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Original Article

Integrated Approach for Enhanced EEG-Based Emotion Recognition with Hybrid Deep Neural Network and Optimized Feature Selection

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Abstract - *Emotion recognition through Electroencephalography (EEG) signals holds significant promise for a wide range of applications, from healthcare to human-computer interaction. This concept introduces a comprehensive approach to improve the accuracy and efficiency of EEG-based emotion recognition. It combines advanced signal processing techniques, hybrid feature selection methods and deep learning architectures, resulting in a robust and innovative framework. The proposed work begins with the preprocessing of EEG signals using an orthogonal wavelet filter. This filter offers exceptional flexibility in balancing the preservation of relevant emotional information and reducing unwanted interference. This initial step is critical in ensuring the processed EEG signals are optimally prepared for subsequent analysis. To capture the time-frequency representations of EEG signals, the Empirical Mode Decomposition (EMD) technique is applied. EMD is known for extracting complex, non-stationary features from EEG data, which are often critical for understanding emotional states. A key innovation in this concept is the hybrid feature selection approach. It combines the Chaotic Squirrel Search Algorithm (CSSA), which leverages chaos theory for optimization, with the Whale Optimization Algorithm (WOA), a nature-inspired metaheuristic algorithm. This combination is designed to curate the feature set, retaining only the most discriminative elements for emotion classification. This process enhances the overall efficiency and accuracy of the classification task. For the final phase of emotion recognition, a novel hybrid deep learning architecture is employed. It combines an Attention-based Deep Convolutional Neural Network (DCNN) with Bidirectional Long Short-Term Memory (Bi-LSTM) networks. The CNN component is adept at automatically learning hierarchical features from EEG data, while the Bi-LSTM network captures temporal dependencies in the signals. Introducing attention mechanisms further refines the network's ability to focus on salient features, improving the overall recognition performance. The resulting framework showcases a holistic approach to EEG-based emotion recognition, addressing challenges related to data preprocessing, feature selection, and deep learning model design.*

Keywords - *EEG-based emotion recognition, Orthogonal Wavelet Filter, EMD, CSSA-WOA, and Attention-based DCNN-BiLSTM.*

1. Introduction

Emotion is recognized as a representation of mental conditions and psycho-physiological manifestations. According to scientists and psychologists, mental stress can be identified early on and prevented from having a detrimental effect [1]. As a result, the subjective approach using self-report questionnaires like the perceived stress scale is the most widely used technique for assessing mental stress [2]. Subjective approaches have the drawback of being time-consuming and inconvenient for more accurate assessments. Regular evaluation is often neglected until co-occurring health issues manifest; therefore, it is impractical in everyday situations [3, 4]. However, objective ways of assessment, like EEG, are regarded as one of the most promising instruments for developing practical applications, enabling people to evaluate themselves without the assistance of specialists [4]. EEG signals are those that are recorded by monitoring voltage variations on the surface of the skull that arise from activated brain neurons. However, developing such an application requires an effective EEG analysis technique, like using the channels and features most relevant to the mental state task [5, 6].

A thorough EEG-based emotion detection procedure typically consists of four steps: preprocessing, feature extraction and selection, classification, and result interpretation [7]. Multiple EEG signals are typically employed for emotion detection, in reality, to thoroughly study the dynamic swings of the brain. EEG signal preprocessing is carried out in multiple processes, including channel, time segment, and frequency band selection, in the EEG-based emotion identification system, eliminating noise from the EEG data and enhancing signal quality [8-10]. The conventional techniques used various filter techniques like Kernel filter [11], median filter [12] and Kalman filter [13] to eliminate noise present in the EEG signals. However, by using those filters, the noises from the signal are not removed appropriately [14]. Henceforth, this work incorporated the advanced orthogonal wavelet filter, which offers exceptional flexibility in preserving relevant emotional information and reducing unwanted interference. Following that, several researchers have already put forth a variety of feature extraction techniques for emotion identification [15]. The primary method used in traditional EEG emotion research is artificial EEG feature extraction related to emotions, such as obtaining the energy ratio between various frequency bands and the power spectrum of a particular frequency [16]. However, it is not appropriate for the analysis of EEG signals since it is unable to capture the time evolution of frequency components, necessitates a high degree of experience and knowledge from EEG analysts, and has a low level of extracted features and weak generalization capacity [17]. To overcome the mentioned issues, the EMD technique is applied in this work to capture the time-frequency representations of EEG signals effectively.

Moreover, finding emotionally salient features from several sources and evaluating feature sets to remove unnecessary or irrelevant features are the key challenges [18]. Choosing the best set of features to save processing time and storage needs while increasing classification accuracy is the main goal of a Feature Selection (FS) model. In order to do this and improve classification accuracy, it is useful to employ optimization techniques to remove unnecessary features from the original feature vector. Researchers have effectively used FS models in a variety of domains. For instance, a large number of optimization algorithms. Nevertheless, discovering substantial discriminative features remains a difficult endeavor [19-21]. Hence, in the present work, the hybrid feature selection approach of Chaotic Squirrel Search Algorithm with Whale Optimization proposes a nature-inspired metaheuristic algorithm. This combination is designed to curate the feature set, retaining only the most discriminative elements for emotion classification. For the final phase of emotion recognition, in order to extract such fractal dimension characteristics from raw EEG and detect emotional states, the features were classified using GA [22], Support Vector Machine (SVM) [23], CNN and LSTM [24] techniques. These techniques are highly redundant and neglect to include the temporal dynamics of EEG signals, which are essential for identifying emotions. Although those approaches are prone to overfitting due to their huge number of parameters and sophisticated design, they are inappropriate for large datasets. [25]. Therefore, the proposed model integrated with the novel hybrid deep learning of DCNN-Bi-LSTM networks improves overall recognition performance.

2. Proposed Modelling

The EEG is regarded as one of the most promising instruments to capture brain waves that provide information about the range of emotions an individual is experiencing. The proposed work for identifying the emotions of an individual's hybrid DCNN-BiLSTM is adopted for classification, and metaheuristic Chaotic Squirrel Search-Whale Optimization is used for superior feature selection. The workflow of the proposed system is illustrated in Figure 1. Initially, EEG data is collected from individuals using electrodes. The collected dataset has to be preprocessed to remove noises and disturbances from the input signal. In this research, preprocessing is carried out using an orthogonal wavelet filter, which offers exceptional flexibility in balancing the preservation of relevant emotional information and the reduction of unwanted interference.

