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Design and Implementation of EEG-Based Smart Structure

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Abstract: It has been shown recently that there is a need to design smart structures, such as smart houses, in order to be controlled in different ways. That will be in high demand due to its usefulness for some people who are incapable of reaching some control units that require direct interaction with human beings. In this paper, we propose and develop a new enhanced electroencephalography (EEG)-based smart structure setup that can be utilized to assist people, with or without disorders, to control devices in an easy and comfortable way. Ten people of a wide range of ages (20–65) and both genders actively participated in this research. Consequently, eight EEG channels are employed in this study to cover most of the brain's regions, and the protocol utilized is suitable for people with disabilities and immobility. Finding the standard or common features for the wide range of participants is a challenge. To mitigate this, reconstruction independent component analysis (RICA), which is a modified technique of the conventional independent component analysis (ICA), was used to obtain the optimum features. In addition, the proposed modified support vector machine (SVM) model classifies the selected features into different classes with the capability of removing the high noise and overlaps that cause misclassification. The identified classes are responsible for actuating the smart house's actuators based on participant status. Real-time classification of multi-channel EEG data into brain wave components, visualization of results, and control of the devices are carried out using MATLAB and an embedded system. With the proposed model, there is only one case of overlap between the classes, compared with 74 cases with conventional SVM. Consequently, the results of misclassification reach zero, and the proposed model enables control of a smart room based on brain waves, achieving an overall accuracy of 98%. With future improvement, the acquired findings would urge the usage of the suggested EEG-based smart structure, which might be helpful for immobile individuals.

Keywords: EEG signal, Feature extraction, Machine learning, Brain waves, SVM, RICA.

1. Introduction

Complex interconnected neural network of the human brain is responsible for the human behaviors and emotions. Among these behaviors, the intention and try of human to do some activities such as opening or closing a door, drinking water and much more. For some people, it is desired for different reasons to implement some of these activities contactless and based on their intention.

This can be possible, if we can extract their EEG signals and interpret them using smart techniques of artificial intelligence (AI), then we can build up the orders that are responsible of implementing the required activities. However, the interpretation of EEG signals is not straight forward and requires complex analysis to solve its difficult classification problem.

A combination of complex network and deep learning has been developed to achieve better feature extraction classification of EEG signals [1].

EEG signal has been exploited to control external devices throughout the brain computer interface (BCI) [2] However, in order to get obvious results from BCI system a multichannel EEG should be utilized.

That requires complex mathematical relationships to overcome lower classification accuracy resulted from individual brain structure variations. Fortunately, a lot of work has been carried out to solve this problem using steady state visual evoked potential (SSVEP)-based BCI system [3-5]

[5] For example, conducted SSVEP experiments for multi-directional motion control of robot and explained their achievement of high efficient results compared with fatigue state.

In addition, many researchers are working on BCI systems that let disabled people use their brain signals to control a wide range of equipment or devices, from wheelchairs to various home appliances.

[6] and [7] used BCI to control the robotic arm based on the thoughts and brain waves, however, the variety of ages among the participants was restricted. [8] Showed how the devices and home appliances could be controlled using IoT and depending on the state of user’s mind. [9] Described the BCI-based system that controls the motion of a robotic vehicle using brainwaves. In contrast, the issue in [8] and [9] is that the authors utilized a limited number of channels (less than 2) for signal collection; hence, only a small portion of the brain was studied (limited regions).

[10] Used the wireless electroencephalogram headset to control a smart house or medical appliances. The researchers collected data from 60 subjects (50% were male and 50% were female); in addition, they selected 50 people aged 50 or older. Nevertheless, the authors only used a single channel to collect brain waves, and they did not describe the model's accuracy. [11] Designed a BCI system to control four popular messaging applications on a smartphone. The overall online accuracy was found to be 86.14 %, but the feature extraction procedure lacked a clear explanation, and the age range of subjects was specific (21.6± 2.5 years). [12] Presented a prototype of an elevator with a BCI system for disabled people to increase their access and mobility within a house or a building. However, the classification technique was not clear, and the authors did not indicate the accuracy of the model. [13] Developed a BCI-based home care system (HCS) that enables end-users or motor-disabled people to independently manage their home appliances or make an emergency phone call. The developed model in [13] failed to provide acceptable results for all subjects, where two participants out of 15 were not able to perform correctly. Consequently, the accuracy rate for this application of a home care system was relatively low.

Although significant work has been done in this field as described, a comfortable, accurate, and easy BCI model appears to be lacking in the literature. Therefore, in this paper, the major objective is to construct a smart structure that would make it easier and more comfortable for disabled people to control devices where they only need to think about doing an

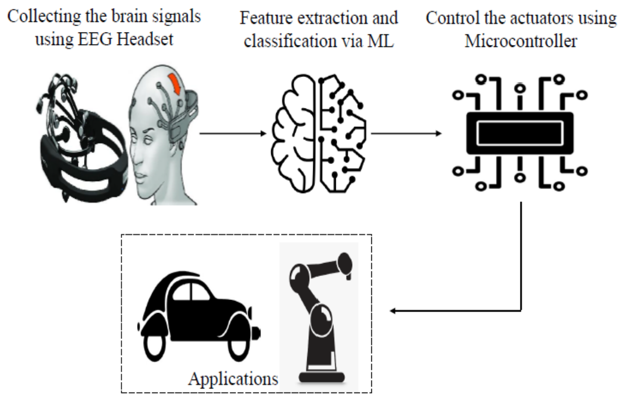

Figure. 1 Brain computer interface based on EEG signals extraction to control external smart structure

action. Thus, this paper presents an intelligent model that includes a number of actuators controlled by the signals and commands generated by an embedded Electronic unit, as shown in Fig. 1.

