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A Flower Pollination Algorithm-Optimized Wavelet Transform and Deep CNN for Analyzing Binaural Beats and Anxiety

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Abstract: Binaural beats are a low-frequency form of acoustic stimulation that may be heard between 200 and 900 Hz and can help reduce anxiety as well as alter other psychological situations and states by affecting mood and cognitive function. However, prior research has only looked at the impact of binaural beats on state and trait anxiety using the STA-I scale; the level of anxiety has not yet been evaluated, and for the removal of artifacts the improper selection of wavelet parameters reduced the original signal energy. Hence, in this research, the level of anxiety when hearing binaural beats has been analyzed using a novel optimized wavelet transform in which optimized wavelet parameters are extracted from the EEG signal using the flower pollination algorithm, whereby artifacts are removed effectively from the EEG signal. Thus, EEG signals have five types of brainwaves in the existing models, which have not been analyzed optimally for brainwaves other than delta waves nor has the level of anxiety yet been analyzed using binaural beats. To overcome this, deep convolutional neural network (CNN)-based signal processing has been proposed. In this, deep features are extracted from optimized EEG signal parameters, which are precisely selected and adjusted to their most efficient values using the flower pollination algorithm, ensuring minimal signal energy reduction and artifact removal to maintain the integrity of the original EEG signal during analysis. These features provide the accurate classification of various levels of anxiety, which provides more accurate results for the effects of binaural beats on anxiety from brainwaves. Finally, the proposed model is implemented in the Python platform, and the obtained results demonstrate its efficacy. The proposed optimized wavelet transform using deep CNN-based signal processing outperforms existing techniques such as KNN, SVM, LDA, and Narrow-ANN, with a high accuracy of 0.99%, precision of 0.99%, recall of 0.99%, F1-score of 0.99%, specificity of 0.999%, and error rate of 0.01%. Thus, the optimized wavelet transform with a deep CNN can perform an effective decomposition of EEG data and extract deep features related to anxiety to analyze the effect of binaural beats on anxiety levels.

Keywords: binaural beats; EEG signals; wavelet transform; flower pollination optimization algorithm; deep convolutional neural network

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1. Introduction

Anxiety has progressively grown in incidence over the last 24 years, particularly among adolescents and young adults [1]. Individuals in the United States were three times more likely to screen positive for anxiety disorders in April/May 2020 than in April/May 2019, due to the COVID-19 pandemic lockdowns [2]. Brainwave entrainment, also known as brainwave synchronization [3,4], is a technique for reducing anxiety and stress. It is said to improve moods, aid in deep sleep, boost the immune system (delta frequency: 1–4 Hz) [5], improve memory, aid in deep relaxation, and meditation (theta frequency: 4–8 Hz), improve positive thinking (alpha frequency: 8–13 Hz), and improved alertness (beta frequency: 14–24 Hz).

A binaural beat is a form of acoustic stimulation that has been shown to help with anxiety reduction and the attenuation or augmentation of various psychological conditions and states [6,7]. The binaural beat is the brain impression of a low-frequency sound that occurs when a person is exposed to two slightly distinct wave frequencies, both between 200 and 900 Hz [8,9]. Recent studies seem to back up the idea that binaural beats can change the operational connectivity between brain regions [10–12] and cortical network connectivity [13–15].

Several experiments have concentrated on the measurement of the effect of binaural beats on anxiety reduction. However, researchers only focused on state anxiety and trait anxiety using the state-trait anxiety inventory (STA-I) [16–18]. Moreover, anxiety has been classified into four categories, minimal anxiety, mild anxiety, moderate anxiety, and severe anxiety, which have not yet been analyzed with binaural beats. To do this, the Beck Anxiety Inventory (BAI) can be utilized, which has a score of 0–63, where BAI scores < 7 represent minimal anxiety, 8–15 represent mild anxiety, 16–25 represent moderate anxiety, and 26–63 represent severe anxiety. Similar to the self-reported analysis through anxiety inventories, the effect of binaural beats is analyzed using electroencephalography (EEG) signals [19].

In the processing of EEG signals, artifact removal is one of the most important stages due to their contamination with other signals. Unwanted signals, called artifacts, are caused by noise in the environment, experimental errors, and physiological abnormalities. Extrinsic artifacts include environmental artifacts and experiment errors, which are caused by external causes, whereas intrinsic artifacts include physiological artifacts caused by the body itself (e.g., eye blink, muscle activity, heartbeat) [20,21]. Significant artifacts in EEG recordings are caused by ocular artifacts, recorded as electrooculogram (EOG) signals [22]. Eye movement and blinks cause ocular aberrations, which can spread over the scalp and be detected as EEG activity. The contamination of EEG data by muscle activity is a well-known and difficult challenge since it manifests as electromyogram (EMG) signals from various muscle groups [23,24]. When electrodes are put on or near a blood vessel [25], cardiac artifacts such as electrocardiogram (ECG) signals can be created, causing the heart to expand and contract. Thus, the objective of this work is to examine the effect of binaural beats on four levels of anxiety and their signal processing. However, the improper selection of the mother wavelet parameter will result in it performing poorlyin artifact removal in EEG signals, which can reduce the original energy of the EEG signal. For feature extraction and classification, MLP was not optimal for brainwaves other than delta waves, which led to a reduction in the accuracy analysis of the binaural beats' effects. However, there is a need to improve this for effective and promising results for the effect of binaural beats on the level of anxiety experienced. The major contributions provided by this paper are as follows:

- In EEG signals, the improper selection of the wavelet parameter reduces the original signal energy, hence an optimized wavelet transform has been introduced using the flower pollination optimization algorithm to remove artifacts from the EEG signal.
- Consequently, the impact of the binaural beats on brainwaves is analyzed via deep-based signal processing which has the capability of extracting all the deep features belonging to anxiety from EEG signals while classifying various anxiety levels.

This paper is presented as follows: some articles related to binaural beats' effect on EEG signals are surveyed in Section 2. The mathematical derivations and the experimental analysis of the optimized wavelet transform with deep CNN-based signal processing are stated in Sections 3 and 4. Lastly, the conclusion to this paper is given in Section 5.

2. Literature Review

Yusim, et al. [26] found that a binaural beat meditation technique reduced self-reported anxiety measurements in psychiatric outpatients and non-patients. Gkolias, et al. [27] found that binaural beats at 5 Hz reduced pain intensity, anxiety, and analgesic usage in chronic pain sufferers compared to sham stimulation. Sekirin et al. [28] found that binaural beating techniques reduced reactive and personal anxiety in individuals scheduled to have hip joint endoprosthesis. Menziletoglu et al. [29] found that both binaural beats and music reduced preoperative dental anxiety, but did not assess which treatment was more successful. Mallik et al. [30] found that a combination of quiet music and theta auditory beat stimulation reduced anxiety measurements in people prescribed anxiolytics. Da Silva Junior et al. [31] found significant changes in high alpha and beta, as well as theta, brainwaves in participants who listened to a 5 Hz binaural beat for 20 min. Amarasinghe et al. [32] used self-organizing maps (SOM) to detect thinking patterns and identify two patterns in five users. El Houda et al. [33] investigated the effects of marijuana binaural beats on EEG signals but found no significant results. Pluck et al. [34] conducted a double-blind study and found no effect of theta-frequency binaural beats on cognitive fluency but found a significant induction of dread in the binaural beat condition compared to control. Lee et al. [35] proposed a combination of 6 Hz binaural beats and ASMR triggers to promote theta brainwaves and psychological stability for sleep induction.