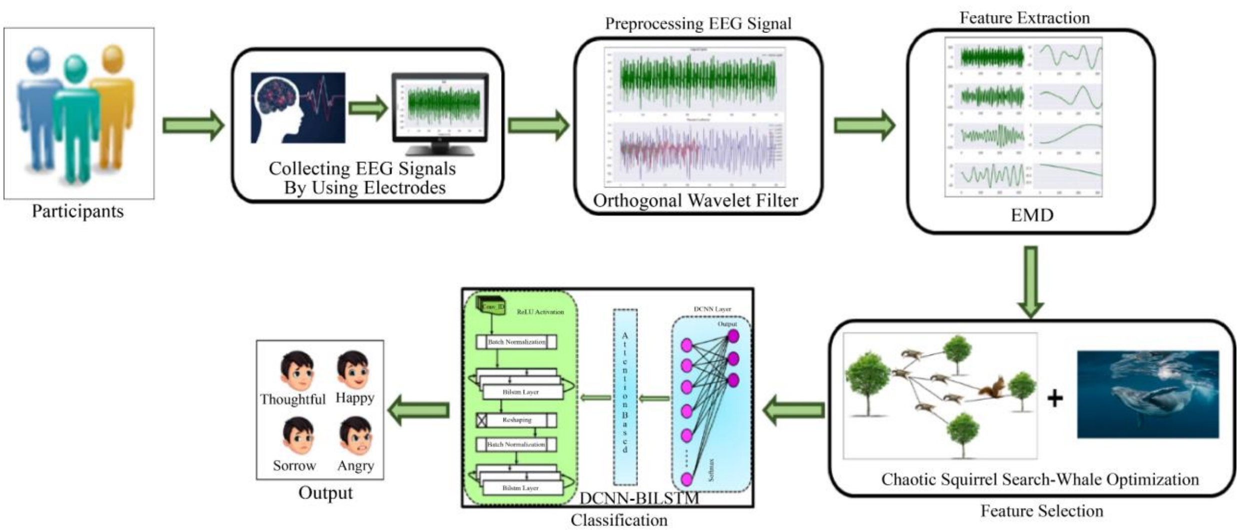

Fig. 1 Flow diagram for the proposed work

Following the preprocessing stage, the noise-free preprocessed output is processed for feature extraction using EMD, which assists in capturing the time-frequency representations of EEG signals and extracting complex, non-stationary features from EEG data. After extracting relevant features, a hybrid Chaotic Squirrel Search-Whale Optimization technique is incorporated to select the finest features. This combination is designed to curate the feature set, retaining only the most discriminative elements for emotion classification. Finally, classification is accomplished by Hybrid attention-based DCNN-BiLSTM; introducing attention mechanisms further refines the network's ability to focus on salient features, improving the overall recognition performance. The overall effectiveness of the model is assessed through performance metrics.

2.1. Preprocessing Using Orthogonal Wavelet Filter

Preprocessing is the preliminary step in solving any form of classification challenge. It makes an effort to purify the data by eliminating noise; it's a procedure that can be employed in front of feature extraction to enhance the efficiency of the ER system. In this work, the raw EEG signals are preprocessed by the orthogonal wavelet filter, which removes a distinct kind of artefact from the raw data. A range of frequencies, from 0-100Hz, are present in an EEG wave. 0–3 Hz is delta, 3–7 Hz is theta, 8–13 Hz is alpha, 13–30 Hz is beta, and 30 Hz and above is gamma. As such, to acquire the specific wave set from the EEG, the proposed filter is applied. This filter eliminates the DC offset of each electrode and 50Hz noise from power lines. The aim behind filter bank theory is to use downsampling and a bank of digital filters to process signals.

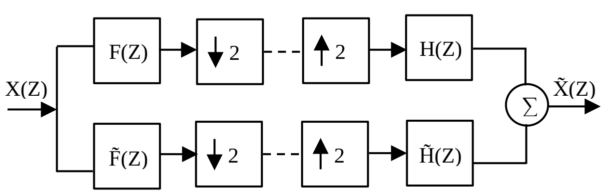

Fig. 2 Two-channel OWF

The supplied signal *x* is run through a low-pass filter with a transfer function and a high-pass filter with a transfer function at each step of the filtering process. Following this, downsampling by a factor of two is performed. In order to provide an orthogonal underlying wavelet basis and allow for flawless reconstruction from the two output signals following downsampling, these two filters need to fulfil specific constraints. As illustrated in Figure 3, the low-pass filter F(z) and high-pass filter Fe(z) comprise the two-channel analysis FB. Every filter in the analysis bank is positioned two steps ahead of the down sampler. Hence, only one filter needs to be developed to create an orthogonal two-channel FB; the other three filters can be deduced from the first filter. He(z), H(z), and Fe(z) are the other three filters that are derived from the design of the analytical low-pass filter F(z).To obtain an OWFB, the product filter, defined as P(z) = F(z)H(z) = F(z)F(z −1), needs to meet the half-band criterion.

$$\mathrm{P(z) + P(-z) = 2} \tag{1}$$

The frequency response is equivalent to $F(e^{j\omega}) = \sum_n f(n)e^{-j\omega n}$.The true coefficient of efficiency of the low-pass analysis filter meets the specified requirements.

$$|F(e^{j\omega})|^2 + |F\left(e^{j(\pi-\omega}\right)|^2 = 2 \tag{2}$$

Furthermore, the product filter's frequency response needs to be non-negative, or $P(e^{j\omega}) = |F(e^{j\omega})|^2 \geq 0$. Therefore, the P(z) must be a non-negative half-band trigonometric polynomial to create a real-coefficient OWFB. Therefore, designing non-optimal OWFBs essentially involves creating a non-negative half-band trigonometric polynomial with specific roots at z = −1. F(z) and H(z), the intended low pass filters, are obtained by spectral factorizing the proposed polynomial P(z).

Using the proposed orthogonal wavelet filter offers exceptional flexibility in balancing the preservation of relevant emotional information and reducing unwanted interference. Following that, the feature extraction process made by adopting the EED technique, which is described below.

2.2. Feature Extraction EMD

To apply robust classification, it is necessary to extract significant features from the preprocessed data. An EEG signal can be used to extract a wide range of information. Because of the intricacy, variety, and subtle variations in non-linear aspects of the expression, accurately recognizing it still presents challenges. Henceforth, the EMD approach is implemented; complex signals are broken down by EMD into an Intrinsic Mode Function (IMF) component sum with the highest local frequency, where the intrinsic characteristics are suitable for automatic identification. In order to locate the IMF, two requirements need to be met:

- Extreme and zero crossing counts must be equal throughout the signal, or they may differ by no more than one.

- At any given point in time, the mean value of the envelopes defined by the local minima and maxima must be zero or nearly zero.

- According to Huang's method, the EMD's algorithm can be summed up in the following six steps for a given signal x (t):

    - Determine the local $Y_0(t) = x(t)$ maxima and minima.

- $E_u(t)$ is the upper envelope and $E_l(t)$ is the lower envelope obtained by interpolating between the maxima and minima.

- Determine the envelope mean, $M(t) = E_u(t) + E_l(t)/2$

- $Y_1(t) = Y_0(t) - M(t)$ is the detail signal to extract. Mean signal − residue equals the original signal.

- Repeat steps 1-4 on the Residual until the detail signal, $Y_2(k), Y_3(k), \dots Y_k(k)$ meets the two requirements above to be regarded as an IMF: Then $C_1(t) = Y_k(t)$ here IMF1=C1.

- To acquire all of the signal's IMFs, $C_1(t), C_2(t) \dots C_n(t)$, repeat procedures 1 through 5 on the residual $R_n(t) = x(t) - C_n(t)$

When there is just one extreme of the function, a monotonic slope, or a constant as the residual $C_n(t)$, the process comes to an end. N IMFs $C_1(t), C_2(t) \dots C_N(t)$ and residue signal $R_N(t)$ are the end products of the EMD process. By superposing all of the IMF, the original signal can be recreated:

$$x(n) = \sum_{n=1}^{N} C_n(t) + R_N(t) \quad (3)$$

The time-frequency representations of EEG signals are efficiently captured by the developed Empirical Mode Decomposition (EMD). Moreover, a novel Hybrid Optimization approach is developed to choose the necessary feature.