This paper proposes a convenient protocol for collecting EEG signals and a new-enhanced model. The model identifies the features extracted from the EEG signals measured from 8 channels across a wide range of ages (10 participants, 20–65 years old). Besides, it can remove the overlaps among classes, providing high accuracy (zero misclassification cases).

The rest of the paper is organized as follows: Section 2 explains the theoretical approach, including the signals' collection, feature extraction, and classification algorithm. Section 3 presents the experimental work, including the used equipment, protocol, decomposition, and control of an application based on the obtained classes. Section 4 shows the results; discuss and compare them with the other studies. The last section, section 5, provides the conclusion of the study.

2. Theoretical approach

Before using the acquired EEG signals, standard preprocessing is applied. The signals are amplified to enhance their strength, filtering the artifact to extract the relevant information and digitized to be utilized properly. The five components: beta, alpha, theta, delta, and gamma of brain waves are responsible of any daily activity of every person. Hence, extracting their features is of high demand in order to interpret the ongoing expected idea, emotion and action [14]. This research, it is aimed to utilize one of the most accurate techniques used with BCI systems, the well-defined SVM classification technique, to get the human intentions of doing some important activities in order to be able in the future to implement the collected signals using artificial smart actuators. This will be in high demand, especially for people with disorders. Collecting the EEG signals was the first step, and it was one of the most important ones.

2.1 EEG signals collecting

The brain is one of the most complicated systems and many of its neurophysiological workings are still unclear. Hans Berger (The German psychiatrist) was the first person to record EEG signals and then publish a paper about scalp EEG. Since then, EEG has been used a lot to study the human brain [15]. A brain–computer interface, often known as a BCI, that is capable of translating the patterns of brain activity produced by a user into messages or commands that may be used by an interactive program [8]. Electroencephalography (EEG) is the typical method that is used for the measurement of the brain activity that is processed by the BCI systems [16, 17] by the electrodes placed on the scalp. The Ultracortex Mark IV headset is used to collect the signals, the voltage values collected are transmitted by cyton board to the computer which receive them by USB dongle and OpenBCI. The voltage values, as shown in Eq. (1).

$$[x] = \begin{bmatrix} x_{11} & \cdot & \cdot & \cdot & x_{18} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{i1} & \cdot & \cdot & \cdot & x_{i8} \end{bmatrix} \begin{bmatrix} F_{P1} \\ F_{P2} \\ C_3 \\ C_4 \\ P_7 \\ P_8 \\ O_1 \\ O_2 \end{bmatrix} \quad (1)$$

where

$[x]$= Raw data (voltage values measured by EEG electrodes.

$[F_{P1} \quad F_{p2} \quad C_3 \quad C_4 \quad P_7 \quad P_8 \quad O_1 \quad O_2]^T$ = EEG channels.

The voltage that is calculated via the Hodgkin-Huxley model was in (mV) [18], and the voltage that is measured by EEG electrodes was in (μV) [19, 20]; due to the drop voltage that happened during the dendrites and skull layers. Then the feature extraction is applied to the collected signals.

2.2 Feature extraction

The purpose of feature extraction is to convert the obtained EEG signal into a set of features that can then be used for classification [21, 22]; wherefore the raw data collected by EEG are translated to features using the Reconstruction Independent Component Analysis (RICA) algorithm which is based on minimizing an objective function, and mapping input data to output features. The new representation of the observations (S) can be obtained using the equation below once the optimum W has been found

$$X = \mu + (S * A) \quad (2)$$

$$S = W * (X - \mu) \quad (3)$$

Where

W=A^{-1}

$W \in R^{k*n}$

RICA works by replacing the orthogonality $(ww^T = I)$ in $min_w \|WX\|_1$ of the standard Independent Component Analysis (ICA) with soft reconstruction penalty. This enhancement allows the algorithm to learn more features than the dimensionality of the raw data (input data), and it is also much faster and less sensitive to pre-processing errors [23-25].

$$min_w \ \lambda \|WX\|_1 + \frac{1}{2} \|W^T W X - X\|_2^2 \quad (4)$$

where

X: Raw data

A: Mixing matrix

μ: Vector of offset values (mean)

W: Weight matrix (unmixing matrix) that maps the raw data x to features s.

S: Features vector

k: Number of features

n: The amount of data vectors in x

λ: Regularization parameter

The new output features S (that resulted from RICA and Transform method), are classified using Machine learning (Support Vector Machine (SVM)) algorithm.

2.3 Classification

One of the more accurate classifiers in BCI research is the Support Vector Machine (SVM) [26]. SVM distinguishes the distinct classes to classify by using a hyperplane or groups of hyperplanes in a very high dimensional space [6]. The performance of a specific linear SVM is determined by the tradeoff parameter, which balances the relative importance of minimizing the training error and maximizing the margins between classes, both of which have a significant effect on the classifier’s generalization performance [27]. The SVM-based classifier’s accuracy is determined by the kernel applied. A Gaussian kernel or a Radial Base Function (RBF) is commonly used in the case of a BCI system.

The equation of hyperplane can be given as [28]

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 \dots \quad (5)$$

$$= w_0 + \sum_{i=1}^{m} w_i x_i \quad (6)$$

$$= w_0 + w^T x \quad (7)$$

$$= b + w^T x \quad (8)$$

Where
w_i: Vectors $(w_0, w_1, w_2, w_3, \dots w_m)$
b: biased term (w_0)
x: Variables (extracted features S)
The hypothesis function

$$y = \begin{cases} +1 \; if \; w^T x + b \; \geq 0 \\ -1 \; if \; w^T x + b \; < 0 \end{cases} \quad (9)$$

The point above or on the hyperplane is classified as positive class, and the point below the hyperplane is classified as negative class, as shown in Fig. 2. In addition, the kernel technique, which is the most well-known part of the SVM, Kernel functions are sometimes referred to as "generalized dot products" since they compute the dot product of two vectors x and y in a (very high dimensional) feature space [29, 30].

$$maximize_\alpha = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(X_i^T . X_j) \quad (10)$$

Subject to $\alpha_i \geq 0$ for all $i = 1,2, \dots, n$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$
$if \; \alpha_i > 0$ Then x_i is a support vector, and when $\alpha_i = 0$, it means that x_i is not a support vector [31].

