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EEG SIGNAL-BASED EMOTION RECOGNITION USING A DEEP LEARNING APPROACH WITH GRU-BGWO

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Abstract

A voluntary or involuntary response to outside stimuli is referred to as emotion. Individuals use body language, words, noises, and facial expressions to convey their feelings. However, genuine feelings cannot always be communicated; people might occasionally alter the emotions displayed in such activities. As a result, it is crucial to comprehend and analyse emotions. Because of the more trustworthy data gathered, investigations on emotion recognition based on EEG signals seem to be in the spotlight. This work developed a deep learning algorithm with an optimizer and analysed emotion using EEG data. There are five phases of the investigation. The suggested framework first preprocesses the data using low-pass filtering to eliminate noise before extracting the delta rhythm. Following the signal processing phase, namely the feature extraction phase, two popular technologies were employed: Higuchi's fractal dimension (HFD) and entropy. Deep feature selection using ResNet50 yields the best features, which are subsequently categorized using the Gated Recurrent Unit with Binary Gray Wolf Optimizer (GRU-BGWO) method. To evaluate the efficacy of our suggested approach, experiments were carried out on the publicly accessible DEAP database using a variety of evaluation criteria, such as accuracy, specificity, and sensitivity. The results showed that the proposed method was effective, as the GRU-BGWO-based method achieved 91.45 percent accuracy.

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Keywords: Emotion recognition, EEG signal, Low pass filter, HFD, ResNet50, GRU, BGWO, accuracy

1. Introduction

Enhancing human relationships and developing technological systems depend on the ability to identify and detect human emotions. A person's emotional states can be better understood by looking at their EEG, which records electrophysiological activity in the brain and shows the neural reactions to different emotional stimuli. This capability provides a potential path toward comprehending the intricate connection between emotions and brain activity.

One of the most popular areas for research in health informatics is the Brain–Computer Interface (BCI). Analysis of the brain's electroencephalography (EEG) data is one of its uses. Detecting emotions and tracking abnormal brain activity, such as psychological seizures, are common uses for brain-computer interfaces (BCI). People with mental disabilities who are unable to articulate their emotions can be identified through the use of emotion detection tools. One important field of human-computer interaction (HCI) is BCI technology, which makes it easier for the brain and computers to communicate [2]. Moreover, it is regarded as one of the most important areas of current machine learning, deep learning, and robotics research.

In order to convert brain signals into actions, BCI technology goes through a number of steps. The signals go through frequency-based processing, time feature extraction, and classification after they are collected. Depending on the application, the results are transformed into instructions for the different devices. The neurons in the brain process the electrical signals. The electrodes pick up the EEG signal, which represents brain waves. EEG data is obtained using a variety of electrodes and channels. Electroencephalography (EEG) devices record brain signals throughout the emotion recognition process. Deep learning algorithms have been used to evaluate the EEG output. Accuracy in identifying emotions is especially important when making medical decisions regarding behavioral and psychiatric diseases. However, it is still difficult to analyses and categorize human emotions, and researchers have shown that different studies that use EEG data for emotion recognition have significantly varying accuracy rates. Numerous factors might be blamed for these disparities, including variations in research procedures, participant experiences, environmental conditions, data preprocessing methods, and classifiers. Therefore, it is crucial to create better techniques to rise the performance of emotion recognition systems.

Contribution of the study

- The paper presents an integrated framework that integrates preprocessing, feature extraction, selection, classification, and optimization, making it valuable to emotion recognition.
- Applying a low-pass filter to EEG signals effectively removes noise and improves the data quality for subsequent analysis.

- Using Higuchi's Fractal Dimension (HFD) and entropy as features provides a new approach to capture the complexity and unpredictability of emotional states in EEG signals. This dual feature extraction method enriches the dataset with meaningful descriptors.
- Improving ResNet-50 significantly contributes to feature selection, identifying the most relevant features in a high-dimensional space. This improves model performance and reduces overfitting.
- Gated Recurrent Units (GRUs) specifically address the sequential nature of EEG data, enabling more accurate classification of emotional states by effectively capturing temporal dependencies in the signals.
- A unique feature of the study is the introduction of binary-based optimization (BGWO) for model optimization. This approach improves the performance of GRU by intelligently adjusting higher criteria, leading to improved classification accuracy.

Aim of the study

- To improve the integrity of the signals used for analysis, preprocess the EEG data and use a low-pass filter to reduce noise and artifacts.
- Use Higuchi's fractal dimension (HFD) and entropy as feature extraction methods to capture the complexity and variability of emotional states reflected in EEG signals.
- Implement ResNet-50 for feature selection to identify the most relevant features of EEG data, thereby reducing dimensionality and improving model performance.
- Use gated recurrent units (GRUs) to characterize emotional states, taking advantage of their ability to manipulate sequential data and capture temporal patterns in EEG signals.
- Use binary -based optimization (BGWO) to optimize the parameters of the GRU model, aiming to improve classification accuracy and robustness.

