami [2] Lama Bou Farah [3]

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Abstract

Further evidence suggests that smart appliances with several types of controllability are necessary, such as smart homes. This practical approach will be greatly appreciated by those who cannot access control of devices that require direct human engagement. This study proposes and constructs a smart home setup based on enhanced electroencephalography (EEG), which could potentially assist individuals with or without movement problems to manage gadgets with greater comfort and ease. In this study, motor/imaginary EEG (MI-EEG) datasets were used. This dataset includes 25 subjects who completed motor and imagery tasks. EEG signals were captured using a 64-channel (BCI2000) instrument. The features are extracted from the CNN's convolutional layers, which are then used to train the classifier. Features are extracted from both the test and training datasets, and the labels are flattened to match the expected input format for the classifier. In addition, the proposed Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Linear Discriminant Analysis (LDA) models can remove the excessive noise and overlaps that lead to misclassification and classify the chosen features into separate classes. Based on the number of classes reached by Arduino UNO, the identified classes are tasked with controlling the smart home. The high overall accuracies using SVM, CNN, and LDA are (99%, 96%, 99%), respectively. According to the current research, the suggested approach for classifying MI-EEG is successful. It may be suitable for BCI applications, allowing for controlling a smart home via brain waves. Results from this study support the idea that the proposed EEG-based smart home could be helpful for older people and others with mobility issues in the future.

***Keywords*—** MI-EEG, BCI, Smart Home, CNN, SVM, LDA

1 Introduction

Disabilities may be defined as impairments, limitations in activities, or restrictions on involvement in daily life brought on by a decline in functional. Persons are considered disabled when they cannot perform daily tasks due to physical limits or impairments resulting from an injury, or other health issue (Ibrahim et al., 2022a). Some conditions that cause brain dysfunction include traumatic brain injury and stroke. Disabilities resulting from disorders of the spinal cord, such as the common spina bifida, are another kind of impairment(Retief & Letšosa, 2018). People with disabilities are among those who are finding that technological advancements have made their lives more difficult rather than easier. Recently developed electroencephalogram (EEG) gadgets that are

Mariam W. Al-Mohammadi
mariam.w.hatem@uofallujah.edu.iq
Auns Q. Al-Neami
auns.q.hashim@nahrainuniv.edu.iq
Lama Bou Farah
l.boufarah@lgu.edu.lb

[1] College of Medicin, Al- Fallujah University, Anbar, Iraq
[2] Biomedical Engineering, Al-Nahrain University, Baghdad, Iraq
[3] Biomedical Engineering Department, Lebanese German University, Sahel-Alma, Jounieh, Lebanon

non-invasive, wearable, inexpensive, wireless, lightweight, and user-friendly have aroused the curiosity of scholars from several fields, especially about their potential usage as command ways in smart homes (Elshenaway & Guirguis, 2021). A network of interconnected computing devices, sensors, and other physical objects that can monitor their own and their environment's conditions, that transmit and receive data, which is known as " the Internet of Things (IoT) " (X. Xu et al., 2018). So, IoT is a system of interconnected computing devices like appliances in homes and cars, which can exchange data and coordinate their actions via various systems, actuators, sensors, and networks. These devices may be remotely controlled and monitored when incorporated with technology that allows them to exchange and connect over the network(Ibrahim et al., 2022b). The term is also being used to describe a system that uses digital sensing and communication technology to provide services via seamless communication(Gram-Hanssen & Darby, 2018) to automate housework or household activities(Jacobsson et al., 2016) via the use of data and little or no human participation, which may generate services and information (Yang et al., 2017). A "smart home" is essentially just a regular house that has been automated to gather data about the surrounding area and facilitate various home services (Balakrishnan et al., 2018).

Brain Computer Interface (BCI) enables the brain to command the body's exterior actions, as shown in

Figure 1. A person with mobility impairments can manage any controllable electronic device or system through a BCI system, which receives, preprocesses, and classifies brain waves from a network of neurons, which are turned into activity using computer chips and programming (Lukoyanov et al., 2018). There are almost 100 billion nerve cells in the brain, and EEG, a non-invasive, portable tool, can detect this dispersed electrical brain activity (Graimann et al., 2010). The electroencephalogram (EEG) is a method for detecting and understanding neuro-electrical patterns by recording and monitoring electrical activity in the brain. It is widely used in BCI applications, like smart homes controlled by the brain, and it can show whether the brain responds to physical or nonphysical stimuli (Ibrahim et al., 2022a).

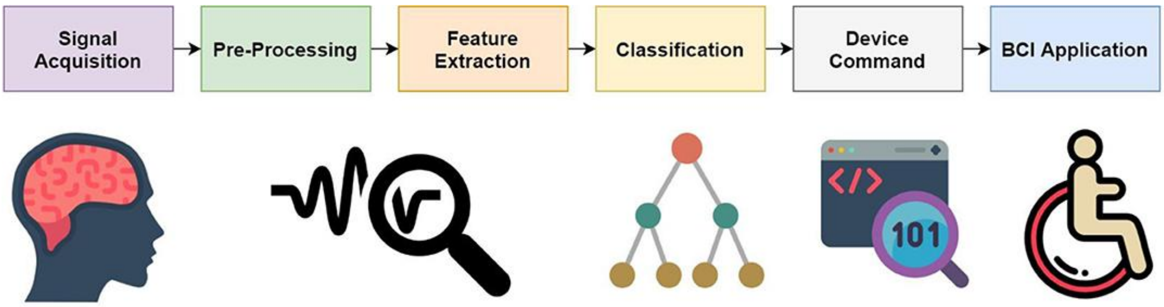


Figure 1: General architecture of a brain-computer interface (Rashid et al., 2020)

EEG is a complicated signal with several applications in biomedicine, including sleep studies and the brain-computer interface (Chaddad et al., 2023). Accurate EEG data collection requires several components, including 1.) an analog-to-digital (A/D) converter, 2.) conductive-medium electrodes, 3.) amplifiers with filters, and 4.) a recording device. The microvolt signals collected from the scalp electrodes were amplified utilizing a voltage converter to produce signals falling within the specified voltage range. Using a converter, the recording device transformed an analog signal into a digital format. One way to look at the possible changes in each EEG electrode over time is as variances between the active electrode (A) and the reference electrode (R). The conductive media (usually gel or saline) must fill the space between the scalp and the electrodes to achieve low contact impedance and good electrical conductivity. The gel ensures a longer-lasting conducting connection between the electrode and the scalp region, reducing artifacts produced by movements and the skin's surface compared to the saline solution (Teplan, 2002). In recent years, BCI has risen to prominence as a prominent area of computing. BCIs facilitate communication between computers and human brains. BCI interprets signals from different brain regions and translates them into instructions and actions for various uses. The components of any generic BCI model are gathering signals, processing data, extracting features, and, finally, classifying data (Edla et al., 2018).

2 Methodology

2.1 Data Collection

Two EEG datasets were used in this study, as illustrated in Figure 2. These data were processed and divided into epochs. Features were extracted from them and applied to the proposed models. They were then classified to control smart home appliances.

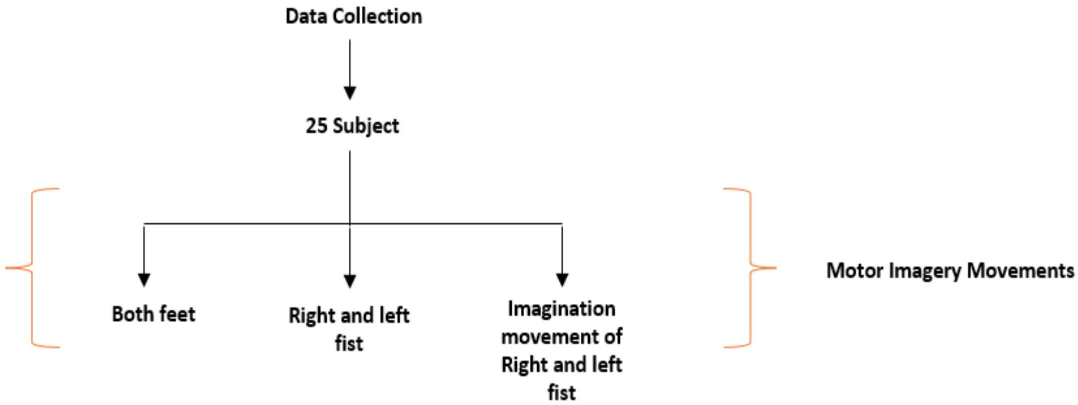


Figure 2: Data Collection

The EEG Motor/Imagery movement dataset is a comprehensive collection of 64-channel EEG recordings contributed to PhysioNet by the developers of the BCI2000 instrumentation system for BCI research (Schalk et al., 2004). More than 1,500 EEG recordings, ranging from one to two minutes in length, collected from 25 different subjects, make up the dataset. Subjects used the BCI2000 device to record their electroencephalograms as they completed a variety of motor and visual tasks as part of the experiment.

Subjects participated in 14 experimental runs, including three two-minute runs for each of the following tasks: 1) open and close the left or right fist when a target appeared on the corresponding side of the screen, 2) imagining open and close the left or right fist when a target appeared on the corresponding side, 3) open and close both fists or movement both feet when a target appeared on the top or bottom of the screen, and 4) imagining open and close both fists or both feet when a target appeared on the top or bottom of the screen, these tasks are repeated three times. The data are achieved in European Data Format (EDF), containing 64 EEG signals sampled at 160 Hz.