2.3. Feature Selection Using Hybrid Chaotic Squirrel Search- Whale Optimization Technique

2.3.1. Chaotic Squirrel Search

In order to enhance searching behavior and avoid being trapped in the local optimal, chaotic dynamics are incorporated into the SSO. For the chaotic SSO, a well-known logistic equation is applied. The logistics formula can be expressed as follows,

$$P_{n+1} = \mu . p_n(1 - p_n), 0 \leq P_0 \leq 1, \quad (4)$$

Where n =0, 1, 2... p stands for variable, and μ stands for control parameter. If the aforementioned equation is determined, nevertheless, chaotic dynamics are revealed at μ = 4, and P_0 ∈{0, 0.25, 0.5, 0.75, 1}.

When the squirrels begin to eat, the search process begins. In the summer, when it's scorching outside, squirrels run from tree to tree in search of water. At that moment, they shift their position and investigate other parts of the forest. They devour the granules as soon as they are discovered because the hot weather makes the udders readily available to meet their regular energy needs more swiftly. Because of its ability to store energy, hickory nuts help people survive longer during difficult times by lowering the cost of food transportation. Due to reduced foliage cover in the feed forests, the risk of predation increases during the winter but subsides in the early spring.

If the population is N, the upper and lower bounds of the work area are fls_U and $fls_{L.}$ Equation (5) produces N randomly generated entities:

$$fls_k = fls_L + rand(1, M) \times (fls_U - fls_L), \quad (5)$$

Entities float to hickory and acorn woodlands to rehearse their roles. The specific update codes are shown in equations (6) and (7), respectively:

$$\begin{cases} {fls_k}^{q+1} = {fls_k}^q + b_f \times H_g \times ({A^q}_h - {A^q}_k \; if r > Y_{ps}. \\ randomlocation \quad\quad otherwise \end{cases} \quad (6)$$

$$\begin{cases} {fls_k}^{q+1} = {fls_k}^q + b_f \times H_g \times ({A^q}_{ck} - {A^q}_k \; if r > Y_{ps}. \\ randomlocation \quad\quad otherwise \end{cases} \quad (7)$$

In order to meet the SSO criterion, the complete population must be updated at the beginning of the summer iteration. Equation (6) evaluates the climatic change after notifying every individual:

$${U^q}_R = \sqrt{\sum_{i=1}^{M} ({A^q}_{ck,i}} - {A^q}_{h,i})^2 k = 1,2, \dots, N_{fls}, \quad (8)$$

Where Q is the maximum number of repetitions if Uq R < Umin signifies that summer has ended and winter has concluded; otherwise, the time of year stays the same. Every entity that flies to A_h is updated after winter.

2.3.2. Whale Optimization

The Whale Optimization method (WOA) is a popular metaheuristic optimization method, a wrapper-based feature selection method that draws inspiration from nature. Humpback Whale behavior serves as the primary source of inspiration for WOA. They attack the target by encircling it or using a bubble-net technique. Equations (7) and (8) state that the whale modifies its position based on the prey, which is the current optimal location in the surrounding activity.

$$\vec{D} = |C.\overrightarrow{X*}(t) - X(t)| \quad (9)$$

$$\vec{X}(t+1) = \overrightarrow{X*}(t) - \vec{A}.\vec{D} \quad (10)$$

Here, X denotes the whale's position vector, t stands for the current iteration, and $X*$ is the vector corresponding to the optimal solution.

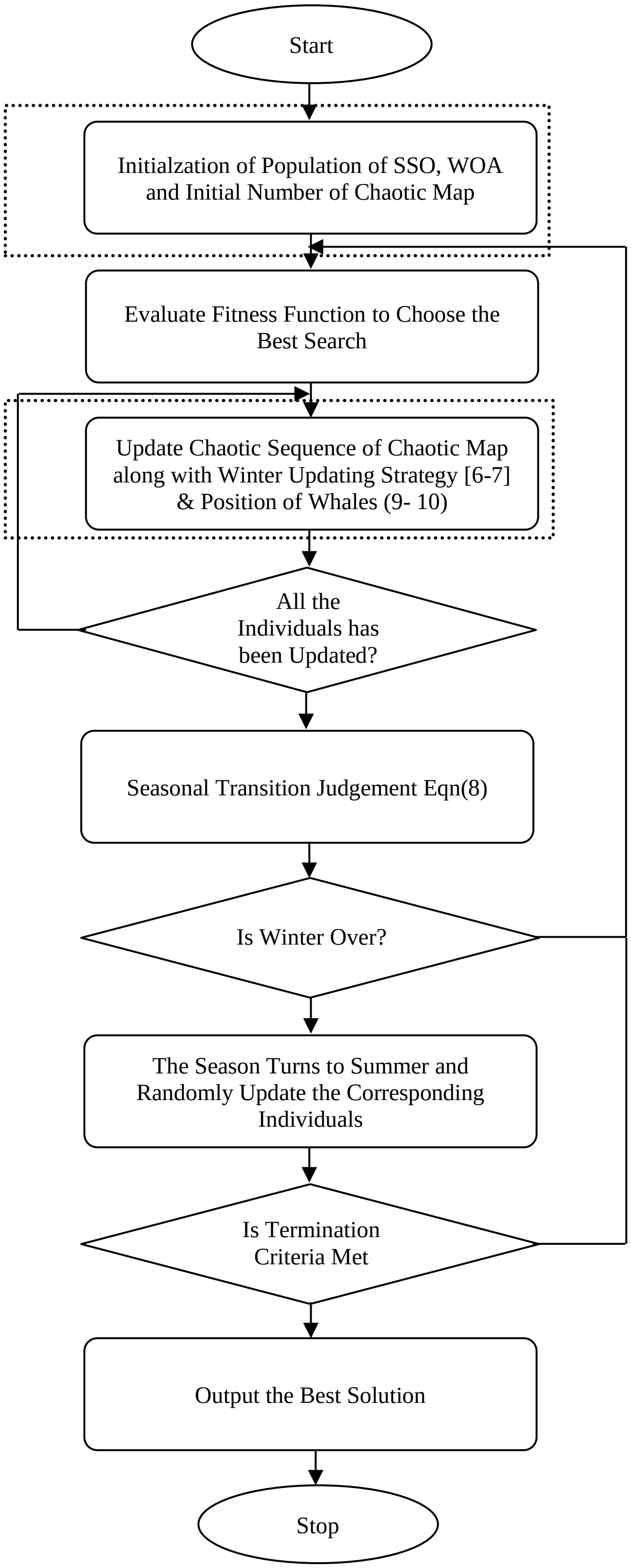

Fig. 3 Flow chart for the proposed optimization approach

Equation (9) simulates the helical pattern where humpback whales manoeuvre around their prey.

$$\vec{X}(t+1) = \vec{D}.e^{bl}.cos(2\pi l) + \overrightarrow{X*}(t) \tag{11}$$

The distance between ith whale as well as the victim is represented by $\vec{D} = |C.\overrightarrow{X*}(t) - X(t)|$, and B is a parameter used to determine the logarithmic spiral's form. The value of l indicates a random number in $[-1, 1]$ that indicates the distance between the victim and the whale's next position.

