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Original Article

EEG Based Emotion Recognition Using Deep CNN Classifier and Hybrid Feature Selection Algorithm

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Abstract *- Electroencephalogram (EEG) based emotional evaluation has achieved excellent outcomes in medicine, security, and interaction between humans and computers. Especially compared with traditional signal processing and Machine Learning (ML) based applications, Deep Learning (DL) based techniques have recently dramatically increased the classification precision. Due to its sufficient spatial accuracy and enhanced temporal resolution, EEG signals typically represent emotional states. It is essential to consider that identifying emotions based on EEG signals relies on the efficacy of three processes: extracting features, selecting features, and classifying the feelings. Therefore, this work proposes a computerized approach for recognizing emotions from EEG signals. High Pass Infinite Impulse Response with Zero-Filtering (HPIIRZ) approach is used to reduce artifacts in EEG signals. Following this, the frequency and spectral features are extracted using Power Spectral Density (PSD), from which the optimal features are selected by a hybrid Improved Artificial Bee Colony algorithm-Particle Swarm Optimization (IABC-PSO). Deep Convolutional Neural Networks (DCNNs) are then used for classifying emotional states at the classification stage. An evaluation model is developed using the Python platform to evaluate the performance of the proposed model, including accuracy, specificity, and sensitivity. The outcomes demonstrate that the proposed method is more efficient; the DCNN-based method achieves a higher accuracy of 95.80%.*

Keywords *- EEG, HPIIRZ Filtering technique, Power Spectral Density, Hybrid IABC-PSO, DCNN.*

1. Introduction

The Brain-Computer Interface (BCI) is an increasingly common research area in health information technology. Its applications include analyzing Electroencephalography (EEG) impulses from the brain. Popular BCI uses include monitoring brain health and aberrant brain activity, such as psychological seizures and emotion detection [1, 2]. Emotion detection techniques aid in detecting the behaviour of mentally challenged individuals who cannot express their emotions. Emotions are an extensive collection of rules representing changes in the human body [3, 4].

Anger, depression, despair, hope, hate, fear, sadness, surprise, happiness, and other emotions have been found and are being utilized to create an emotion recognition system. In the past few years, work that uses emotion identification from EEG has captured the attention of many disciplinary domains ranging from psychology to engineering, including basic investigations on emotion concepts and their applications to BCI. BCI technology, which allows communication between the brain and the computer, is an essential area of Human-Computer Interaction (HCI) [5]. It is also regarded as one of the most critical current fields in machine and deep learning and automation. BCI technology operates in a series of processes to recognize human brain impulses and transform them into actions [6, 7].

After the signals are gathered, they are processed by frequency and temporal features are extracted before being categorized. Depending on the application, the results are transformed into orders for the various devices [8]. As a result, EEG data, which indicate electrical information from the brain, have gained popularity in the past few decades. As demonstrated in Figure 1, the dimensional method portrays emotional states as continuous values that vary in various dimensions, including Valence-Arousal (VA) space [9].

Many research endeavours have been undertaken in emotion recognition to optimize computing based on multiple inputs; some research is described below. The use of spatial and frequency characteristics in a DL framework with adaptive regularization for EEG-based emotion identification is put forward in [10]. Due to its parallelizability, the suggested approach is highly efficient. However, it is necessary to evaluate the model's adaptability using independent dataset verification. In [11], it has been proposed to employ EEG signals for Multiple Feature Fusion for Computerized Emotion Recognition.

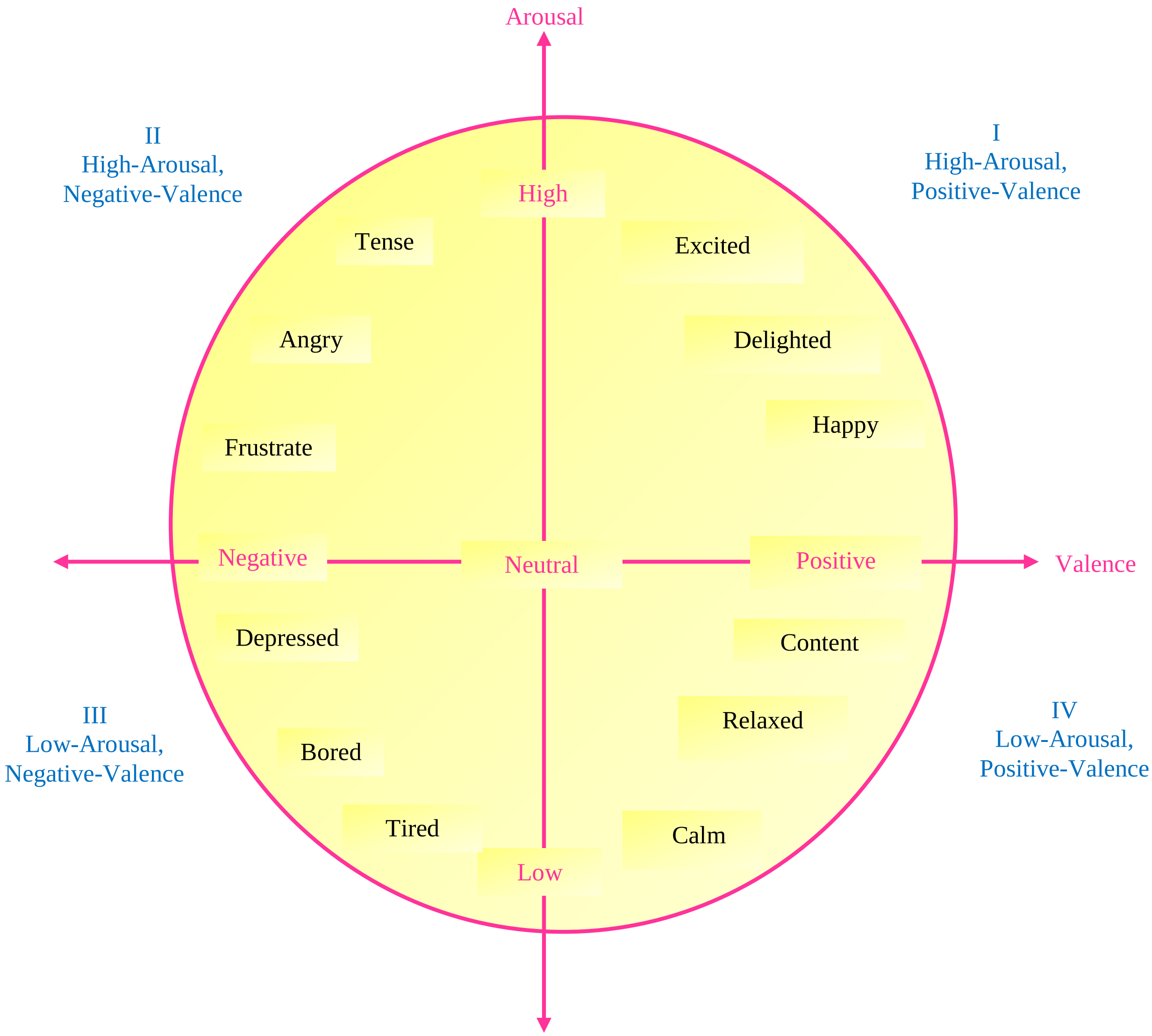

Fig. 1 Valence-arousal space in two dimensions

The outcomes demonstrate the utility of the proposed framework for categorizing emotions. However, by analyzing the data obtained from other people's EEG signals, it might be challenging to forecast the emotional state of an unidentified person. Employing flexible GCNN, EEG emotion detection is reported in [12].