Da Silva Junior et al. [31] examined the effects of binaural beats on brainwaves and found significant changes in higher alpha, high beta, and theta brainwaves using multi-layer perceptron (MLP) and LORETA methods. Chouhan et al. [31,36] used an entropy-based approach to assess a person's degree of attentiveness using EEG signals recorded from an Emotiv EPOC headset. Lee et al. [35] investigated the effects of different binaural beat frequencies on EEG signals and found that a combination of binaural beats and ASMR triggers induced sleep. Jayasinghe et al. [37,38] presented software that uses feedback from the Apple Health Kit and Google Fit to identify and minimize stress using machine learning classifiers, including k-nearest neighbors and Naive Bayes. Amarasinghe et al. [32] proposed an approach based on self-organizing maps (SOM) for detecting thinking patterns using EEG signals and a feed-forward ANN. That et al. [39,40] investigated the use of an ANN classifier to classify EEG data from stressed and non-stressed females women using energy spectral density (ESD) characteristics. Advanced et al. [41] presented a CRNN for simultaneous sound event detection. Cheah et al. [42] found that a CNN can categorize EEG signals without the need for manual features. Andrian et al. [43] used brainwave stimulators to enhance alpha brainwaves and alleviate stress, while El Houda et al. [33] examined the impact of marijuana binaural beats on the brain. Zaini et al. [44,45] monitored EEG data and evaluated the correlations between binaural beats' characteristics and mental states using a Bayesian Networks Processor. Jirakittayakorn et al. [46] investigated the impact of a 3 Hz binaural beat on snooze phases using EEG data and event-related potential analysis.

In addition, Loong et al. [47] conducted a prospective, randomized controlled study to examine the analgesic and anxiolytic benefits of binaural beat audio in cataract surgery patients. Abu-Taieh et al. [48] used an expanded TAM model to investigate the effect of parents' anxiety and depression on children's anxiety and depression when SNs were used. Lee et al. [49] investigated the brainwave entrainment impact of binaural beats as an adjunct treatment for insomnia symptoms. Yi et al. [50] studied the effects of audible and inaudible binaural beat stimuli on alpha brainwave elicitation, whereas Ignatius et al. [51] investigated the use of audiometric EEGs for identifying certain binaural hearing properties. These studies add to our understanding of the numerous applications and consequences of binaural beats in different neurological situations.

However, some studies did not consider artifacts due to eye blinking and muscle movements, while others used techniques that could reduce the original energy of the EEG signal. Thus, there is a need to improve the performance of these studies to provide an accurate analysis of binaural beats.

3. Optimized Wavelet Transform with Deep CNN-Based EEG Signal Processing

Binaural beats are produced when sine waves are transmitted to each ear separately and are near one another, which reduces anxiety by affecting mood and cognitive functions. The binaural beat is the brain perception of a low-frequency sound that occurs when a person is exposed to two wave frequencies that are very slightly different from one another (by a maximum of 30 Hz), both of which have frequencies between 200 and 900 Hz. To investigate the possible impacts of binaural beats on EEG signals, various transformation techniques have been used previously, but the selection of an incorrect mother wavelet reduces the system's accuracy and overlaps with the original signal, which can lower the EEG signal's initial energy. Hence, a novel resource-constrained model named the optimized wavelet transform has been proposed, in which optimized wavelet parameters are extracted from the EEG signal by integrating the flower pollination optimization algorithm with the wavelet transform for the selection of wavelet parameters. Thus, the proper wavelet parameters are selected to lessenthe reduction of the original signal's energy. Thus, an optimization that is based on the multi-objective function of a lower mean square error (MSE) and higher signal-to-noise ratio (SNR) removes the artifacts from the EEG signal to keep the valuable information, thus removing the artifact from the EEG is important to secure the quality of the EEG signal.

EEG signals have five types of brainwaves, which are delta, theta, alpha, beta, and gamma, but the existing models for binaural beats are not optimal for brainwaves other than delta waves. Furthermore, in this study, the level of anxiety has been categorized into minimal, mild, moderate, and severe anxiety, which has not yet been analyzed about binaural beats. Hence, novel, deep CNN-based signal processing has been integrated into EEG signal processing to analyze the effect of binaural beats on anxiety. The deep CNN model extracts all the deep features related to anxiety from EEG signals, which leads to more precise results for binaural beats' impacts on anxiety in terms of brainwaves, thereby achieving an effective and feasible result for the effect of binaural beats on minimal, mild, moderate, and severe of anxiety and accuracy for the analysis of binaural beats' effects.

Figure 1 shows a block diagram for proposed EEG signal processing based on a deep CNN with optimized wavelet transform, in which a raw EEG signal is transformed into a wavelet parameter and is analyzed in time–frequency space. Then, by integrating the flower pollination algorithm, the optimized wavelet parameters are obtained without artifacts in EEG signals, and the deep CNN is then used to extract features and classify the various levels of anxiety in the extracted signal.

3.1. BAI with Alpha Binaural Beats

The level of anxiety was determined by examining the effect of binaural beatsusing the Beck Anxiety Inventory (BAI), which meant in terms of determining the severity of the physical and cognitive symptoms of anxiety throughout the previous week, a four-point scale was considered that included more self-reported items. To accomplish this, some physically healthier subjects were selected and they filled in the BAI inventory. Based on their BAI scores, the subjects were divided into five groups, the minimal, mild, moderate, and severe anxiety groups, as well as a control group. The typical cut-offs are as follows: 0–9, minimal depression; 10–18, mild depression; 19–29, moderate depression; 30–63, severe depression. Multiple statements with the same score were noticed for some BAI items. For these statements, the four groups of subjects were listening to alpha binaural beats for a particular period, with ranges in a frequency of 7–13 Hz which may encourage relaxation. Although not quite meditation, alpha waves are connected to profound physical and mental calm. The consequences of stress are countered by the slight euphoria/excitement and tranquility brought on by alpha waves, which also lower cortisol levels and improve the immune system. Melatonin production is also increased by alpha waves, which significantly enhances the quality of sleep. The control group subjects, however, were not subjected to any music therapy. After the stimulation, all the subjects filled out the BAI inventory as a self-reported analysis of the effect of binaural beats on anxiety.

3.2. Optimized Wavelet Transform

The EEG signals acquired from all the subjects before and after stimulation are processed to technically analyze the effects of the binaural beats. Optimized wavelet transform (OWT) is applied to obtain information from non-stationary signals like EEGs in both the temporal and frequency domains. The contributions of the OWT towards extracting features from the source signal rely on the precise choice of wavelet parameters. Despite this, there is not a clear cutoff formula for choosing a wavelet basis function to effectively use this optimized wavelet, transform, in which artifacts are removed from the EEG signal using the concept of flower pollination optimization, which is integrated with the wavelet transform for the optimal selection of wavelet parameters to select the optimal parameter. A lower mean square error (MSE) and higher signal-to-noise ratio (SNR) are considered objective functions for solving optimization problems. The efficiency of noise reduction and unique feature extraction relies on the selection of optimized wavelet parameters. The optimized wavelet denoising process has two phases: first, the wavelet parameters are selected based on the decomposition level of the EEG signal, and second, the selection of appreciating parameters based on the flower pollination algorithm produces the denoised EEG signal.