The SVM Gaussian kernel maps data from feature space to higher-dimensional kernel space, resulting in nonlinear separation in kernel space [32].

$$k(x_i, x_j) = \exp\left(-\gamma \left\| x_i - x_j \right\|^2\right) \quad (11)$$

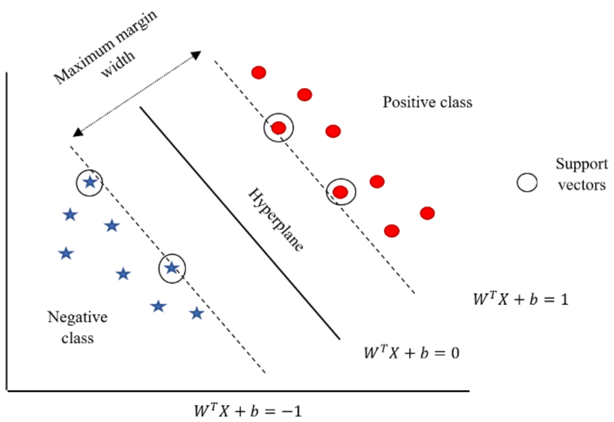

Figure. 2 SVM hyperplane

$$\gamma \; k = \sqrt{p} \quad (12)$$

where
$k(x_i, x_j)$: Gaussian Kernel function
$\left\| x_i - x_j \right\|$: Euclidean distance between x_i & x_j
γ: It is a parameter that determines whether the model is overfit or underfit. (When it increases, the model becomes overfit, and when it decreases, the model becomes underfit).
p: The number of features or the dimension size of x_i.

Finally, the data is classified as $\begin{cases} Posative \; classes \\ Negative \; classes \end{cases}$

After the classification, the output decision controls the smart room, which contains (lights, curtain, and a fan). For instance, if the data is classified as a positive class, the lights and fan turn on, and the curtain closes. When the data is classified as a negative class, the lights and fan turn off, and the curtain opens. All these process steps are explained in the flow chart shown in Fig. 3.

3. Experimental work and methods

3.1 Volunteers recruitment and EEG recording strategy

The protocol that used for collecting the EEG signals was divided into four segments, each one was followed by 3 seconds resting period. The steps were as following: opening the eyes for 1 minute with relaxation and concentration, closing the eyes for 1 minute with relaxation, then opening the eyes with relaxation and counting down 100 to 0 by 5, and finally closing the eyes with relaxation and counting down 100 to 0 by 5, as the scheme shows in Fig. 4.

Eleven volunteers of various genders and ages were recruited from within and outside the University of Baghdad/AL Khwarizmi College of Engineering to collect their EEG signals (as shown in Table 1 and Fig. 5. During the collecting of brain waves via EEG headset and OpenBCI, the signals are filtered by notch filter (50 Hz) and band pass filter (1-100 Hz) without smoothing. All received proper consent under an approved protocol from Al-Khwarizmi College of engineering / Mechatronics engineering department. The headset was adjusted based on the head size of each participant.

3.2 Open-BCI ultracortex mark IV headset

Open-BCI Ultracortex Mark IV headset 16 channels was utilized to collect the brain waves which is shown in Fig. 6, and the EEG electrodes were Placed according to 10-20 system. Eight channels only from the sixteen were used in the work,

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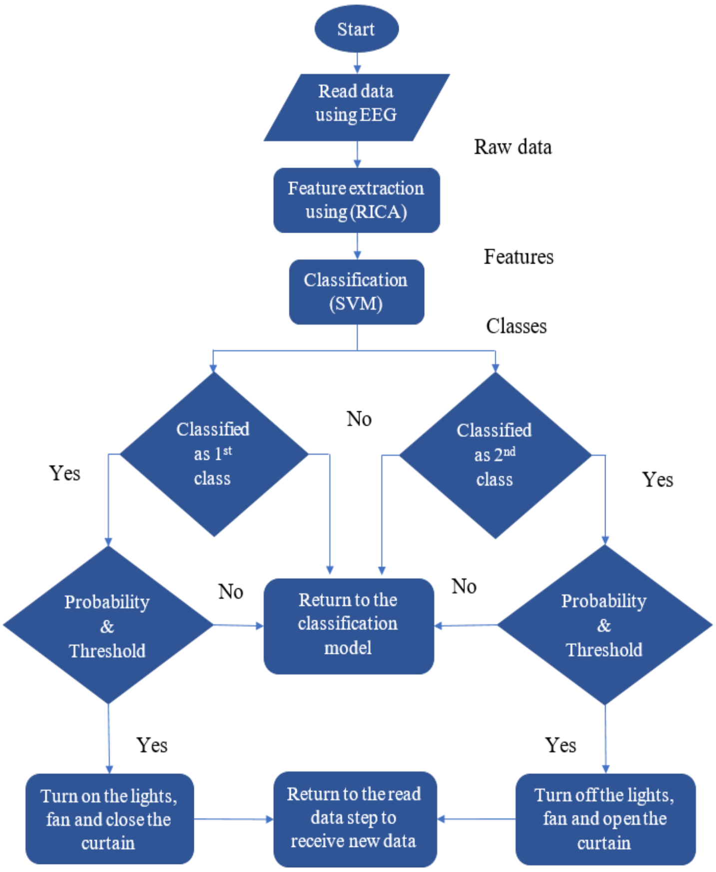