The proposed DGCNN produces more reliable outcomes than SVM. Although still uncertain, The EEG data deployed in the trials would not be sufficient to develop more robust deep neural network models.

In [13], a newly developed convolutional layer termed the scaling layer is presented for obtaining valuable data-driven spectrogram-like characteristics from unprocessed EEG signals. It overcomes numerous issues with earlier techniques that relied on manually extracted features and robust assumptions. Nevertheless, not all activities and scaling levels require attention to the identical brain regions. A physiological signal information set demonstrates using DCNN to recognize emotions [14].

This model improves the ability to forecast human emotions. However, it has been seen that the videos tend to have a neutral level of arousal, which means that the emotion's strength is not as strong. A dynamic windowing of informational EEG using mutual data for emotion identification has been suggested in [15].

The proposed reduction of the information method may still be a quicker means for developing the EEG emotion classifier, depending on the feature extraction technique utilized. However, using most noise elimination approaches, it is difficult to tell which portion of the signal is connected to emotions. Deep learning network-based emotion identification using EEG feature maps was proposed in [16]. The findings collected demonstrate that the suggested strategies increase the rate of emotion recognition on datasets of various sizes.

Nevertheless, real-time emotion recognition is not possible with the proposed methodology. [17, 18] introduces a deep learning architecture called (TSception) for detecting emotions through EEG. Additionally made open access is the TSception code. But it's also essential to investigate the possibility of TSception.

Henceforth, this work explores the emotions of humans based on EEG signals by adopting the DL method to identify and categorize human mental states. In the beginning stage, the HPIIRZ filter technique removes the artefacts in the EGG signals. The optimal features are extracted and selected using PSD and Hybrid IABC-PSO. Finally, the emotions are classified efficiently using Deep CNN with improved accuracy.

2. Proposed System Description

This work uses Electroencephalography (EEG) signals to develop an emotion identification system based on the valence/arousal framework. Figure 2 indicates the EEG-based emotion detection using hybrid optimized feature selection with Deep CNN.

The raw EEG signal is always corrupted by various artefacts, including muscle movements (electromyographic artefacts), eye blinking (electrooculographic artefacts), and power line disruptions. For proper data analysis, all artefacts need to be eliminated. However, different noise reduction approaches substantially impact the final structure of the EEG signal, as well as its characteristic values, latency, and amplitude. As a result, the HPIIRZ filter is used in this work to reduce noise, beginning with the processing of EEG data.

The HPIIRZ filtering technique separates EEG signals into alpha, gamma, beta, and theta frequency bands. The most discriminating features of the signals have been discovered utilizing the PSD technique feature extraction. After that, the most desirable traits from the frequency domain are selected through the hybrid PSO-ABC algorithm.

Finally, based on the emotion model, the Deep CNN classifier recognizes emotions. The primary objective of this DCNN is to evaluate the data and detect a psychological pattern precisely. Each component of the proposed system is described in depth below.

2.1. EEG Signal Preprocessing Using HPIIRZ Filter

Eliminating mobility artifacts in ECG signal preprocessing is difficult, considering the broad range of motion aberration frequently coincides with the highly significant spectral elements of the ECG signal. Hence, HPIIRZ filter is used in the present research to decrease motion artefacts in EEG signals.

The periodic difference equation that describes IIR filtering is as follows:

$$y(n) = \sum_{m=0}^{M} b_m x(n-m) - \sum_{m=1}^{N} a_m y(n-m) \quad (1)$$

Where $y(n)$ is the filtered signal, $x(n)$is the input signal, N is the filter order, and b_m, a_m denotes the filter coefficients. IIR filters have a substantially lower minimum filter order than FIR filters, allowing them to achieve the necessary stop-band retardation.

The delay period of the various spectral elements in the input ECG signal will differ after filtration because IIR filters possess non-linear phase responses, leading to misinterpretation of the ECG waveform. To solve this issue, the IIR filter must be implemented with the zero-phase filtering approach. The zero-phase filtering method reduces distortions by analyzing the input signal forward and backward. In the advancing step, the input signal is processed with the developed filter and in the backwards phase, the outcome achieved is flicked in time before the sifting with the identical filter.

Emotion-relevant EEG characteristics have been identified and associated with psychological conditions after signal preprocessing. These features are extracted from the frequency domain utilizing PSD, which is described in the following section.

2.2. EEG Signal Feature Extraction Using PSD Method

Throughout frequency-domain research, power features related to distinct frequency bands employed for EEG rhythms are discovered in the frequency phase. The coefficients of the integrated three power attributes for specific frequency bands are calculated as follows.

2.2.1. Features of Power Spectral Density (PSD)

PSD is an effective response sequence for the frequency characteristics index and is employed to clarify the pattern of signal shifts in frequency when unanticipated vibrations generate power. The auto-correlation function $t(k)$ of the randomized signal $x(t)$is defined by equation (2) as follows:

$$\gamma_X(k) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} S_t(w) e^{jwk}\, dw \quad (2)$$

Where E is the expected value and $x(t + k)$ denotes the conjugated function of $\overline{x(t + k)}$. Equations (3) and (4) are used for expressing the appropriate inverse transform and Fourier transform of the function of auto-correlation$t(k)$, respectively, when it satisfies the requirement.