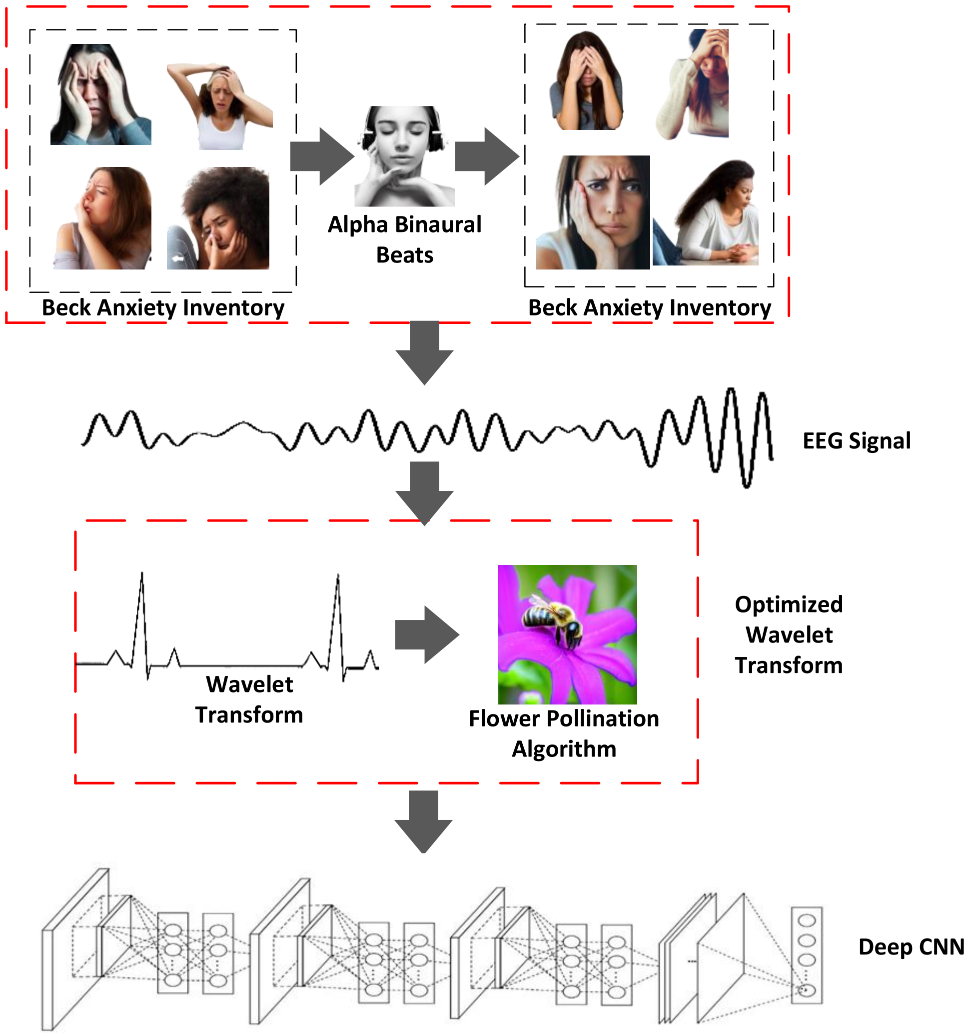

Figure 1. The architecture of the proposed EEG signal processing is based on a deep CNN with optimized wavelet transform.

The original (mother) wavelet $h_{m,k}(t)$ is often the source of the set of wavelet functions in the EEG signal. It is dilated by a value of a = 2m, translated by the constant b = k 2m, and normalized so that it is given by Equation (1), as follows:

$$h_{m,k}(t) = 1\ \sqrt{a}h(\ t - b\ a\ ) = 1\ \sqrt{2m}h(2 - m\ t - k) \quad (1)$$

According to the given integer values of m, k, and the initial wavelet, which is either determined analytically or by solving a dilation equation which is given in Equation (2) below.

$$x(n) = a_0 + \sum_{m=0}^{s-1} \sum_{k=0}^{2^{s-m-1}} a_{2^{s-m-1}+k} - h\left(2^{-m} n - k\right) \quad (2)$$

The $x(n)$, the dilation equation, is transformed to x_i^{t+1} due to the wavelet parameter initialization of the constant value, which is the global pollination operator, to determine the best suitable wavelet parameter. Thus, the modified form of the dilation equation is given by Equation (3).

$$x_i^{t+1} = x_i^t + L\left(X_i^t - g_*\right) \quad (3)$$

The levy distribution (L) is given in Equation (4), as follows:

$$L \sim \frac{\lambda \Gamma\ (\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}} (s \gg s0 > 0) \quad (4)$$

where λ is the wavelength parameter and s is the step vector, which is in the threshold limit of the transformed EEG signal for the distribution. Similarly, for local pollination, Equation (5) is used to update the x_i with the local parameter, k, of the decision factor, and ε is the switching probability. The local pollination operator x_i^{k+1} in the updation of the wavelet parameter is given by,

$$x_i^{k+1} = x_i^k + \varepsilon\left(x_i^k - x_t^k\right) \quad (5)$$

The proposed optimized wavelet transforms, via the flower pollination optimization algorithm, have two objective functions: $min\ (MSE)$ and $max\ (SNR)$ which are given in Equation (6), as thus the fitness function of the proposed system is given in Equation (6):

$$f = Min(Max(1 - SSIM(X\ N)) \quad (6)$$

The two objective functions, which are the mean squared error (MSE) and signal-to-noise ratio (SNR), are formulated in Equation (6). The fitness formulation makes use of the (1-SSIM), also known as the dissimilarity index, which is generated for each picture in the iteration and tends to further minimize its maximum value. Thus, the fitness function of the system is given by the minimum mean square error and the maximum signal-to-noise ratio in the optimized wave transform. The process takes place in an optimized wavelet transform using the flower pollination algorithm.

Figure 2 illustrates the conceptual diagram of an optimized wavelet transform using the flower pollination algorithm, in which the contaminated EEG signal is expanded using an optimized wavelet transform to obtain optimized wavelet coefficients, and then the wavelet transform is integrated with the flower pollination optimization algorithm to select the best wavelet parameters that remove the most artifacts from the EEG signal.

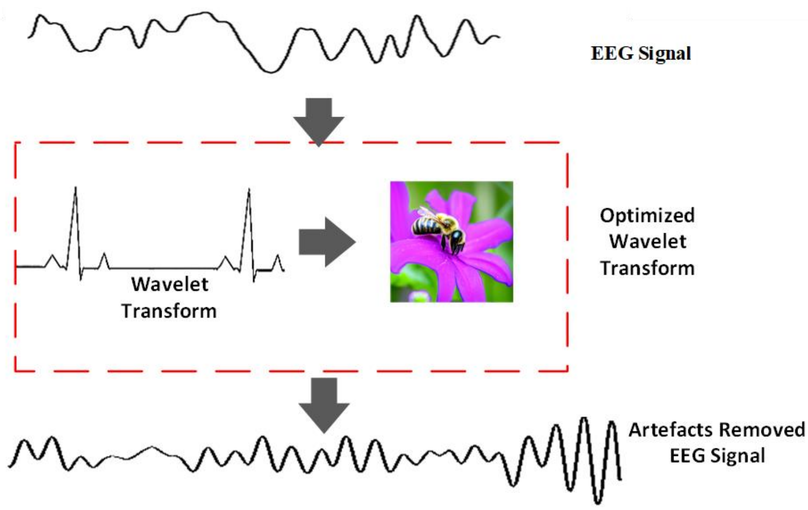

Figure 2. Conceptual diagram of optimized wavelet transform using flower pollination optimization.

The Algorithm 1 for the flower pollination optimization of the optimized wavelet parameter has been explained as follows:

Algorithm 1: Flower pollination optimization of the optimized wavelet parameter

Input: Wavelet parameter
Output: Best wavelet parameter without noise
Initialize: n parameters with random solution
Define a switch probability $p \in [0, 1]$
Calculate all f for n solutions
$t = 0$
while $(i \geq N)$ do
    for $i = 1, \ldots, N$ do
        if $rnd \leq p$ then
            Draw a (d-dimensional) step vector in the L which obeys a Levy distribution
            Perform $x_i^{t+1} = x_i^t + L\left(X_i^t - g_*\right)$
        else if
            Perform $x_i^{k+1} = x_i^k + \varepsilon\left(x_i^k - x_t^k\right)$
        Select $x_i^{t+1}(t) \leftarrow 1;$
        Else
          Draw from a uniform distribution $\in$ [0,1]
          Select $x_i^{k+1} \leftarrow 0;$
        end if
        Calculate $f'(x)/{*}f'$ is the fitness function calculated at random distribution */
        if $f'(x^*) \leq f(x)$ then $x^* = x$
        end if
    end for
    Find the current best solution g * among all x_i^k
    $t = t + 1$
end while

The flower pollination algorithm with optimized wavelet parameters shows the initialization of the n parameters with a random solution. The input is the wavelet transform parameter and the output obtained from the optimized wavelet parameter with the flower pollination algorithm is given as the best wavelet parameter with the solution to the input, thus, the uniform distribution of the parameters is taken into account to obtain the best solution g among all x_i^k of the probability switching function of the wavelet transform. The switching function determines the difference due to the high probability of the wavelet transform being in the best wavelet selection. It also generates a random function for the flower pollination optimization algorithm and the wavelet transform to obtain the step vector s from the levy distribution that provides the performance of global and local pollination, thus, the best solution is obtained by calculating the decision factors x_i^k of the current solution via the top solution discovered globally in a global pollination operator x_i^t. The improvement loop must be exchanged either locally or globally by the switch operator i, therefore, up until a point of stagnation, this procedure is repeated.

Figure 3 depicts the flow diagram of an optimal wavelet transform, which begins with the signal's initialization pattern for data collection. The input signal data is read first, then an efficient wavelet transform is performed for each signal to choose the best wavelet parameters. A greater signal-to-noise ratio (SNR) and a lower mean square error (MSE) are considered to be the objective functions for addressing optimization problems that remove artifacts from the EEG signal.