Figure. 3 Flow chart of the work

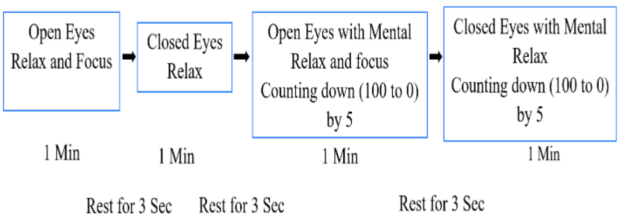

Figure. 4 The followed protocol in extracting the participants EEG signals


Figure. 5 The participants during EEG signals collecting

which are: $F_{P1}, F_{P2}, C_3, C_4, p_7, P_8, O_1$ and O_2 . The Ultracortex is a 3D-printable open-source headset that can receive EEG signals from any OpenBCI Board [33, 34] The most recent version of the Ultracortex is the Ultracortex Mark IV, which uses dry EEG sensors in its design. In addition, the Cyton OpenBCI Board is an 8-channel neural interface with a 32-bit processor that is Arduino-compatible.

The Cyton OpenBCI Board is used PIC32MX250F128B microcontroller, which provides plenty of local memory and excellent processing speed. The chipKITTM bootloader and the most recent OpenBCI firmware are pre-installed on the board. Up to 16 channels of brain activity

Table 1. The age and gender of the participants

participant	Age	Gender
1	20 - 30	Male
2	20 - 30	Female
3	20 - 30	Male
4	20 - 30	Female
5	30 - 40	Male
6	30 - 40	Male
7	40 - 50	Male
8	40 - 50	Male
9	40 - 50	Male
10	50 - 60	Male
11	> 60	Male

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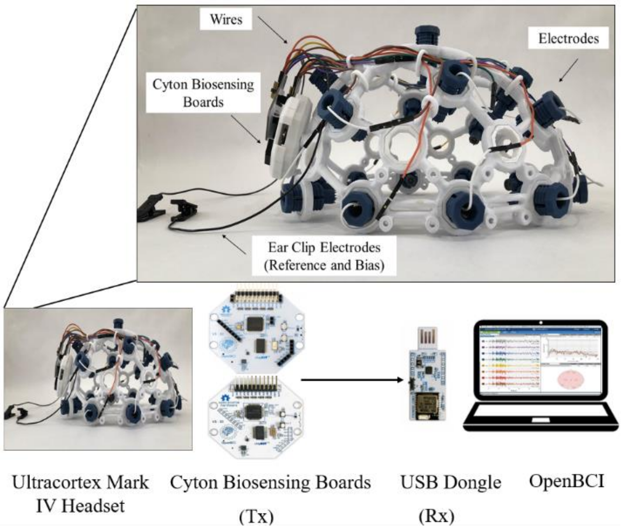

Figure. 6 EEG headset communication with computer system

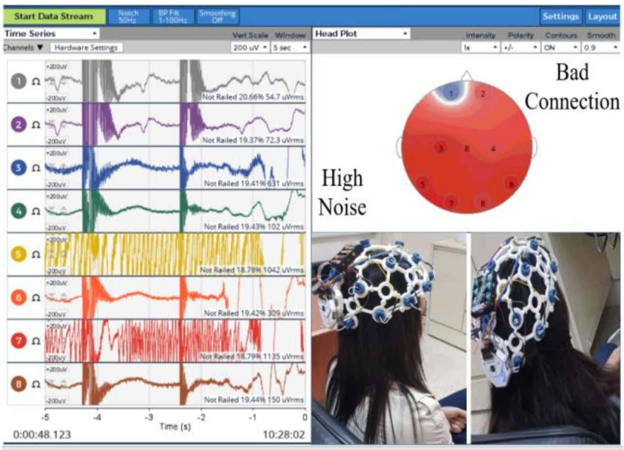

Figure. 7 The bad connection and high noise during the collecting of signals from women

(EEG), muscle activity (EMG), and heart activity (ECG) can be sampled using the OpenBCI Cyton Board and OpenBCI Daisy Module (which connects into the OpenBCI Cyton Board). An OpenBCI USB dongle and RFDuino radio modules allow the system to communicate wirelessly with a computer, using Bluetooth Low Energy as shown in Fig.6. Each of the Cyton Daisy Board's 16 channels is sampled at 125 or 250 Hz [35].

There were many problems with collecting EEG signals from women using the OpenBCI Ultracortex Mark IV headset, including high noise and a bad connection, as shown in Fig. 7.

Due to the long hair that wraps around the dry electrodes and prevents them from properly attaching to the scalp. The electrodes were like screws, and the wiring technique was ineffective, because the wireswere not specially designed or suited for this operation, so they may cut when the electrodes were tightened clockwise and counterclockwise in each session for each person.

3.3 Block diagram

The block diagram shown in Fig.8, illustrates the process of the work, starting with collecting the EEG signals and sending them wirelessly to the computer via OpenBCI, and ending with the control of the smart room using the collected brain waves.

3.4 Data selection

The collected signals were decomposed by independent component analysis (ICA) to separate the signals into components (as shown in Fig. 9) by multiplying the data by the weight matrix (unmixing matrix) according to the Eq. (13) [36].

$$u = wx \tag{13}$$

Where
u = ICA activity
w = Weight matrix
x = Data

At first, the decomposition was applied to all participants together, and the operation failed after Two hours and 17 minutes, because of the different atmosphere, place, light intensity, quietness, and age.

