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Intelligent assistant to predict and control the home appliances in user environment through brain computer interface using hybrid deep learning model

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ABSTRACT

Brain Computer Interface (BCI) is the fast-growing research area that focuses on establishing the symbiotic relation between human brain and artificial intelligence. BCI enable the users to directly communicate with a computer by means of brain activity. Disability of a person due to medical issues such as spinal cord injury or cervical issues makes him/her to depend on caretakers for operating the home appliances. With the advancements in BCI technology, disabled people can control the home appliances through their brain activity without depending on caretaker. The existing models have accessibility challenges for the disabled people in two aspects Viz. accuracy and interaction time. The lack of high prediction accuracy as well as longer interaction time makes the existing models ineffective for the usage. To address the issues, hybridized deep learning model comprising Stacked Denoising Autoencoders and Extreme Machine learning is proposed and examined in this research. The proposed model acquires and preprocess the brain data of user and predicts the user intention with the improved accuracy. The proposed model is compared with different existing models investigated in the literature. The proposed approach achieves the maximum testing accuracy of 91.8% with 70% of training (10,500 Sample) and 30% of test validation (4,500 Sample) on the brain data of single user and takes interaction time of 0.48 seconds. The evaluation results of model validate the effectiveness of the proposed methodology.

Keywords: Brain Computer Interface; Controlling Home Appliance; Extreme Machine Learning, Stacked Denoising Autoencoders;

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INTRODUCTION

A severe form of physical disability is mobility impairment. This affects the person daily life such as the ability to carry out work activities. Mobility impairment does not completely stop the person carrying out tasks but makes them very challenging. This includes simple tasks like switch on their home appliances such as Fan, Television, Light and Air conditioners. People with mobility impairment need support from caretakers to operate home appliances in their living room. People may be born with mobility impairment or get the disability due to medical side effects, illness, spinal cord injury, and cervical issues.

These days, the challenges of mobility impairment are well addressed by the introduction of disruptive technologies such as Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Internet of Things (IoT). Many lead IT industries such as Amazon, Google, and Microsoft have applied the technologies to build the intelligent assistant in order to help mobility impaired people. Amazon echo device help the disabled people to use smart speakers and get connected with gadgets such as light, television, door, and thermostat. Google home product helps people with disability to connect with IoT light bulbs, switching on or off without reaching to a light switch. Microsoft AI based app is helping the disabled people to control their home appliances through voice driven commands.

All these intelligent assistant devices from IT giants build the confidence among disabled people to achieve good level of independence in spite their physical limitations. A person with deaf and dumb disability has limitation in using these intelligent assistants which are normally controlled through voice or hand gesture commands. To address this limitation of intelligent assistance, many researchers have extensively used Brain Computer Interface (BCI) to analyze the brain data of disabled person and interpret the command and execute it to control the desired home appliances. Globally, many researchers are involved in interpreting the human brain activities and translate into commands for controlling the various applications such as music player, robotic arm, and phone dialing.

Researchers have extensively using different types of non-invasive BCI devices [1] such as Neurosky, Emotiv, Neurowear, and indendiX-Speller to read the brain data from the person. In this paper, brain activity of human is captured using the Emotiv EPOC 14+ EEG Sensors device. The rationale behind choosing EMOTIV EPOC over other BCI devices is that RAW EEG (Electroencephalogram) data of the human brain can be captured with a high quality. The quality of the brain data is very important to achieve good prediction accuracy using any ANN, ML and DL based model. EMOTIV EPOC provides the brain data with minimum noisy and redundant features. Hence, the research work uses the EMOTIV EPOC 14+ sensor data to build a model for achieving a higher accuracy without occurrence of model overfitting and under fitting.

There are many research efforts to apply different ML algorithms such as Support Vector Machine (SVM), Back propagation (BP), Decision Tree (DT) and Naïve Bayes (NB) on brain data of disable people in controlling various home appliances. Most important issue with ML/DL algorithms is correct selection of features from brain data and classifier in order achieve higher prediction accuracy.

