Brain Computer Interface using hybrid adaptive filtering and Higher order Crossing Analysis based on Modified DNN

Shwetav Sharad (trilokkumarjain5@gmail.com)
BBDIT

Sugandha Chakraverti
Indraprastha Engineering College

Shakti Kundu
Manipal University Jaipur

Ashish Kumar Chakraverti
Sharda University

Murari Kumar Singh
Sharda University

Research Article

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Brain Computer Interface using hybrid adaptive filtering and Higher order Crossing Analysis based on Modified DNN

[1]Sugandha Chakraverti, [2]Dr. Shakti Kundu, [3]Dr. Shwetav Sharad,

[4*]Dr Ashish Kumar Chakraverti and [5]Murari Kumar Singh

[1]Assistant Professor, Department of Computer science and Engineering,

Indraprastha Engineering College, Ghaziabad,

Affiliated to AKTU, Lucknow, UP, India.

[2]Associate Professor, Directorate of Online Education,

Manipal University Jaipur, Rajasthan, India.

[3]Professor, Department of Computer Science and Engineering,

BBDIT, Ghaziabad, UP, India.

[4]Associate Professor, Department of Computer Science and Engineering,

School of Engineering and Technology, Sharda University,

Greater Noida UP, India.

[5]Assistant Professor, Department of Computer Science and Engineering,

School of Engineering and Technology, Sharda University,

Greater Noida UP, India,

***Corresponding author Mail id: ashishkumar.shardauniv@gmail.com**

Abstract: Brain computer interface (BCIs) aims to communicate with external devices and also recognize human activities through brain signals. However, existing algorithms have some drawbacks, such as poor resolution, high-frequency noise, risk, and low accuracy. Various machine learning algorithms have been used to recognize human activities, but it is more complex to recognize the activities of humans. In order to solve these issues BCIs system based on modified DNN is proposed. Using a modified DNN algorithm, all human activities are recognized through the brain signals. The proposed method contains two phases such as

training and testing the data. First, the Brain signal is taken as input, and then the next phase is pre-processing. The signal is pre-processed using a bandpass filter to remove noise present in the signal. Then the next phase is feature extraction, for that features are extracted from the pre-processed signal using Hybrid Adaptive Filtering (HAF) and Higher Order Crossing (HOC) analysis. In order to evaluate the HAF-HOC performance on a user-independent basis, a set of brain signals for each human activity was analyzed and pre-processed. The next phase is classification. For classifying the brain signal, a modified DNN algorithm is used. The Sailfish Optimization technique is used to train the neural network and also used to optimize the weights of the DNN classifier. The results show that the proposed method can obtain 98% accuracy and 0.03 Error, and 10% False Positive Rate. An existing system such as SVM, KNN, RF, and NB reached 86%, 90%, 83% and 70% accuracy, respectively, which is lower than our proposed method.

Keywords: Brain computer interface (BCIs); Bandpass filter; DNN; Hybrid Adaptive filtering (HAF); Higher Order Crossing (HOC); sailfish optimization.

1. INTRODUCTION

BCIs (Brain-Computer Interfaces) allow individuals to communicate with external devices directly through their brain signals. And it also allows humans to engage with external artificial devices by using their brain activity as a channel (He, B. et al. 2020). Brain computer interface aims to communicate with external devices and also recognize human activities through brain signals (Ramadan, R.A., et al. 2015). BCIs are systems that help the brain communicate with various technological gadgets. In the field of neuroscience, one such new technology is the brain-computer interface (BCI) (Miranda, R.A et al. 2015). In a nutshell, brain-computer interface (BCI) technology allows direct communication between the brain and an external device, bypassing the typical neuromuscular routes (Mudgal, S.K., et al. 2020).

BCIs are complete systems, including the software and hardware that manipulate human signals to control Computers and different communication devices (Papanastasiou, G et al. 2020). BCI is used not just in the medical profession and in health care but also in entertainment, gaming, education, self-control, marketing, and other areas of human existence (Abdulkader, S.N et al. 2015). In addition to its benefits, BCI has drawbacks that fall into several areas, including technological, neurological, and ethical. Recent advancements in the field of BCIs have been striking (Ienca, M. and Haselager, P. 2016).

A BCI is a system that analyses the operation of the Central Nervous System (CNS) and converts it into an artificial output that substitutes, recovers, and improves the output of the natural CNS, hence altering the CNS's ongoing interactions with its internal or external environment (Vourvopoulos, A., et al. 2019). BCI assists in the management of applications by combining brain activity measures, classifying them to control tools such as spelling apps, computer games, and creative expression, and lastly, providing feedback on behaviour (Vasiljevic, G.A.M. and Miranda, L.C.D., 2020). Significantly, brain signals play a role in the occurrence of any feeling, such as comfort, focus, concern, and awareness (Koch, C. 2019). However, real-world EEG based BCI systems are still immature due to diverse open challenges. First, EEG signals usually have a mass of noises (Zhang, D et al. 2018)a.

Deep learning, as a subcategory of machine learning, is currently the state-of-the-art method in computer vision and natural language processing applications. Various deep learning algorithms have been used to recognize that human activities through brain signals are more complex. However, BCIs have some difficulties, such as low accuracy, high-cost devices, low-quality signal etc. (Faust, O., et al. 2018). In order to solve these issues, we propose Modified DNN. First, features are extracted from the signal for extracting the features. Hybrid Adaptive Filtering (HAF) and Higher Order Analysis (HOC) techniques are used. Furthermore, the

proposed deep learning technologies have the potential to attain high accuracy compared to other deep learning techniques.

The proposed method has overcome the certain limitation of the previous method of brain-computer interface. The key objectives of the proposed method are given below.

- Brain signal datasets are analyzed and used to predict human emotions using modified DNN.
- The first phase is brain signal acquisition, and then the signal datasets are taken and pre-processed in order to remove the noise from the signal. Pre-processing the signal is done by using a Bandpass filter.
- Next, extract the features of the pre-processed signal using hybrid adaptive filtering and higher-order crossing analysis.
- Then the extracted signal is given to the classifier for classifying the signal to recognize the human activities, and classification is done by using a modified deep neural network.

The remaining part of the manuscript is structured as follows, and section 2 describes several researches related to the existing BCIs to recognize human activities through brain signals using various deep learning techniques. Section 3 contains the proposed methodology of the brain-computer interface. Section 4 discusses the results attained through the implementation of the proposed method. Section 5 contains the conclusion of the proposed model.

2. LITERATURE REVIEW

Some of the relevant reviews based on the Brain-Computer Interface to recognize human emotions through brain signals that were previously proposed using various deep learning techniques have been discussed in this section.

Raja Majid Mahmood et al. (Mehmood, R.M et al. 2017) had developed an Optimal Feature Selection and Deep Learning Method for Emotion Recognition from Human Brain signals. The features of EEG data were analyzed, which are obtained from non-invasive EEG signals that measure the electrical activity of neurons inside the human brain and pick the best combination of these features for emotional state recognition. The results revealed that the proposed method outperforms the commonly utilized spectral power band method in terms of emotion recognition rate. However, the results showed a higher recognition rate for the optimal feature selection but not for all extracted features.

Siavash Sakhavi et al. (Sakhavi, S., et al. 2018) have suggested a Learning Temporal Information for Brain-Computer Interface Using Convolutional Neural Networks. A classification framework was proposed for MI data by using a convolutional neural network (CNN) architecture and presenting a new temporal representation of the data. The new representation is created by tweaking the filter-bank common spatial patterns approach, and the CNN is built and optimized to fit the new representation. On the BCI competition IV-2a 4-class MI data set, our system exceeds the best classification approach in the literature by 7% in average subject accuracy.