Figure 4 illustrates that l=−1 is the place closest to the victim. It is important to keep in mind that humpback whales will swim in a decreasing circle around their prey while also circling it.

2.3.3. Hybrid Chaotic Squirrel Search-Whale Optimization Technique

The foraging technique is similar in many natural organisms; the SSO incorporates chaotic dynamics to enhance the searching behavior and avoid being trapped in the local optimal state. Whales, for instance, use bubble nets for hunting prey in a way that is distinct from other predatory behaviors.

The WOA mimics the predation behavior of whales by designing an upward spiral attack method and a diminishing encircling mechanism. In order to solve global optimization issues, this research proposed a hybrid Chaotic Squirrel Search-Whale Optimization with Whale Optimization that primarily combines the flying behaviors of the squirrel with the shrinking encircling mechanism of the WOA. Figure 3 specifies the flow chart of the proposed Chaotic Squirrel Search-Whale Optimization algorithm.

2.4. Classification Using Attention-Based Hybrid DCNN-BiLSTM Technique

The emotion classification task is addressed through an innovative Attention-based Hybrid DCNN-BiLSTM technique. Combining the strengths of DCNN and BiLSTM, this approach excels in capturing both local features and temporal dependencies in sequential data associated with emotions.

The DCNN-BiLSTM captures nuanced temporal relationships in emotional content. Including an attention mechanism further refines the model's ability to pay attention to crucial elements within the input sequence, dynamically weighing their importance. This hybrid architecture enhances the overall accuracy of emotion classification by providing a comprehensive understanding of both spatial and temporal features in the data. The combined classification strategy is illustrated in Figure 4.

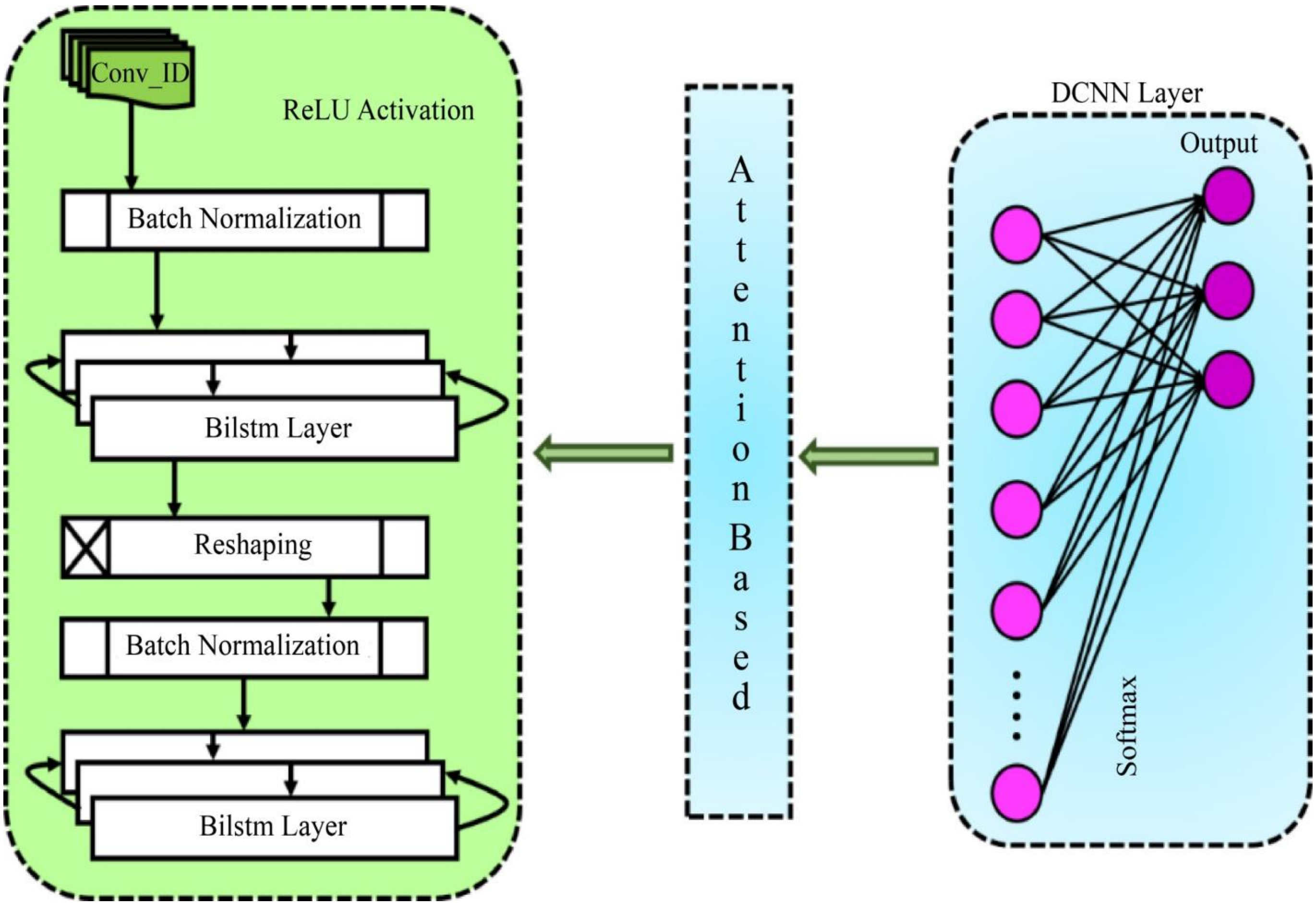

Fig. 4 Schematic diagram of Hybrid attention-based DCNN-BiLSTM classifier

2.4.1. Deep Convolution Neural Network

The DL architecture is known as a Deep CNN to ascertain whether or not an individual is stressed. Several layers are integrated into DCNN to get reliable results. The DCNN comprises two convolutional layers: the input and activation layers. The Maxpool layer comes next, followed by the flattening layer and the output activation and softmax layers.

The convolutional ReLu layer receives the input and performs an activation function to activate the necessary features. The max pooling layer is the next layer, and it uses a 2-D filter to do the pooling process and determine the necessary data or features. The "flattening" procedure produces the next layer's 1-D array of characteristics. A 1-D vector is produced by using the output of the preceding layer as the input. It is also connected to the ultimate categorization model, also called a fully connected layer. The final output layer is enhanced with the Softmax activation algorithm.

The model moves the encoded illustration from the deep CNN layer to the high-level attention layer to assign a proportionate score based on relevance. Equation 12 is used to teach a feed-forward NN the encoded representation f_n of a feature f by receiving the hidden representation f_n. Additionally, between f'_n and the dot product is practical and a context tensor at a high level to calculate the similarity. Lastly, the softmax function, as provided in Equation 13, is used to compute the attention score, $\alpha_f f$. During the training process, the vertex tensor V_h is simultaneously learned and initialized randomly.