Then the decomposition was applied to each participant separately, as illustrated in Table 2 and Fig. 9. According to the Table 2, the best components were different from one participant to another due to different ages and circumstances (light intensity, place of collecting the signals and the noises around it) hence, the classification applied to all eight channels.

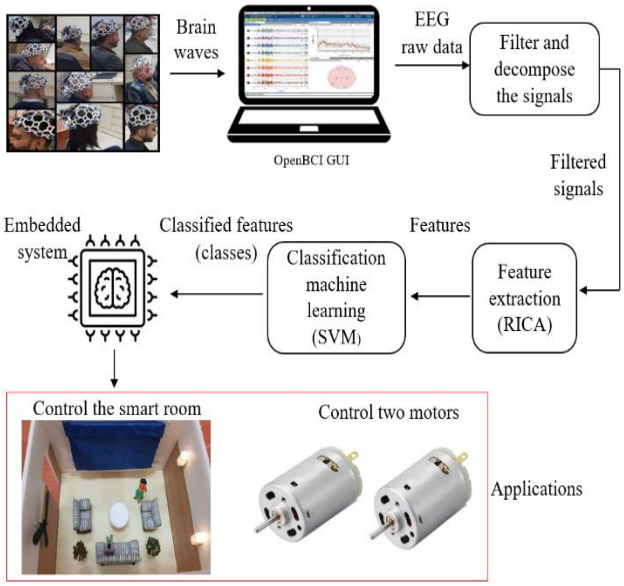

Figure. 8 The block diagram

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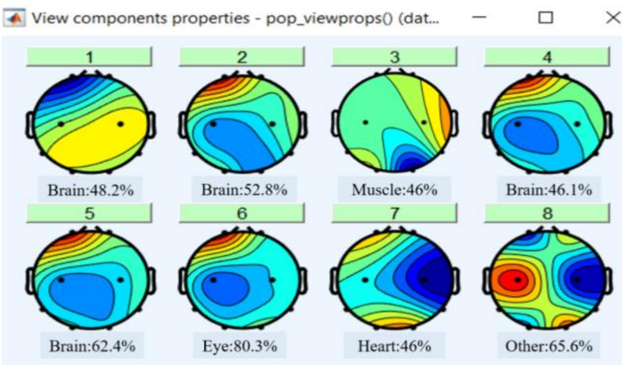

Figure. 9 Samples of the components properties after decomposition

3.5 Classification

First, all of the data were combined and categorized together. Only two sessions for each participant have been chosen because of the actions needed to control the smart room (on/off or open/close). The data were labeled according to their state (closed eyes, open with mental), then the data were translated into some features, and lastly, the support vector machine algorithm (SVM) was used to classify the features into two categories.
Fig. 10 shows the classification for the whole dataset and time period. There was high noise and overlap between the classes (misclassifications). Therefore, the technique used in this study was that the session for collecting the brain waves was segmented into many epochs, and the epochs that were responsible for the overlap between the classes were removed depending on the status of the participants. For instance, during the sessions of opening and closing the eyes with or without mental arithmetic, the numbers and calculations remained in consciousness for a few seconds before they faded [37]. Consequently, the participants still had some precipitates in their minds from the previous session and cause the overlaps.

Table 2. The best components for each participant after ICA decomposition

Participants	Closed Eyes	Open Eyes with Mental
1	3,4,5	3,4
2	2,8	1,2,7
3	7,2	4,6,8
4	4,5,7	2,4,6
5	3,4,8	2,6,8
6	1,2,4	2,4,5
7	7,3	1,4
8	2,5,7	6,7
9	1,2,5	5,6,7
10	2,3,4	2,3,5

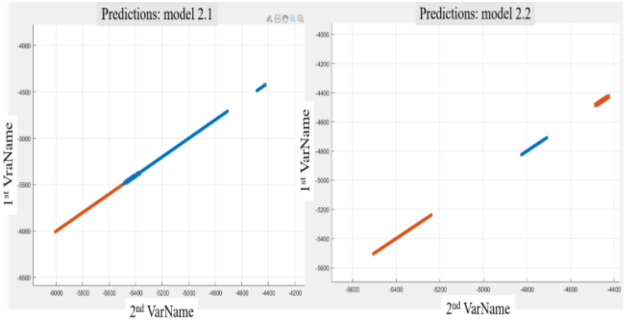

Figure. 10 Classification without the modification

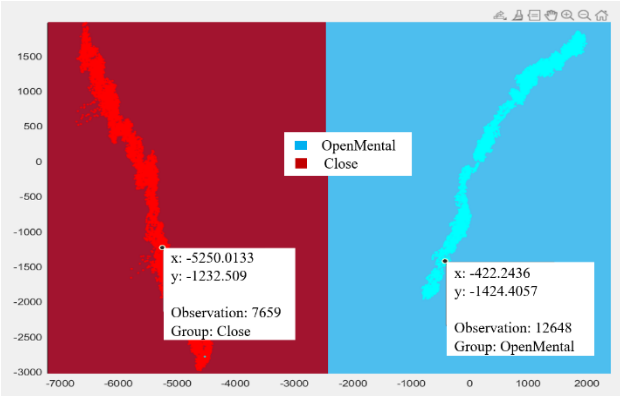

Figure. 11 Classification of with the hyperlink after the modification

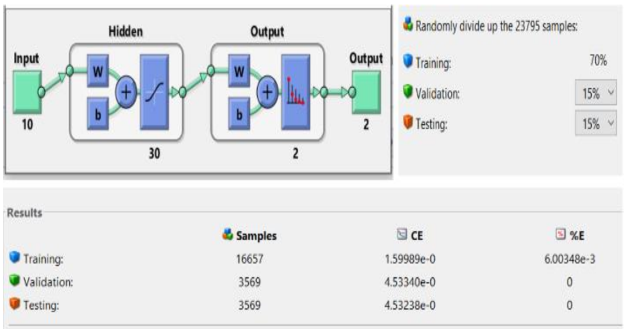

Figure. 12 Neural network

Fig. 11 shows the enhancement that achieved in the classification after the modification.