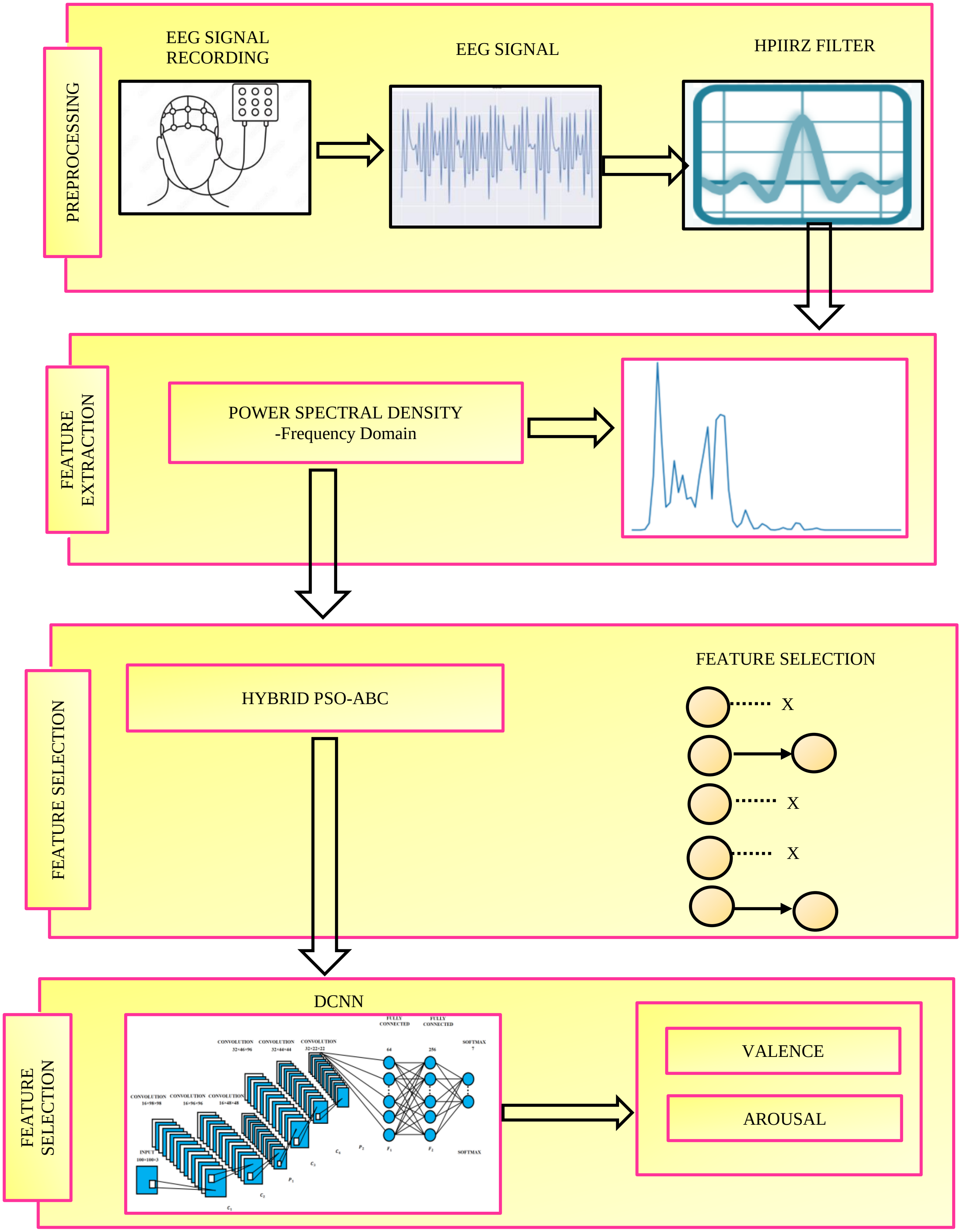

Fig. 2 Deep CNN **for emotion recognition using EEG signal**

$$FV_{psd} = S_t(w) = F[\gamma_X(k)] = \int_{-\infty}^{+\infty} \gamma_t(k) e^{-jwk} dk \quad (3)$$

$$\gamma_t(k) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} S_t(w) e^{jwk}\, dw \quad (4)$$

When $k = 0$, the autocorrelation function $t(k)$displays the signal's amplitude. The Fourier transformS_t(w), at the unit frequency, represents the PSD of the signal. The four bands powers theta (4–8 Hz), alpha (8–14 Hz), beta (14–30 Hz), and gamma (30–50 Hz) are believed to be featured in the present study. A hybrid PSO-ABC strategy is used in this study to select the ideal characteristic combination from a range of dimensions. The following provides a full explanation of the proposed feature selection method.

2.3. EEG Signal Feature Selection Using Hybrid IABC-PSO

The present research integrates the ABC phases with PSO and mutation operations. In Figure 3, this combination is referred to as ABC-PSO mutate. The ABC exhibits a bad balance between exploitation and exploration, which is the reason for it.

To offer superior solutions, mutations have been created in both Onlookers and Scout Bees, and PSO particles are contrasted with employed bees to take benefit of them. Additional benefits of the ABC algorithm include excellent reliability, quick convergence, and significant flexibility. Premature convergence in the subsequent search phase is a drawback, though. Sometimes, the precision of the ideal value falls short of the standards. To overcome this issue, Improved ABC optimization is provided here. This IABC-PSO method aims to enhance the search capabilities of Bees when their behaviour does not supply good source foods.

Initially, PSO velocity is used to improve ABC employed Bees, and the fitness of employed bees solutions and Particle solutions are compared. The very best value is preserved, and in addition, in the observer phase, GA mutation is utilized. After enough iterations, if the likelihood of the food source (i) is not increased, the solution is modified, and its fitness is compared to the previous value; if the new solution is superior, the old food source is swapped out for the new one.

Scout bees look for fresh approaches when put to work, and observers become trapped. Therefore, the proposed algorithm suggests that 'the worst solution' and two 'random good options' be changed to change how scouts behave. The most excellent food source is the new one.