Dalin Zhang et al. (Zhang, D., et al. 2018) had developed a Cascade and Parallel Convolutional Recurrent Neural Networks on EEG-Based Intention Recognition for Brain-Computer Interface. Both cascade and parallel convolutional recurrent neural network models were proposed for accurately recognizing human intended movements and instructions by effectively learning the compositional spatiotemporal representations of raw EEG streams. The created models are then tested using a real-world BCI, and they obtain a recognition accuracy of 93% over five different instruction intentions. This shows that the presented models can be applied to a variety of intentions and BCI systems. However, in the pre-processing data stage, the labels of the subjects were severely damaged.

Swati Aggarwal et al. (Aggarwal, S. and Chugh, N., 2019) have introduced an MI-BCI (Motor Imagery Brain-Computer Interface) that provides a non-muscular communication route for those with neurological diseases. A comprehensive review of dominant feature extraction methods and classification algorithms provided in the brain-computer interface for motor imagery tasks. The authors discuss existing challenges in the domain of motor imagery brain-computer interface and suggest possible research directions. However, the resolution of FFT could be improved by applying window functions such as the Hanning window, but still, it has poor resolution.

Jiahui Pan et al. (Pan, J., et al. 2016) had developed an EEG-Based Brain-Computer Interface for Emotion Recognition., An EEG-based brain-computer interface (BCI) system used for emotion recognition is proposed to detect two basic emotional states. Instead of using fixed frequency bands for emotion recognition, this research investigates a new strategy for selecting appropriate subject-specific frequency bands. For two classes, an average online accuracy of 74.17 per cent was reached. In terms of accuracy, the proposed method based on subject-specific frequency bands outperformed the method based on fixed frequency bands, according to the data analysis results.

Aayush Bhardwaj et al. (Bhardwaj, A et al. 2015) have suggested that SVM and LDA Classifiers are used to extract human emotions from EEG information. In the last few decades, emotion detection has been a hot focus of study. It is crucial in the development of human-computer interfaces. Electroencephalography (EEG) signals are used to determine emotions in this study. The electrical activity of the brain's neurons is recorded by EEG. It is calculated and compared to the accuracy achieved by both algorithms. With an average overall accuracy of 74.13 per cent and 66.50 per cent, can distinguish seven emotions using the two algorithms, SVM and LDA.

Haiyun Huang et al. (Huang, H. and Li, Y. 2019) had developed Human emotion recognition using electroencephalogram (EEG) data has gotten a lot of interest. The majority of existing research has focused on offline analysis, and real-time emotion recognition using a brain-computer interface (BCI) method has yet to be explored. An EEG-based BCI system for emotion recognition was proposed in this paper. The findings of the experiment showed that our system had successfully generated and recognized the subjects' emotions.

Qiqi Zhang and Ying Liu (Zhang, Q. and Liu, Y. (2018) have suggested Data augmentation with conditional Deep Convolutional Generative Adversarial Networks improves the performance of the brain-computer interface. A conditional Deep Convolutional Generative Adversarial Network was proposed for automatically generating more artificial EEG signals for data augmentation in order to improve the performance of convolutional neural networks in the brain-computer interface field and overcome the problems of small training datasets. The results revealed that Gaussian noise-generated artificial EEG data could learn features from raw EEG data and has classification accuracy comparable to raw EEG data in the testing dataset. However, this method may result in insufficient high-frequency noise at the intersection of two segments.

Anala Hari Krishna et al. (Krishna, A.H., et al. 2019) had developed Emotion recognition using EEG signals based on tuneable-Q wavelet transform. EEG signal plays a critical function in recognizing emotional state since it gives an immediate reaction to every state of change in the human brain. Experimental results of the proposed method show better four emotions classification performance when compared with the other existing methods. However, still, there is scope for the improvement of the emotion classification performance of the proposed method.

Based on the above-revealed article, several significant challenges arise in BCIs for recognizing human emotions through brain signals are. The results showed a higher recognition

rate for the optimal feature selection but not for all extracted features (Mehmood, R.M et al. 2017). In the pre-processing data stage, the labels of the subjects were severely damaged (Zhang, D., et al. 2018). The resolution of FFT could be improved by applying window functions such as the Hanning window, but still, it has poor resolution (Aggarwal, S. and Chugh, N., 2019) and insufficient high-frequency noise at the intersection of two segments (Zhang, Q. and Liu, Y. (2018). There is scope for the improvement of the emotion classification performance of the proposed method (Krishna, A.H., et al. 2019). In order to overcome these issues, a modified DNN was proposed to recognize human activities through brain signals in Brain Computer Interface.

3. PROPOSED METHODOLOGY

BCIs (Brain-Computer Interfaces) allow individuals to communicate with external devices directly through their brain signals. And it also allows humans to engage with external artificial devices by using their brain activity as a channel. In this method, modified DNN is proposed for recognizing human activities through brain signals. In the Brain computer interface, brain signals are evaluated for recognizing various human activities. This work aims to recognize human activities through brain signals. Brain-computer interface (BCI) technology allows direct communication between the brain and an external device, bypassing the typical neuromuscular routes. However, the existing BCI technology still relies on stimuli that are unnatural to human activities, so we proposed a modified deep neural network to recognize human activities.

First, the Brain signal is taken as input, and then the next phase is pre-processing. The signal is pre-processed using a bandpass filter to remove noise present in the signal. Then the next phase is feature extraction, for that features are extracted from the pre-processed signal using Hybrid Adaptive Filtering (HAF) and Higher Order Crossing (HOC) analysis. In order to

evaluate the HAF-HOC performance on a user-independent basis, a set of brain signals for each human activity was analyzed and pre-processed. The next phase is classification. For classifying the brain signal modified DNN algorithm is used. Modified DNN contains the input layer, hidden layer, and output layer. The problem solving and the fault learning ability of DNN is based on activation function. Activation functions are mostly preferred for the rectified linear unit (ReLU) and sigmoid. The extracted signal is given to the classifier, and then the signal is classified using modified DNN to recognize the human activities through brain signals. The architecture of the proposed method is shown in figure 1.

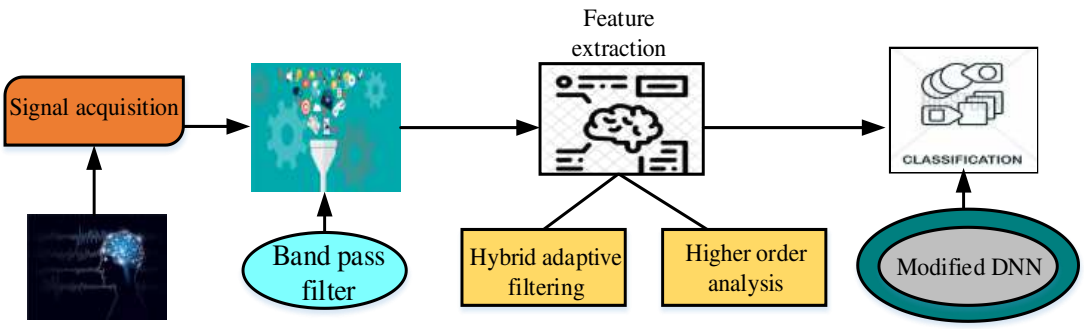


Figure 1. Architecture of proposed method

In this work, Brain Computer Interface is used to recognize human activities through the brain signals using Modified DNN. The first stage of this process is the signal acquisition, where the signals are acquired from the brain according to the emotional expression of the brain. After acquisition then, we have to pre-process the signal in order to remove the noise from the brain signal.