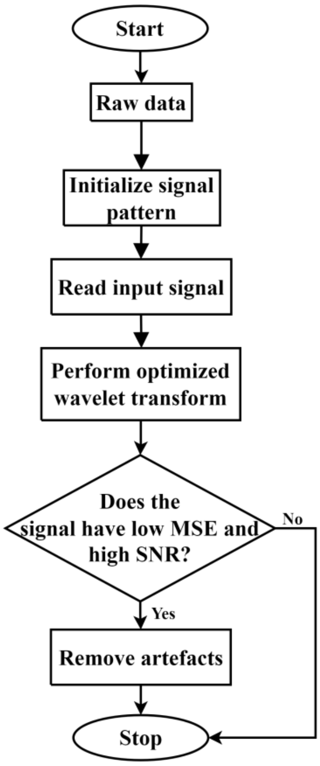

Figure 3. Flow chart of optimized wavelet transform.

3.3. Deep CNN-Based Signal Processing

Deep CNN-based signal processing extracts features and combines various classification elements, it also offers a good path for the precise detection of various brain states. Thus, several features were recovered from the denoised EEG signal to extract features such as the alpha, beta, theta, delta, and gamma brainwaves and both their time and frequency domains, including the mean, standard deviation, entropy, and energy, four widely used measurements of the signal. The electroencephalogram, with its mean value, provided the iteration varies from 1 to L, has a standard deviation with a different set of signal processing, thus, the energy of the system is given by the delta frequency domain, thus, the entropy of the electroencephalogram is also given by the DCNN-based signal processing. Therefore, to extract usable features from the EEG signal of each participant, the DCNN is trained individually. Each participant's number of channels that recorded high-quality data varied during the pre-processing stage, it was discovered. The EEG signal of each participant was left with a variable number of channels and some channels were eliminated based on the signal-to-noise ratio and low mean square error, therefore classification was accomplished via DCNN to extract useful features such as delta, theta, alpha, betta, and gamma brainwaves from the optimized wavelet coefficients. The DCNN predicts the associated class to which an independent variable belongs using a variety of independent variable values' features as input. For instance, for a specific feature x of a class y, the classifier is a function f that predicts the class $y = f(x)$. The DCNN's architecture has interconnected nodes that store and process data through connections formed between its nodes as a result of a learning process that recognizes patterns in the training data.

The input layer function based on time-frequency analysis is formalized as Equation (7):

$$I_t = \varphi(g_i *.(h_{t-1},\ x_i^{t+1}) + x_i \tag{7}$$

The hidden layer function based on time-frequency analysis is formalized as Equation (8):

$$h_t = \varphi(g_f\ *.\ (h_{t-1},\ x_i^{t+1}) + x_f \tag{8}$$

The output layer function based on time-frequency analysis is formalized as Equation (9):

$$O_t = \varphi(g_o * . (h_{t-1}, \ x_i^{t+1} \ )+x_o \tag{9}$$

The output with the activation function of the deep CNN is formalized as Equation (10):

$$a = \varphi[\sum_j \ g * x_i^{k+1} + x] \tag{10}$$

where x_i^{k+1} are the unit inputs, b is the bias, φ is the nonlinear activation function, and a is the activation unit. As a result, a separate set of cases is used to test the classifier's performance, which gives the accurate classification of the anxiety level as mild, moderate, minimal, or severe. Thus the $g*$ is the output from the optimized wave parameters. Here, x_i is the unit of the input layer of the DCNN, x_f is the unit of the hidden layer function of the DCNN, and x_o is the unit of the output activation function of the DCNN. Thus, the activation unit of the deep convolution neural network is given by the summation of the EEG signal with the product of the best solution obtained from the wavelet parameter, thus, the activation unit stimulates the deep convolution neural network to classify the performance as a different level of anxiety. The architecture of the deep CNN-based signal processing's feature extraction and classification is shown in Figure 4.

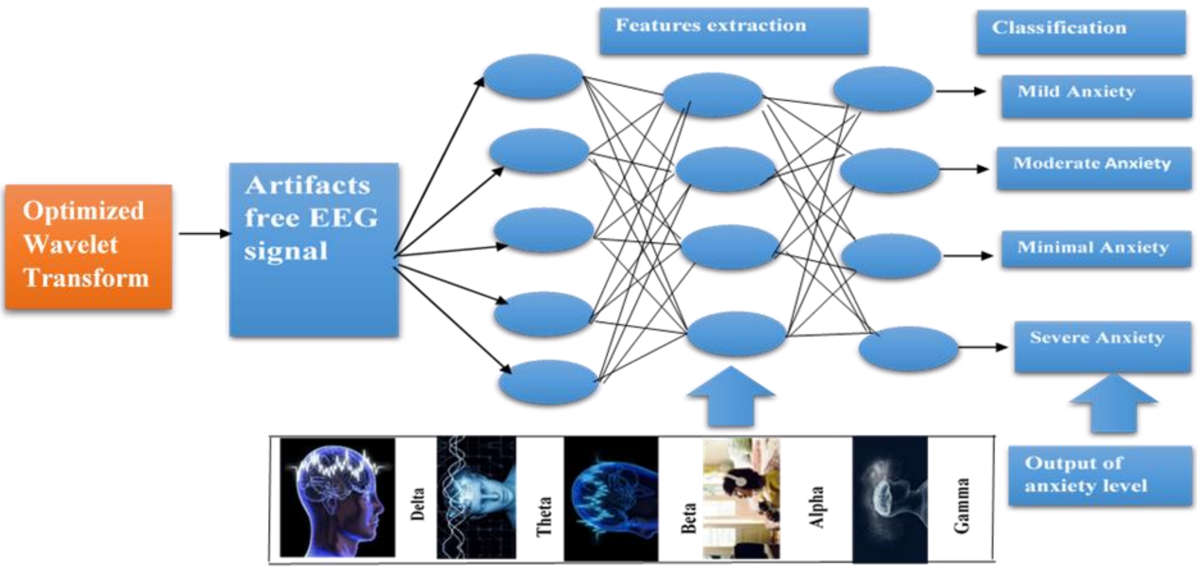

Figure 4. The architecture of deep CNN-based signal processing's feature extraction and classification.

Figure 4 shows the deep CNN-based signal processing's feature extraction and classification, in which five features were extracted from the artifacts-free EEG signal, which was the alpha, beta, theta, delta, and gamma time and frequency domains in brainwaves. Therefore, this model predicts the anxiety level of each feature by using a non-linear activation function in its classification.

Overall, the optimized wavelet transform removes artifacts from the EEG signal using the concept of flower pollination optimization, which is integrated with the wavelet transform for the optimal selection of wavelet parameters. Deep CNN-based signal processing has been integrated into the EEG signal's processing to analyze the effect of binaural beats on anxiety by extracting all the features belonging to anxiety from the EEG signal, providing more accurate results for the binaural beats' effects on anxiety in terms of brainwaves. The next section explains the results obtained from the proposed model in detail.

4. Results and Discussion

This section provides a detailed description of the implementation results as well as the performance of the proposed system and a comparison section to ensure that the proposed system works effectively.

4.1. Simulation Setup

This work has been implemented in the working platform of Python with the following system specifications, and its simulation results are discussed below.

- Platform: Python;
- OS: Windows;
- Processor: 64-bit Intel;
- RAM: 8 GB.

4.2. Dataset Description

The dataset used in this research was the EEG Brainwave Dataset: Feeling Emotions, in which data were gathered from two individuals, namely a man and a woman, for three minutes in each of the three states, namely positive, neutral, and negative. It also usedMuse EEG headgear to capture the EEG locations at TP9, AF7, AF8, and TP10 using dry electrodes. The stimuli used to create the emotions were collected for six minutes along with the neutral data. The parameters used in the flower pollination algorithm are described in Table 1.

Table 1. Parameters of flower pollination algorithm.

Parameters	Value
Maximum generation	1000
Switch probability	0.8
Population size	25
Upper boundary	−10
Lower boundary	10
Model order	3
Number of parameters	6

4.3. Simulated Output of Proposed System

The simulated output of the proposed system in the analyses of anxiety levels after hearing alpha binaural beats is explained in this subsection.