2.2 Data Loading and Preprocessing

EEG signals are subjected to preprocessing procedures to eliminate or significantly decrease artifacts and noise. The objective is to improve the signal-to-noise ratio (SNR) and subsequently isolate the signal. There are numerous potential sources of noise and artifacts in EEG recordings, including the subject's eye blinking or movement, EMG from the subject's scalp muscle contractions, and ECG artifacts. EEG signals measured from the scalp do not accurately represent signals originating from the brain. Therefore, preprocessing and denoising to the recorded EEG data. Preprocessing steps include transforming or reorganizing the recorded EEG data by removing artifacts, normalizing the data, and segmenting from continuous raw signals without changing the data. The dataset is checked for NaN values to ensure data integrity. The EEG Dataset instance is created, and data loaders for training, validation, and testing are set up with appropriate batch sizes and shuffling.

2.2.1 EEG Data Filtering

Electrooculography (EOG) signals occupy a portion of the recording channels. In this investigation, EOG channels are disabled. To eliminate line voltage interference, as shown in Figure 3. This figure shows raw electroencephalography (EEG) signals recorded from the first five channels over time. The x-axis represents time (seconds), while the y-axis shows the signal amplitude in microvolts (μV). Each colored line corresponds to a different channel, illustrating the variability of brain electrical activity across electrode locations. Apply a bandpass filter ranging from 5 to 50 Hz. Then, use a 50 Hz notch filter as illustrated in Figure 4 .

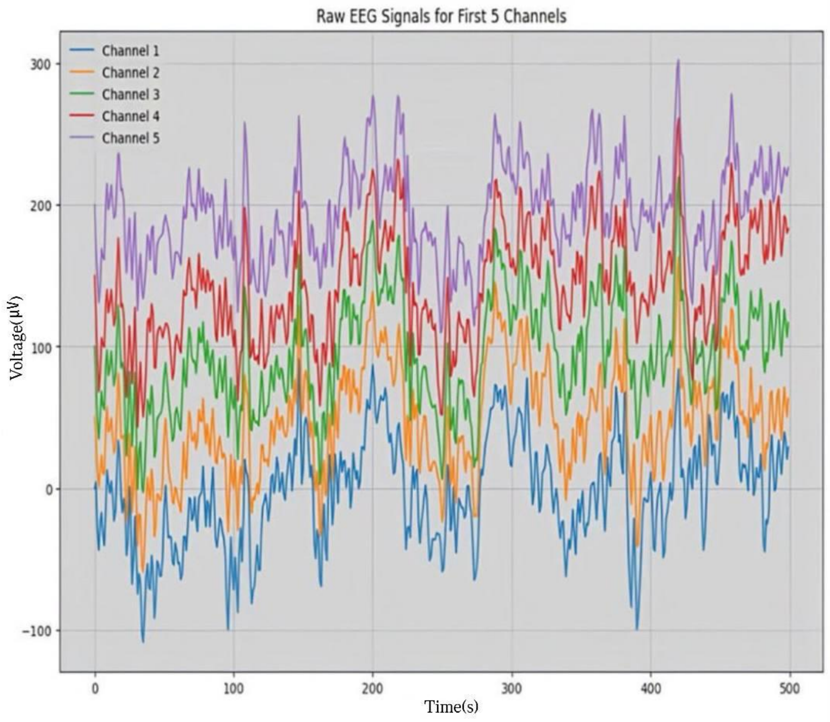


Figure 3: Raw EEG data

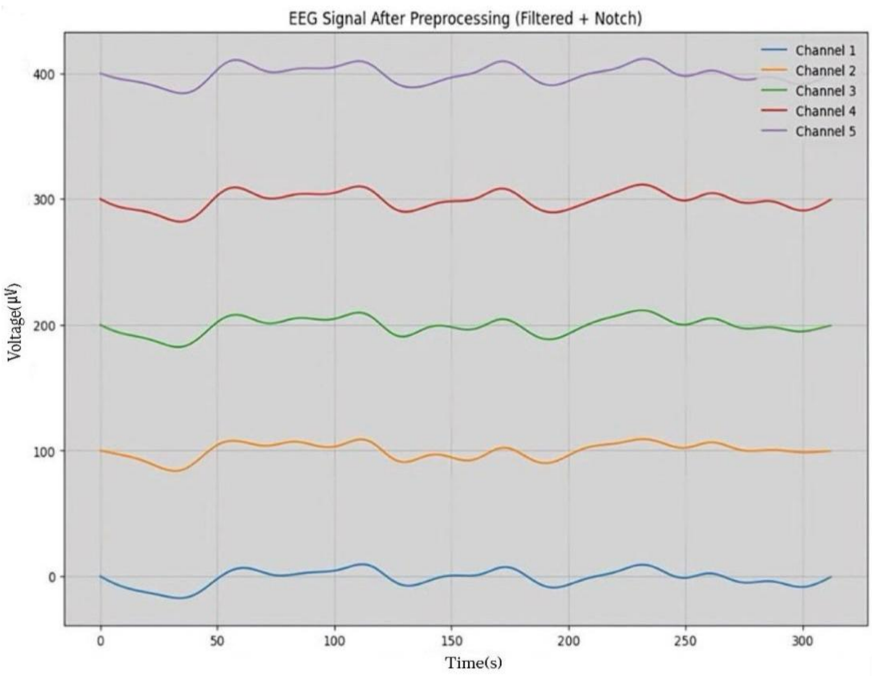


Figure 4: EEG Signal After Filtering

2.2.2 Independent Component Analysis (ICA)

The primary goal of ICA is to find a linear transformation that reduces the statistical dependency between the signal's constituent parts. Because rejected contaminated EEG segments result in an unacceptable data loss, some artifact issues restrict the interpretation and analysis of clinical EEG signals. The analysis of the EEG signal is done using the ICA approach, as illustrated in Figure 5 This contribution included training an ICA algorithm using EEG data from these sessions to identify statistically independent source channels that may be subsequently processed via other signal-processing methods.

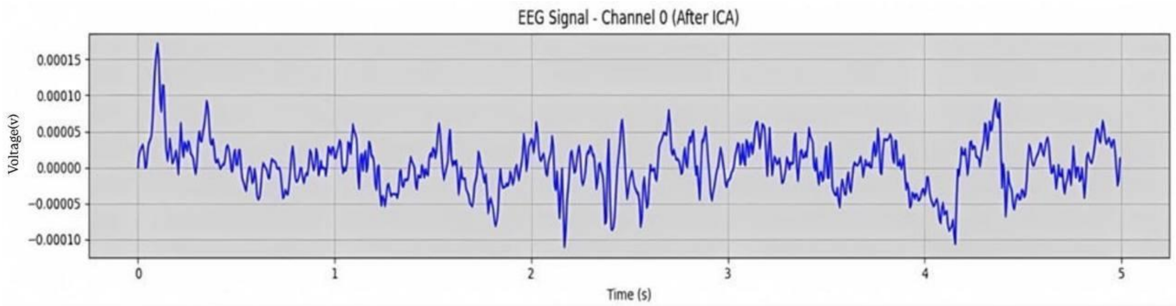


Figure 5: EEG Signal After ICA.

2.3 Normalization

`Standard Scaler` is used to normalize the flattened data. Event codes are converted to numeric labels and store them in `y`. Check for consistency between the number of samples in the data and the labels, as shown Figure 6.

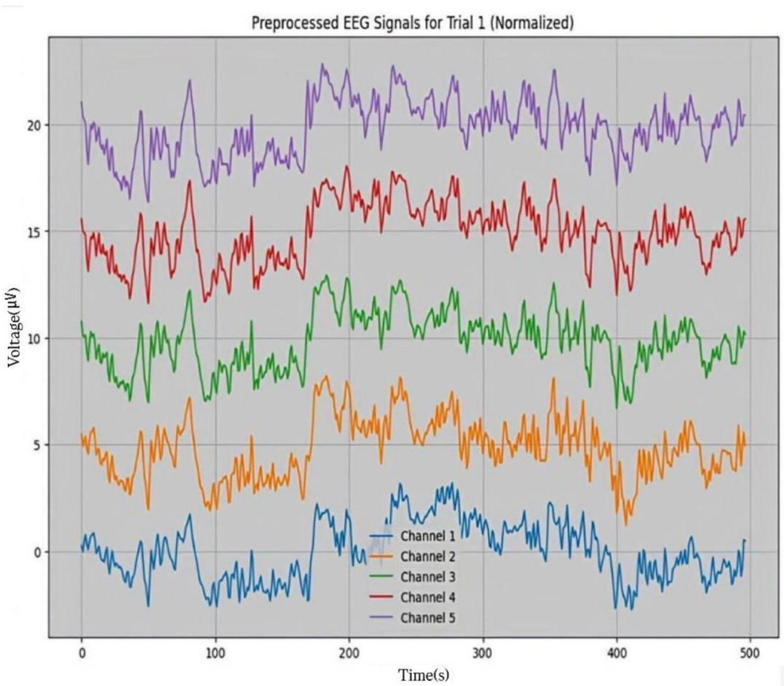


Figure 6: Normalized EEG signal.