3.1 Pre-processing

In this method, the brain signal is pre-processed using a bandpass filter. Firstly the noises are removed from the signal in order to improve the quality of the signal, so we used a bandpass filter.

(a)Bandpass filter

A bandpass filter is used to remove the noise present in the signal and is also used to smoothen the data. A bandpass filter allows the signal within a particular frequency, and the main aim is to reduce the high-frequency noise present in the signal to improve the quality of the signal. The bandpass filter is calculated using Eq. (1) (Zhang, Q. and Liu, Y. (2018),

$$g(t,d) = \frac{1}{2\pi}\int_{\omega_{0-\omega_c}}^{\omega_{0+\omega_c}} I(\omega - \omega_0)\, X(\omega_r) \exp[i(\omega_t - k_d)] \quad (1)$$

Where I ($I(\omega - \omega_0)$ is a symmetric bandpass filter at $\omega = \omega_0$ and t denotes the time and d denotes the distance, ω is the angular frequency, k_d denotes the wave number in the dth node.

3.2 Feature Extraction

Feature extraction is an important step in the process of signals. In this method, we used the HAF-HOC (Higher Adaptive Filtering – Higher-Order Crossing) analysis scheme to extract the features from the brain signals in order to recognize the characteristics of the brain signal.

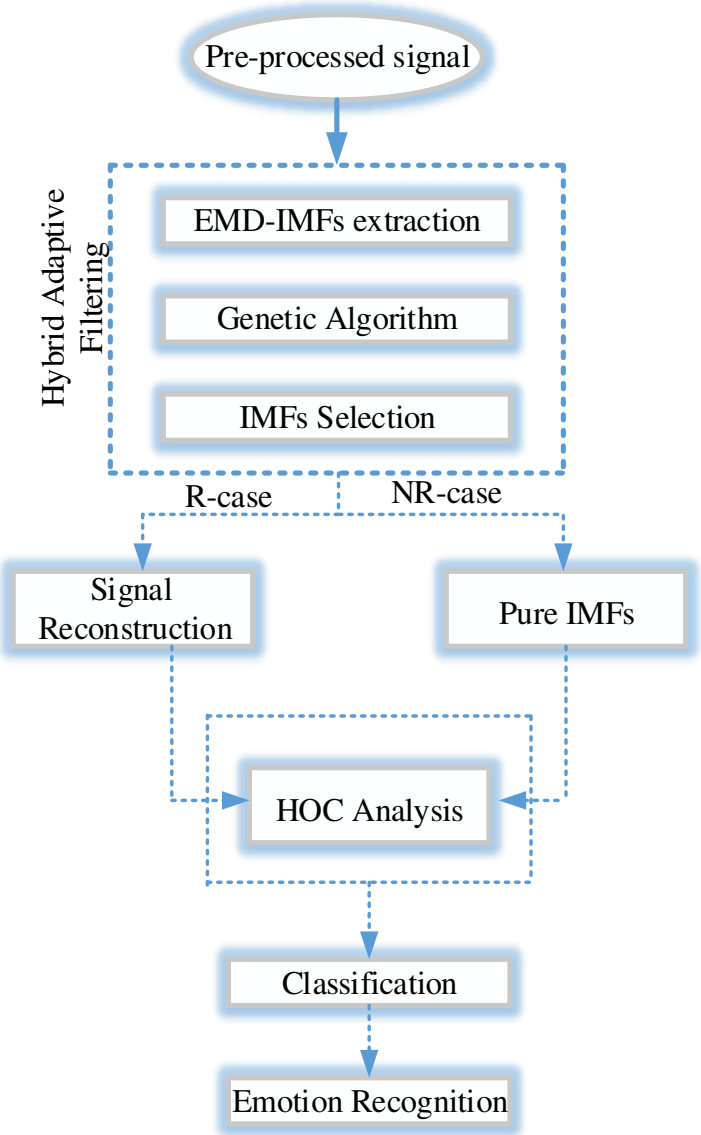


Figure 2. Process of HAF-HOC analysis

(a)Hybrid Adaptive Filtering- Higher Order Crossing Analysis (HAF-HOC)

After pre-processing the signal, the signal feature is extracted. For that, we used the HAF-HOC scheme (Higher Adaptive Filtering- Higher Order Crossing). The pre-processed signal is given as an input to the HAF section in the HAF-HOC scheme. The role of HAF is to isolate the emotion-based signals and facilitate the features from the brain signals. To achieve this process, HAF incorporates GA that acts upon the representation of brain signals in the EMD space. Later the brain signal shifts into the iterative process into a series of Intrinsic Mode Functions (IMFs) that correspond to the different oscillatory modes of brain signals. At the end of the

EMD process, the data series can be decomposed into M intrinsic mode functions and a residue. Then use the GA algorithm to select the optimum IMFs that relate the most with the emotion-related brain signal characteristics. HAF result consists of the selected IMFs that could be either combined with the reconstruction process (r-case or used directly without employing any reconstruction process (NR- case). Under both R-case and NR-case, then the HAF output is given as the input to the HOC section of the HAF-HOC scheme. Their HOC analysis is performed to extract the features of the signal corresponding to the R and NR-case. Then the result of the HAF- HOC process is forwarded to the next stage, that is, classification. The process of HAF-HOC analysis is shown in figure 2.

(b)Hybrid Adaptive Filtering (HAF)

In order to follow the brain signal characteristics and focus on the ones that mostly relate to the emotional information, a HAF approach was developed as a hybrid declares two processing tools is, EMD and GA algorithms, in order to construct a filtering process adapted to specific characteristics of the filtered signal. EMD is used to decompose a signal in modes and residuals, which are intuitively interpreted as a "spectral" representation. Moreover, he further argues that a consequent result of the above is that the selection of modes corresponds to an automatic and adaptive time-variant filtering. In order to exploit the capability of the EMD algorithm, a new GA-based approach was developed for the optimized selection of modes that correspond to a specific feature of a signal. The initial brain signal is decomposed into the corresponding IMFs according to the EMD shifting process. The GA is applied to the extracted IMFs, and those which are selected are used either to reconstruct the new signal(R-case) or to provide separate signals (NR-case) that represent specific modes of oscillation coexisting in the initial brain signal.

One of the most important modules in the filtering procedure which is selected for GA is the fitness function. In this work, we used two types of fitness functions called energy-based fitness function and fractal dimension based fitness function.

(c)Energy-based Fitness Function (EFF)

The aim of using EFF was to conduct a filtering procedure by selecting the IMFs which embed the majority of the energy of the brain signal. Thus, an IMF selection procedure using an energy-based criterion directly related to the brain signal would result in a filtered signal with boosted information related to emotion expression in brain signals. Energy-based fitness function expressed in Eq. (2), (Zhang, Q. and Liu, Y. (2018)

$$f(s) = \frac{\sum_{\{s/s_{r=1}\}} E\{C_r(n)^2\}}{\sum_{i=1}^{M} E\{C_i(n)^2\}}, \text{ n=1… N} \qquad (2)$$

Where S is the string of 1s and 0s, Sr = 1 is the set of the elements of S with value 1, and C (n) represents an IMF. According to 1, it is obvious that, during the GA selection phase. IMFs are more likely to give offspring to the next generation. As a result, a bunch of IMFs that are the majority of the initial signal energy is finally selected; in this way, energy-based filtering is accomplished.