Lastly, representation depending on attention, the weighted sum of hidden representations is denoted by f_n, which is obtained from Equation 14 of the feature vector,

$$f_n = \tanh\left(w f_n + b\right) \tag{12}$$

$$\alpha_f = \frac{\exp\left(f'_n V_h\right)}{\sum_f \exp\left(f'_n V_h\right)} \tag{13}$$

$$f_n = \sum_f (\alpha_f\, f_n) \tag{14}$$

2.4.2. Bidirectional Long Short-Term Memory

A BiLSTM layer receives the output from a high-level attention layer to determine the long-range contextual dependencies. Recurrent Neural Networks like BiLSTM are an advancement over LSTM network decisions. It can learn long-range contextual information thanks to this functionality, which also helps it remember what to remember and what to forget. An LSTM cell is made up of an output gate (o_t), an input gate (i_t), a forget gate (f_t) as well as a memory cell state (C_t).

The forget gate determines how much data should be wiped at time t using Equation 15, whereas the input gate, at timestamp t, controls the flow of data in a cell and updates its state to a new value using Equation 16. Equation 17 calculates the value of the candidate cell.C_t. The input for the BiLSTM at timestamp t, derived from high-level attention, is represented by F_t . In these equations, the weight vector, bias vector, sigma function, and hyperbolic tangent function are represented by W, b, σ, and tanh correspondingly.

$$i_t = \sigma(W_i.[h_{t-1}.F_t] + b_i) \quad (15)$$

$$f_t = \sigma\left(W_f.[h_{t-1}.F_t] + b_f\right) \quad (16)$$

$$\widetilde{C_t} = tanh(W_C.[\, h_{t-1}.F_t] + b_c \quad (17)$$

$$\widetilde{C_t} = F_t \otimes C_{t-1} + i_t \otimes \widetilde{C_t} \quad (18)$$

$$\sigma_t = \sigma(W_o.|h_{t-1}, F_t| + b_o) \quad (19)$$

$$h_t = \sigma_t \otimes tanh(C_t) \quad (20)$$

This study uses BiLSTM rather than LSTM to gather the appropriate information in both directions. BiLSTM is made up of two LSTMs: the forward LSTM processes the data in a left-to-right sequence to capture the context of an impending event, while the backward LSTM processes the data in a right-to-left sequence to capture the context of a previous event.

3. Results and Discussion

In this research work, Hybrid DCNN-BiLSTM and Chaotic Squirrel Search-Whale Optimization-based feature selection are implemented to enhance EEG-based emotion recognition. The proposed work is executed in the Python platform, and the comparative analysis is made using conventional techniques to demonstrate the proficiency of the developed work. Using the proposed hybrid deep learning approach, high accuracy, F1 score, specificity, sensitivity, recall, and precision are attained. The input EEG signal from the EEG dataset for classification is illustrated in Figure 5. The observed Figure 5 is utilized as input for the classification process.

Table 1. Comparison of Classification Strategy

Data Set	Participants	Stimulus	Obtained data modalities	Method	Accuracy	Qualification of emotion
DEAP [26]	32 participants. (15 female, 17 male)	40 video clips	10 EEG channels	SVM, KNN, ANN	91.1%	Continuous type valence/arousal model
Benchmark dataset[27]	32 (16 males and 16 females)	56 video clips	Data from an EEG with 32 channels	CNN	85%	Continuous type valence/arousal model
Facial landmarks data [28]	Fifty- (35 male and 25 female)	30 video clips	EEG raw data of the 14 channels	LSTM	87.25%	Six facial emotions (happiness, sadness, anger, fear, disgust, and surprise)
EEG Based on the brainwave data set	27 (12 male, 15 female)	29 video clips	Peripheral physiological data (blood volume pulse, galvanic skin response, respiration, skin temperature, electromyography), 32-channel EEG	Attention-based DCNN-BiLSTM	97.5%	Continuous type (Arousal, Valance, Dominance)