The structure of the paper is as follows; Section 2 briefly describes the current start-of-art machine learning technique used in the domain. Section 3 presents proposed methodology used to carry out prediction of commands from brain profile. Section 4 discusses the implementation and results of Hybridized model. Section 5 presents the conclusion.

LITERATURE SURVEY

Many researchers have used non-invasive BCI technology to collect the brain profile of subject and processed it with their own model to predict the mental command of the subject. We carried out survey on prime studies related to our research work and discussed it in this section.

Authors [2] have used the combination of Fast Fourier Transform (FFT) and Back Propagation (BP) model to preprocess the signal and predict the mental command respectively. BP is supervised learning algorithm of ANN using gradient descent. The performance of the model is affected with its limitation of catastrophic forgetting. Once a model learns set of weights, any learning of new data causes the catastrophic forgetting.

Hundia [3] has developed an assistant that control the external devices such as robotic arms and wheel chairs using the alpha brain waves and its Mu rhythm. Author has focused on collecting brain data response while user makes the eye movements [4] such as opening, closing, moving left and right. Author has applied signal processing and filtering techniques to determine peak amplitude of alpha wave and its Mu rhythm [5]. Author has differentiated the eye movements based on the measured peak amplitude and controls the robotic arms and wheel chairs accordingly. Due to the occurrence of noisy feature in Alpha brain wave, the performance of the model is affected despite of using filtering technique.

Ambica and Sujatha [6] have used the FFT technique to analyze the Alpha and Beta brain waves of user in controlling robotic arm movement [7]. The performance of system is affected by not finding precise signal frequency due to the non-availability of quality samples for performing FFT [8]. Neurosky brainwave sensor [9] [10] is used to detect the brain signal amplitude while user making eye blinks. External devices are controlled according to brain attention values and eye blinks.

Authors [11] have introduced a framework comprising Hidden Morkov Model (HMM) and Discrete Fourier Transformation (DFT) to classify and pre-process the EEG waves respectively for operating a smart phone by disabled person. HMM can achieve classification accuracy of 68.69%.

Authors [12] have used the EMOTIV EPOC sensor to collect the brain wave while user is making facial expression such as movement of mouth, eyes, and brow. Authors have applied Decision Tree (DT) and Support Vector Machine (SVM) Techniques to classify the facial expression of the user from brain data. Authors have controlled the robotic movement based on the classification of facial expression. DT and SVM can achieve the classification accuracy 72.6% and 77.3%.

Authors [13] have used the P300 based BCI to collect the brain data of subject and classify the intention to control external devices [14], Authors have used Bayesian Linear Discriminate Analysis (BLDA) to classify the pre-processed brain data into different intentions.

Authors [15] have developed internet browser which works in conjunction with BCI. Disable people can use the browser to perform action like clicking hyperlink and scrolling on the web page displayed. P300 BCI system is used to collect the brain data and SVM used for the classification of user intention over the web page displayed in the browser.

MATERIALS AND METHODS

Architecture of Hybridized Learning Model

Accurate prediction of mental command is particularly important because it helps the disabled person in controlling the applications/devices without the support of caretakers. However, a correct mental command prediction is a challenging task. In this paper, hybridized learning model is proposed to make a correct prediction of user commands. Figure 1 depicts the detailed architecture of the proposed model. The proposed work has been divided into 3 layers that are Brain data acquisition layer, Pre-processing layer, and hybridized machine learning model layer. Further, the third layer is divided into Stacked Denoising Autoencoders (SDAEs) and Extreme Machine Learning. The proposed model is investigated to improve the prediction accuracy in recognizing the commands of the user.