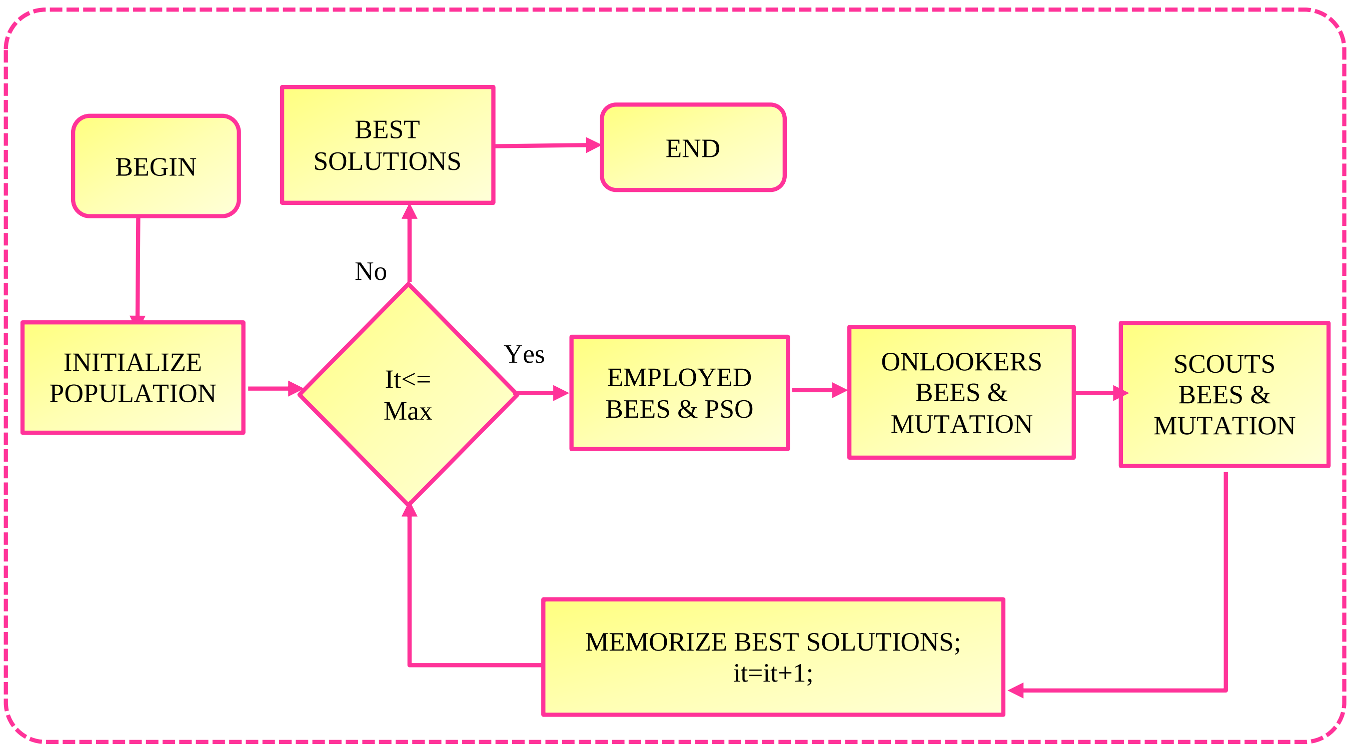

Fig. 3 Feature selection using hybrid IABC-PSO

HYBRID ABC-PSO ALGORITHM
Input : Data.class, NB features, PSO parameters
Output : Finalsubset, accuracy;

1. Initialize the population of solutions Xi ,∀i,i=1,….,NB.
2. Evaluate the population Xi ,∀i,i=1,….,NB.
3. Copy the population Xi and its fitness in PSO initialization population.
4. for cycle=1 to Maximum Cycle Number do
5. Improved Employed Bees();
   For each Employed Bees i
   Produce new solutions Vi using Equation (1) and evaluate it.
   V(i,j)=X(i,j)+phi(i,j)*(X(i,j)-X(k,j))
   J is a feature index 1…D.
   Calculate new velocity Vel (i+1) PSO and new position X (i+1)
   Compare fitness X(i+1) and new source food V(i).keep the best (Vi,Xi+1).
   Update pbest and gbest and apply the greedy selection process.
   If fitness(V(I,:)>Fitness(X(I,:)) then X(I,:)=V(I,:)
   End for
6. Onlooker Bee phase;
7. Scout Bees phase
8. Memorize the best solution achieved; cycle=cycle+1

End for

This IABC-PSO supports competitive behaviour among onlooker bees and PSO particles to create an improved balance between exploration and exploitation. First, concerning fitness, all initially employed bees are replicated into swarm PSO particles. Additionally, employed bees and particles work together to estimate the location and velocity of the particles, and the employed bees also determine the new food sources. Each option is assessed and contrasted, then the optimal solution is determined. The DCNN classifier is utilized in this system to perform classification, which is explained below.

2.4. EEG Signal Classification Using Deep CNN

The deep convolutional neural network's framework for identifying sequences of proteins is shown in Figure 4. It consists of 14 layers, including an input layer, a flattening layer, a fully connected layer, a convolutional layer, and an output layer. The output layer now uses the softmax function to calculate the possibility of the 1195 data. The initial layer has input numbers that indicate the location data of a parameter length of the sequence of proteins.

In the convolution layer, the filter is employed to input layer to produce hidden features by batch normalization, convolution and non-linear change of its components with an activation function. Two window sizes close to the median lengths of a protein's beta-sheet and alpha-helix have been chosen after various window sizes in the one-dimensional convolution layer have been investigated.

The second convolution layer is similarly converted utilizing the hidden features produced by the ten filters using two different-sized windows in the initial layer. Level 10 of the convolution layer is selected.

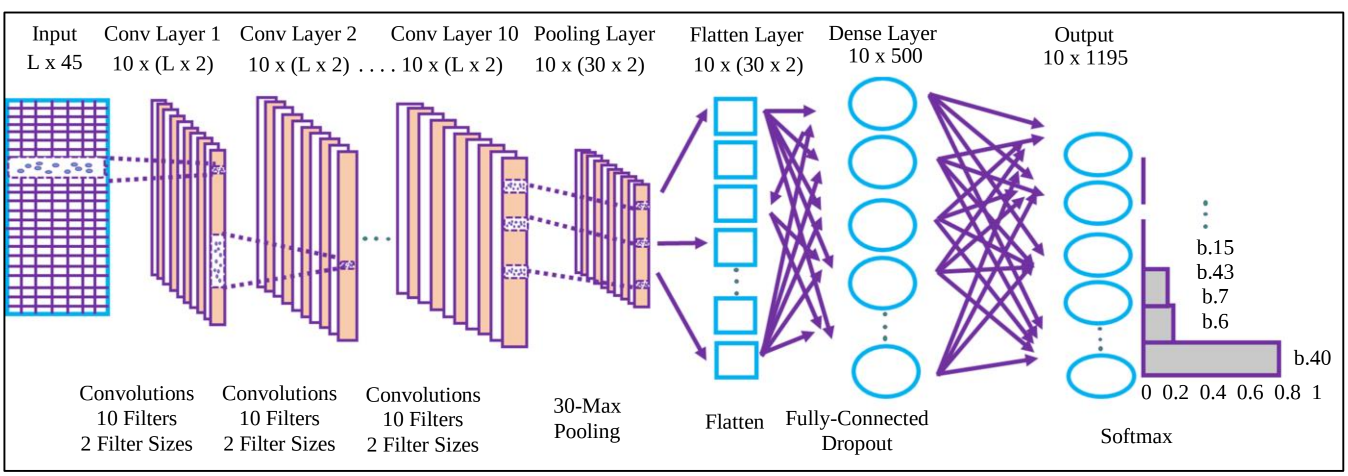

Fig. 4 Prediction model architecture of DCNN

The max pooling layer was added based on design to convert the variable number of hidden features in the convolution final layer to a fixed number of elements; in this case, K is set to thirty. For each feature map formed by a window size with a filter, the 30 highest values are obtained and concatenated. A brief explanation of the various output stages is provided in the following section.

3. Results and Discussion

The present research analyses human emotions using EEG signals and the DL method to recognize and categorize different emotional states. The HPIIRZ filter technique is used in the initial stage of eliminating the artefacts in the EGG signals. Employing PSD and hybrid IABC-PSO, the best features are retrieved and chosen accordingly. Subsequently, Deep CNN is successfully used to classify the emotions accurately. The proposed system was implemented using the Python platform to verify its performance, and the obtained results are explained in the below section.

The input EEG signal waveform is illustrated in Figure 5. Similarly, the waveform for a sampling frequency signal is seen in Figure 6. The arousal level displays the degree of excitation and relaxation. At the same time, the valence indicates the degree of pleasurable and uncomfortable (i.e., positive and negative) emotions.