2.4 Segmentation

The continuous EEG signals were segmented using an event-based epoching method. Event markers provided in the dataset (etyp, epos, and edur) were used to identify the onset and duration of each task. EEG samples corresponding to these event intervals were extracted from the continuous signal (s) to form individual epochs representing task-related brain activity. By segmenting EEG signals, it becomes easier to extract relevant features for further analysis. Continuous EEG data is segmented according to event markers, also known as triggers, which are defined in the file, such as epos (event positions), edur (event durations), and etyp (event types).

2.5 Feature Extraction

Three convolutional blocks in the CNN model automatically extract features from the EEG signal; each block is designed to learn increasingly more intricate temporal patterns from the input EEG data. At the outset, a 1D convolutional layer (nn. Conv1d (1, 32,...)) is used to apply 32 learnable filters across the time dimension of the EEG signal. Like pattern detectors, these filters pick up on local temporal features like spikes or oscillations in brain waves, as well as oscillatory activity. The model improves the efficiency and performance of training by stabilizing and normalizing the outputs after each convolution. The model can learn complex correlations in the data because the ReLU activation introduces non-linearity. After that, MaxPooling reduces the temporal resolution by selecting the most significant features in each window, and Dropout helps prevent overfitting by randomly deactivating neurons during training. The number of filters is increased to 64 in the second convolutional layer and to 128 in the third convolutional layer by integrating simpler characteristics gathered in earlier layers. Because of this, the network can identify more complex traits. Using these layers, the CNN gradually compresses the original EEG signal into a higher-level representation that may catch significant temporal changes. In the future, fully connected layers can use this representation for classification tasks like recognizing mental states, deciphering motor/imaginary movements, or detecting seizures. By using hierarchical filtering, normalizing, activating, pooling, and regularizing, the model can autonomously extract robust and discriminative features from unprocessed EEG data.

2.6 Dataset Splitting

The data was split into 80% training, 10% validation, and 10% test sets to achieve the desired data distribution for modelling. This distribution is very suitable for the present dataset because it is crucial to split the data into (test, train, validation) to validate the training data to avoid overfitting.

2.7 Classification Methods

By utilizing a classification system on the EEG data, one may readily ascertain the BCI's performance. The purpose of this research is to assess and create state-of-the-art deep learning and machine learning algorithms that can accurately categorize EEG signals. Proper operation of a BCI relies on four main processes: signal recording, preprocessing, feature extraction from recorded signals, and classification of harvested information. The classification methods of SVM, CNN, and LDA were the main emphasis of this research.

2.8 Support Vector Machine Model

The process involves using a Support Vector Machine (SVM) for classification by extracting features from a pre-trained CNN. The extracted features are used to train the SVM classifier, which is then evaluated on both training and test datasets. The performance is visualized and analyzed, combining CNN's feature extraction capabilities with SVMs' robustness.

2.9 Linear Discriminant Analysis Model

The process demonstrates using Linear Discriminant Analysis (LDA) for classification by extracting features from a pre-trained CNN. The extracted features are used to train an LDA classifier, which is then evaluated on both training and test datasets. This method effectively combines CNN's feature extraction capabilities with LDA's linear classification, making it suitable for complex datasets like EEG signals.

2.10 Convolutional Neural Network Model

The EEG CNN class defines the architecture of the convolutional neural network. The three convolutional layers include regularization via dropout, batch normalization, max-pooling, and ReLU activation. The final output is generated by flattening the output of the convolutional layers and passing it through fully connected layers. The model can process and categorize electroencephalogram (EEG) inputs. Figure 7 show the CNN model for EEG data. The proposed architecture employs a CNN to classify EEG signals. The input EEG signals are processed through three sequential Conv1D blocks, each consisting of a convolutional layer with a 3×3 kernel, followed by Batch Normalization, ReLU activation, MaxPooling (2×2), and Dropout. By these layers temporal features are extracted and dimensionality is reduced while preventing overfitting. The repeated convolutional blocks enabled hierarchical feature learning, where low-level EEG patterns are captured in early layers and more complex motor-imagery features are extracted in deeper layers. The extracted features are then passed to fully connected (dense) layers, for the final classification. The output layer predicts the imagined movement class, including left fist, right fist, both fists and feet, and imagined both fists and feet, based on the patterns learned from the EEG signals.

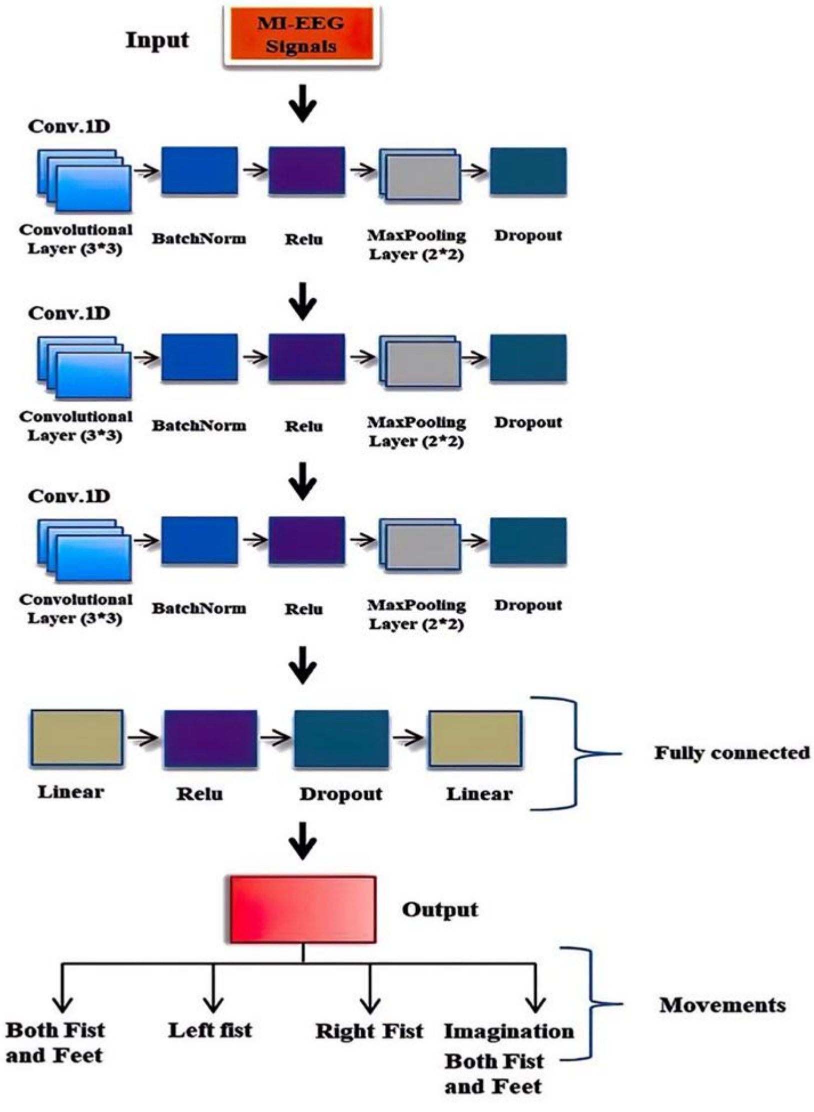


Figure 7: CNN Architecture

3 Hardware and Software Requirements

The system development, training, and evaluation processes need specific hardware and software design as follows: -

3.1 Hardware Requirements

The suggested motor/imaginary electroencephalography (MI-EEG) signal-based system operates by using the following hardware requirements (Electronic and Electric Equipment):

- Arduino UNO
- The Espressif Systems Platform (ESP) module is frequently used to refer to modules that support Bluetooth and Wi-Fi.
- Relay switch
- Connector
- Buzzer
- Light
- Fan
- Wires
- Power

3.2 Software Requirements

In the present model, the required models are implemented by (Google Colab's Python Integrated Development Environment (IDE)), with necessary libraries such as (Magnetoencephalography and Electroencephalography (mne), Operating System (os), Regular Expressions(re), NumPy(np), matplotlib, torch, lightning, pytorch, sklearn.

4 Smart Home Design

Smart home technology is commonly defined as the integration of services and devices through home networking to enhance the quality of living. In this work, smart home technology was utilized to develop an assistive environment aimed at supporting elderly individuals and people with disabilities. The proposed system leverages MI-EEG signals to enable users to control household devices without physical interaction.

The system controls the smart home design, as shown in Figure 8, based on brain waves. The structure of the prototype system is designed using a 3D sketch program. The devices or equipment are controlled by using a microcontroller as an embedded system, and according to the classes of signals.

Three classes are chosen to control the three actions of devices or equipment in the home:

- Class one (imagine closing and opening left or right fist), the buzzer will be turned on for a limited time.
- Class two (imagine movement of the feet), the light will be turned on for a limited time.
- Class Three (motor movement of both feet), the fan will be turned on for a limited time.