(d)Fractal Dimension based Fitness Function (FDFF)

Fractal Dimension (FD) is used as a measure of the signal complexity, Calculating fractal dimension for fast computing. The aim of FDFF is to capture the variations in the complexity of the brain signals. In the end, FDFF is used in order to select the optimum IMFs from an FD-based perspective. FDFF is expressed in Eq. (3) (Krishna, A.H., et al. 2019),

$$f(s) = \sum_{(s/s_{r=1})} FD\{C_r(n)\} \quad \text{n=1… N} \qquad (3)$$

(e)Higher Order Crossing Analysis (HOC)

In HOC analysis, it has been clear that emotion differentiation from brain signals is highly related to the power spectrum of EEG signals in certain brain locations and specific frequency bands. These facts facilitate the development of a feature vector-extraction technique that

considers the spectrum-related attitude of the signals, and it is highly dependent on the power of a certain frequency in a specific subband of the whole frequency spectrum. The HOC-based analysis provides such a perspective by rigorously analyzing the signal in the time domain and without employing the spectral transform.

In general oscillating behaviour can be expressed by the zero-crossing count. Under this perspective, an iterative procedure regarding the sequential application of a filter to a time series and the counting of the corresponding zero-crossing can be assumed. The resulting zero crossing counts are referred to as HOC. And zero-crossing can be used to refer to the initial brain signal (Petrantonakis, P.C. and Hadjileontiadis, L.J. 2010).

(f)HOC based Feature Extraction Technique

There are two different approaches implemented for HOC based feature extraction method, following R-case and NR-case, respectively. HOC based analysis is used to construct the feature vector by the following expression,

$$FV^{HOC} = [D1, D2, \dots, DL]\,, 1 < L \leq J \tag{4}$$

Where J represents the maximum order of the estimated HOC and L denotes the HOC order up to which they were used to form the FV^{HOC}

Moreover, an important advantage of using HOC is that the number of zero-crossings is not only referred to the initial signal but also to signals that consist of the output of high-pass filtering of the initial. As a consequence, the dominant frequency principle is applied to a set of subbands of the initial signal. This is one of the major advantages of the HOC as a feature vector extraction technique. It becomes a robust and efficient feature vector for recognizing human activities from brain signals (Bai, Y.W. and Lu, C.L. 2005).

3.3 Classification Using Modified DNN

Brain signal Classification is the process of recognizing human activities through the brain signal. A modified deep DNN classifier is used to classify the signal. Modified DNN is a class of deep learning neural networks. DNNs have an input layer, output layer, hidden layer and the hidden layer consist of a convolutional layer, the ReLU layer.

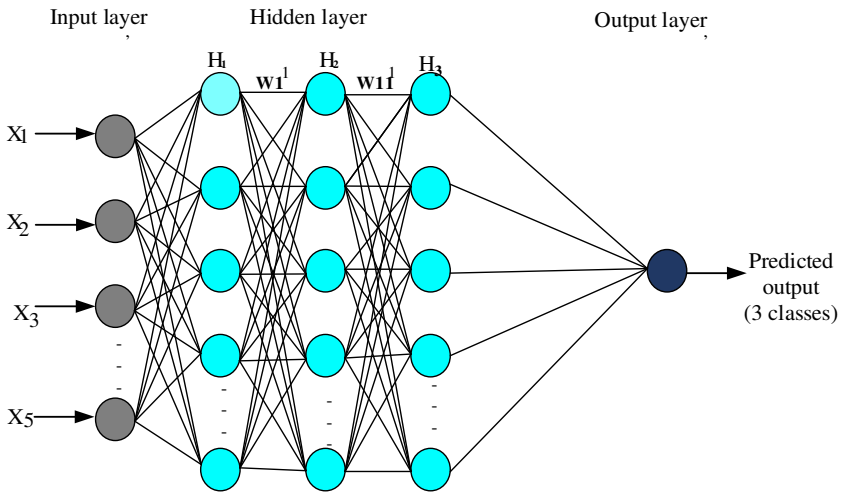


Figure 3. Architecture of Modified DNN

Modified DNN consists of 5 input neurons and 1 output neuron with three classes. A lot of neurons are overfitting, so only a small amount of neurons are underfitting. Due to the above reason, the hidden layer neuron size and numbers are chosen carefully. Each layer of neurons is computed practically. The hidden layer size is set as hyperparameters, so it is executed by the Tensor flow. The problem solving and the fault learning ability of Modified DNN is based on activation function. Activation functions are mostly preferred for the rectified linear unit (ReLU) and sigmoid.

Same layer neurons are not allied in the forward propagation, but in connection, mode neurons are connected fully. Neurons outputs are specified by using Eq. (5)

$$y_q^{n+1} = \sigma(z) = \sigma\left(\sum_{i=1}^{m} \omega_{iq}^{n} y_i^{n} + b_q^{n+1}\right) \tag{5}$$

Where, y_q^{n+1} denotes the output of q neuron in n+1 layer, $\sigma(z)$ denotes activation function, and sigmoid can be used, b_q^{n+1} signifies the bias of linear relationship, ω_{iq}^{n} represent the weight among n layer's i neuron and n+1 layer q neuron.

(a)Training the dataset

In the proposed work, weights are used to connect the layers. The weights are optimized by the use of the sailfish optimization approach. Sailfish is the fastest swimming fish; it can swim at a maximum speed of 100 km/h. The prey of these fish is smaller fish. Certain behaviour of sardines, such as acceleration and manoeuvrability, is considered quite challenging for sailfish while hunting these sardines. To attack sardines, sailfish attempt a slashing motion by injuring many sardines. These injured small fishes are detected to easily capture for their food. The steps of sailfish optimization are as follows

(i)Step 1. Initialization:

Initiate the weight as an input,

$$weight = \{W_1, W_2 \ldots\ldots W_n\} \tag{6}$$

(ii)Step 2. Fitness function

Select the fitness value, and here the error is computed to find the fitness value.

$$fitness\ value = E\ (\theta) = -\frac{1}{N}\sum_n \sum_q t_{nq} \log y_{nq} \tag{7}$$

Where, θ signifies the parameter of ω and$b$, t_{nq} actual values of qth sample nth element, N denotes the number of samples, y_{nq} is the projected value of qth sample nth element.

Step 3. Updating the value:

Update the value to detect the best solution, and the activity is analyzed based on the updated value.

$$X^i_{new\_S} = r \times \left(X^i_{elite\_SF} - X^i_{old_S} + AP\right) \tag{8}$$

Where $X^i_{old_S}$ is the current sardine position, $X^i_{elite\_SF}$ is elite sailfish's best position formed so far, r is a random number between 0 and 1, as well as AP represents sailfish's Attack Power at each iteration.

$$Ap = A \times \left(1 - (2 \times Itr \times \varepsilon)\right)$$

Where, A and ε are coefficients for reducing the value of attack power linearly from A to 0.

(iv)Step 4. Termination

The final step is termination. When the best solution is obtained, the process is terminated.

(b)Testing the dataset

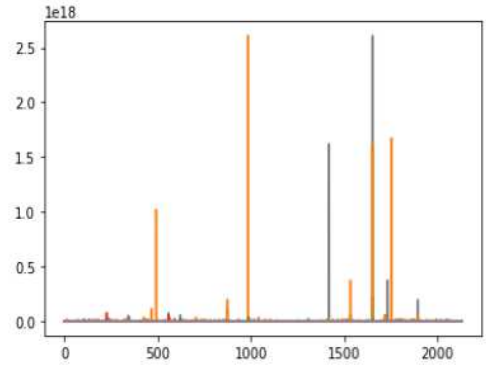
For testing purposes, brain signals are taken in order to recognize human activities. The system classifies the signal as suspicious or normal based on our trained model. In the data set, 80% of data are trained to remain 20% of data are tested in the classification system. Finally, the system classifies the brain signal using Modified DNN, and the human activities are recognized using the classifier.