Figure 5 shows the channel frequency by varying the time before the applying wavelet transform. The channel frequency ranges from −2000 to 2000 in the time range of 0.1 to 80,000 ns. From these channel frequencies, it is difficult to obtain the important parameters of the signal. Hence the wavelet transform has been applied to extract the signal parameters.

Figure 6 shows the channel frequency obtained by varying the time after applying the wavelet transform. The channel frequency ranges from −2000 to 2000 in the time range of 0.1 to 90,000 ns. The channel frequencies are optimized by selecting the best wavelet parameters by incorporating the flower pollination algorithm, and the level of anxiety is then analyzed via the DCNN based on the frequency range of the signal.

Figure 7 shows the classification results of the proposed system for the level of anxiety. The classification results show a mild level of anxiety in 20 cases, moderate anxiety in 30, minimal anxiety in40, and severe anxiety in 10, based on the EEG signal processing of brainwaves.

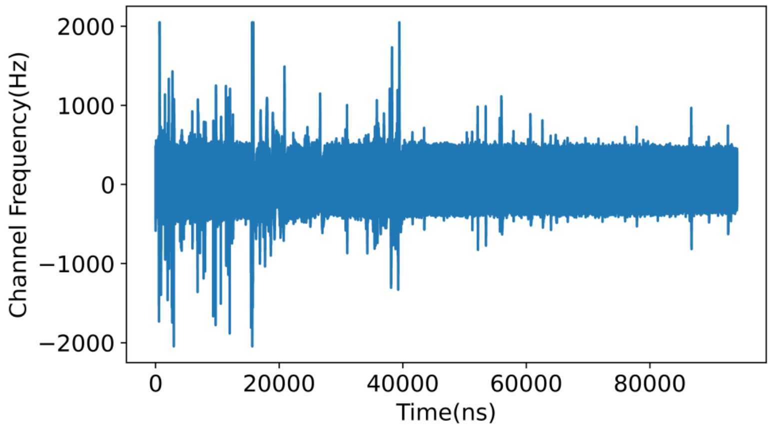

Figure 5. Channel frequency before wavelet transform.

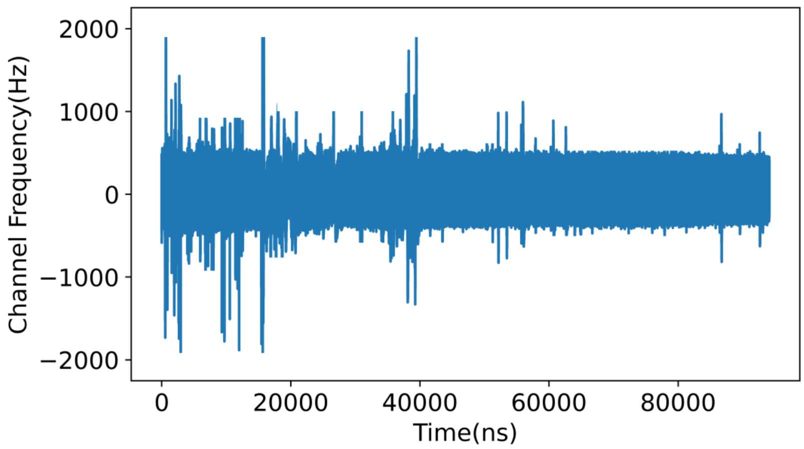

Figure 6. Channel frequency after wavelet transform.

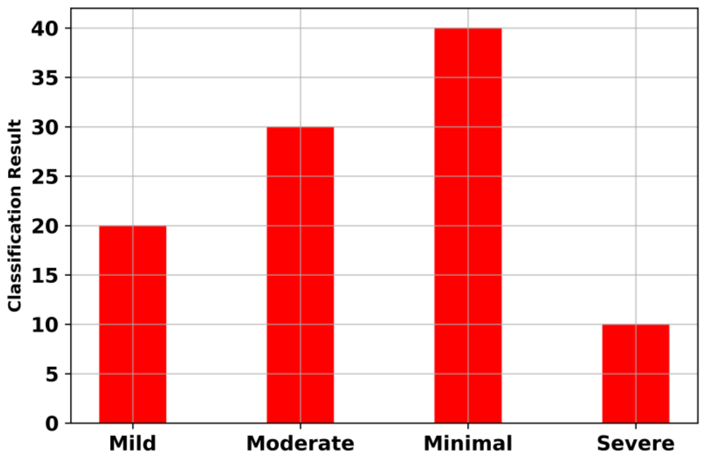

Figure 7. Classification results of the proposed system for determining anxiety levels.

4.4. Performance Metrics of the Proposed System

The performance of the proposed approach and the achieved outcomes are explained in detail in this section.

Figure 8 shows the accuracy of the proposed system with varying numbers of epochs. The accuracy attains a minimum value of 0.65 at the initial stage and attains a maximum value of 0.98 at 27 epochs. Thus, it was noticed that the accuracy increased with the increase in epochs. The accuracy of the proposed system was increased using deep CNN-based signal processing, which extracted all the features associated with anxiety from the brainwaves in the EEG signals.

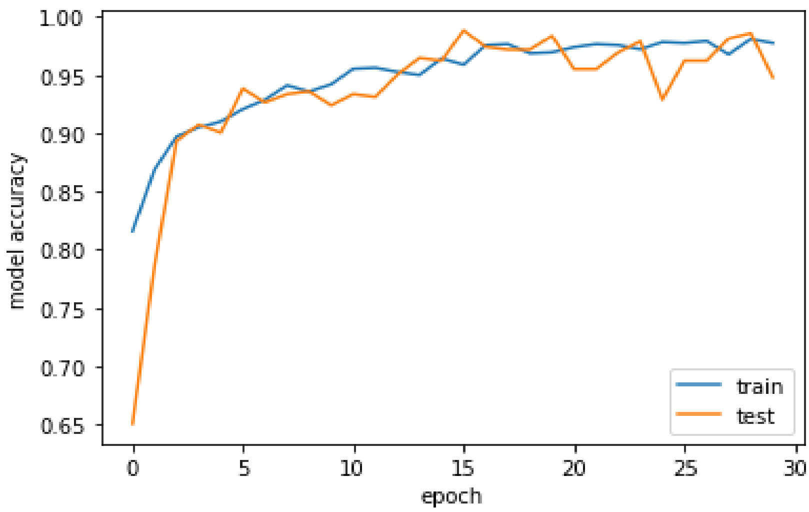

Figure 8. Accuracy of the proposed system with varying epochs.

Figure 9 shows the loss of the proposed system with varying numbers of epochs. The loss has a minimum value of 0.5 at one epoch. The loss of the proposed system has a maximum value of 2.5 at the initial stage. The loss of the proposed system is decreased byusing deep CNN-based signal processing to extract all the characteristics linked to the anxiety of brainwaves in an EEG signal-optimized wavelet transform, in which artifacts are removed from the EEG signal, which does not reduce the original energy of the EEG signal.

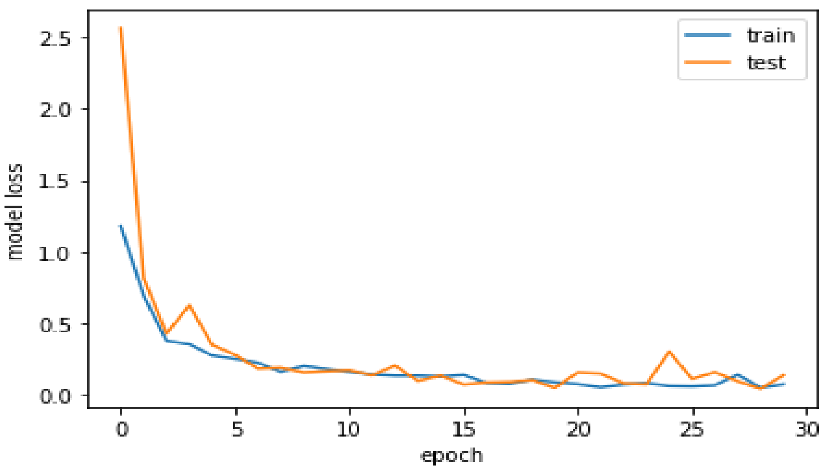

Figure 9. Loss of the proposed system with varying epochs.