Brain Data Acquisition Layer: Accuracy of the prediction model is heavily depending on the quality of the user brain data. In this research work, RAW EEG of user brain is collected as input data and used it in the process of building a model. Brain data acquisition is carried out with the support of EMOTIV EPOC 14+ Channel EEG Headset. The headset has built-in sensors for recoding electrical signal generated by brain activity. EPOC 14 +, which is a research-oriented wireless headset that records 14-channel EEG. It has the capability to scale as well as capture the brain activity of user at any point of time. The headset can be connected to mobile devices and personal computer through Bluetooth. The headset supports both Bluetooth and Nordic protocol and easy to carry the device anywhere.

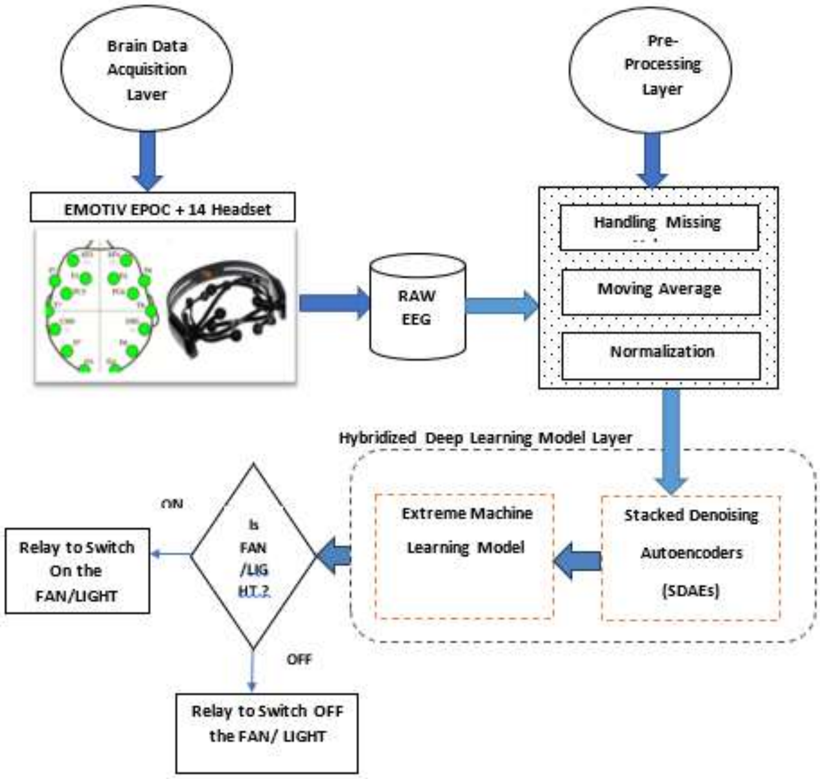

Figure 1. Architecture for the prediction of Mental Commands using Hybridized Deep Learning Model

EMOTIV EPOC 14+ headset offers the detections such as mental commands, Facial expression, performance metrics and RAW EEG. In this work, EPOC 14+ channel has been used to collect the brain data from 14 reference points of the brain. Figure 2 shows the 14 sensors locations and 2 reference points of the sensors connected with the Headset. The RAW EEG wave from the 14 reference points of the Headset is collected and used as input data for the model. Each channel has its own label based on its position on the head: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The sampling frequency of the device is 2048 Hz. With the device built-in software tool, developer can read electrical potential values from all the sensors during the brain activity of the user. After establishing a valid session with EEG EPOC +14 channel Headset, the various type of data streams can be received from it. Each data stream is identified by the name.