The proposed system's preprocessed signal description is shown in Figure 7. EEG signal waveforms that have been smoothed were demonstrated in the outcome. Artefacts are eliminated from the EEG signals using preprocessing, which involves filtering, epoch selection, and signal averaging.

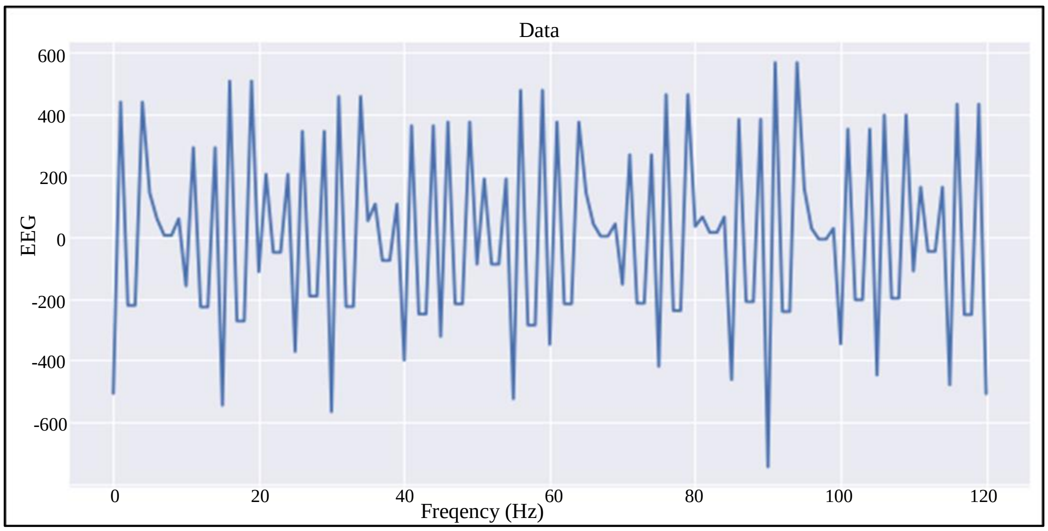

Fig. 5 Input EEG signal

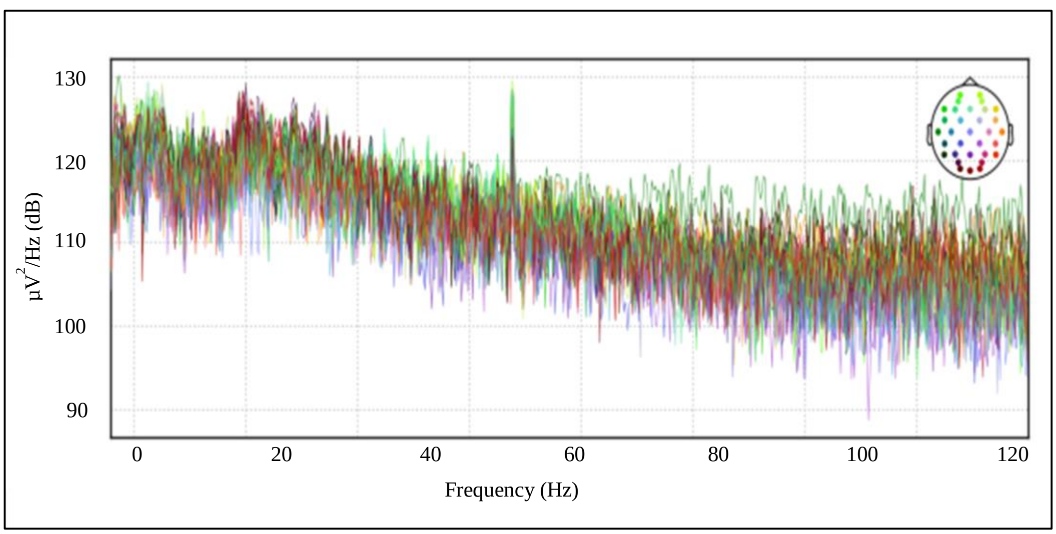

Fig. 6 EEG signal with a sampled frequency

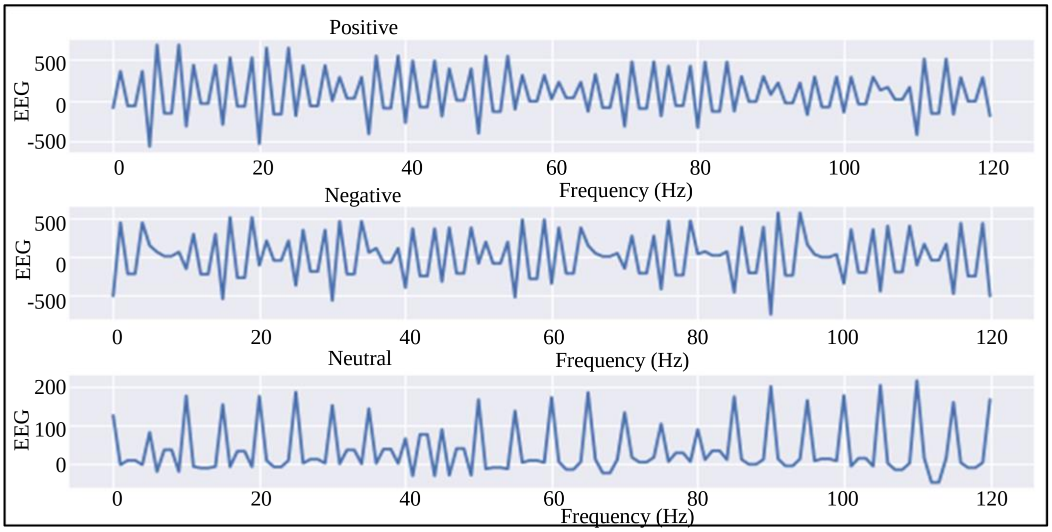

Fig. 7 Preprocessed by using HPIIRZ filter

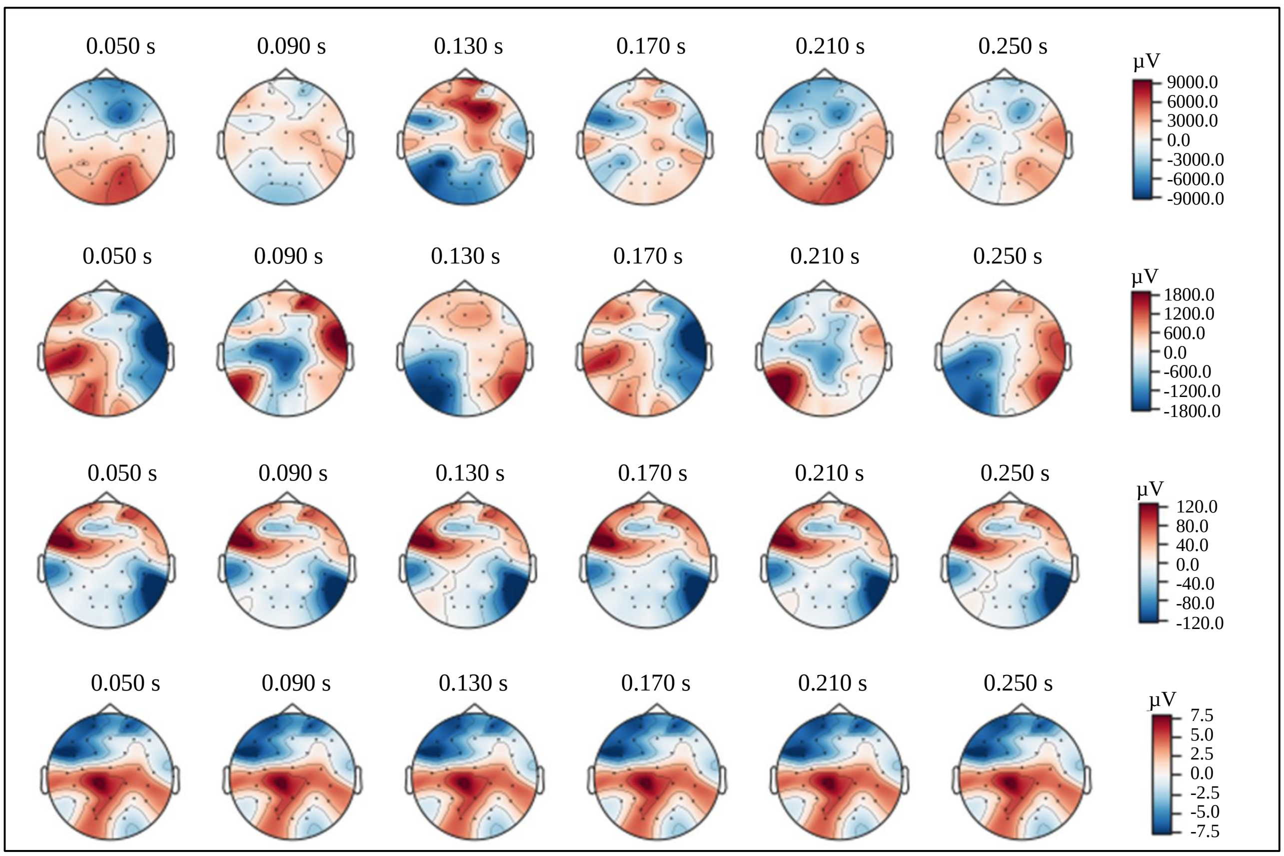

Fig. 8 Artifact detection from brainwaves, including beta, theta, gamma, and alpha

Signals captured by EEG that aren't produced by the brain are called artefacts. Some artefacts may resemble seizures or actual epileptiform aberrations. It's critical to differentiate between artefacts and brain waves by looking at the logical topography field of distribution for actual EEG abnormality. The movement artefact is subsequently extracted using the HPIIRZ filter, and it can be eliminated from the ECG signal by subtracting the extracted one, as illustrated in Figure 8. Figure 9 illustrates the theta, alpha, beta and delta waveforms. Here, Alpha brainwaves