4. RESULT AND DISCUSSION

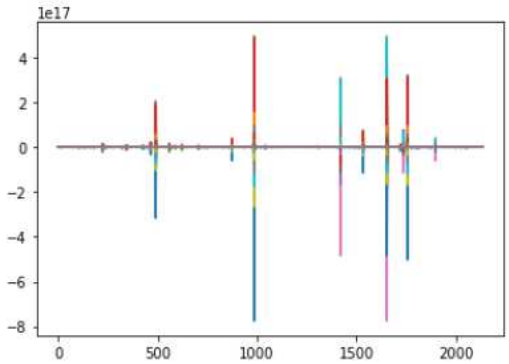
The purpose of this method is to recognize the human activities in Brain-Computer Interface (BCIs) through brain signals. The proposed modified Deep Neural Network (MDNN) is evaluated in this section. The testing is performed with the help of python 3.8 (spider) with CPU: Intel Core i5, GPU: NVidia GeForce GTX 1650, RAM: 16GB. DNN examines the data entered to determine whether the human activities in the BCIs system are recognized or not. EEG signal datasets are taken from (https://www.kaggle.com/birdy654/eeg-brainwave-dataset-feeling-emotions - Google Search), which are used for analysis purposes. An optimization is utilized to solve the DNN optimal problem to optimize the weights of the input layer. The data was initially taken, and it consisted of two phases such as training and testing the data. The extracted features of the brain signal data are used in the present model as the input of the modified DNN classifier. Moreover, the Sailfish Optimization Algorithm is used to train the neural network. The classifier predicts three classes for analyzing human activities.

First, the extracted data was taken, and it consisted of two phases such as training and testing. The extracted features of the brain signal data are used in the present model as the input

of the modified DNN classifier. Modified DNN contains four layers that are input layer, hidden layer and output layer. The Sailfish Optimization technique is used to train the neural network and also used to optimize the weights of the Modified DNN classifier in order to reduce the errors in each layer. The output layer contains three classes which are positive, negative, and neutral that are predicted by the proposed classifier.



(a)



(b)

Figure 4. Sample signals (a) Input signal
(b) pre-processed signal

In figure 4 (a), the input signal for the proposed system was given. After that, the input signal was pre-processed using a bandpass filter in order to remove the noise present in the input signal. The pre-processed signal is shown in figure 4 (b).

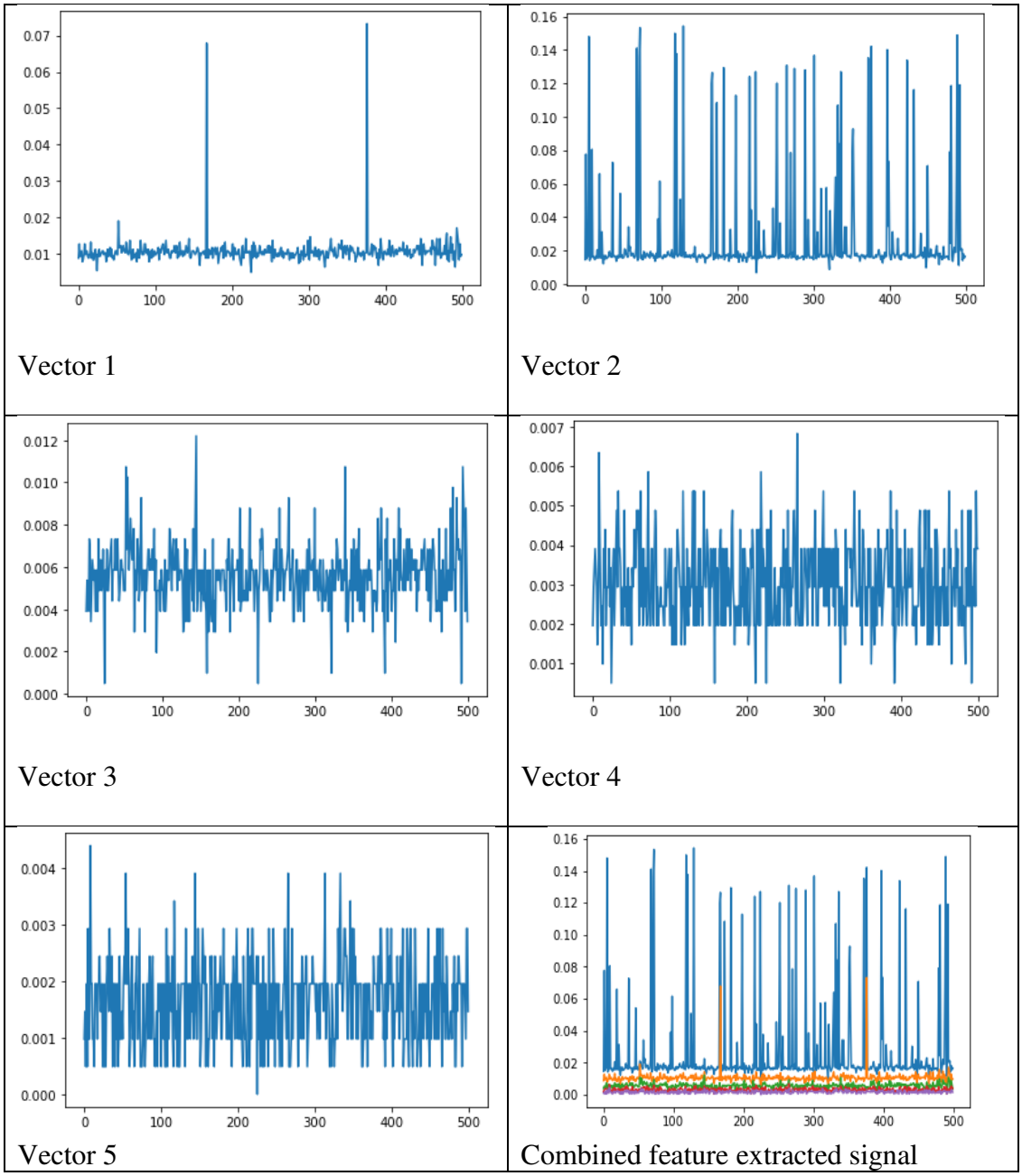


Figure 5. Extracted HAF Features from the sample signals

After pre-processing the signal, the features are extracted from the pre-processed signal using HAF-HOC analysis. In figure 6, each variant of the HAF signal is plotted and also the overall feature extracted signal is given.

Table 1. Parameters of MDNN classifier

Parameters	Range
Learning rate	0.01
Momentum	0.9
Epoch	100
Learning Algorithm	SGD
Activation function for hidden layer	elu
Activation function for output layer	softmax
Loss function	'sparse_categorical_crossentropy'

Table 1 contains the parameters of the M-DNN classifier. In the proposed and existing technique, the learning rate is referred to as 0.01, the momentum rate is 0.9, and the epoch value is referred to as 100. Stochastic Gradient Descent (SGD) is used as a learning algorithm. The activation function for the hidden layer is referred to as 'elu', and the activation function for output layer is softmax. Then the loss function is referred to as 'sparse_categorical_crossentropy.