Moreover, the neural network was used to classify the data and compare the results with the SVM model. The neural network pattern recognition was used with 30 hidden layers, 10 inputs, and 2 outputs, as shown in Fig. 12, to obtain more details about (training, Validation, test) confusion matrix, ROC curve, and error histogram, as well as compare the results with (SVM) model.

3.6 Control an application

The trained model was used to predict and test the new signals. Two classes were chosen only to control the two actions of actuators (open/close and on/off)

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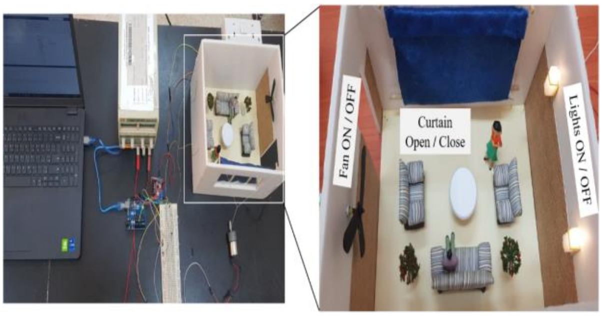


Figure. 13 Control the smart room with the hardware circuit

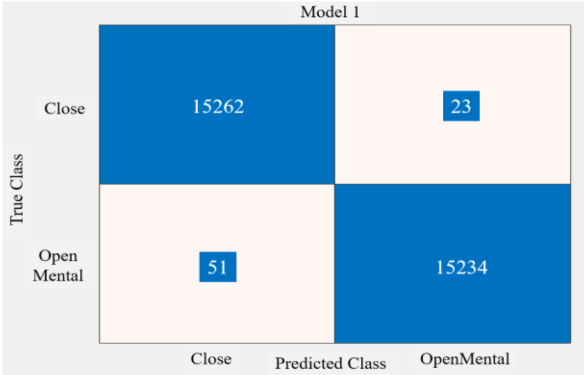
using a simple protocol and several actions. This makes the control of a smart room easy, convenient, and useful for immobile and disabled people without any movement or effort. The first class (closed eyes) was labeled as number 1, while the second class (open eyes with mental) was labeled as number 2. The application was controlling the smart room (shown in Fig. 13) based on brain waves. Moreover, the probability with a threshold was added besides the SVM classification. That means, to execute any action, the probability after test and prediction should become greater than the threshold value. The actuators were controlled by using a microcontroller as an embedded system, and according to the status of the new participant. The steps were as follows:

- Collect signals from a new person.
- Extract features from the raw data.
- Test them with the training model and
    1. If they belong to class A (closed eyes and relaxed) and the probability is greater than the threshold value, then the curtain will close and the lights and fan will turn on.
    2. Alternatively, if they belong to class B (open eyes with mentality) and the probability is greater than the threshold value, then the curtain will open and the lights and fan will turn off. As shown in Fig. 13.

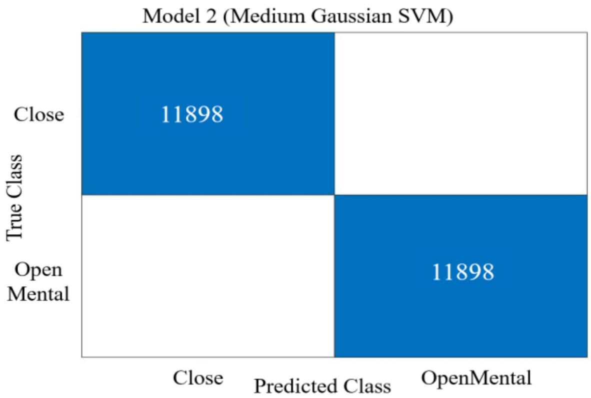
4. Results and discussion

Fig. 14 presents the confusion matrix, which describes the number of observations in the true and predicted classes. The figure shows the difference before and after the enhancement. Prior to using the technique, there were (74) cases of overlap between the closed and open mental classes, as shown in Fig. 14 (a). Whereas the Fig. 14 (b) shows the confusion matrix after the enhancement.

Fig. 15 shows the confusion matrix in detail for the training, validation, and test, using a neural network. There was only 1 case of overlap between the two classes and the results were as the SVM model shown above. Consequently, the results of misclassification reach zero, indicating that there was no overlap between classes and the classification



(a)



(b)

Figure. 14 (a) Confusion matrix before the modification and (b) Confusion matrix after the modification