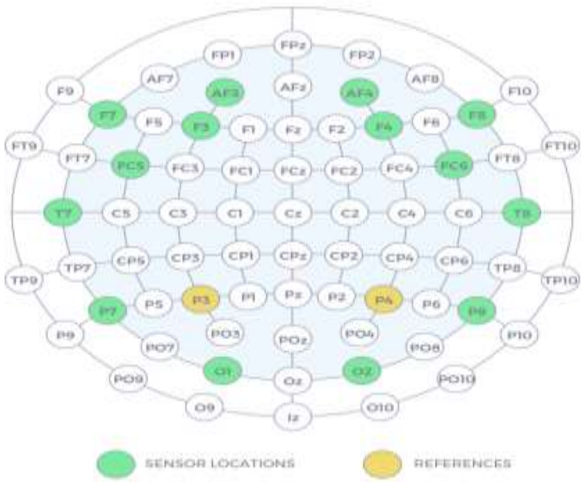

Figure 2. EMOTIV **EPOC+ 14 SENSORS LOCATIONS AND REFERENCES**

In this work, **RAW EEG data set of user** is collected through EPOC +14 channel Headset when user intends to switch ON/OFF the FAN. Table 3 shows the different fields in each tuple of the data set. The first 14 columns represents 14 sensor EEG values got from all the sensors. Dataset contains 15,000 samples that are measured response values (in micro Volts) from 14 sensors placed on the user scalps.

Pre-Processing Layer: Dataset collected from EPOC +14 sensors are subject to pre-processing for preparing it as suitable input to hybridized learning model. During the data collection, there is a possibility for missing values due to malfunctioning or poor contact of any sensors placed on subject scalp. In this work, missing values are handled using the imputation method called Last Observation Carried Forward (LOCF). According to this method, if the sensors are failed to give a value, then the last observed value of sensor on the dependent variable is used for filling the missing value. In the next step, moving average smoothing technique is used to remove the fine-grained variation between time steps. In this work, Dataset is built based on response values from 14 different sensors over the period of 2 seconds. In this work, a rolling function is used to automatically group the observations into a window. The size of window is 3. Once the windows is created, the transformed value at time (t) is calculated as mean value for the past 3 responses as given in the following Equation (1.1)

$$R(t) = \frac{R(t-2)+R(t-1)+R(t)}{3} \quad (1.1)$$

R (t) is response value from all the sensors at Time 't'.

In the next step, normalization is performed on the dataset to make it suitable for giving as input to deep learning model. In this work, min-max normalization technique is used to scale the response value so that it falls in a smaller range, such as 0.0 to 1.0. Min-Max normalization is performed on the dataset according to the following Equation (1.2)

$$R_{new} = \frac{R_{old} - \min(SA)}{Max(SA) - Min(SA)} \left(new\_\max(SA) - new\_\min(SA)\right) + new\_\min(SA) \quad (1.2)$$

Where R_{new} = new respond sensor value

R_{old} = old respond sensor value

Min (SA), Max (SA) are the minimum and maximum absolute value of sensor attribute respectively.

new_max(SA), new_min(SA) is the max and min value of the range (1 to 0).

Hybridized Learning Model Layer: The proposed hybridized deep learning model comprises Stacked Denoising Autoencoder(s) (SDAEs) [16] and Extreme Machine learning. The main objective of the Hybridized deep learning model is to classify the intention of the user from their brain activity. Generally, the performance of classifier is degraded by the presence of noisy features in the dataset. Hence, it is important to improve the quality of dataset by reconstructing the original input from noisy data in the dataset.

Stacked Denoising Encoder(s)

In the proposed model, the role of SDAEs is to reconstruct the original input from the noisy features available in the brain profile of the user. SDAEs is constructed with many number of de-noising autoencoders, which are deeply stacked one over another. During the training process, each layer of SDAEs attempts to reconstruct input from noisy feature based on the concept of minimizing errors. SDAEs is divided into two parts where all the layers in first part performs encoding operation and second part perform decoding operation. The feature representation of the corrupted and noise in the input is learned through the encoding operation. The cleaned input is constructed from the noisy feature through the decoding operation. During the subject interaction with a model, EMOTVE EPOC Headset captures the brain activity of the subject and shares it with a computer as 'N' vector of values. In the proposed model, the R-Layer SDAE used in getting solution as per the equation given below

$$\min_{W_r b_r} ||N - N_r||^2 + \lambda \sum_r ||W_r||^2 \quad (1.3)$$

Where N_r is the layer r[th] output in network. W_r and b_r represents the weight matrix and bias vector of the layer r in stacked network respectively.