Various literatures on emotion recognition from EEG signals are presented in Section 2 under the heading “Related work”. Section 3, “Proposed Methodology,” outlines the methodology used in our approach to emotion recognition. In Section 4, “Results and Discussion,” we analyse the EEG signals and present the findings. Finally, Section 5, “Conclusion”, summarizes the proposed methodology and its implications.

2. Related work

Human communication, decision-making, and learning all depend on the ability to recognize emotions. EEG-based multimodal emotion recognition (EMER) is becoming more popular because of its high speed, temporal resolution, and non-invasiveness. Nevertheless, current studies lack a methodology-agnostic viewpoint and concentrate on broad combinations of modalities (**Huan Liu et al., (2024)**). Automated emotion recognition from EEG signals with 14 channels of dynamic epic equipment 28 participants. Reduced the computing time and produced the 99.99% accuracy (**Akhilesh Kumar and Awadhesh Kumar., (2021)**). Several deep learning and machine learning models, such as the recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU), are employed to identify emotions and enhance the architecture. According to **Kalpana et al. (2022)**, the average accuracy for GRU, LSTM, and RNN was 96%, 97%, and 95%, respectively.

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Multi-scale principal component analysis (MSPCA) denoising method is used for preprocessing, while Tunable Q-Wavelet Transform (TQWT) is used for feature extraction. The classification stage employs the rotation forest ensemble classifier together with additional techniques, achieving an accuracy of over 93% through the usage of RFE (rotation forest ensemble) + SVM (support vector machine) (**Abdulhamit Subasi et al., (2021)**). Models are tested using subject-dependent and -independent scenarios. For subject-dependent and subject-independent participants, the average classification accuracy of the model is 99.20% for arousal and 99.10% for valence. It is powered by a Raspberry Pi CPU and is portable **(Mehdi Bazargani et al., 2023**). The technique created seven CNN-based models by extracting frequency information from the EEG data. The models' average accuracy was 73.2%; multi-band features improved performance (**Jieun Kim et al., (2022)**). The FD-CART feature classification method yielded the highest average classification accuracy for arousal (84.55%) and valence (85.06%) across five separate datasets. The consistency of these results indicates that FD features derived from EEG data are reliable for emotion recognition (**Rajamanickam Yuvaraj et al., (2023**). Although physiological signals such as EEG and GSR are dependable for identifying emotions, conventional techniques fall short because of their noise and non-stationarity. This study presents a deep learning method for analyzing physiological signals for emotion recognition utilizing CNN-Vision Transformer (CVT) and ensemble classification. The approach outperformed current emotion charting techniques with 98.2% accuracy, 99.15% sensitivity, and 99.53% specificity (**Amna Waheed Awan et al., (2024)**).

In order to identify human emotional states, this work develops a mean-threshold decision-level fusion method that incorporates physiological inputs. Salient characteristics are identified using electroencephalograms and peripheral physiological data, and classification criteria are determined using GNB, LR, and SVM **(Qiuju Zhang et al., (2023)**). In the DEAP and SEED datasets, the FL (Federated learning) technique, which may work with various clients, obtains an accuracy of 90.74%. However, employing local data results in a 29.31% loss in accuracy, underscoring the necessity of FL in emotion recognition tasks (**Chang Xu et al., (2022)**). The valence and arousal dimensions train the 1D-CNN for emotion identification. With an average accuracy rate of 97.47% and 97.76%, respectively (**Yu Chen et al., (2021)**). The addition provides an extensive examination of EEG emotion recognition, with a focus on DL techniques, with deep belief networks (DBN), CNN, and RNN. An EEG identification model that makes use of bandpass filters, tri-classifiers such as LSTM, DBN, and RNN, and the Shark Smell Updated BES Optimisation (SSU-BES) model for weight tuning (**Awwab Mohammad et al., (2023)**). The SVM classifier classifies the six emotions as neutral, happy, sad, disgust, fearful, and motivational, averaging 79.34% accuracy (**Swati Shilaskar et al., (2023)**).

The researchers tested several preprocessing methods to enhance the convolutional neural network technology and pinpoint seven basic emotions. The dataset consists of 32,298 images for training and testing, and the preprocessing method removes noise from the input image. The proposed method displays the same seven emotions as the facial acting coding system (FACS) (**Tarun et al., (2022)**). Machine learning algorithms can detect complex interactions between variables, and their potential in studying ADHD is discussed. However, caution is needed due to interpretability and generalization limitations of machine learning strategies

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(**Meng Cao et al., (2023)**). Neural networks are used in affect recognition to map complicated emotions onto valence and arousal measures. Fuzzy ART (FA), in conjunction with stochastic resonant noise and SMOTE sampling, is utilized to overcome these problems (**Wei Shiung Lie et al., (2021)**). To generate rules from RVM, the Random Forest technique focused on the average energy spectrum within each frequency band. Compared to previous rule-based systems, the suggested approach, RVM_RF, predicts negative emotions with an average accuracy of 85.33% and a precision 0.933. This method shows how EEG waves detect unpleasant feelings (**Adhi Dharma Wibawa et al., (2021)**).