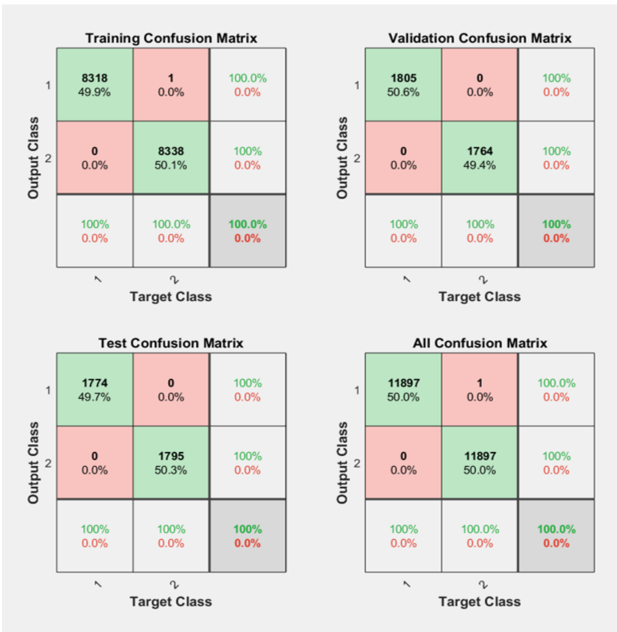


Figure. 15 Confusion matrix of training, validation and test

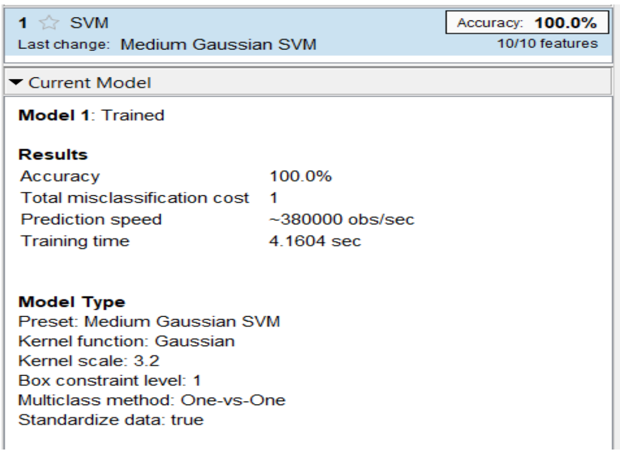
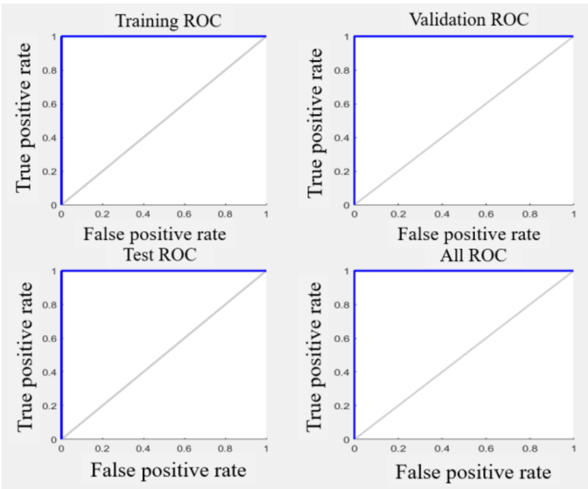
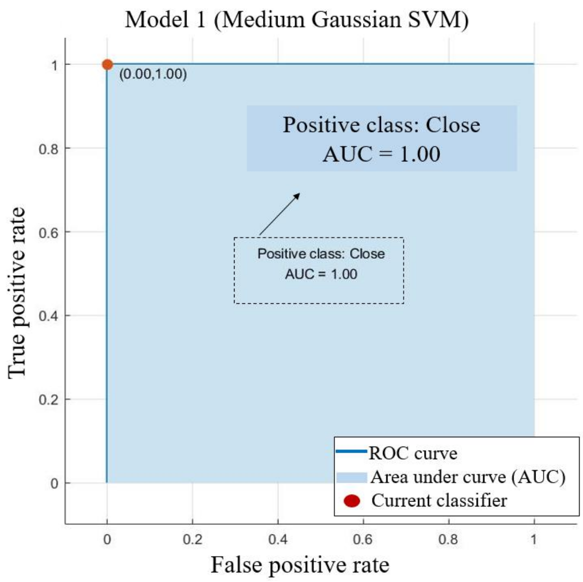


Figure. 16 Classification model information



(a)



(b)

Figure. 17 (a) ROC curve and (b) AUC curve

accuracy represented in Fig. 16. As well as, it illustrates the prediction speed, training time, kernel function, kernel scale, and the other model's information.

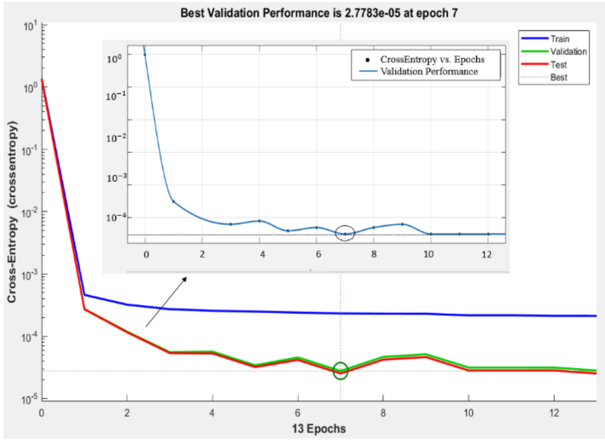


Figure. 18 Train, validation, test and the best performances

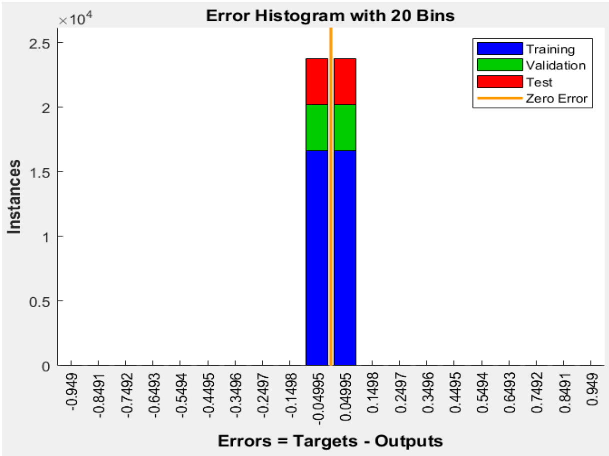


Figure. 19 Error histogram

Fig. 17 shows that the Receiver Operating Characteristics (ROC) curve and the Area under the Curve (AUC) were close to 1, indicating that the model had a high level of separability. ROC is a probability curve that indicates how much the model can distinguish between classes. Whereas AUC is a performance measure for classification issues, and represents the measure of separability and it indicates how well the model distinguishes across classes [38, 39]. When AUC is close to 1, it means the model is better and it has a high level of separability, as shown in Fig. 17 on the right. Moreover, the figure on the left, shows the ROC curve for training, validation, and test using a neural network. It is close to 1 as the SVM model results.