Figure 10 shows the precision of the proposed system with varying numbers of epochs. The precision has a minimum value of 20 at one epoch and attains a maximum value of 100 at five epochs. The precision of the proposed system is increased using deep CNN-based signal processing, which extracts all the features belonging to anxiety from brainwaves in EEG signal, and classification is conducted after extracting all these features.

Figure 11 shows the recall of the proposed system with varying the numbers of epochs. The recall has a minimum value of 19.5 at one epoch and a maximum value of 99 at five epochs. The recall of the proposed system is increased using deep CNN-based signal processing, which extracts all features associated with anxiety from the brainwaves in an EEG signal.

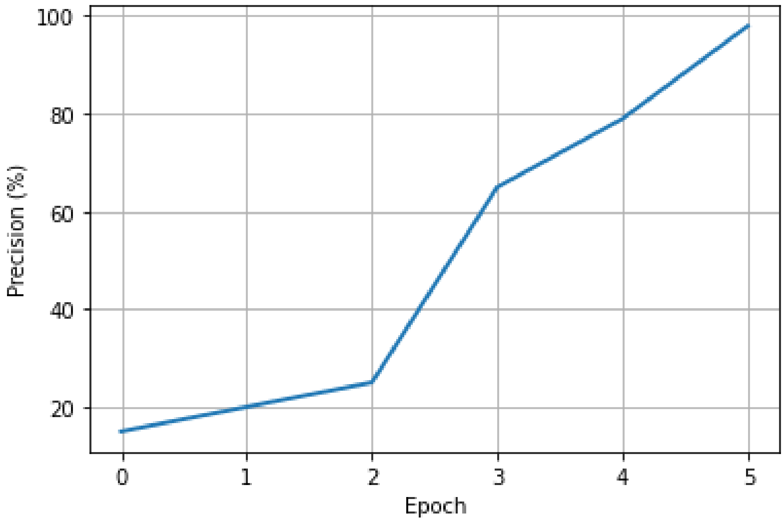

Figure 10. Precision of proposed system with varying epochs.

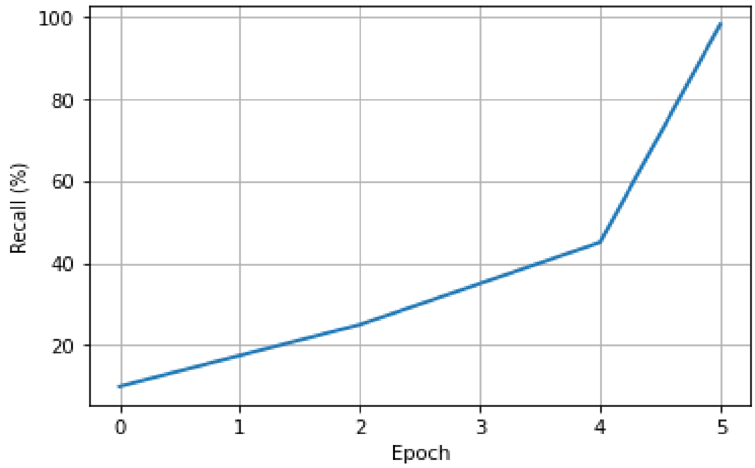

Figure 11. Recall the proposed system with varying epochs.

Figure 12 shows the F1-score of the proposed system with varying numbers of epochs. The F1 score has a minimum value of 17.5 at one epoch and a maximum value of 99.5 at five epochs. The F1-score of the proposed system is increased using deep CNN-based signal processing, which removes artifacts and extracts all the deep features belonging to anxiety from the brainwaves in the EEG signal.

Figure 13 shows the sensitivity of the proposed system with varying numbers of epochs. The sensitivity has a minimum value of 80 in epoch 25 and a maximum value of 99.8 in epoch 200. The sensitivity of the proposed system is increased using the optimized wavelet transform, which provides the process for artifact removal and examines the sensitivity of the brainwave EEG signal.

Figure 14 depicts the specificity of the proposed system with varying numbers of epochs. The specificity has a minimum value of about 85 in epoch 23 and a maximum value of about 98 at the specificity of about 200 epochs. The specificity of the proposed system is determined using the flower pollination optimization algorithm.

Figure 15 shows the sensitivity of the proposed system by varying the numbers of data counts. The sensitivity has a minimum value of about 94% with a data count of about 1000 and a maximum value of 98% in the realm of 6000 data counts. Thus, the sensitivity of the proposed system is increased using the optimized wavelet transform, in which the artifacts are removed and thus the sensitivity of the proposed system increases with the increasing data count.

Figure 16 shows the specificity of the proposed system with varying data counts. The specificity has a minimum value of about 96.75% at 2000 data counts and a maximum value of 99% at 6000 data counts. The specificity of the proposed system initially decreases suddenly with the increasing number of data counts and then it starts increasing with further increases in the number of data counts. Thus the specificity of the proposed system isat a maximum at the highest data counts due to the use the optimized wavelet transform.

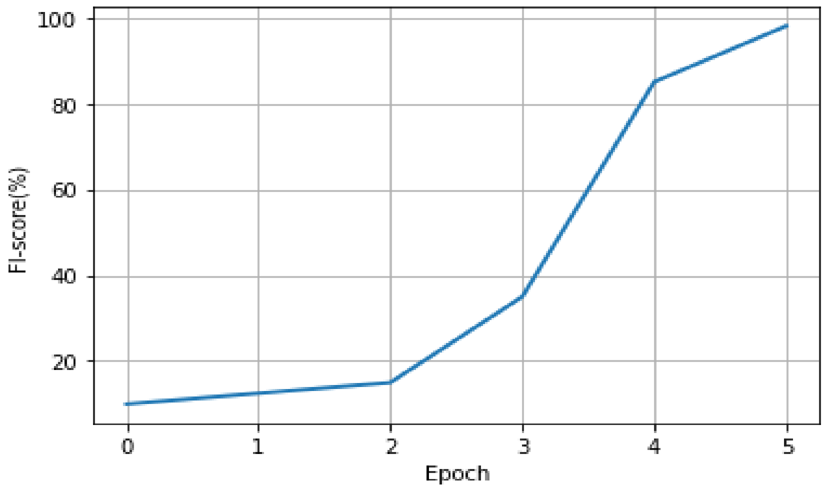

Figure 12. F1-score of the proposed system with varying epochs.

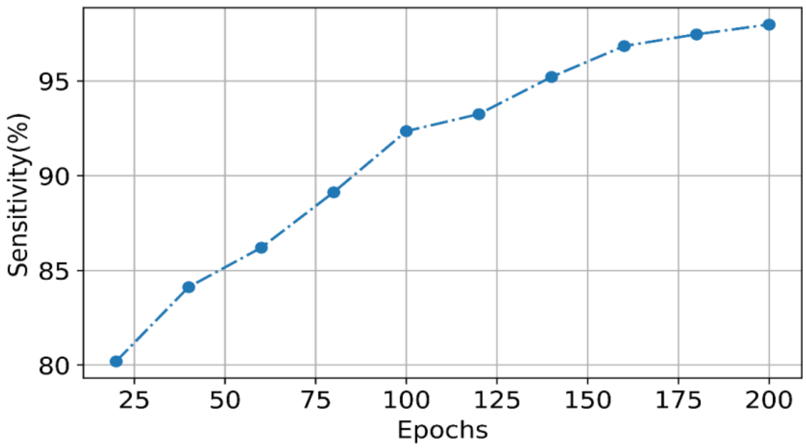

Figure 13. Sensitivity of the proposed system with varying epochs.