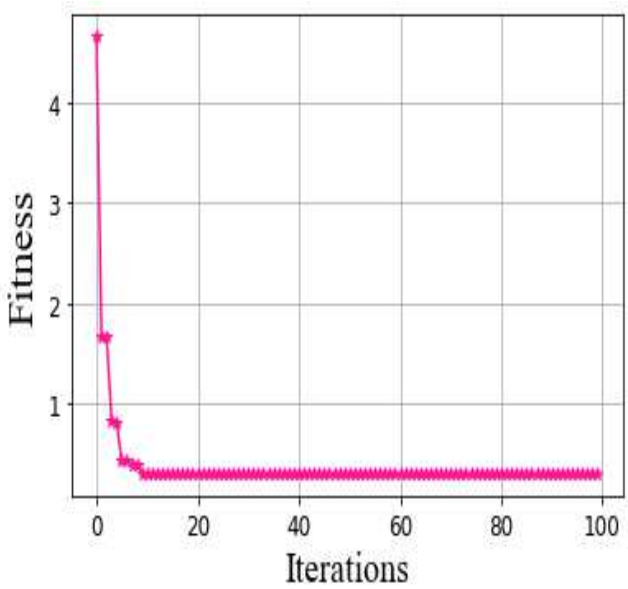


Figure 6. Convergence graph for the proposed system

Two or more objects merging together, joining together, or growing into one is referred to as convergence. When a crowd of people joins together to form a unified group, this is an example of convergence. When a sequence converges, it indicates that the words move closer and closer to a given limit as you progress through the sequence. In figure 6, the convergence graph of the proposed optimization is plotted between fitness and iteration. The convergence value of the graph is 0.2 at the 8th iteration. After that, it goes constant up to the 100th iteration.

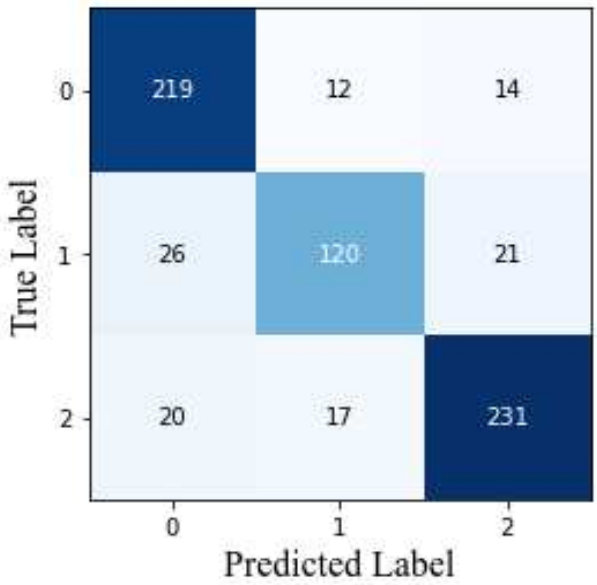


Figure 7. Confusion matrix of the proposed method

A confusion matrix is a method of summarising a classification algorithm's performance. Calculating a confusion matrix can help to understand what your classification model is getting right and where it is going wrong. A confusion matrix is a valuable method for examining classification models. It gives a clear picture of how well the model identified the classes based on the data supplied to it, as well as how the classes were misclassified. Important predictive analytics such as specificity, accuracy, and precision are visualized using confusion matrices. Confusion matrices are important because they allow comparing values such as False Positives and False Negatives in a straightforward manner. In figure 7, the confusion matrix for the

proposed method is plotted. For class 0 predicted label is 219. For class 1 predicted value is 120. For class 2 predicted value is 231.

4.1 Comparison Analysis

The performance of the proposed modified PNN process is compared with some of the existing approaches. Some of the existing features selection techniques used for the comparison study are ANN (Artificial Neural Network), SVM (Support Vector Machine), and KNN (K- Nearest Neighbour). The performance attained using these existing techniques is compared with the proposed Modified DNN algorithm. Some of the performance metrics used for comparison are accuracy, specificity, F-1 score, and precision, False Positive Rate (FPR), False Negative Rate (FNR), Negative Predictive Value (NPV), error. Table 2 illustrates the comparison study done using the proposed and existing deep learning algorithms. The mathematical formulation for each performance metric is given in below equations,

$$\text{Accuracy rate}=\frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Where, TP = True Positive, TN = True Negative, FP = False Positive, FN= False Negative.

Precision is the percentage of introduced mutations accurately detected, while recall is the percentage of introduced mutations correctly identified. Because it is evident that precision metric measure, we decided to test our proposed technique using the F - measure to achieve a balance between the two. F-Measure generates a single score that accounts for both precisions and recalls concerns in a single number.

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$F1\ score = \frac{2 \times (precision \times recall)}{precision + recall} \tag{11}$$

$$Specificity = \frac{TN}{TN+FP} \tag{12}$$

$$False\ Positive\ Rate = \frac{FP}{FP+TN} \tag{13}$$

$$False\ Negative\ Rate\ = \frac{FN}{FN+TP} \quad (14)$$

The number of true negatives divided by the total number of negatives yields the negative predictive value.

$$Negative\ Predictive\ Value = \frac{number\ of\ true\ negatives}{total\ number\ of\ negatives} \quad (15)$$

$$Error = 1 - Accuracy \quad (16)$$

Table 2. Comparison Investigation between Proposed and Existing algorithms

Performance Metrics	DNN	ANN	SVM	KNN
Accuracy	0.96	0.90	0.80	0.77
Specificity	0.94	0.89	0.80	0.68
F-1 score	0.95	0.82	0.81	0.56
Precision	0.96	0.84	0.82	0.69
False Positive Rate (FPR)	1.00	1.7	1.8	2.5
False Negative Rate (FNR)	0.50	1.00	1.23	2.00
Negative Predictive Value (NPV)	0.93	0.84	0.81	0.60
Error	0.07	0.11	0.20	0.24

The above table contains the value obtained for various metrics using the proposed and existing algorithms. The value for the performance metrics such as error, false-negative rate, false-positive rate and negative predictive value is smaller for the proposed algorithm compared to other performance metrics. The rest of the metrics, such as accuracy, specificity, F1 score, precision and, are greater for the proposed algorithm in comparison to other existing techniques. The graphical representation for this comparison investigation is given below.