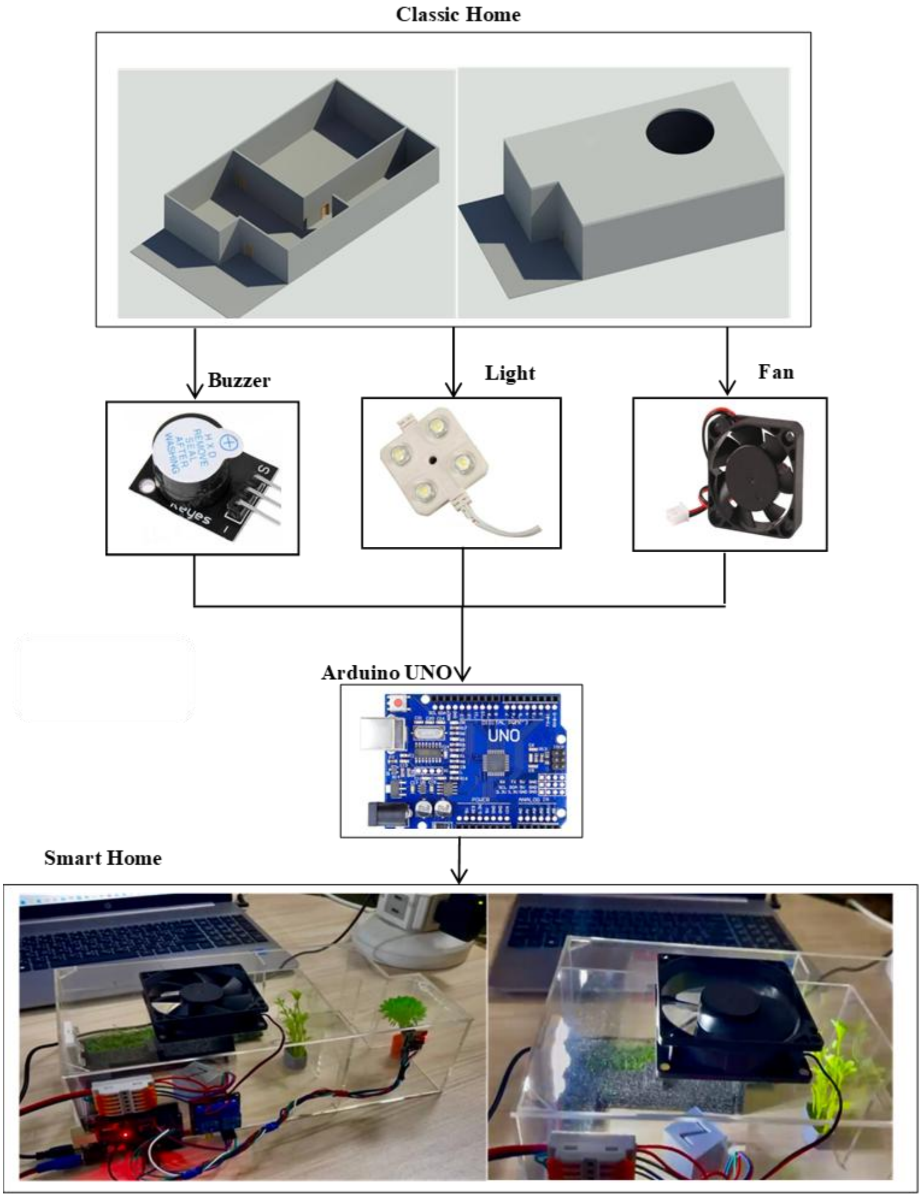


Figure 8: Smart System Design.

5 Circuit Design

Integrating EEG-based machine learning and deep learning into smart home design represents a groundbreaking advancement in neuroscience and smart technology. EEG is a method used to record the electrical activity of the brain, providing real-time insights into brain function and cognitive states. By leveraging these insights, smart home systems can be designed to respond to their residents' mental and emotional states, creating a more intuitive and responsive living environment.

The proposed model's circuit, shown in **Error! Reference source not found.** The Python program will receive a classified MI-EEG signal, which is transmitted to the ESP modules (that support AT commands and facilitate task execution, such as Wi-Fi connection), and then be processed. Depending on the number of classes that reach it, the ESP will send commands to the Arduino UNO to control the appliances, such as the light, fan, and buzzer. The system operation, from collecting raw signals to controlling the appliance, is illustrated in

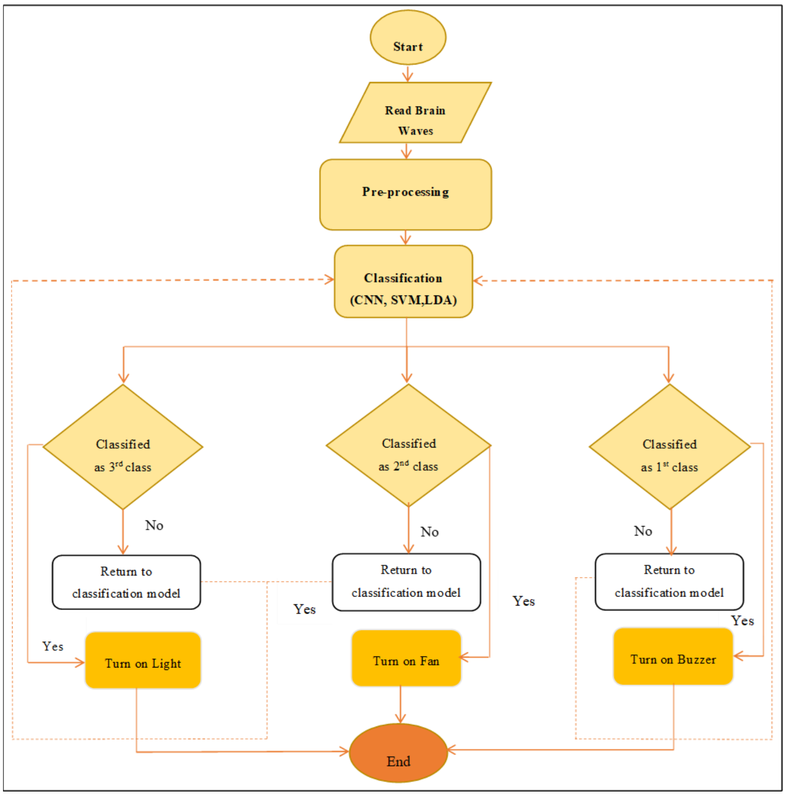
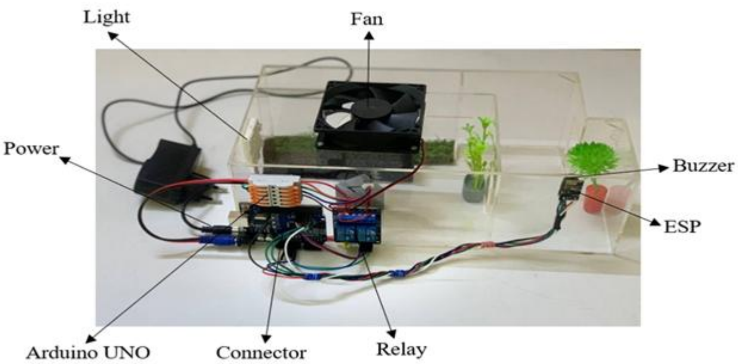


Figure 10.