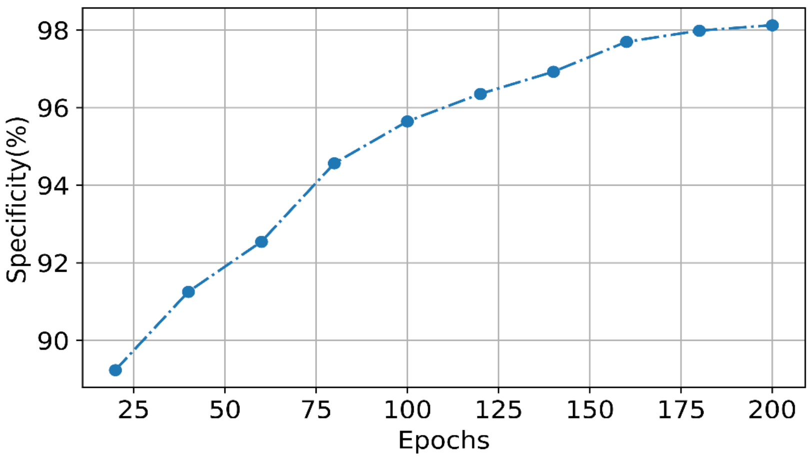

Figure 14. Specificity of the proposed system with varying epochs.

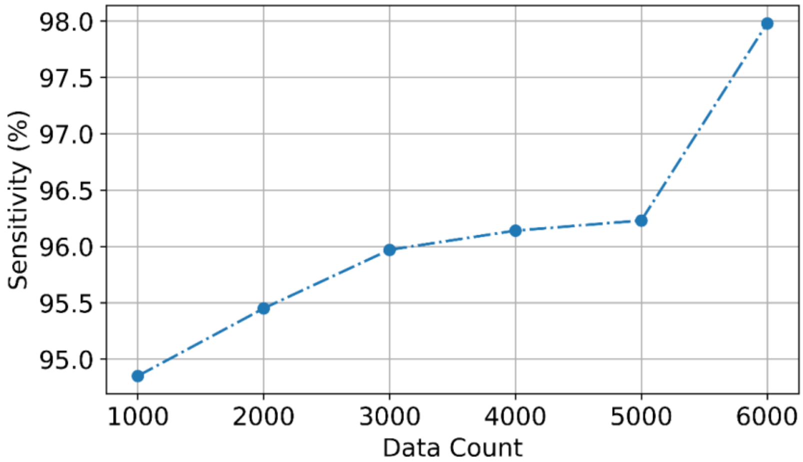

Figure 15. Sensitivity of the proposed system with varying data counts.

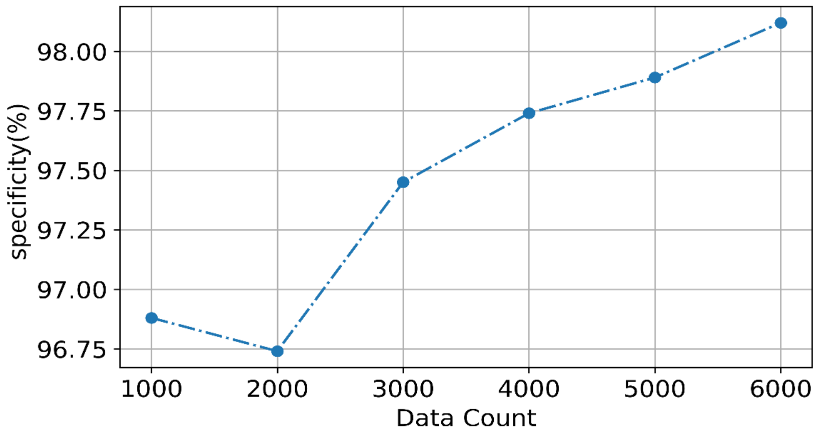

Figure 16. Specificity of the proposed system with varying data counts.

Figure 17 shows the accuracy of the proposed system with varying data counts. The accuracy has a minimum value of 96.3% at 1000 data counts and a maximum value of 98.0% at 6000 data counts. The accuracy of the proposed system is increased using the optimized wavelet transform of the EEG signal to remove artifacts via the concept of flower pollination optimization, which is integrated with the wavelet transform for choosing the best wavelet parameters to then choose the optimal parameter.

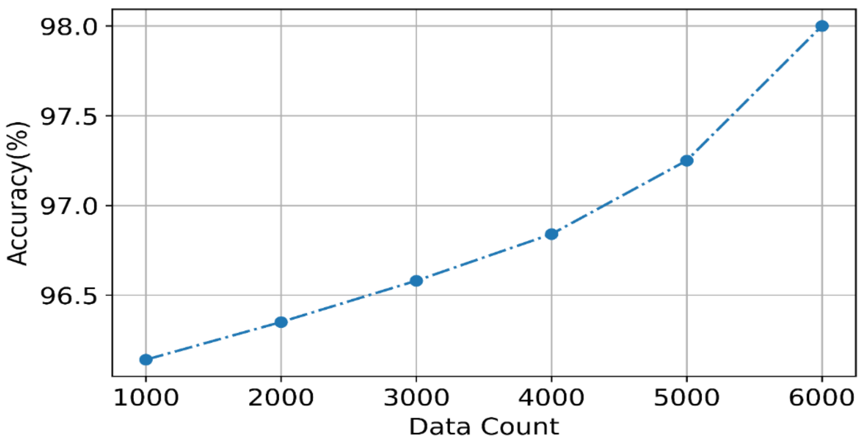

Figure 17. Accuracy of the proposed system with varying data counts.

Figure 18 shows the recall of the proposed system with varying data counts. The recall has a minimum value of 93.1% at 1000 data counts and a maximum value of 95.0% at 6000 data counts. The recall of the proposed system is increased via the optimized wavelet transform of the EEG signal, which removes artifacts using the flower pollination algorithm for choosing the best wavelet parameters to then choose the optimal parameter.

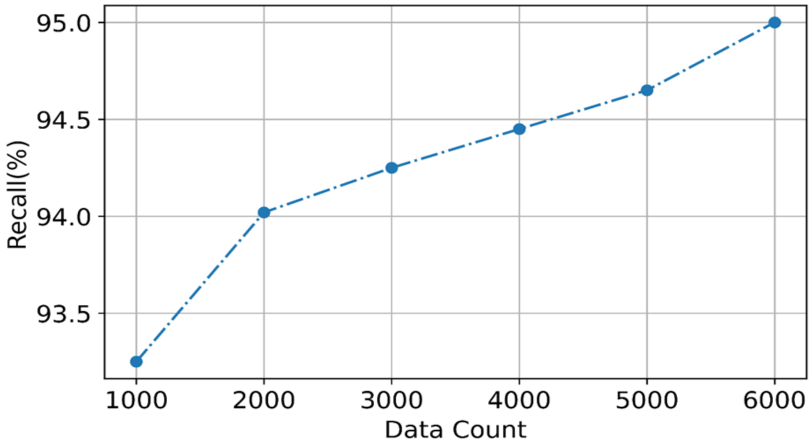

Figure 18. Recall the proposed system for varying data counts.

Figure 19 shows the F1-score of the proposed system with varying data counts. The F1-score has a minimum value of 94.2% at 1000 data counts and a maximum value of 95% at 6000 data counts. The recall of the proposed system is increased using the optimized wavelet transform of the EEG signal, in which the main objective of this WT approach is to identify an effective decomposition of the input EEG data that produces distinctive features from each sub-band using the flower pollination optimization algorithm, which is used to select optimal wavelet parameters to remove artifacts from EEG signals.

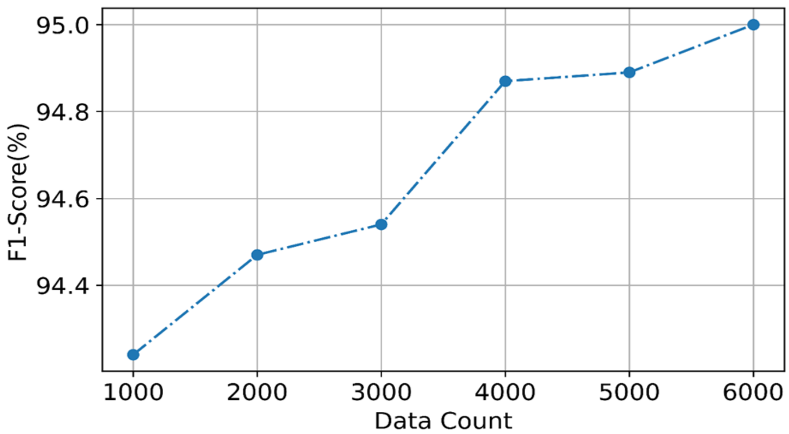

Figure 19. F1-score of the proposed system with varying aata counts.