After the training of model, the actual feature is reconstructed from a $N_{r/2}$ layer of the network. In the SDAE model, each of autoencoders in the layer comprises of input, hidden and output layer. The output layer of the model is set with the constraint of generating values that are close to the input. The model attempts to find the hidden representation h(y) of the input vector 'y'. The model transforms the given input vector 'y' to hidden representation $h(y) \in N^s$, where's' and 'N' are the number of hidden units and input units respectively.

$$h(y) = g(W^{(1)} y + b^{(1)}) \quad (1.4)$$

where g(.) is sigmoid activation function. $W^{(1)} \in R^{(s.N)}$ denotes weights from input unit to the hidden units. $b^{(1)}$ denotes the bias of the hidden unit. The activation function is given by the following equation

$$g(y) = \frac{1}{(1+\exp(-y))} \quad (1.5)$$

The hidden representation h(y) is used to reconstruct the input 'y' without any noisy feature by using the following equation which tries to minimize the difference between y and y'

$$y' = f(W^{(2)} h(y) + b^{(1)}) \quad (1.6)$$

In the proposed model, the corrupted input is induced in the dataset by introducing noises to actual input. The quantity of noise is kept as 40% on the input dataset. According to the Equation 1.6, our model takes an attempt to clean the corrupted feature by generating the output which is most similar to the input. The process of reconstructing the input is iterated till the minimized loss achieved through the loss function. The condition for exit of the iteration is set to achieve minimum loss value between the corrupted input and output node.

Extreme Learning Machine

In this work, ELM is used to perform classification task on the user brain profile. As discussed in the previous section, SDAE's is used to reconstruct the original input from all the corrupted input available in the brain profile of user. After reconstructing the corrupted features, brain profile is fed to ELM for performing the classification task of finding the intent of the user. ELM [17] are feedforward neural networks which are well known for achieving excellent generalization and fast learning compared with other back propagation neural networks. In this work, single hidden layer ELM is used to perform the classification tasks. According to ELM algorithm, initially random weight W_i and b_i are assigned to the nodes in Hidden Layer. The output of the network is computed according to the following equation

$$G_L(x) = \sum_{i=1}^{L} \beta_i \, f_i(x) \quad (1.7)$$

$$= \sum_{i=1}^{L} \beta_i \, f(w_i * x_j + b_j) \quad (1.8)$$

Where j = 1,…,N

Where 'L' represents hidden units, 'N' is a number of training samples,' β' is a weight vector between the hidden layer and output, 'w' is a wieght factor between input and hidden layer,'f' is an activation fuction, 'b' is a bias vector 'and 'x' is an input vector.

The value of 'β' is computed using the following Equation

$$\beta = H^{-1} T \quad (1.9)$$

Where 'H' is Matrix of order (N x L) and it is given by

$$H = \begin{bmatrix} f(w_1 * x_1 + b_1) & \ldots. & f(w_L * x_1 + b_L) \\ \ldots & .. & .. \\ f(w_1 * x_N + b_1) & .. & f(w_L * x_N + b_L) \end{bmatrix} \quad (1.10)$$

Where 'T' is a training data target matrix.'β' is a special matrix which is called as pseudo-inverse.For any new instance of data, the following can be used to classify the new instance to target label.

$$T_n = H\beta \quad (1.11)$$

Where 'T_n' is a new instance of data which need to be classified to target label which denotes user intention.

RESULTS AND DISCUSSION

During the subject interaction with a model, data samples are collected from EMOTIVE EPOC device. The following table 1 provides the details of both the input and output features in each data sample of dataset.