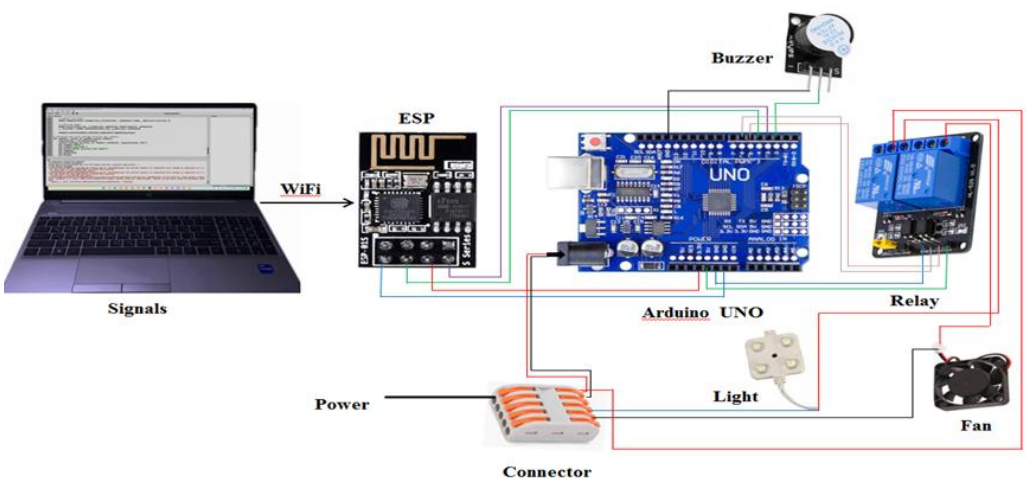


Figure 9: Circuit Diagram

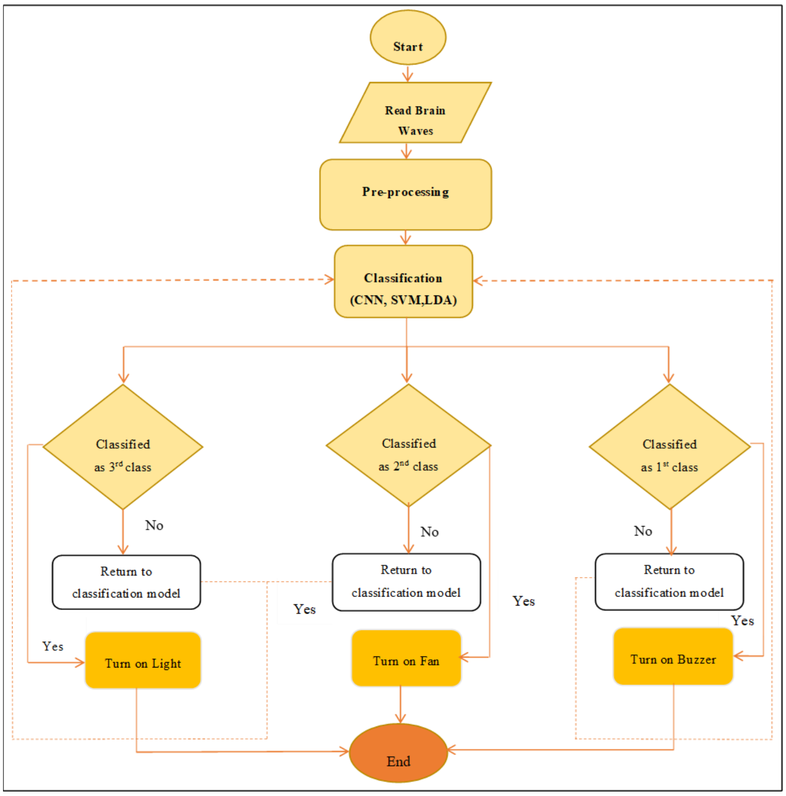


Figure 10: System Operation Flowchart

6 Result and Discussion

This part presents the obtained results along with their interpretation and analysis as follows:

- **Accuracy Analysis**

The Accuracy is used to evaluate the overall performance of the proposed model. the accuracy increases gradually with epochs, indicating that the model successfully learns the underlying patterns of the data. The slight difference between training and validation accuracy suggests a minor overfitting, which is acceptable.

- **Loss Analysis**

The Loss Function represents the error between predicted and actual values. The loss decreases as the number of epochs increases, which confirms that the model is improving during training. Any fluctuations in the curve may be due to noise in the dataset or batch variations.

- **Confusion Matrix Analysis**

The Confusion Matrix is used to analyze classification performance in detail.

The EEG data is divided into sections, each of which contains binary classes, making the classification method easy and clear. The classifications of the dataset done by CNN, SVM, and LDA, averaged across all task types and participants, are illustrated as follows:

A. Section one

Open and close both fists and move both feet.

B. Section two

Imagination of open and closed fists and movement of both feet.

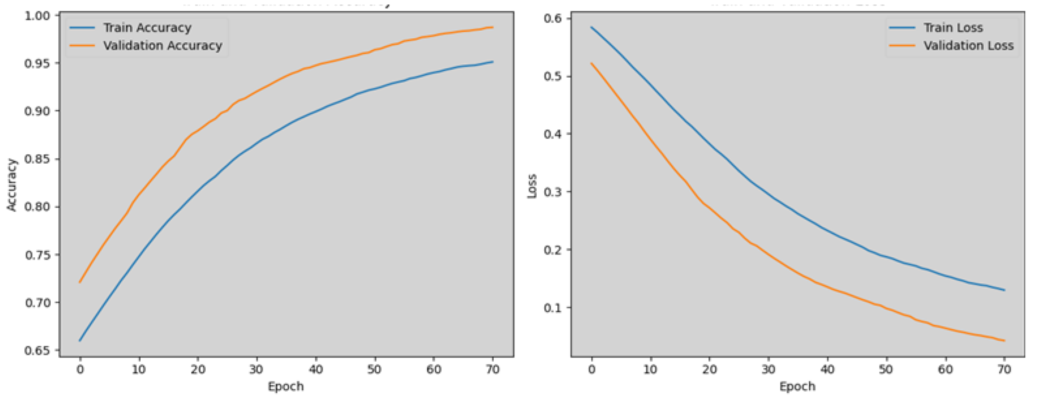
C. Section three

Imagination of open and closed (right and left fists).

6.1 Convolution Neural Network

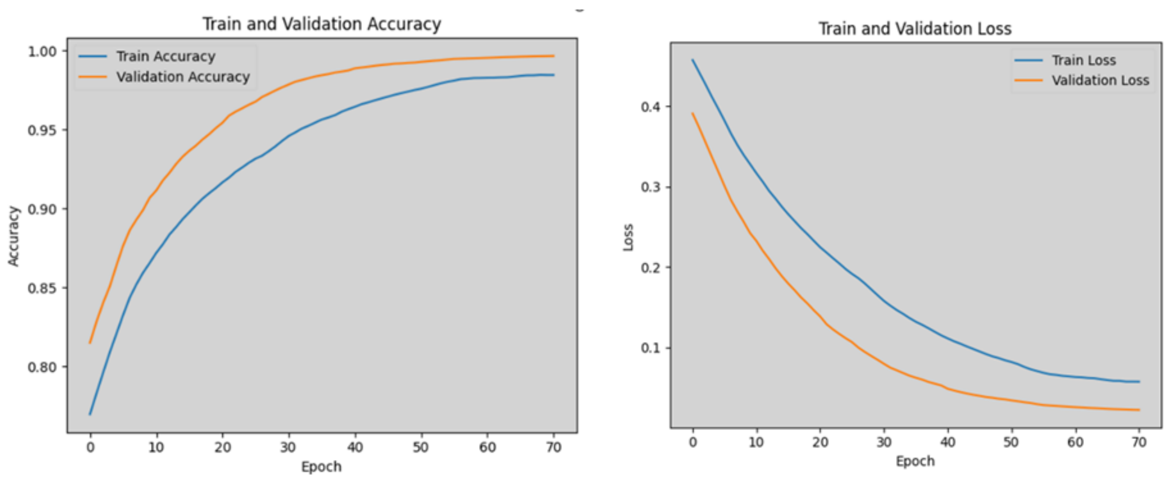
Accuracy and Loss Analysis

The CNN technique is used to classify the EEG signal. Figure 11 presents the training and validation accuracy and loss curves for the classification of open and closed fists as well as the movement of both feet. The curves that illustrate the classification of the imagination of open and closed (right and left fists) are shown in **Error! Reference source not found.**. Figure 12 illustrates the accuracy and loss curves of the imagination of open and closed fists and the movement of both feet.



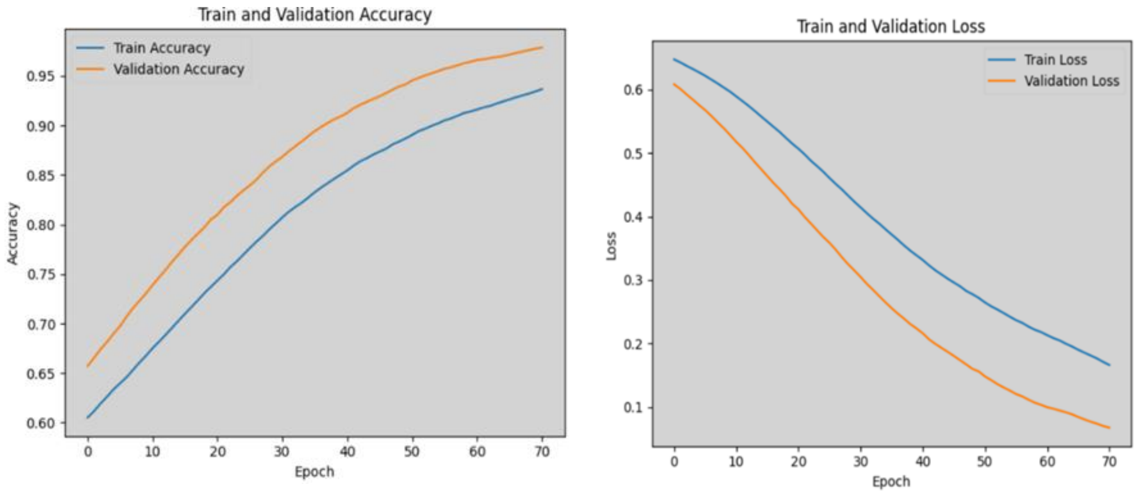
(a) (b)

Figure 11: (a) CNN Train and Validation Accuracy Curves, (b) CNN Train and Validation Loss Curves of open and close both fists and move both feet class



(a) (b)

Figure 12: (a) CNN Train and Validation Accuracy Curves, (b) CNN Train and Validation Loss Curvesof imagination of open and closed fists and movement of both feet class



(a) (b)

Figure 12: (a) CNN Train and Validation Accuracy Curves, (b) CNN Train and Validation Loss Curves of imagination of open and closed (right and left fists) class

The training and validation accuracy curves show a steady increase as the number of epochs increases, indicating that the model progressively learns the underlying patterns in the EEG data. Initially, the accuracy is low due to random weight initialization; however, it improves significantly as the model parameters are updated during training.

In contrast, the training and validation loss curves exhibit a continuous decrease over the epochs. This decline in loss reflects the reduction in prediction error, with a sharp decrease in the early stages of training followed by a more gradual decline as the model approaches convergence.

Furthermore, the close agreement between the training and validation curves suggests good generalization performance and indicates that overfitting is minimal. The model achieves a high classification accuracy, confirming its effectiveness in classifying EEG signals for both motor execution and motor imagery tasks.