are related to imagination and meditation, Beta brainwaves are generated during intense thought, Theta brainwaves are present during deep sleep, and Gamma brainwaves are related to solving issues, joy, and compassion.

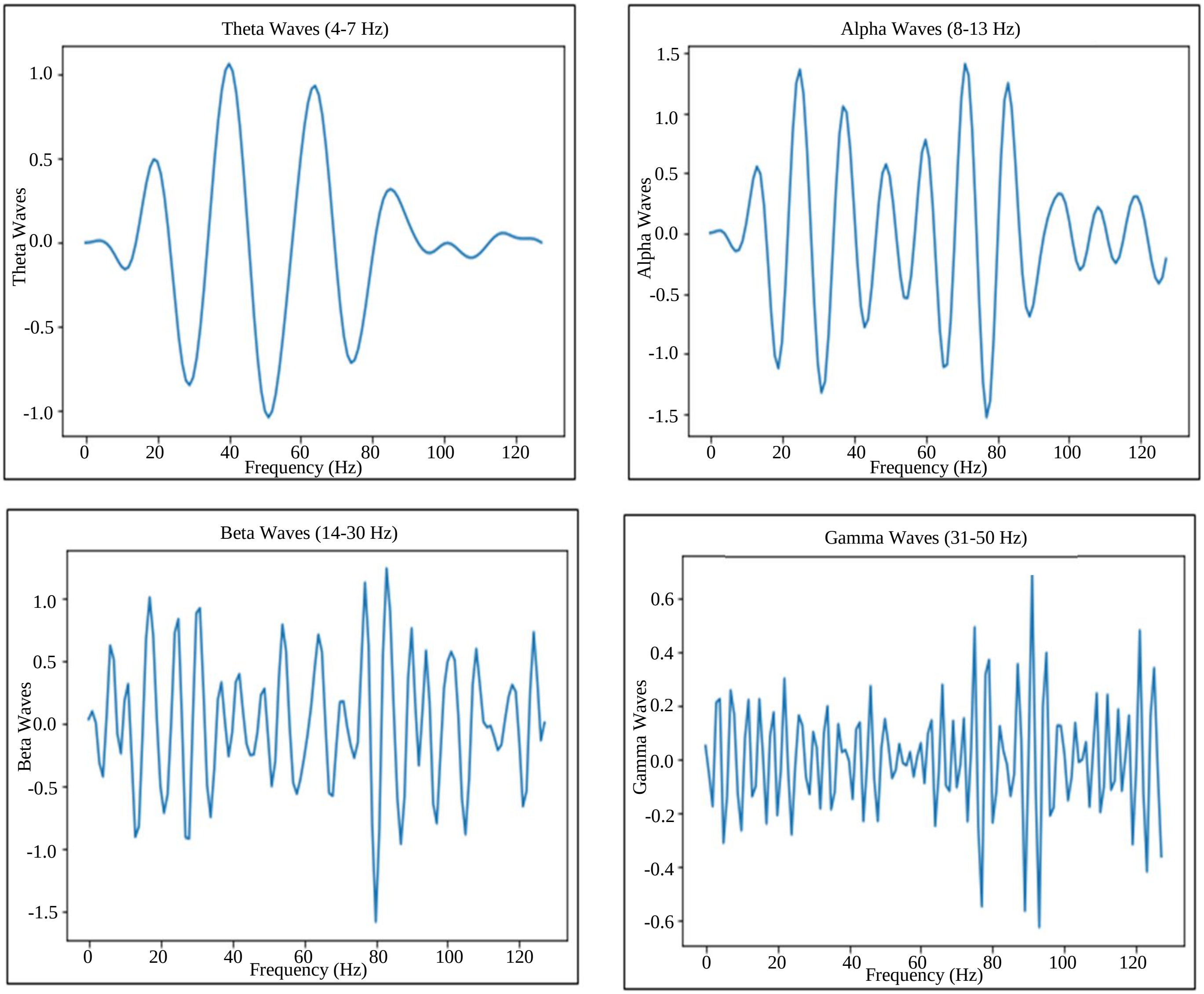

Fig. 9 Representation of a sample dataset shows several brainwaves

According to Figure 9, the human brain's electrical wave is made up of the following five primary frequency bands: delta (1-3Hz), alpha (8-13Hz), beta (14-30Hz), theta (4-7Hz) and gamma (31-50Hz). Each band's properties can be used to infer a subject's cognitive and emotional states. The efficacy of the classification is improved by using The Power Spectral Density (PSD) feature extraction approach to derive the features based on several frequency transformations. Figure 10 illustrates how a signal's PSD examines the power distribution throughout the frequency range. The accuracy and loss of the DCNN classifier's testing and training periods are shown in Figure 11. The proposed DCNN classifier has enhanced performance with minimal testing and training loss, as shown by the graph. Consequently, the proposed approach distinguishes different emotional states from the EEG signals.