Table 1. Previous literature on the emotion recognition

Author	Algorithm	Dataset	Results
Mona Algarni et al., (2022)	Bi-Directional Long Short-Term Memory (Bi-LSTM)	DEAP	accuracy with 99.45% valence, 96.87% arousal, and 99.68% liking averaging
Awf Abdulrahman et al., (2022)	VMD (Variance Mode Decomposition) and EMD (Empirical Mode Decomposition)	DEAP and SEED	accuracy is 70.89%
Huan Liu et al., (2024)	LSTM, CNN	SEED	Accuracy 69.5%, and 76.7%
Sara Bagherzadeh et al., (2023)	CNNs and multiclass support vector machines (MSVM)	DEAP and MAHNOB-HCI	accuracy rates of 77.47% and 87.45%,
Liumei Zhang et al., (2023)	Density-Based Spatial Clustering of Noisy Applications (DBSCAN)	DEAP	accuracy of 92.98%
Jun Liu et al., (2022)	Xception deep neural network	DEAP	70.19%
Bhuvaneshwari et al., (2022)	ResNet-152	SEED -V	98% accuracy
Harshil Gupta et al., (2023)	Gated Recurrent Unit (GRU) and 1D-CNN.	DEAP	Accuracy 99%

3. Proposed methodology

The suggested method for identifying emotions from EEG signals combines several state-of-the-art methods, including a binary grey wolf optimizer (BGWO) and a gated recurrent unit (GRU) optimized for classification. The process starts with a low-pass filter to remove noise from EEG signals, ensuring clean data for analysis. For feature extraction, we use Higuchi fractal dimension (HFD) and entropy metrics, which capture the complexity and unpredictability of the signals. To improve the feature selection, we use the ResNet-50 framework, which effectively identifies the most relevant features from the extracted data. The overall architecture is illustrated in Figure 1, showing the workflow from raw EEG signal processing through feature extraction and selection, ending in emotion classification using the GRU model optimized by BGWO.

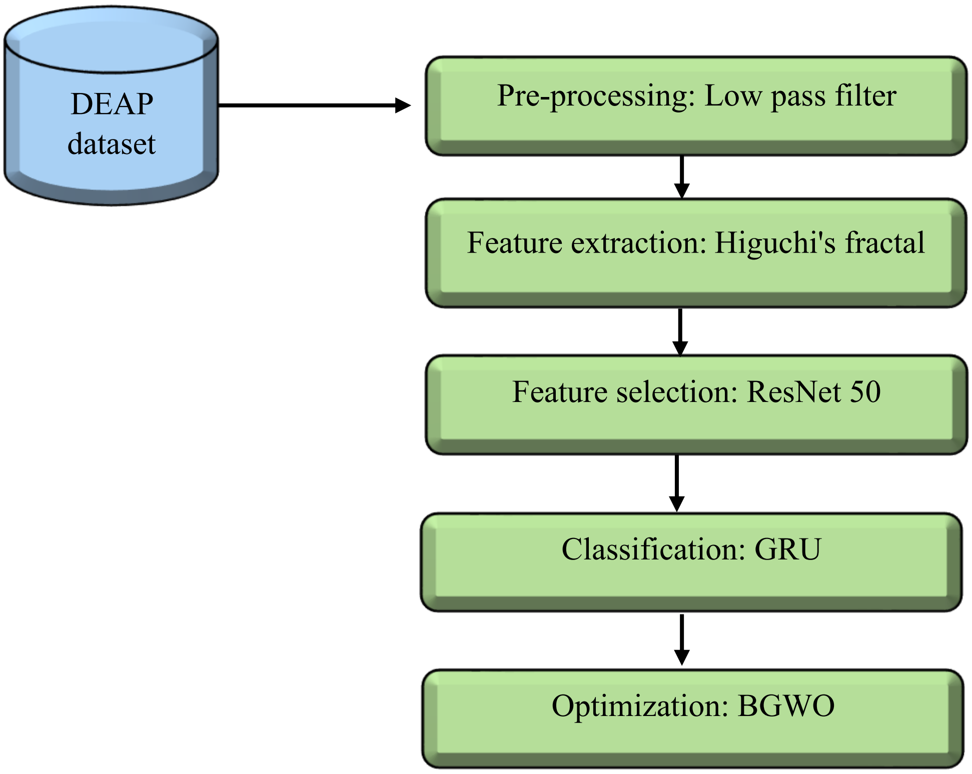

Figure 1. Overall architecture of the proposed emotion recognition

Dataset: DEAP

In an online self-assessment, 14–16 volunteers rated 120 one-minute music video samples on three criteria: awareness, intensity, and dominance. As part of an experiment involving facial videos, physiological data, and participant ratings, 32 participants watched a subset of the 40 music videos mentioned above. Physiological and EEG data were recorded while each participant rated the videos as described above. In addition, 22 subjects were videotaped in front of their faces.