Confusion Matrix

A confusion matrix is a standard evaluation tool in classification problems, used to assess the performance of a model by comparing the predicted labels with the true labels. It provides detailed insight into classification results through four key components: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), which collectively reflect the accuracy and types of errors made by the model.

The confusion matrix resulting from the classification of the open and closed fists and the movement of both feet is shown in Figure 13. Figure 14 illustrates the confusion matrix of imagination, the movement of the right and left fists. Figure 15 shows the confusion matrix of two classes of the imagination of open and closed fists, and the movement of both feet.

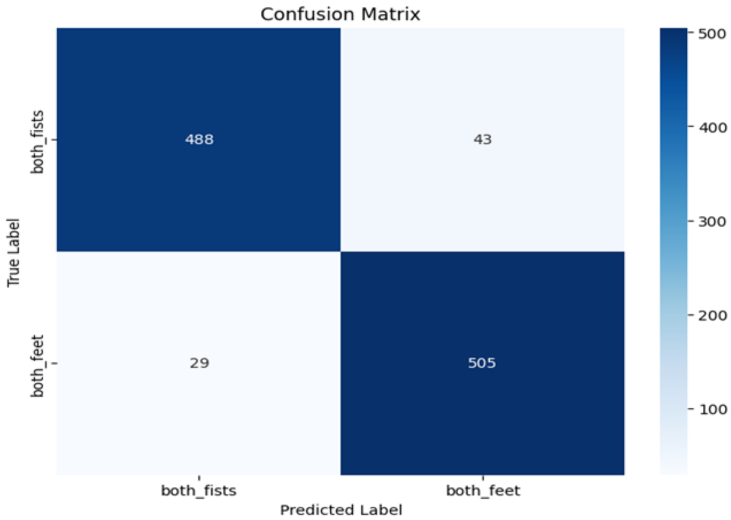


Figure 13: CNN Confusion Matrix of open and close both fists and move both feet class

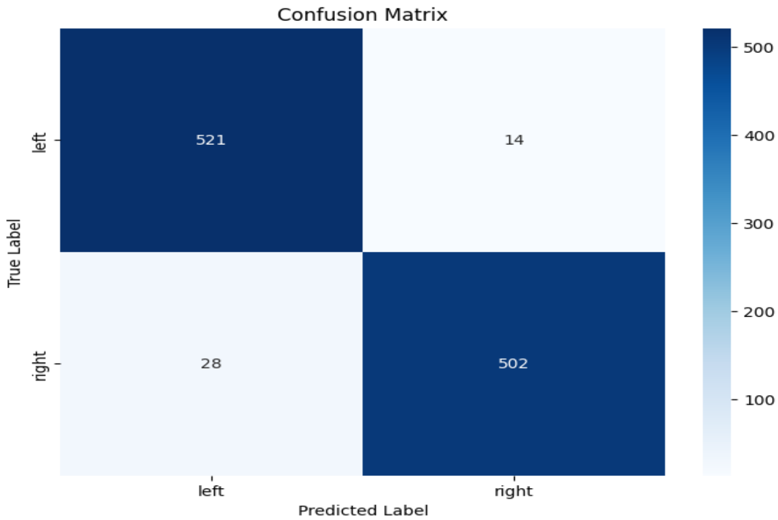


Figure 14: CNN Confusion Matrix of imagination of open and closed fists and movement of both feet class

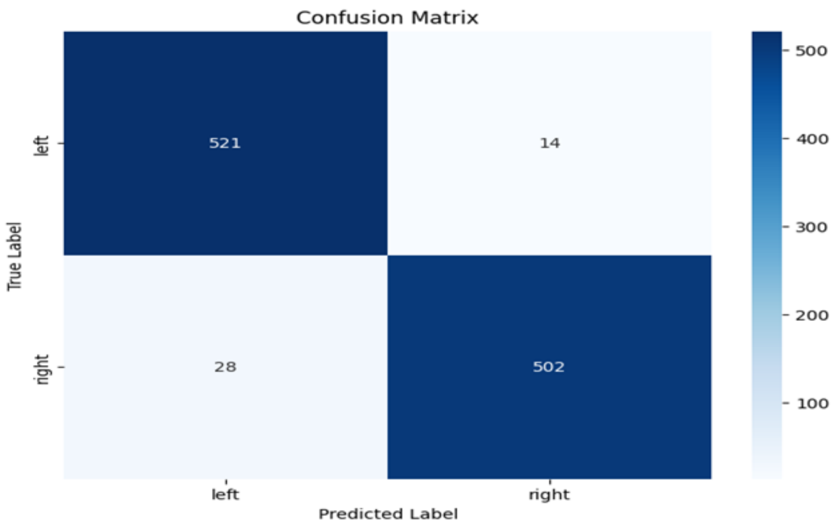


Figure 15: CNN Confusion Matrix of imagination of open and closed (right and left fists) class

- **Classification Report**

The classification report of using CNN is shown in Table 1.

Table 1: Classification report

Classes	Precision	Recall	F1-score	Accuracy
Both fist	0.92	0.95	0.93	0.93
Both feet	0.94	0.92	0.93	
Left fist	0.95	0.97	0.96	0.96
Right fist	0.97	0.95	0.96	
Imagination movement fists	0.94	0.93	0.94	0.94
Imagination movement feet	0.93	0.94	0.94	

- **Test Metrics**

The test metrics, such as test accuracy and test loss, are shown in Table 2 for open and closed fists. Table 3 shows the movement of both feet classes.

Table 4 shows the test metric of the imagination of open and closed fists and the movement of both feet.

Table 2: Test metric of the classification of open and closed fists, and the movement of both feet

Test metric	Data Loader θ
Test_acc	0.99
Test_loss	0.018

Table 3: Test metric of the classification of the imagination of open and closed right and left fists

Test metric	Data Loader θ
Test_acc	0.99
Test_loss	0.023

Table 4: Test metric of the classification of the imagination of open and closed fists and the movement of both feet

Test metric	Data Loader θ
Test_acc	0.99
Test_loss	0.026

6.2 Support Vector Machine

- **Confusion Matrix**

The confusion matrix of open and closed fists and the movement of both feet classes using SVM is illustrated in Figure 16. Figure 17 shows the confusion matrix resulting from the classification of the right and left fist movements. Figure 18 illustrates the confusion matrix of imagination fists and feet movement.

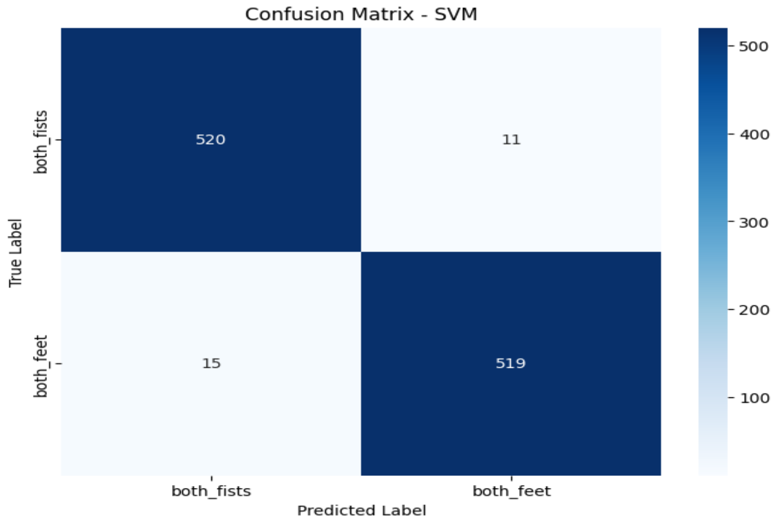


Figure 16: SVM Confusion Matrix of open and close both fists and move both feet class

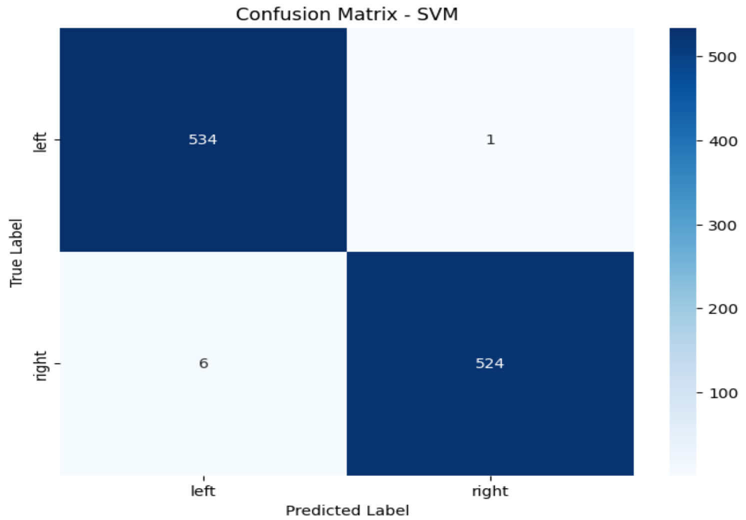


Figure 17: SVM Confusion Matrix of imagination of open and closed fists and movement of both feet class

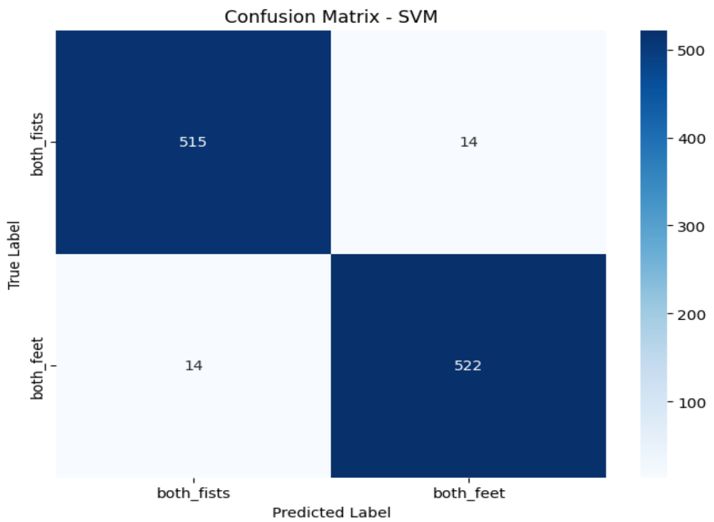


Figure 18: SVM Confusion Matrix of imagination of open and closed (right and left fists) class

- **Classification Report**

The classification report of using SVM is shown in Table 5.