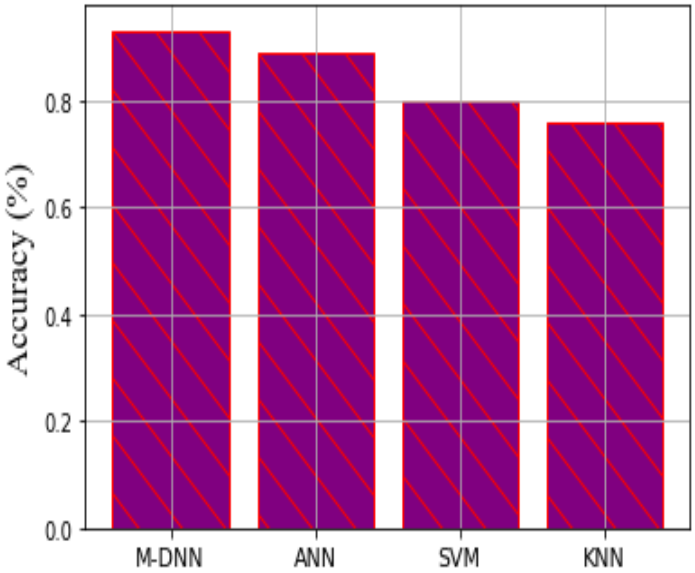


Figure 8. Comparison of proposed and existing accuracy metric

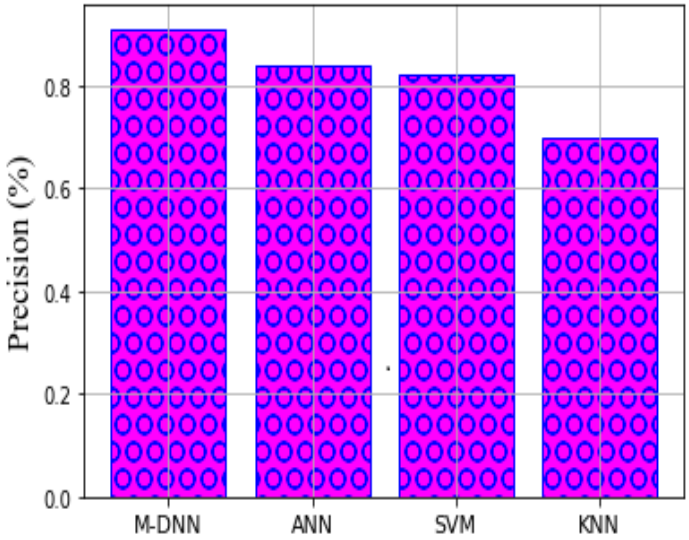


Figure 9. Comparison of proposed and existing precision metric

The comparison of proposed and existing accuracy metrics is given in figure 8. The graph is plotted against different existing algorithms on X-axis and obtained accuracy values on Y-axis, respectively. The accuracy value for the proposed DNN classifier is 96%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose values for accuracy are 0.90, 0.80, and 0.77. This comparison shows that the proposed DNN classifier gives better performance compared to other existing approaches. Figure 9 shows the comparison of proposed and existing precision metrics. In this analysis also, a graph is plotted against different existing algorithms on X-axis, and the precision value is plotted on the Y-axis,

respectively. The Precision value for the proposed DNN classifier is 96%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose values for precision are 0.84, 0.82, and 0.69, respectively.

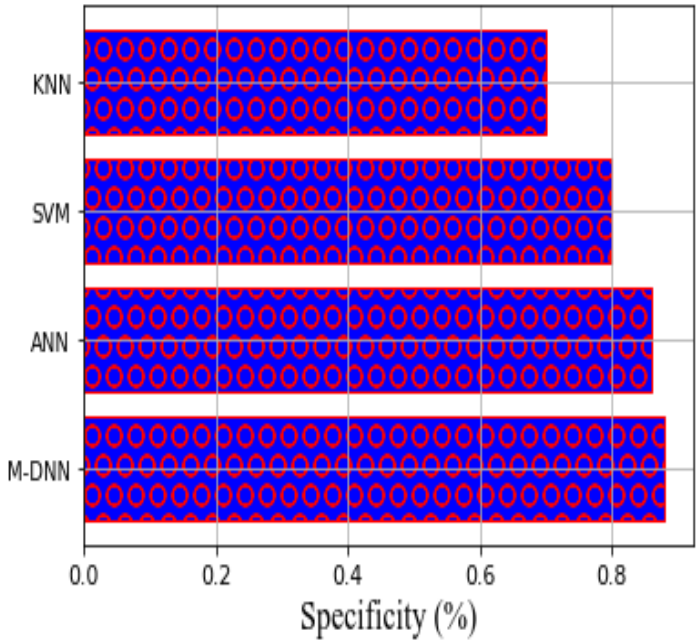


Figure 10. Comparison of proposed and existing septicity metric

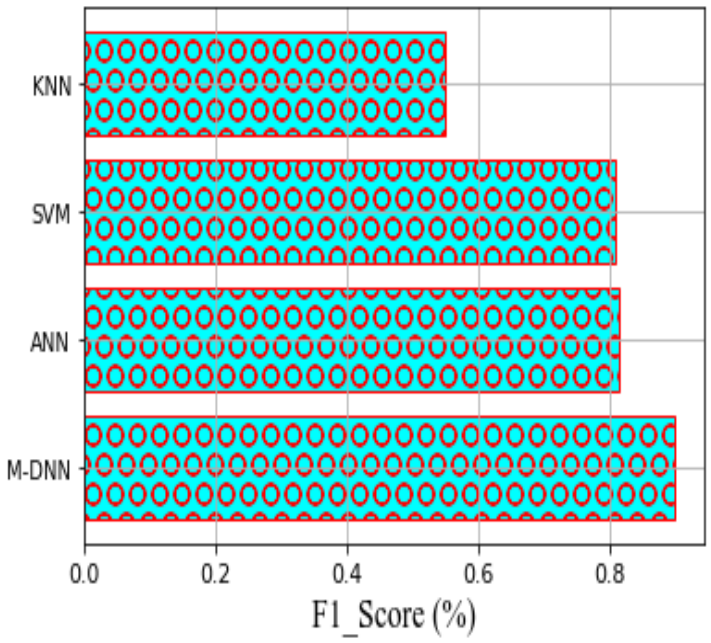


Figure 11. Comparison of proposed and existing F1 score metric

The comparison of proposed and existing Specificity metrics is given in figure 10. The graph is plotted against different existing algorithms on Y-axis and obtained specificity values on X-axis, respectively. The specificity value for the proposed DNN classifier is 94%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM and KNN, whose values for specificity are 89%, 80%, and 68%. This comparison shows that the proposed DNN classifier gives better performance compared to other existing approaches. Figure 11 shows the comparison of the proposed and existing F1_Score metric. In this analysis also, a graph is plotted against different existing algorithms on Y-axis, and the F1_Score value is plotted on the X-axis, respectively. The F1_Score value for the proposed DNN classifier is 95%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM and KNN, whose values for F1_Score are 82%, 81%, and 56%, respectively.