Preprocessing: Low pass filter

A low-pass filter reduces frequencies overhead the cutoff frequency (called the stopband) while allowing signals below the cutoff frequency (called the passband) to flow through. Low-pass filters are frequently used to average data, smooth signals, eliminate noise, and serve as interpolators and decimators. Savitzky-Golay and moving average filters are especially popular. These filters minimize signal deterioration, improve the overall signal-to-noise ratio, and make it easier to identify trends by introducing smooth variations in output values.

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The fundamental low-pass RC filter's response is solved to determine the low-pass filter's time response. By definition, the smoothing factor falls between 0 and $\propto \leq 1$, and the expression provides the corresponding time constant RC in terms of the sampling periods ΔT and smoothing factor $\propto$.

$$RC = \Delta T \left(\frac{1-\propto}{\propto}\right) \quad (1)$$

$$RC = \frac{1}{2\pi f_c} \quad (2)$$

$\propto$ and f_c are related by

$$\propto = \frac{2\pi \Delta T f_c}{2\pi\, \Delta T f_{c\,+1}} \quad (3)$$

$$f_c = \frac{\propto}{(1-\propto)2\pi\Delta T} \quad (4)$$

Feature extraction: Higuchi's fractal dimension (HFD) and entropy

One of the difficulties in recovering EEG data is dealing with complicated, nonlinear, and nonstationary signals. Although the signal properties are inconsistent, they are considered constant over an extended period. In reality, various linear extraction methods track EEG data using the short-term windowing methodology. However, this assumption is inaccurate under common brain states, even during mental and physical exercise. Transitions between awareness and wakefulness can reveal nonstationary EEG patterns. Since the time series entropy calculation incorporates the unpredictability of nonlinear time series data, several nonlinear research options, including entropy, have also been presented. In brain-computer communication systems, the device's degree of instability can be determined using entropy.

This computation is nonlinear. A time series' total uncertainty is measured. The degree to which the outcomes of each trajectory may be predicted from one another is indicated by entropy. In the end, more complex or chaotic systems are implied by higher entropy. To date, spectral entropy has been successfully applied to extracting EEG features. Entropy was, therefore, not applied to instantaneous appreciation. They contend that entropy offers valuable data and distinctive characteristics that can be applied to the categorization of people. However, HFD, a nonlinear technique, has taken a substantial position in biological signal processing. The HFD approach differs from the commonly used linear methods in speed, accuracy, and cost when applied to research and medical diagnostics. However, accurate and dependable analysis of various neurophysiological data can only be achieved by combining HFD with other nonlinear techniques.

Feature selection: ResNet 50

ResNet is used in this study's studies primarily because it fixes the "gradient disappearance" problem. The entire connection layer is changed by the Global Average Pooling (GAP) layer, down sampling is done directly using convolution with a step size of two, and the residual unit is added using a short circuit technique. Two residual elements are the main components of the ResNet model. The deep network is represented by the bottleneck block on the right and the

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shallow network by the building block on the left. The input information can go in two different directions. Identity mapping is the first. Identity mapping guarantees that all of the knowledge acquired is retained. Any necessary improvements are made through direct mapping or f(x). The model performs better when f(x)alters the information between blocks more effectively.

Maintaining the neural network's ability to perform basic identity mapping is the goal of the residual structure. When networks are stacked, this feature can ensure that the training results won't degrade. Assuming that x is the neural network's input parameter, the network's desired output is h (x). The intrinsic structure of H (x) might not be clearly expressed. ResNet prevents the accuracy and performance deterioration brought on by an excessive number of convolution layers by allowing the submodule to directly learn the residual $f(x) = H(x) - X$ to produce the goal output $f(x) + X$.

The shortcut link is represented by the building on the right. Use the shortcut operation to add the outputs before and after this layer's network before activating the function to obtain the layer's total output. Send the extra value to the activation function after that. The shortcut connection in ResNet means that if the input is x, the output y is,

$$y = F(x, \{W_i\}) + x \qquad (5)$$

The neural network's output and the typical data input are connected. Given the double-layer weight and the activation function ReLU in the center, there are

$$F = W_z \sigma(W_1 x) \qquad (6)$$

The weights W1 and W2 of the function and structure layers are typically associated with the activation function ReLU, which also increases nonlinearity. The signal's input and output data size can be altered by altering the number of channels. Here, create a linear transformation WS for X during shorting in the manner described below:

$$F = W_z \sigma(W_1\ x) \qquad (7)$$

Classifier: gated recurrent unit (GRU)

GRUs are an advancement over conventional recurrent neural networks (RNNs) and use gating techniques to control the flow of information between cells in the neural network. GRUs are designed to capture short- and long-term dependency, similar to long-short-term memory (LSTM) networks. However, their simplified architecture often results in better performance.