Table 1. Features of Dataset for classifying intention of the user

Features	Attribute	Description and Attribute values
1 – 14	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4	Numerical Value (in microvolts) Amplitude of generated electrical signals measured through sensors.
15	Type of Brain Wave	Categorical Type Alpha, Beta, Delta, Gamma, Theta
16	RAW EEG	Image Type Recorded EEG waves during the interaction
17	Intention Label	Numerical Value 1 - Switch ON FAN 2 - Switch OFF FAN 3 - Switch ON LIGHT 4 - Switch OFF LIGHT

For classifying 15,000 data samples, all the 16 features are used as it is classified into intention label of 13 classes. During the data preprocessing phase, all the missing values in the data samples are handled. Also, the smoothing and normalization operations are performed over the data samples. As a next step, pre-processed are fed to the SDAE's for reconstructing the original values from corrupted/noisy feature values. ELM is applied over the dataset to classify the intention of the user. The evaluation of the model can be made based on the decision support accuracy metrics [18]. The proposed model and other variant models are implemented using Keras in Python.

Decision support accuracy metrics

The proposed model is compared with other variant model based on the following decision support accuracy metrics. They are

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1.14)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (1.15)$$

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (1.16)$$

$$\text{F1-Score} = \frac{2*(Sensistiviy*Precision)}{(Sensistivy+Precision)} \quad (1.17)$$

*Where 'TP' is Tru*e positive (*TP*): Prediction is +ve and user is also intended the same. True negative (*TN*): Prediction is -ve and user is also not intended the same. False positive (*FP*): Prediction is +ve and user is not intended the same. False negative (*FN*): Prediction is -ve and user is intended the same.

Figure 3 and Figure 4 shows that the hybridized model achieves the better accuracy, precision, sensitivity and F1-Score compared to other variant models during training and testing process. In the proposed model, the brain profile of subject is preprocessed as well as noisy features are reconstructed to original using SDAE's. Also, ELM is achieving high level of generalization while processing the brain profile of subject. ELM is most suitable to the problem which requires retraining of the model in real time. Hence, it is observed that the testing accuracy of 91.8% is achieved which validate the effectiveness of the proposed model. Further, the performance of the proposed model is analyzed based on interaction time taken for predicting the intention of the user. Figure 5 shows that hybridized model has taken less interaction time of 1.8 seconds in capturing the intention of user when subject engage with a system.

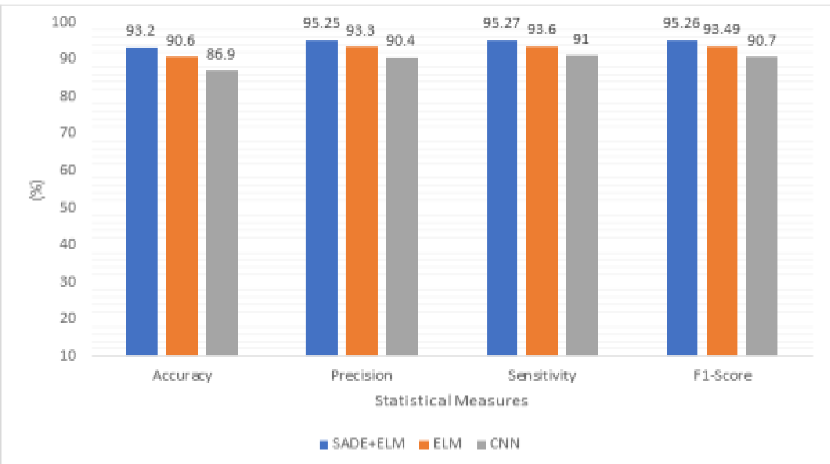

FIGURE 3. Comparison of training accuracy of hybridized deep learning model with other variant models