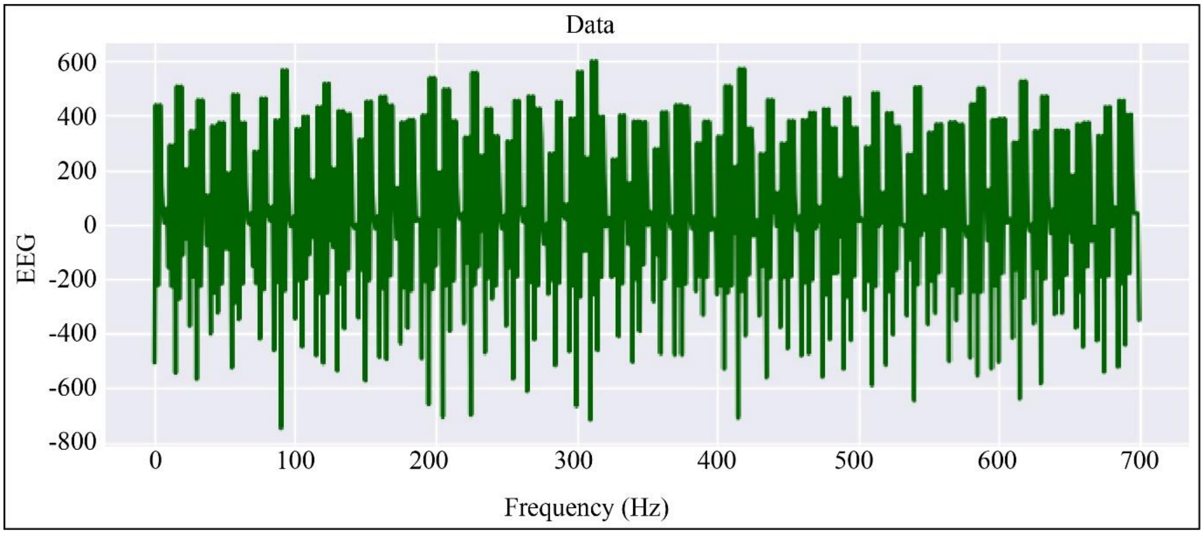

Fig. 5 Input EEG signal

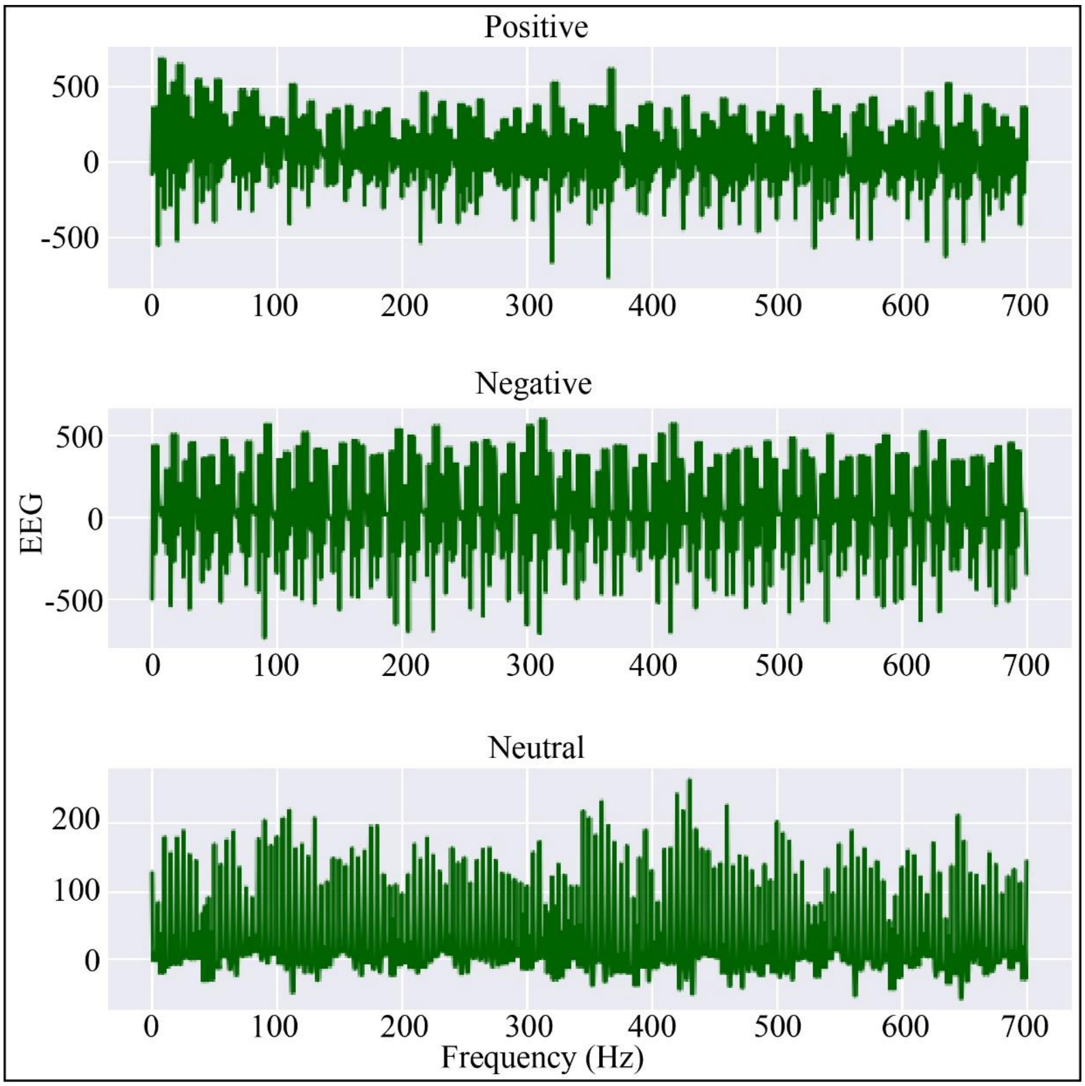

Fig. 6 Input EEG signal's positive, negative and neutral waveform

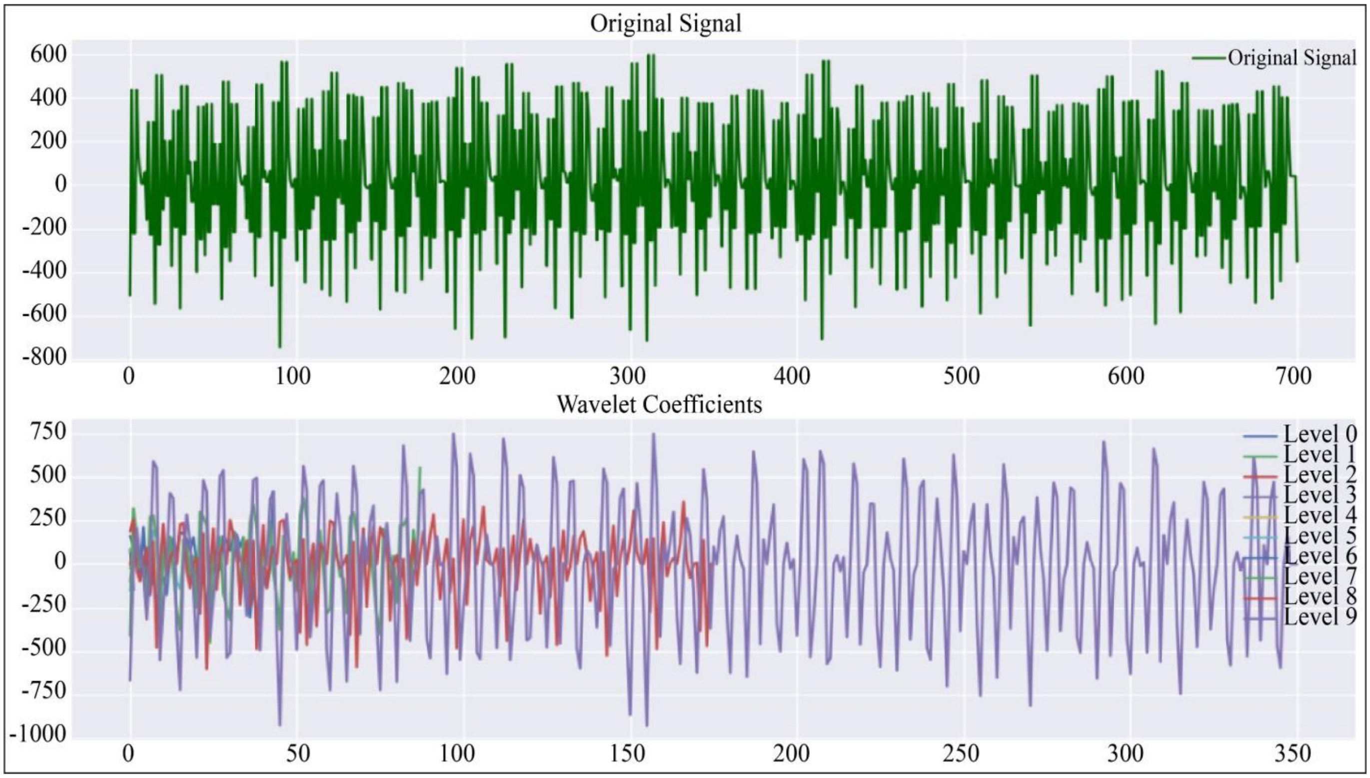

Fig. 7 Filtered EEG signal

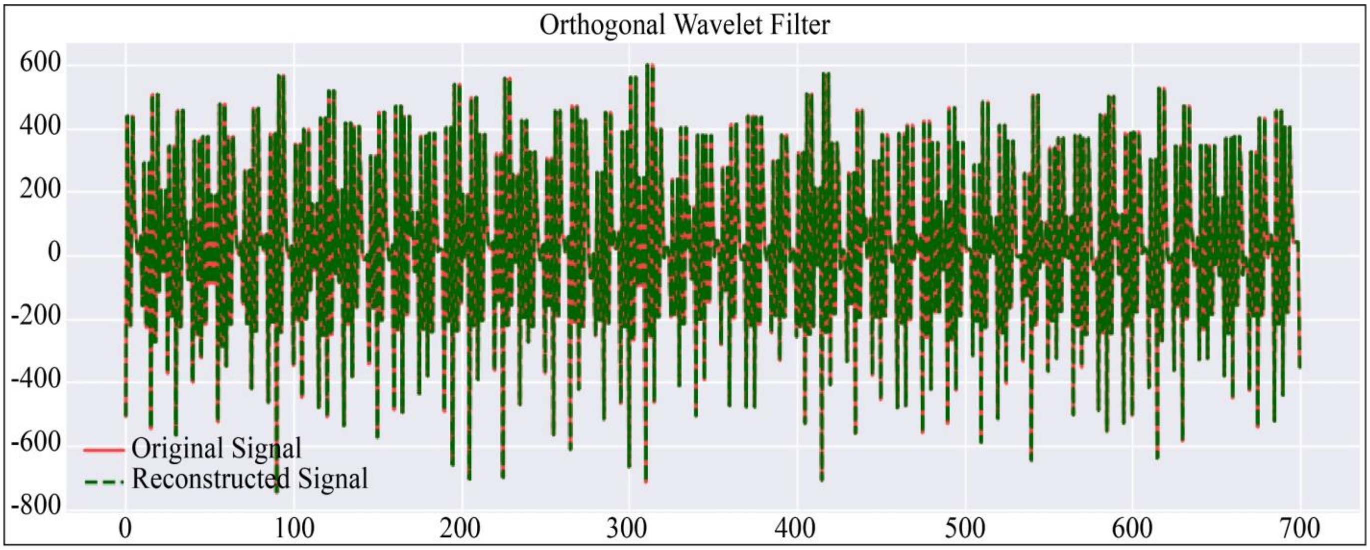

Fig. 8 Artifact removing processing orthogonal wavelet filter

The input EEG signal's waveform is seen in Figure 6, which illustrates that positive EEG signal values result in descending waves, and negative values result in ascending waves.

After extracting the movement artefact with the Orthogonal Wavelet filter, as illustrated in Figures 7 and 8, it can be eliminated from the ECG signal by deleting the obtained one.

First, as shown in Figure 9, spectrogram data is collected from the EEG signals of physically fit and depressed individuals by applying the EED to detect key time-frequency patterns. This modification captures variations in spectral content, providing a comprehensive view of the emotional state throughout time. The EED-obtained spectrogram data is then used as input for the classification model.