When the samples were randomly divided up in the neural network: 70% training, 15% validation, and 15% testing, the cross-entropy and percentage error were as shown in Fig. 12. The percentage error gives an indication of the proportion of samples that were incorrectly classified. A number of 0 indicates that there are no misclassifications, while a value of

Table 3. The related work

Study	The aim	No. of participant	Brain waves collecting	No. of channels	Feature extraction	Classification	Accuracy
[6] **(2018)**	Controlling a robot arm based on the user's thought	4 subjects (1 female, 3 males) aged between (20 - 29) years	EMOTIV EPOC headset	4	Principal Component Analysis (PCA) with Fast Fourier transform (FFT)	Support Vector Machine (SVM)	Averaged accuracy of 85.45%
[8] **(2018)**	Control home appliances and devices implemented in the field of (IoT), using concentration and meditation state of mind	40 subjects (33 males, 7 females)	Neurosky Mindwave Mobile	1	statistical measures	Random forest classifier	75% in predicting the classes
[7] **(2019)**	Control of a robotic arm (reach and grasp) using a brain–computer interface (BCI)	11 healthy subjects (9 males, 2 females) aged (24 – 30) for offline, and 5 for online	Brain Products GmbH	32	common spatial pattern (CSP)	Linear Discriminant Analysis (LDA)	Higher than 80%. For online, Individually for each participant for offline
[9] **(2019)**	Perform motion control in a mobile robot using brain waves	12 subjects 4 females, 4 males aged (20-28) and (2 female, 2 male) aged (32-40) years.	Gold-plated electrodes	2	Discrete Fourier Transform (DFT)	Multi-layer Perceptron (MLP) neural network	Overall accuracy 92.1%.
[10] **(2019)**	Design and assess a wireless system to help immobile, disabled, or elderly persons with daily tasks.	60 subjects (50% each male and female) (50 and older than 50 years old)	ThinkGear ASIC Module (TGAM)	1	Mean attention and time for each subject		
[13] **(2020)**	Develop a BCI-based home care system (HCS) that enables end-users or motor-disabled people to independently manage their home	15 healthy and 7 motor-disabled subjects	Braintronics B.V. Company	3	ERP components N200, P300, and N2P3 values		Average online accuracy was 81.8% and 78.1%, respectively

	appliances or make an emergency phone call.						
[11] **(2021)**	Control of four popular messaging apps operating on a smartphone (WhatsApp, Telegram, SMS, and e-mail)	12 subjects 6 males, 6 females aged (21.6 ± 2.5 years)	Brain Products GmbH	8	EEG channel (signals at a specific location), time following stimulus	standardized SWLDA from BCI2000	Overall online accuracy of 86.14%
[12] **(2022)**	Present a case study of an elevator BCI system that might be part of a smart home for disabled people to increase their access and mobility	5 subjects (9-46) years old (3 males, 2 females)	Emotiv Epoch+	14			The experiment to validate the concept was successful.
This paper	Construct a smart structure that includes number of actuators derived by a control signal generated from an embedded electronic unit	10 subjects (9 males, 1 female) Aged (20 – 65) years old	UltraCortex Mark IV	8	Reconstruction Independent Component Analysis (RICA)	Support Vector Machine (SVM)	Classification accuracy of 100% and overall accuracy of 98%

100 indicates that there are the maximum misclassifications. In addition, a good classification can be achieved by minimizing the amount of cross-entropy, because lower values are better, and zero signifies no error [40].

Fig. 18, also depicts the training, validation, test, and best performance, and it shows that the best validation performance is at epoch 7.

Fig. 19, illustrates the error histogram centered at zero, that means the predict values are equal to the target values, because the error histogram describes the distribution of neural network errors on testing instances. In other words, the error values show how the predict values differ from the target values. A histogram organizes numerical data into "bins" or "intervals" of equal width, and the height of each bar in a bin corresponds to the amount of data points contained in that bin. Moreover, all the details are discussed and compared with the most recent works, as shown in Table 3.

5. Conclusion

The current work presents the control of a smart room with a fan, curtain, and lights based on brain waves with a high level of classification. Eleven volunteers of different ages participated in collecting the signals, and a non-invasive BCI based on EEG is used for that. The signals of one of the females are neglected because of the problems explained and shown in Fig. 11. The other collected signals are categorized and labeled according to the participant status, (open eyes with concentration and mental arithmetic activity) and (closed eyes with relaxation). Then, finding common features for all participants in a specific action with the large difference in age range is not easy. The RICA algorithm is used to Translate the raw data into optimum features. Moreover, the numbers and calculations from mental arithmetic activity remained in consciousness for a few seconds before they have faded. That causes overlaps between the classes; therefore, an enhanced SVM model is utilized for the classification. The model reduced the misclassification to almost zero. In addition, achieved a classification accuracy of 100% and an overall accuracy of 98%.

Also, the results were checked with a neural network, and a high level of separation between the classes was reached.

Finally, the actual benefit of this study will be significant to people with disabilities, such as elderly people who cannot open doors and windows or simply move from their position. Also, those suffering from the usual activities of daily living and who cannot reach control devices.

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Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, supervision, and project administration have done by Y. Alazzawi.

Software, validation, formal analysis, data curation, visualization, and writing—original draft preparation have done by O. Amanuel.

Investigation, writing—review and editing, and resources have done by Y. Alazzawi and O. Amanuel.

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