Long-term and short-term storage are provided by the two distinct states of LSTMs: cell and hidden states. In contrast, GRUs pass through a single hidden state in between time steps. GRUs are able to successfully sustain both types of reliance due to their gating mechanisms, which process the incoming data and hidden state concurrently. The model creates a new hidden state$h_t$at to each time step t-1 using the input X_t and the hidden state h_{t-1}since the previous time step t. This new hidden state is then sent to the following step.

Deep learning is very useful for detecting complex temporal correlations and extracting important features from EEG data, as shown by the GRU model. The update gate used to manage long-term memory is controlled by the equation below.

$$U_t = \sigma(X_t * U_u + h_{t-1} * W_u) \quad (8)$$

Here

U_u and W_u $- weight\ metrics$

To preserve the range from 0 to 1, this number is additionally compressed using the sigmoid function. The update gate solves the issue of disappearing gradients in this way.

By using the reset gate to determine whether the previous state of the cell is significant, we can choose how much of the previous data can be discarded. The formula for the reset gate, which controls short-term memory, is shown below.

$$r_t = \sigma(X_t * U_r + h_{t-1} * W_r) \quad (9)$$

The calculation of the potential hidden state is shown below. The sigmoid function converts values between 0 and 1; values closer to 1 are processed further, while values closer to 0 are ignored. The candidate hidden state was determined by feeding this into the tanh function after calculating the Hamdard product between the hidden state of the preceding timestep and the reset gate.

$$\bar{h} = \tanh\,(X_t U_h + r_t . h_{t-1} W_h) \quad (10)$$

To make a new update gate, subtract one from the vector. Next, take the Hadmard product of the potential hidden state and the new vector. Add the two vectors to create the vector that now represents the concealed state.

$$h_t = U_t . h_{t-1} + (1 - U_t) . \bar{h} \quad (11)$$

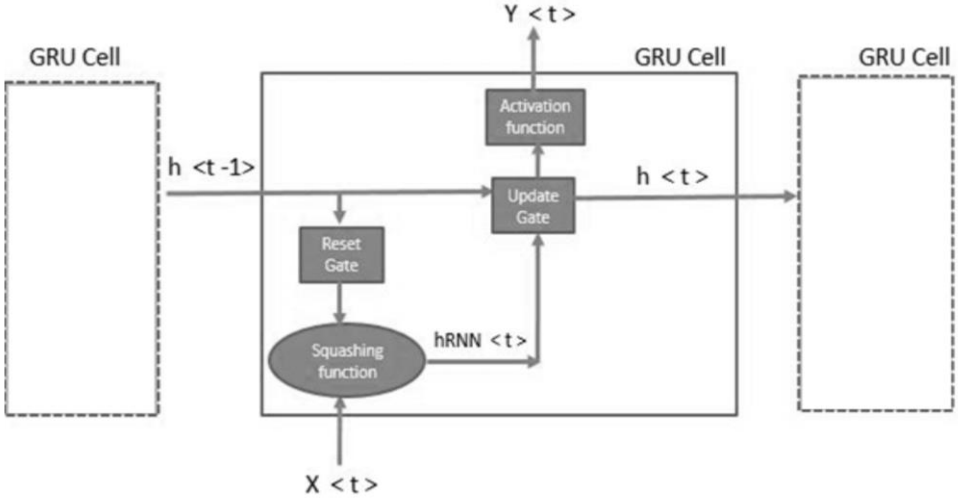

Figure 2. GRU architecture

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Optimization: Binary Grey wolf optimization (BGWO)

According to the study's findings, the Grey Wolf Optimization (GWO) algorithm improves the accuracy of EEG signal classification. GWO makes it easier to find the best answers and operates with a high probability. Alpha (α), beta (β), delta (δ), and omega (ω) are the four bands into which the data is divided during this procedure. In this model, the remaining wolves (ω) are led by the three fittest wolves, who stand in for the α group. The wolves move about the α, β, or δ groups as part of the optimization process. The wolves' efficient exploration of the search space is made possible by this movement technique, which improves the classification algorithm's overall performance:

$$\vec{D} = |\vec{c}.\overrightarrow{Z_p}(t) - \vec{Z}(t)| \tag{12}$$

$$\vec{Z}(t+1) = \overrightarrow{Z_p}(t) - \vec{A}.\vec{D} \tag{13}$$

The α, β, and δ groups in the BGWO (Biogeography-Based Grey Wolf Optimization) framework stand for the optimal prey placements. The three best results corresponding to α, β, and δ are found during the optimization process. The next equations can efficiently update the wolves' positions, even if Equations (14) through (20) are derived from figuring out their final positions.