Figure 20 shows the precision of the proposed system with varying data counts. The precision has a minimum value of 92.14% at 1000 data counts and a maximum value of 95% at 6000 data counts. The precision of the proposed system is increased by selecting the optimum wavelet parameters using the optimized wavelet transform of an EEG signal with a flower pollination algorithm.

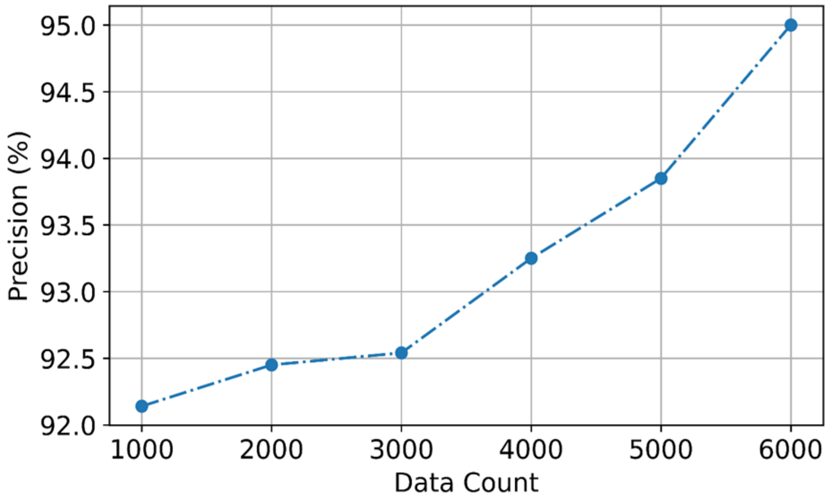

Figure 20. The precision of the proposed system for varying data counts.

4.5. Comparison of the Results of the Proposed Method

This section highlights the proposed system performance by comparing it to the outcomes of existing approaches and showing their results based on various metrics.

Below, Table 2 shows the comparison of the proposed model with the existing models such as KNN, SVM, LDA, and Narrow-ANN [38–42]. Compared with the existing models, the proposed deep CNN achieves a high accuracy of 0.99%, a precision value of 0.99%, and a specificity of 0.999%. The F1-score and recall of the proposed system have the maximum values of 0.99% and 0.99%, whereas the existing models KNN, SVM, LDA, and Narrow-ANN, have F1-scores of 0.90%, 0.98%, 0.921%, and 0.983%, respectively, and recalls of 0.90%, 0.98%, 0.92%, and 0.985%, respectively. Also, the proposed model attains a low error of 0.01. This shows that the proposed model achieved a better performance than the existing models.

Table 2. Comparison table.

Specification	KNN	SVM	LDA	Narrow-ANN	Proposed
Accuracy (%)	0.90	0.98	0.92	0.985	0.99
Recall (%)	0.90	0.98	0.92	0.985	0.99
Precision (%)	0.90	0.98	0.93	0.985	0.99
F1-Score (%)	0.90	0.98	0.921	0.983	0.99
Specificity (%)	0.975	0.995	0.980	0.9951	0.999
Error (%)	0.01	0.02	0.08	0.01	0.01

Table 3 depicts the cumulative survey on binaural beats processing and, from this table, it is understood that the accuracy can be further improved. The existing research that uses machine learning techniques such as KNN, MLP, and SVM, has accuracy values in the range of 60 to 75%, whereas the existing techniques that use some advanced deep learning techniques such as CNNs and ANNs have accuracy values in the range of 80 to 97%. However, these existing techniques have error and generalization issues while achieving high accuracy. Hence, the proposed model used an optimization algorithm along with a deep learning model to achieve a high accuracy of 99% without any error.

Table 3. Cumulative survey on binaural beats processing.

Ref.	Technique Used	Benefits	Limitations	Result Obtained
[31]	e-LORETA	Visual depiction of the impact of binaural beats	MLP shows better performance only on delta waves	Accuracy: 64.77%
[36]	Modified sample entropy feature	The interface system takes only 3 sec to determine the effect of stimuli	Attention-related movements can reduce accuracy	Takes only 3 seconds to determine the effect of audio and visual stimuli.
[35]	ASMR	Can lessen the annoyance of binaural beats while improving brainwave entrainment	N/A	CS could cause 6 Hz activity for inducing NREM sleep stage 1
[38]	Artificial neural network	Can identify and eliminate stress based on user preferences and treatment records	K-nearest neighbor shows better performance on some brainwaves only	Accuracy: 90%
[32]	DFT-SOM-ANN	Mental pattern recognition with high accuracy	Artifacts introduced in older adults cannot be removed via DFT	Accuracy: 98.68%
[40]	ESD-ANN	Excellent accuracy in identifyingwoman with and without stress, using the entire brain	Optimal channel selection difficult with ANN	Accuracy: 89.19%
[41]	C3RNN	Better performance than baseline CRNN with the same weights and high training speed	The error can be generated due to backpropagation	Accuracy: 84.1%
[42]	CNN	Accurately distinguishes EEGs of individuals listening to music from those of subjects without auditory input	May not consider the generalization issue	Accuracy: 97.68%
[43]	Brainwave stimulator	Promotes the production of alpha brainwaves to decrease stress	Artifacts due to eye blinking and muscle movements are not considered	A significant increase in the number of alpha brainwave PSD observed
[33]	Bi-spectral analysis	Extracts features providing information about the distribution and dispersion of signals	The usage of discrete Fourier transform for filtering could reduce the original energy of the EEG signal	The degree of synchronization ranged from 52.1% to 83.4%
[45]	Semantic-based Bayesian network engine	Records and analyzes correlations between binaural beats, EEG, and perceived mental states	Implementation outcomes are not provided in a detailed manner	Performance: 72.25%
[46]	Fast Fourier transform	Shows entrainments after the perception of binaural beats based on an associated EEG rhythm	The technique should be time-fixed for assessing the brain's reaction to quick shifts in auditory intensity	Absolute power value ranges between 5 and 15 μV^2
Proposed model	Deep CNN-based signal processing	Extraction of deep features from EEG signals, enabling precise identification of the impacts of binaural beats on various types of brainwaves and anxiety levels. This provides more accurate and detailed insights into the effects of binaural beats on different levels of anxiety, leading to a more effective and feasible outcome.	N/A	Accuracy: 99%

Overall, the optimized wavelet transform using deep CNN-based signal processing outperforms existing techniques such as KNN, SVM, LDA, and Narrow-ANN (andvarious forms of ANNs with a high accuracy of 0.99%, precision of 0.99%, recall of 0.99%, F1-score of 0.99%, specificity of 0.999%, and error rate of 0.01% in identifying an effective decomposition of the input EEG data and extracting all deep features belonging to anxiety and analyzing the effect of binaural beats on the level of anxiety.

5. Conclusions

An optimized wavelet transform with the flower pollination optimization algorithm has been proposed to remove artifacts from EEG signals without reducing the original signal's energy, in which the flower pollination optimization algorithm is integrated with the wavelet transform for the optimal selection of wavelet parameters, the result of which are that the artifacts are removed from the EEG signal with aminimum loss value of 0.4 and a high accuracy of 99%. Then, EEG signals have five types of brainwaves, delta, theta, beta, alpha, and gamma, which are optimally analyzed via deep CNN-based signal processing that is integrated into EEG signal processing and helps with analyzing the effect of binaural beats on the four levels of anxiety (minimal, mild, moderate, and severe). This model can extract all the deep features belonging to anxiety from EEG signals, which provide more accurate results for establishing binaural beats' effects on anxiety via brainwaves. Thus, the results obtained from the proposed method outperform existing techniques with a high accuracy of 99%, precision of 96%, recall of 97%, and F1-score of 96%. As a result, the novel methodology provides effective and promising results for determining the effect of binaural beats on four levels of anxiety.

While the deep CNN model extracts deep features from EEG signals, the complexity of interpreting brainwave patterns, especially in the context of anxiety, can pose challenges. There may be inherent difficulties in accurately quantifying the relationship between binaural beats and specific brainwave activities related to anxiety. Future studies might concentrate on developing real-time monitoring systems that use the proposed methodologies to offer instant feedback on the efficacy of binaural beats in controlling anxiety levels, allowing for immediate treatment.

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