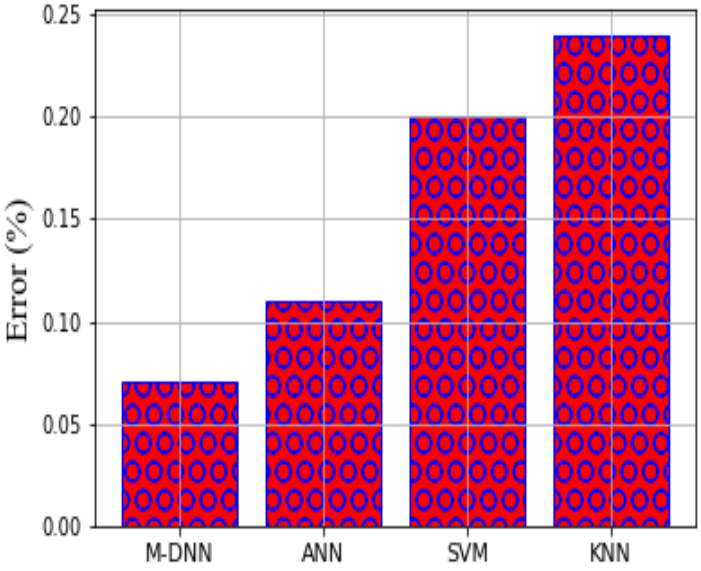


Figure 12. Comparison of the proposed and existing Error metric

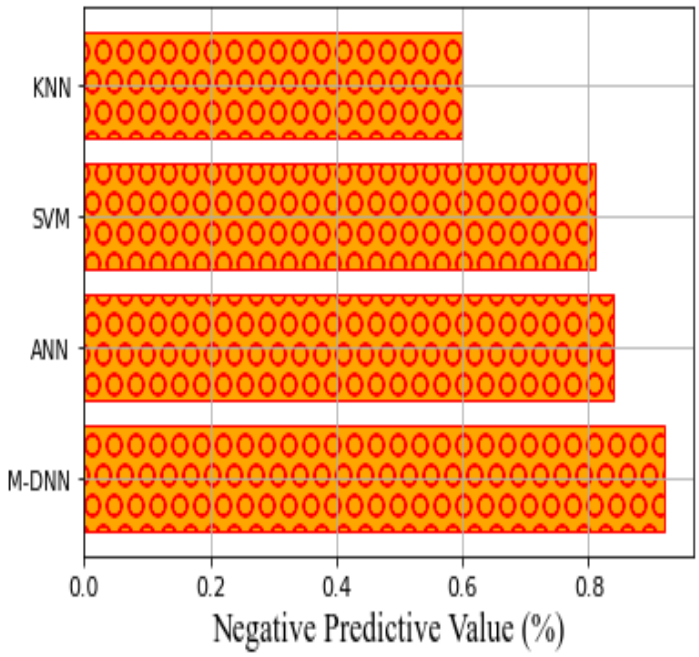


Figure 13. Comparison of proposed and existing negative predicted value

The comparison of proposed and existing Error Value metrics is given in figure 12. The graph is plotted against different existing algorithms on X-axis and obtained Error-values on Y-axis, respectively. The Error value for the proposed DNN classifier is 0.07%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose

values for error are 11%, 20%, and 24%. This comparison shows that the proposed DNN classifier gives better performance compared to other existing approaches. Figure 13 shows the comparison of proposed and existing Negative predictive Rate metrics. In this analysis also, a graph is plotted against different existing algorithms on Y-axis, and the Negative predictive Rate value is plotted on the X-axis, respectively. The Negative predictive Rate value for the proposed DNN classifier is 93%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose values for Negative predictive value Rate are 84%, 81%, and 60% respectively.

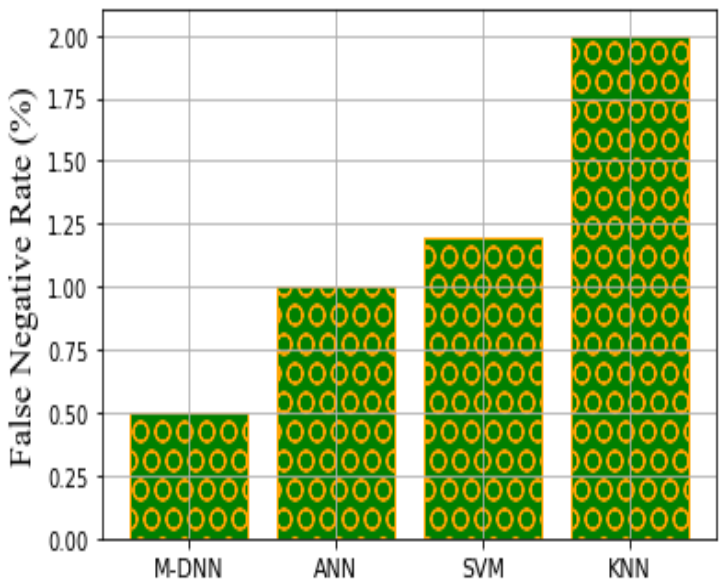


Figure 14. Comparison of proposed and existing false-negative rate value

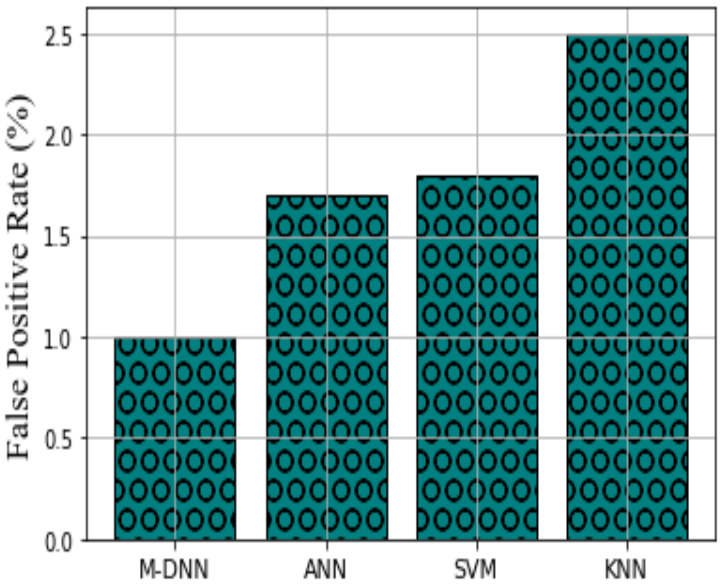


Figure 15. Comparison of proposed and existing false positive rate value

The comparison of the proposed and existing false-negative rate Value metric is given in figure 14. The graph is plotted against different existing algorithms on X-axis and obtained false-negative rate values on Y-axis, respectively. The false-negative rate value for the proposed DNN classifier is 0.50%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose values for the false-negative rate of 1.00%, 1.23%, and 2.00%. This comparison shows that the proposed DNN classifier gives better performance compared to other existing approaches. Figure 15 shows the comparison of proposed and existing false-positive Rate metrics. In this analysis also, a graph is plotted against different existing algorithms on X-axis, and the false-positive rate value is plotted on the Y-axis, respectively. The false-positive rate value for the proposed DNN classifier is 1.0%, and it is seen to be greater in comparison to other existing systems such as ANN, SVM, and KNN, whose values for false-positive rates are 1.7%, 1.8%, and 2.5% respectively.

The experiment's outcome shows that the Modified DNN classifier can discover the optimal solution of the classification system, which increases the accuracy and reduces the complexity time. BCIs are still a challenging problem even for recent and modern approaches. In this

system modified DNN classifier was proposed. According to the outcomes, the suggested modified DNN classifier is best suited for recognizing human activities and should be used in real-time applications.

5.CONCLUSION

Brain Computer Interface (BCIs) is necessary to recognize human activities through brain signals. This work presented a Modified Deep Neural Network (MDNN) classifier to recognize human activities through brain signals. The brain signal was pre-processed using a bandpass filter, and then the features of the pre-processed signal were extracted using HAF-HOC analysis. Finally, the extracted signal was classified using Modified DNN for training the neural network and optimizing the weights of the neural network sailfish optimization was used. For analyzing the prediction level of the BCIs system, the classifier predicts three classes called positive, negative, and neutral. Further, the performance of the proposed Modified DNN algorithm is validated and compared with the existing techniques such as ANN, SVM, and KNN. The proposed method attained 96% accuracy. Precision, specificity, and F-measure values attained for the proposed method are 96%, 94%, and 95%. Results showed that the proposed modified DNN approach could produce an optimal solution compared to our existing approaches, such as ANN, SVM, and KNN. Therefore the proposed approach can be a good alternative for improving the existing approaches. In future work, developers are planning to handle untrained data to recognize human activities through brain signals.

DECLARATIONS

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Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Informal Consent: Informed consent was obtained from all individual participants included in the study.

Consent to participate: I have read and I understand the provided information.

Consent to Publish: This article does not contain any Image or video to get permission.

Data availability statement: If all data, models, and code generated or used during the study appear in the submitted article and no data needs to be specifically requested.

Code availability: No code is available for this manuscript.

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