$$\vec{D}_\alpha = |\vec{c}_1.\vec{Z}_\alpha - \vec{Z}| \tag{14}$$

$$\vec{D}_\beta = |\vec{c}_2.\vec{Z}_\beta - \vec{Z}| \tag{15}$$

$$\vec{D}_\delta = |\vec{c}_3.\vec{Z}_\delta - \vec{Z}| \tag{16}$$

$$\vec{Z}_1 = \vec{Z}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \tag{17}$$

$$\vec{Z}_2 = \vec{Z}_\beta - \vec{A}_2.(\vec{D}_\beta) \tag{18}$$

$$\vec{Z}_3 = \vec{Z}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{19}$$

$$\vec{Z}(t+1) = \frac{\vec{Z}_1+\vec{Z}_2+\vec{Z}_3}{3} \tag{20}$$

The GWO method's capabilities are expanded to handle binary optimization problems by the BGWO. GWO increases the possibility of discovering the best answers by directing wolves' movements during the hunting process. The grey wolf's food-searching behavior is imagined as a cell space to evaluate the cell structure based on the connections between cells. This cell space is separated into an endless number of virtual grids, each containing a distinct solution that cannot be further subdivided. The wolves are separated from possible candidate solutions by the clever cells. These intelligent cells represent a wolf's search space in the GWO framework. A cell's response is not considered intelligent if it does not exhibit the best wolf-searching behaviour. The clever cells can successfully create a community by utilizing the neighbourhood function, which will divert the wolf from the cell's core pathways. The range of two variables is considered a divide inside the search space, represented as a plane. All of

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the wolves' ideal locations (α, β, and γ) are covered by this plane, and the virtual grids are made to divide the search space. One of the more effective fixes for the wolves' placement issue may be found within each grid.

Many meta-heuristic computations have recently been developed and used to address different estimate problems. The main argument is that by using a valid numerical representation and computations to recognize them, we can address most real-life problems. GWO is basic, easy to use, flexible, and versatile because it has few boundaries to adjust and a good balance between studies. The BGWO Algorithm flowchart is displayed in Figure 3.