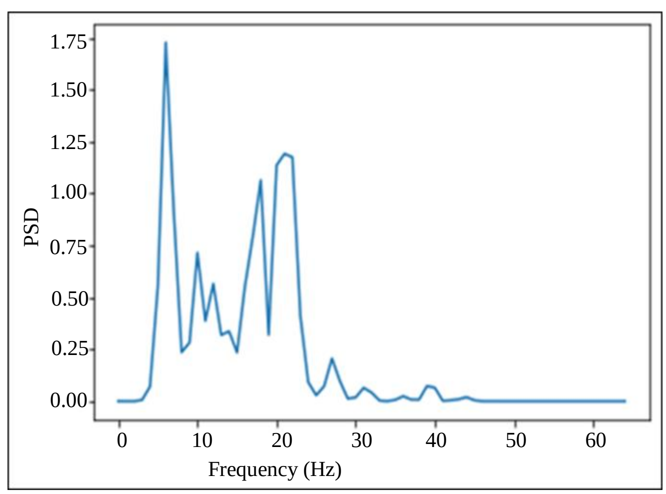

Fig. 10 Feature extraction using PSD

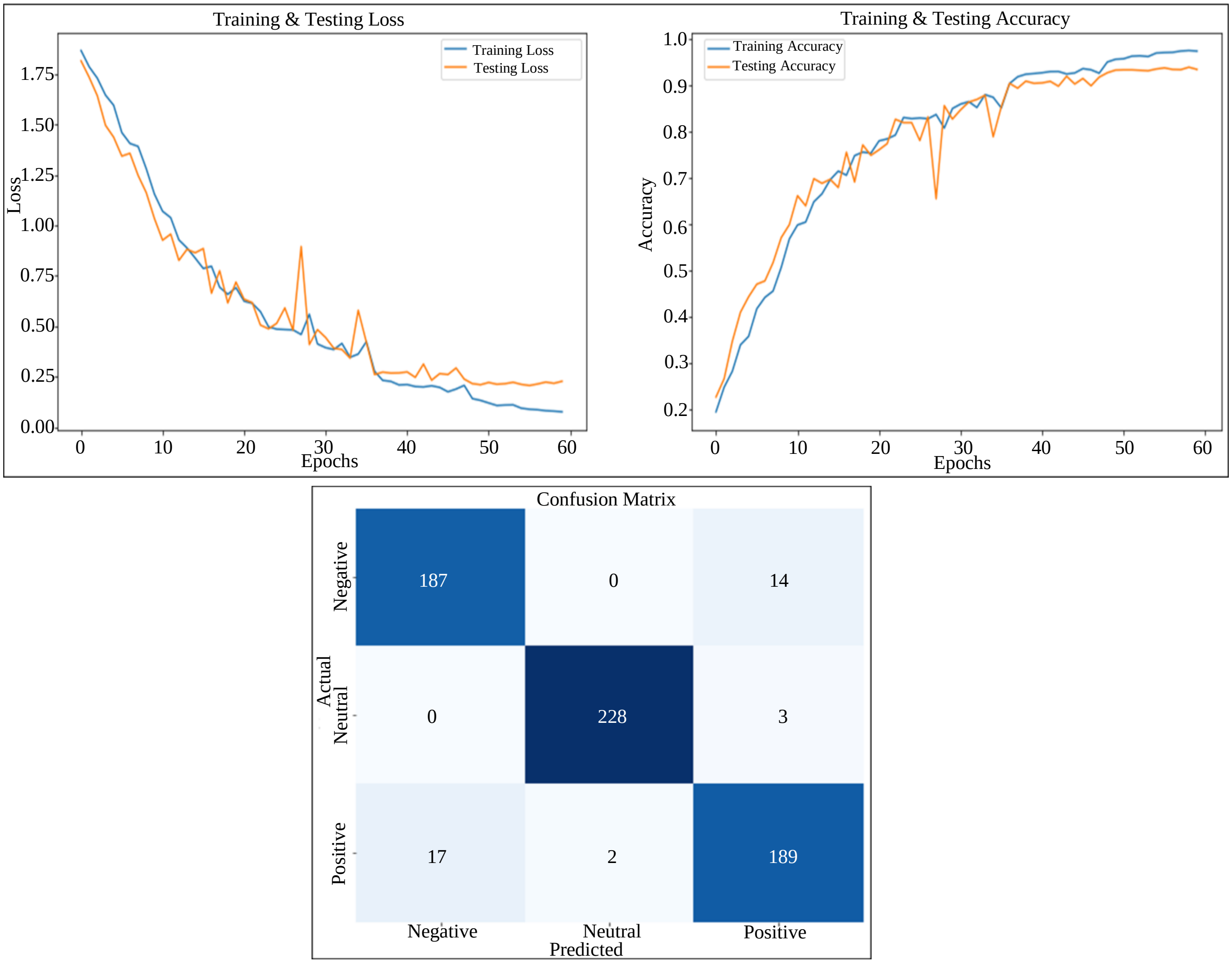

Fig. 11 Outcome of accuracy and loss of Deep CNN

3.1. Comparison Analysis

Here, the proposed methods with various existing approaches are carried out in this section. From the analysis, it is clear that the proposed system has high accuracy in identifying the different mental states of humans. Figure 12 shows how the proposed filter processing affects the ECG signal appearance.

Figure 11 illustrates that IIR filtering deforms the ECG waveform somewhat, whereas zero-phase IIR filtering preserves its original structure. Consequently, the zero-phase method is essential for HPIIRZ filtering to eliminate motion artefacts and maintain the system of the ECG signal.

Table 1 shows a comparative investigation of proposed Deep CNNs with various classifiers, including KNN [19], DBN [20], and MLP [21, 22], and Figure 13 shows the corresponding graph. The findings show that the proposed classifier has an outstanding accuracy for predicting human emotions, which is 95.80%.