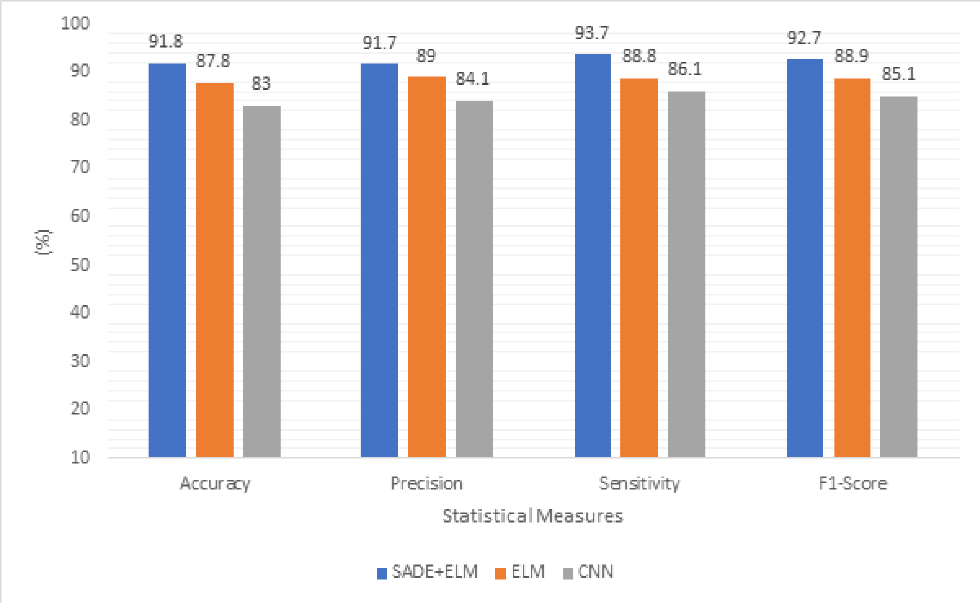

FIGURE 4. Comparison of testing accuracy of hybridized deep learning model with other variant models

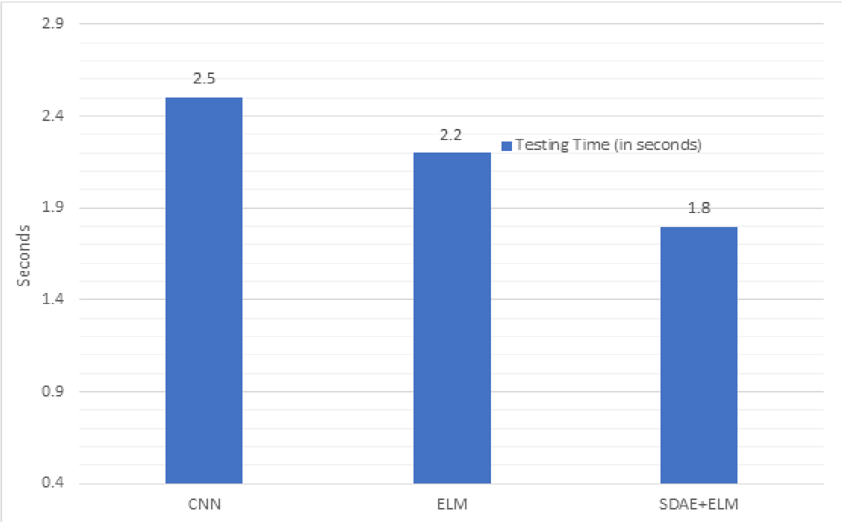

FIGURE 5. Comparison of interaction time taken by the models to predict the user intention

CONCLUSION

Design of intelligent assistant to control the home appliances from user brain activity is a very challenging task. In this work, a hybridized deep learning model has been proposed to predict the intention of user from their brain profile. The proposed system uses the SDAE's to improve the quality of user brain profile by reconstructing the actual value from noisy data. Further, ELM is used to perform high level of generalization to predict the predefined intention of the user. The proposed model achieves 91.8% accuracy which much better than other variant models such as CNN and ELM. Also, it is observed that the time taken by the proposed model to predict the user intention is 1.8 seconds which much lesser than other approaches. In the future work, the proposed model will be tested and investigated with brain profiles of different users, and learning algorithms.

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