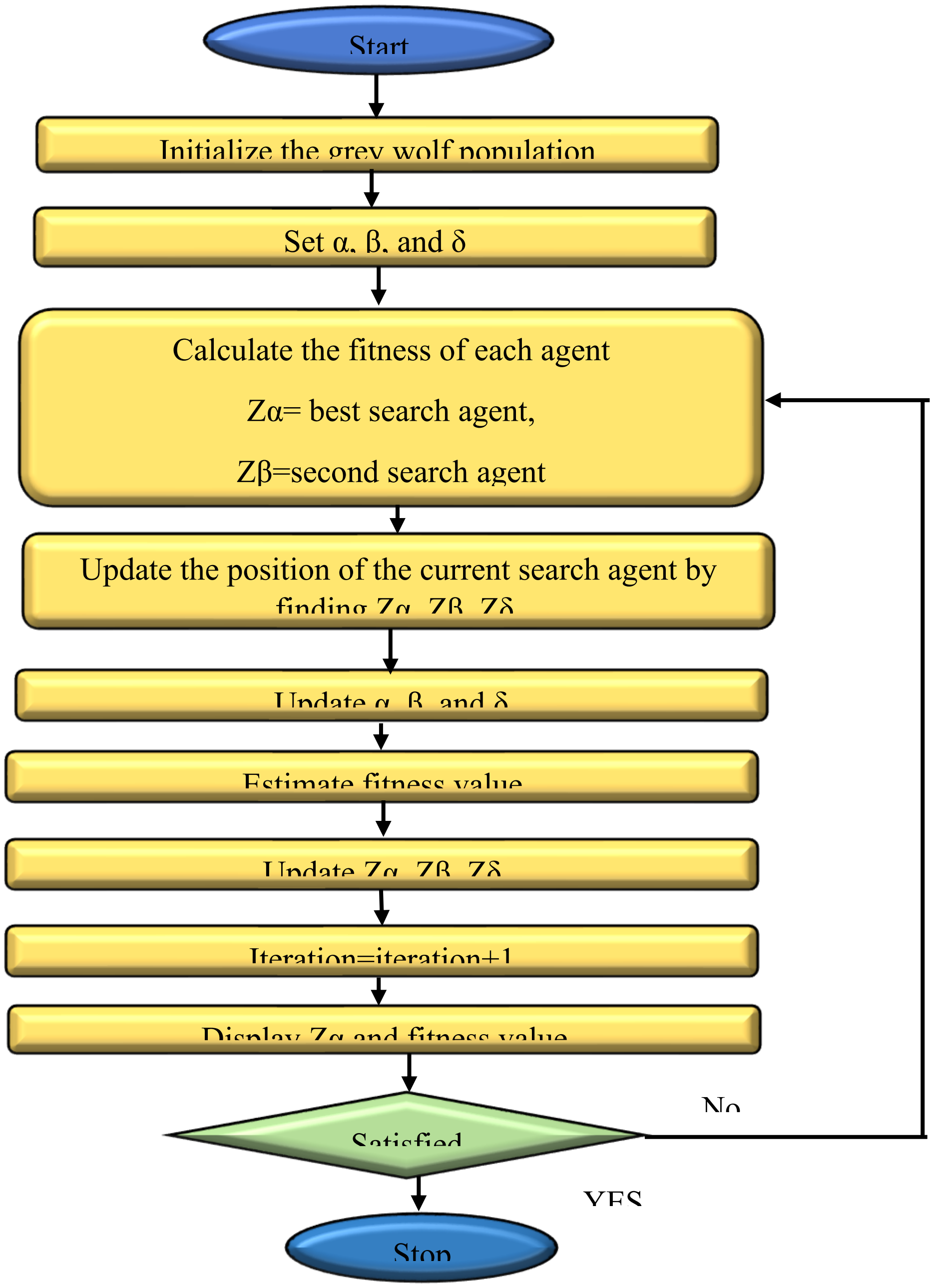

Figure 3. Implementation steps for BGWO

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4. Result and discussion

Low-pass filtering is usually one of the initial steps in the processing workflow when interpreting EEG data. This conventional technique also eliminates higher frequencies beyond 40 or 50 Hz, as are slow frequencies below 0.1 Hz or even 1 Hz. Figure 4 shows the efficiency of the low-pass filter in processing the EEG signal.