Three examples of data splitting used to train and test classifiers are shown in Tables 2 and 3. Every splitting outcome is shown in the results. According to the table findings, the suggested DCNN outperforms existing algorithms regarding accuracy, specificity, sensitivity, FI, and precision.

Table 1. Accuracy comparison of classifier

Classifier	Accuracy
KNN [19]	86.75 %
DBN [20]	87.62 %
MLP [21]	78.11%
Proposed Deep CNN	95.80 %

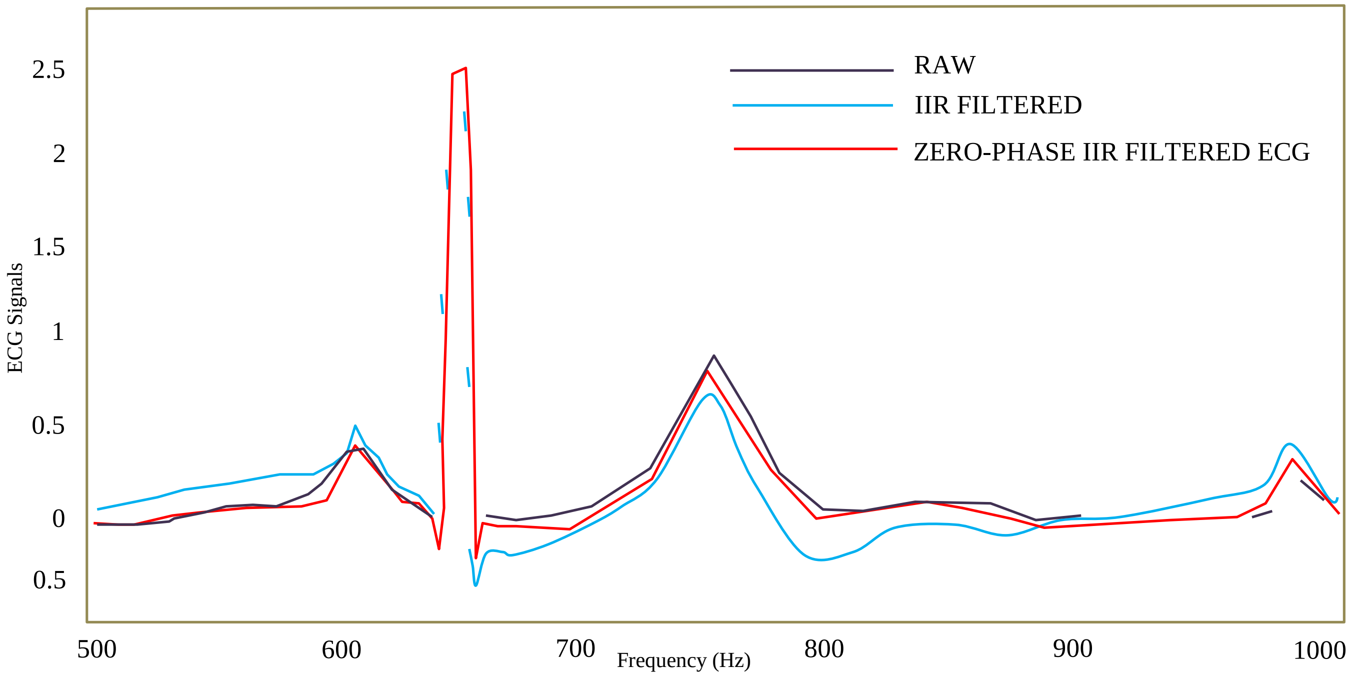

Fig. 12 Comparison of filtering methods

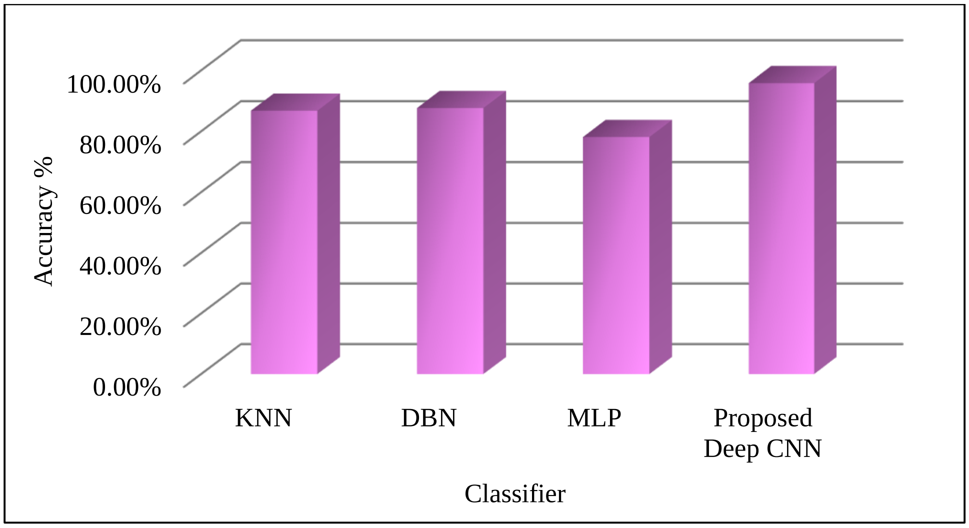

Fig. 13 Accuracy comparison

Table 2. Classification outcomes of testing and training of EEG signals (arousal and valance)

	Valance			**Arousal**		
Classifier	F1	Recall	Precision	F1	Recall	Precision
DCNN	94.56	94.7	95.3	94.44	94.97	95.67
KNN [24]	93.32	93.18	93.09	93.35	93.95	93.60
DT [24]	92.06	91.23	92.65	91.28	91.56	91.22
NB [24]	91.72	92.51	91.93	92.80	92.62	92.32

Table 3. Classification outcomes of testing and training of EEG signals (accuracy (ACC), sensitivity (SN), specificity (SP), and positive predictive (PPV))

Classifier	SN	SP	PPV	ACC
DCNN	95.23	94.76	94.34	95.80
KNN [24]	94.03	94.03	94.03	94.03
DT [24]	88.50	88.50	88.50	88.50
NB [24]	92.27	92.27	92.26	92.27

4. Conclusion

Over the past ten years, EEG-based emotion identification has expanded in popularity as a BCI technology. Feature extraction and selection, preprocessing, and classification are all steps in an emotion identification system. Currently, deep learning is successfully applied to categorize emotions in BCI systems, and the outcomes have been enhanced concerning conventional classification methods. Hence, this research presents a computerized method for deriving feelings from EEG information. HPIIRZ filtering approach is initially implemented to reduce artifacts in EEG signals. Then, employing a hybrid IABC-PSO, the frequency and spectrum features are retrieved using the PSD method, from which the best parts are picked. At the classification stage, DCNNs are subsequently employed to categorize emotional states. To assess the efficacy of the proposed model, including accuracy, specificity, and sensitivity, a model of evaluation is established using the Python platform. According to the results, the proposed technique is effective, while the DCNN-based method has a greater accuracy of 95.80%.

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