Table 5: Classification report

Classes	Precision	Recall	F1-score	Accuracy
Both fist	0.98	0.97	0.98	0.98
Both feet	0.97	0.98	0.98	
Left fist	0.99	1.00	0.99	0.99
Right fist	1.00	0.99	0.99	
Imagination movement fists	0.97	0.97	0.97	0.97
Imagination movement feet	0.97	0.97	0.97	

6.3 Linear Discriminant Analysis

- **Confusion Matrix**

The confusion matrix of open and closed fists and the movement of both feet classes using LDA is illustrated in Figure 19. Figure 20 shows the confusion matrix resulting from the classification of the right and left fist movements. Figure 21 illustrates the confusion matrix of imagination fists and feet movement.

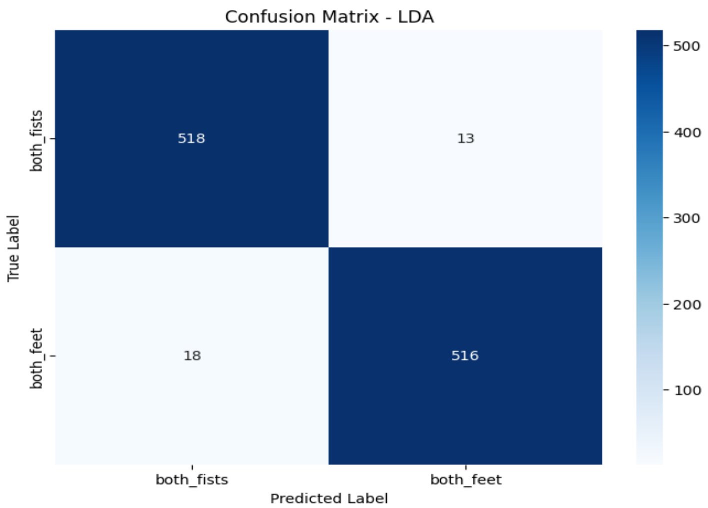


Figure 19: LDA Confusion Matrix of Open and close both fists and move both feet class

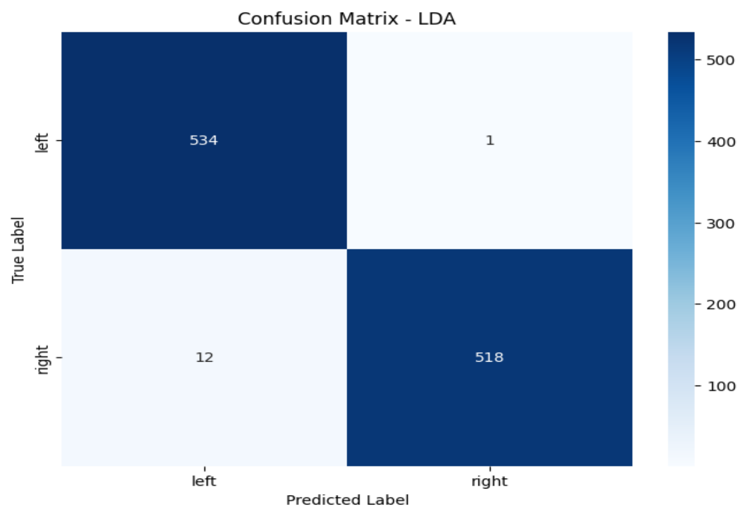


Figure 20: LDA Confusion Matrix of imagination of open and closed fists and movement of both feet class

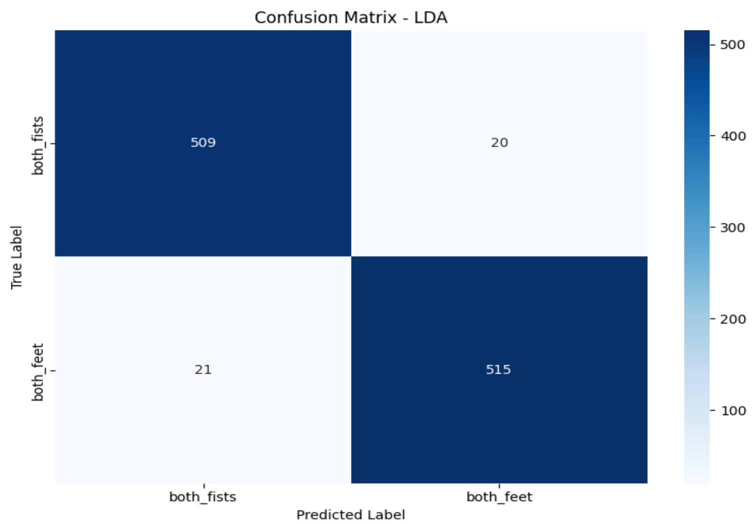


Figure 21: LDA Confusion Matrix of imagination of open and closed (right and left fists) class

- **Classification Report**

The classification report of using LDA is shown in Table 6.

Table 6: Classification report

Classes	Precision	Recall	F1-score	Accuracy
Both fist	0.98	0.97	0.97	0.97
Both feet	0.97	0.98	0.97	
Left fist	0.99	1.00	0.99	0.99
Right fist	1.00	0.99	0.99	
Imagination movement fists	0.96	0.96	0.96	0.96
Imagination movement feet	0.96	0.96	0.96	

6.4 Comparison With Other Studies

Finally, Table 7 presents a comparison between the proposed method and existing studies. The results demonstrate that the proposed model achieves competitive (or superior) performance compared to previous approaches, confirming the validity and effectiveness of the proposed system.

Table 8: Comparisons between the different studies

Survey	Aim	Number of participants	EEG Collecting	Classification	Feature Extraction
(Gunawan et al., 2017)	Design a prototype of home automation for remotely switching on or off any household appliances based on the Internet of Things (IoT).	Unknown	Electrode's plate		
(Pelayo et al., 2018)	Control the robotic arm	3	Ultra-Cortex.	Steady State Visual Evoked Potentials (SSVEP)	"Fast Fourier Transform (FFT)"
(Bousseta et al., 2018)	Controlling a robotic arm Movement through Thought	4	EMOTIV EPOC headset	SVM	"Fast Fourier transform (FFT)" with "Principal Component Analysis (PCA)"
(Edla et al., 2018)	Control devices and appliances in the home based on the user's mental state	40	A single-channel Neurosky Mindwave Mobile headset	The random forest classifier was utilized	The statistical measurements
(Y. Xu et al., 2019)	Use of BCI for robotic arm control (reach and grasp).	11	The 32-channel Brain Products GmbH headset	LDA	Common Spatial Pattern (CSP)
(Korovesis et al., 2019)	Control the robotic arm	12	Electrode plate.	Multi-layer Perceptron (MLP)	Discrete Fourier Transform (DFT)
(Sun et al., 2020)	Develop a home care system (HCS) based on a BCI and smartphone. The HCS provides daily help for people with motor disabilities who do not have access to a caretaker.	22	Braintronics B.V. Company		
(Nasir et al., 2021)	Design and Implementation of a Brain Wave-Based System for Home Appliance Control.		Neurosky Mindwave Mobile 2 headset	BlueSMiRF module	Fast Fourier Transform (FFT)
(Chatziparasidis & Sfampa, 2022)	Give a case study of a BCI elevator system that could be included in a smart home to improve accessibility and mobility for individuals with disabilities.	5	Emotiv Epoch+		

(Amanuel & Alazzawi, 2023)	Create a smart structure based on electroencephalography (EEG) to help people with or without disorders easily and comfortably control their devices.	10	Open BCI Ultracortex Mark IV headset	SVM	Reconstruction Independent Component Analysis (RICA)
(Govindaraj et al., 2024)	Design a robotic system for controlling movement that is based on electroencephalogram (EEG) data	10	Electrode plate.	Machine Learning	
(Rahman et al., 2024)	designed a BCI device that enables direct communication between the human brain and a digital computer to help physically impaired patients.		Mind wave sensor		
(Arachchige & Nafea, 2025)	Control a smart home through an improved brain-computer interface (BCI) system for the disabled and the elderly.		EMOTIV Insight headgear		
M Al-Mohammadi et al.	Design and implement a smart system appliance to assist people with movement disability and elderly people.	25	Electrodes plates	CNN, SVM, and LDA	CNN features selected

6.5 Discussion

The experimental results demonstrate a high classification accuracy that surpasses the typical ranges, which typically fall between 85% and 95%, as reported in MI-EEG research. It is crucial to stress that these outcomes reflect the actual performance of the suggested model and have been thoroughly validated. Our preprocessing pipeline's rigor is the main reason for this better performance. We were able to uncover unique neural features that enabled more accurate classification by efficiently removing artifacts and improving the Signal-to-Noise Ratio (SNR) using ICA, specialized band-pass filtering, and a notch filter. As a result, the great accuracy attained highlights how important thorough data preparation is to optimizing the effectiveness of BCI systems.