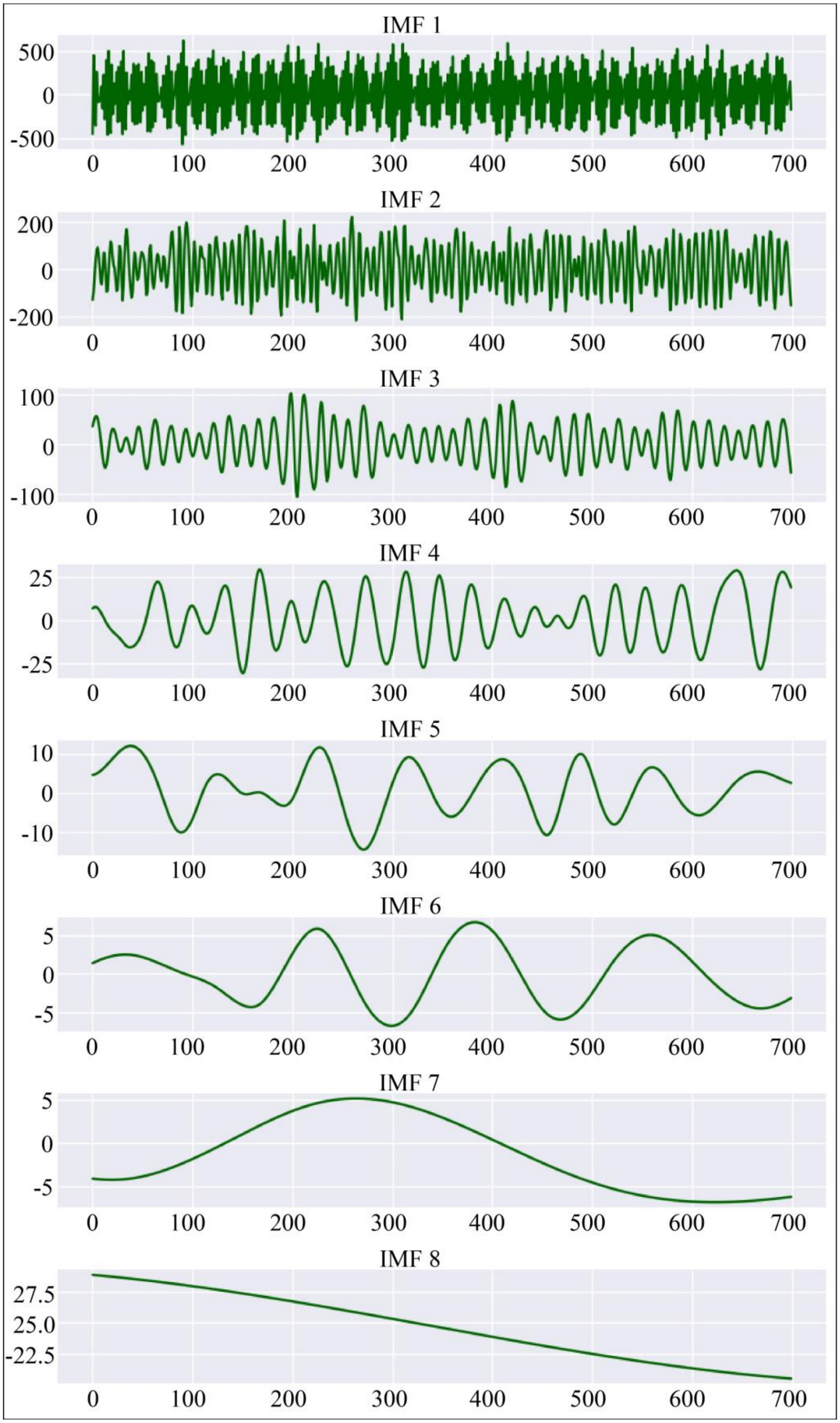

Fig. 9 Feature extraction using EMD approach

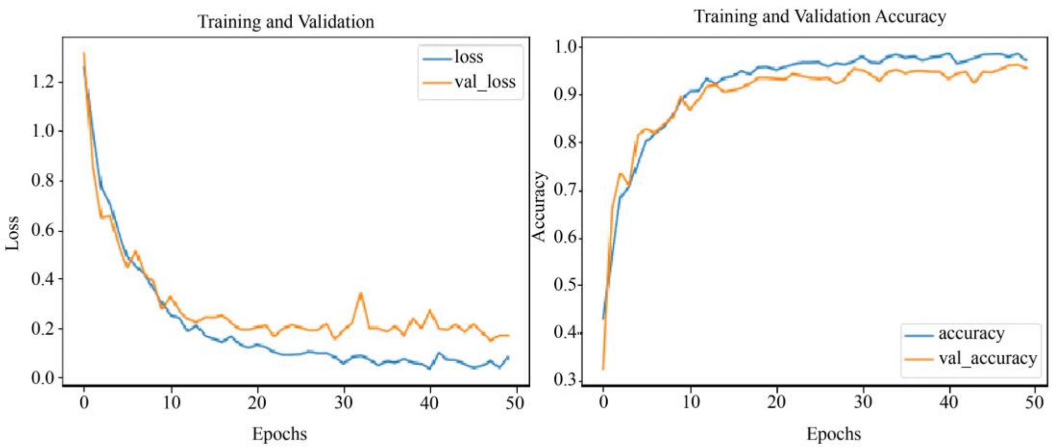

Fig. 10 Training and validation results of attention-based DCNN-BiLSTM

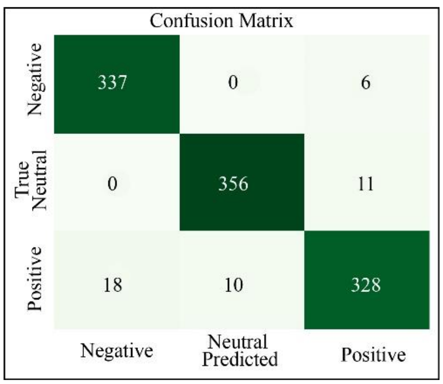

Fig. 11 Confusion matrix

The attention-based DCNN-BiLSTM training and validation results are shown in Figure 10, from which the suggested classifier achieves the maximum accuracy value of 97.5 % with the least amount of loss. Based on the results of identifying each mental state, Figure 11 presents the confusion matrix associated with the tests using the brain wave dataset. Each row in the confusion matrix represents the target class, and each column represents the projected class. The results show that, overall, neutral emotion is identified with great precision, but negative emotion is harder to identify and frequently confused with positive feelings.

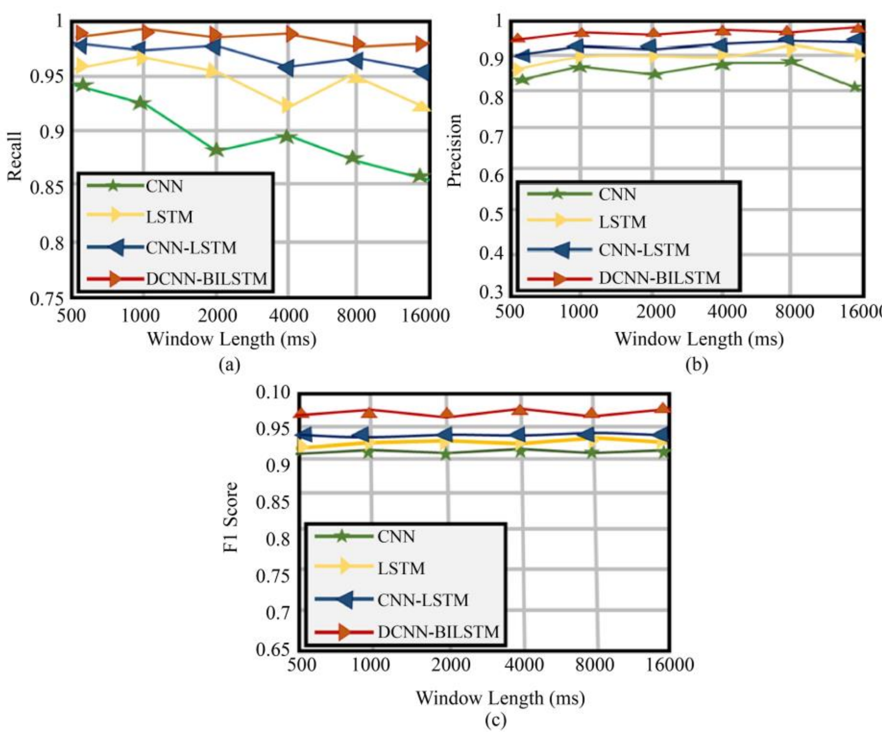

Fig. 12 Performances metrics of classification (a) Recall, (b) Precision, and (c) F1 score.

The proposed DCNN-BiLSTM approach is compared with the conventional topologies like CNN, LSTM and CNN-LSTM for recall, precision and F1 score. From the graph it is analyzed that the proposed DCNN-BiLSTM approach attained better results in terms of recall, precision and F1 score compared to the existing topologies.

Table 2. Comparison of different approaches for classification

Approaches	Accuracy (%)	Specificity (%)	Sensitivity (%)
SVM[29]	65	45	35
ANN[29]	70	55	47
CNN-LSTM [29]	95	92	95
Proposed DCNN-BiLSTM	97.6	95	98

Table 2 represents the Comparison of different classification approaches like SVM, ANN and CNN-LSTM with the proposed DCNN-BiLSTM for accuracy, specificity and sensitivity, which is observed that the implemented approach has high accuracy, specificity, as Sensitivity by the value of 97.6%, 95% and 98% compared to the conventional approaches.

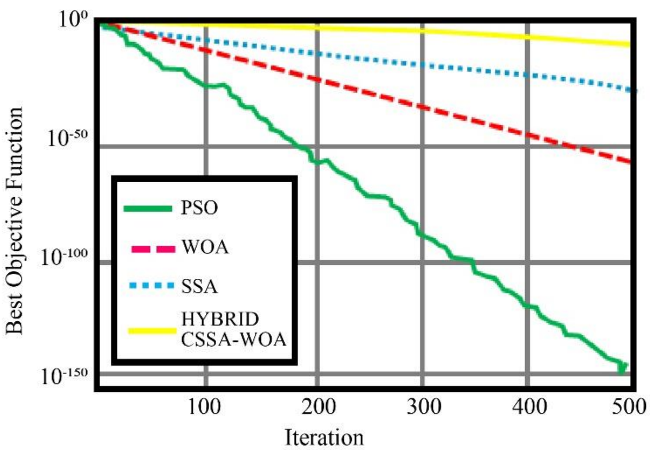

Fig. 13 Comparison of Convergence speed

The proposed Hybrid Chaotic Squirrel Search and Whale Optimization approach is compared with the conventional PSO, WOA and SSA optimization topologies. From the graph, it is evident that the developed technique achieves rapid convergence speed compared to the existing approaches.

4. Conclusion

This work presents a complete strategy to develop precision and efficiency of emotion identification based on EEG data. Deep learning architectures, hybrid feature selection strategies, and sophisticated signal processing techniques are all combined to create a strong and creative framework. Using an orthogonal wavelet filter, the suggested method first preprocesses EEG signals. An orthogonal wavelet filter is used to preprocess EEG data. This filter is incredibly flexible in how it strikes a balance between reducing unwanted interference and preserving vital emotional information. The EMD method is used to record the time-frequency representations of EEG signals. The hybrid feature selection approach in this notion is a significant advance. It blends the nature-inspired metaheuristic algorithm Whale Optimization with the chaos-theoretic Chaotic Squirrel Search Algorithm.

A novel hybrid deep learning architecture is utilized for the last stage of emotion recognition. Bi-LSTM network and Attention-based Deep CNN are combined in this model. The proposed work is executed in Python software, and the comparative analysis is carried out in terms of accuracy, F1 score, sensitivity, specificity, precision recall, and convergence speed. Consequently, it is concluded that the proposed DCNN-BiLSTM classifier attains a high accuracy of 97.5%, and the Hybrid Chaotic Squirrel Search-Whale Optimization achieves rapid convergence speed compared to the other conventional topologies.

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