7 Conclusions and Future Works

This research shows that support vector machines (SVMs) are superior to convolutional neural networks (CNNs) and linear discriminant analysis (LDAs) for MI-EEG signal classification. This study is optimistic about the potential for MI-EEG signal categorization accuracy to reach new heights, and we believe that the suggested machine and deep learning techniques might be an excellent option for BCI applications if more research follows our methodology and using CNN model for classification, which gives the best results.

This study focuses on designing smart systems for elderly and disabled individuals using human EEG signals. The system is cost-effective, small, responsive, and easy to use. Machine learning and deep learning algorithms (CNN, SVM, and LDA) were developed for classification. The system can control a smart home with a fan, buzzer, and lights using classified signals. This technology benefits individuals with impairments, such as the elderly and those injured while using the controls.

Future improvements are suggested as follows:

- Using a dataset of EEG signals with a group of participants with some medical conditions, because our work is applied to normal participants.
- Apply other deep learning and machine learning algorithms for classification.

Authorship Contributions

The first author conducted all aspects of the research, including study conception and design, data collection, analysis, interpretation of results, and manuscript preparation. The second and the third authors supervised the research process and provided scientific guidance and critical revision of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Data Availability

The data that support this study are available from the corresponding author upon request

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript

References

Amanuel, O., & Alazzawi, Y. (2023). Design and Implementation of EEG-Based Smart Structure. *International Journal of Intelligent Engineering & Systems*, *16*(1). https://doi.org/10.22266/ijies2023.0228.28

Arachchige, M. D. J., & Nafea, M. (2025). Brainwave and head motion control of a smart home for disabled people. In *Signal Processing Strategies* (pp. 195–215). Elsevier. https://doi.org/10.1016/B978-0-323-95437-2.00006-9

Balakrishnan, S., Vasudavan, H., & Murugesan, R. K. (2018). Smart home technologies: A preliminary review. *Proceedings of the 6th International Conference on Information Technology: IoT and Smart City*, 120–127. https://doi.org/10.1145/3301551.3301575

Bousseta, R., El Ouakouak, I., Gharbi, M., & Regragui, F. (2018). EEG based brain computer interface for controlling a robot arm movement through thought. *Irbm*, *39*(2), 129–135.https://doi.org/10.1016/j.irbm.2018.02.001

Chaddad, A., Wu, Y., Kateb, R., & Bouridane, A. (2023). Electroencephalography signal processing: A comprehensive review and analysis of methods and techniques. *Sensors*, *23*(14), 6434. https://doi.org/10.3390/s23146434

Chatziparasidis, I., & Sfampa, I. K. (2022). Residential buildings with brain-computer interface functionality: An elevator case study. *Building Services Engineering Research and Technology*, *43*(2), 261–272 .https://doi.org/10.1177/01436244211043997

Edla, D. R., Mangalorekar, K., Dhavalikar, G., & Dodia, S. (2018). Classification of EEG data for human mental state analysis using Random Forest Classifier. *Procedia Computer Science*, *132*, 1523–1532. https://doi.org/10.1016/j.procs.2018.05.116

Elshenaway, A. R., & Guirguis, S. K. (2021). Adaptive thresholds of EEG brain signals for IoT devices authentication. *IEEE Access*, *9*, 100294–100307. https://doi.org/10.1109/ACCESS.2021.3093391

Govindaraj, R., Ranjith, S., Deepthi, K., Babu, K. K., Bodkhe, R. G., & Amer, A. (2024). Developing an Electroencephalogram Based Robotic Motion Control System Using Brainwaves Enabled Signal Processing Technique. *2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*, 1–6. https://doi.org/10.1109/ICSES63760.2024.10910554

Graimann, B., Allison, B. Z., & Pfurtscheller, G. (2010). *Brain-computer interfaces: Revolutionizing human-computer interaction*. Springer Science & Business Media. https://doi.org/10.1007/978-3-642-02091-9

Gram-Hanssen, K., & Darby, S. J. (2018). “Home is where the smart is”? Evaluating smart home research and approaches against the concept of home. *Energy Research & Social Science*, *37*, 94–101. https://doi.org/10.1016/j.erss.2017.09.037

Gunawan, T. S., Yaldi, I. R. H., Kartiwi, M., Ismail, N., Za’bah, N. F., Mansor, H., & Nordin, A. N. (2017). Prototype design of smart home system using internet of things. *Indonesian Journal of Electrical Engineering and*

Computer Science, *7*(1), 107–115. https://doi.org/10.11591/ijeecs.v7.i1.pp107-115

Ibrahim, A. K., Hassan, M. M., & Ali, I. A. (2022). Smart Homes for Disabled People: A Review Study. *Science Journal of University of Zakho*, *10*(4), 213–221. https://doi.org/10.25271/sjuoz.2022.10.4.1038

Jacobsson, A., Boldt, M., & Carlsson, B. (2016). A risk analysis of a smart home automation system. *Future Generation Computer Systems*, *56*, 719–733. https://doi.org/10.1016/j.future.2015.09.003

Korovesis, N., Kandris, D., Koulouras, G., & Alexandridis, A. (2019). Robot motion control via an EEG-based brain–computer interface by using neural networks and alpha brainwaves. *Electronics*, *8*(12), 1387. https://doi.org/10.3390/electronics8121387

Lukoyanov, M. V, Gordleeva, S. Y., Pimashkin, A. S., Grigor'ev, N. A., Savosenkov, A. V, Motailo, A., Kazantsev, V. B., & Kaplan, A. Y. (2018). The efficiency of the brain-computer interfaces based on motor imagery with tactile and visual feedback. *Human Physiology*, *44*, 280–288. https://doi.org/10.1134/S0362119718030088

Nasir, T. Bin, Lalin, M. A. M., Niaz, K., & Karim, M. R. (2021). Design and implementation of eeg based home appliance control system. *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, 445–449.https://doi.org/10.1109/ICICT4SD50815.2021.9396982

Pelayo, P., Murthy, H., & George, K. (2018). Brain-computer interface controlled robotic arm to improve quality of life. *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 398–399. https://doi.org/10.1109/ICHI.2018.00072

Rahman, M. S., Sourav, M. S. I., Hossain, M., Sultan, R. Bin, Hossain, M. R. T., & Rahaman, M. F. (2024). Neuro-Wave-Controlled Home Automation System for the Physically Disabled. *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, *2*, 1–5. https://doi.org/10.1109/IATMSI60426.2024.10502774

Rashid, M., Sulaiman, N., PP Abdul Majeed, A., Musa, R. M., Ab. Nasir, A. F., Bari, B. S., & Khatun, S. (2020). Current status, challenges, and possible solutions of EEG-based brain-computer interface: a comprehensive review. *Frontiers in Neurorobotics*, *14*, 25. https://doi.org/10.3389/fnbot.2020.00025

Retief, M., & Letšosa, R. (2018). Models of disability: A brief overview. *HTS Teologiese Studies/Theological Studies*, *74*(1). https://doi.org/10.4102/hts.v74i1.4738

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on Biomedical Engineering*, *51*(6), 1034–1043. https://doi.org/10.1109/TBME.2004.827072

Sun, K.-T., Hsieh, K.-L., & Syu, S.-R. (2020). Towards an accessible use of a brain-computer interfaces-based home care system through a smartphone. *Computational Intelligence and Neuroscience*, *2020*, 1–17. https://doi.org/ 10.1155/2020/1843269

Teplan, M. (2002). Fundamentals of EEG measurement. *Measurement Science Review*, *2*(2), 1–11.

Xu, X., Fu, S., Qi, L., Zhang, X., Liu, Q., He, Q., & Li, S. (2018). An IoT-oriented data placement method with privacy preservation in cloud environment. *Journal of Network and Computer Applications*, *124*, 148–157. https://doi.org/10.1016/j.jnca.2018.09.006

Xu, Y., Ding, C., Shu, X., Gui, K., Bezsudnova, Y., Sheng, X., & Zhang, D. (2019). Shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance. *Robotics and Autonomous Systems*, *115*, 121–129. https://doi.org/10.1016/j.robot.2019.02.014

Yang, C., Mistretta, E., Chaychian, S., & Siau, J. (2017). Smart home system network architecture. *Smart Grid Inspired Future Technologies: First International Conference, SmartGIFT 2016, Liverpool, UK, May 19-20, 2016, Revised Selected Papers*, 174–183. https://doi.org/10.1007/978-3-319-47729-9_18