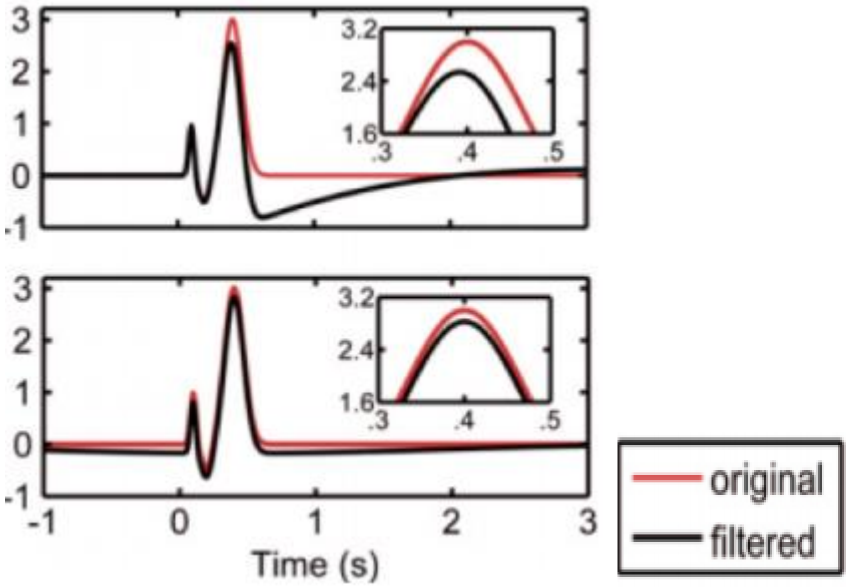

Figure 4. Low pass filter-original image and filtered image

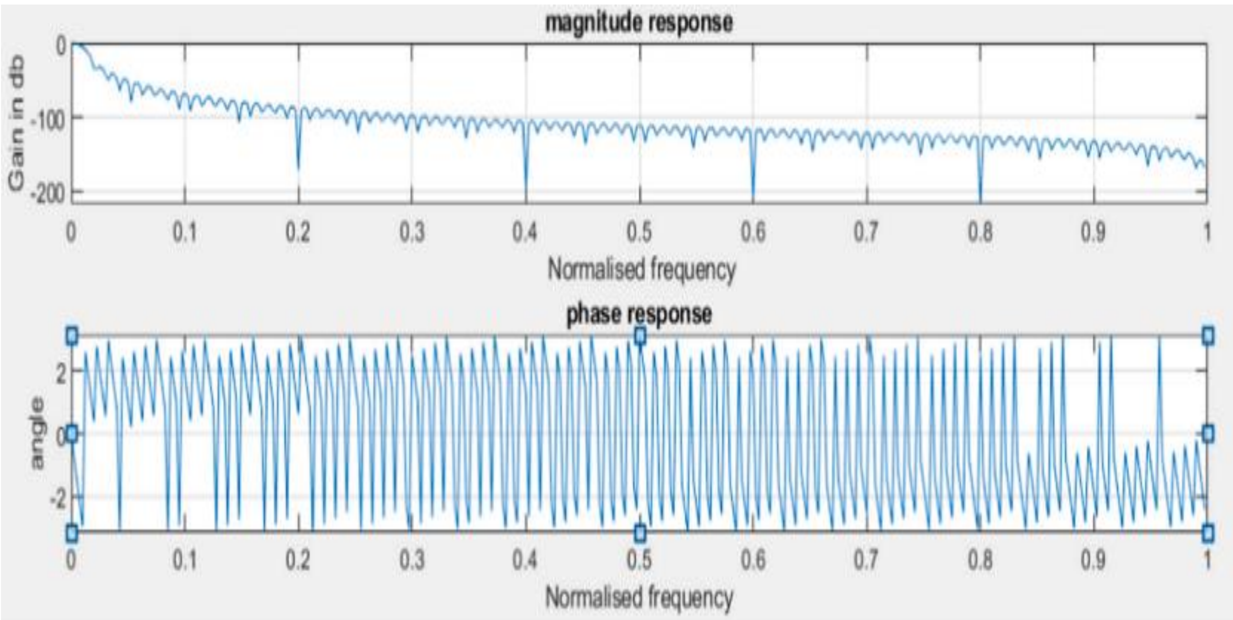

Figure 5. Low pass filtering for delta EEG waves

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The Anaconda Spyder software simulates filtering EEG signals spanning alpha, beta, gamma, theta, and delta frequency bands using the low pass filter approach in conjunction with low-pass, high-pass, bandpass, and band-stop filters for processing EEG signal shown in table 2. This simulation is run using Python.

Table 2. Response time for various EEG filters and brain wave patterns.

Brain waves	Low pass	High pass	Band pass	Band stop
Alpha waves (8-12 Hz)	16.706	21.816	44.969	39.108
Delta wave (0.1-4Hz)	14.125	14.516	17.087	16.475
Theta waves(4-8Hz)	14.319	11.965	19.90	16.182
Gamma waves (40-80Hz)	14.634	11.349	17.229	17.743
Beta waves (12-40Hz)	15.202	38.704	16.595	20.501

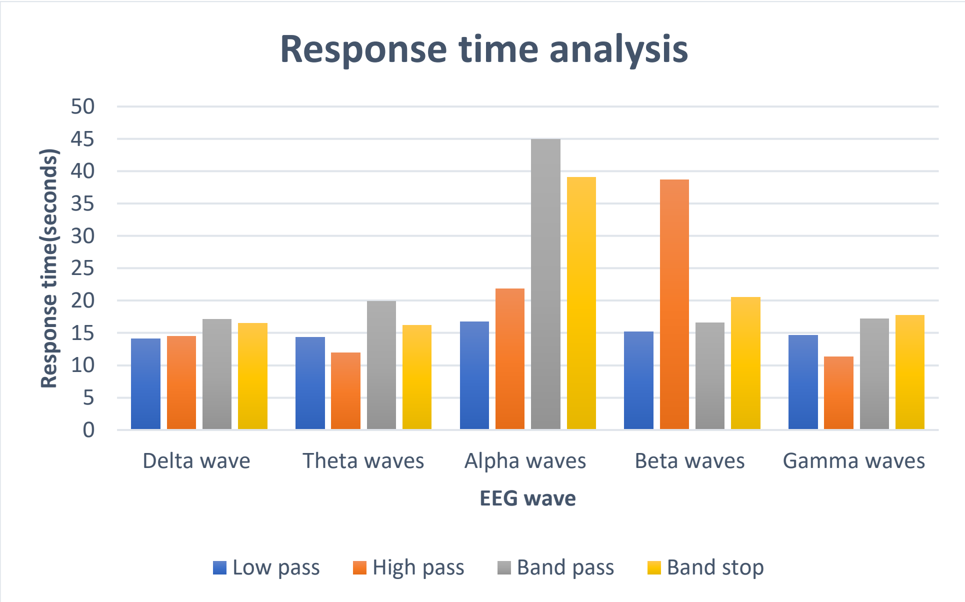

Figure 6. Analysis of response time of various EEG signal

This study used and evaluated the KNN, SVM, GRU and GRU-BGWO classifiers for EEG-based emotion recognition. The model was trained and tested using data from the first eight testing sessions, and the data from the last four sessions were reserved for testing. The number of hidden nodes, graph regularization parameter $\lambda 1$, and L2 norm regularization parameter $\lambda 2$ are the three most important parameters for BGWO. The amount of hidden nodes has no discernible impact on BGWO's performance, according to earlier studies. For all testing, we therefore set this value to 10 times the input data's dimension. Only two regularization parameters were changed in this investigation.

For the GRU-BGWO method, we develop a GRU model with two hidden layers. The unsupervised learning phase of the architecture is set to 310-100-30 and the supervised learning

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phase is set to 310-100-30-2. The supervised and unsupervised learning rates are set to 0.05 for both levels and the block size is set to 200.

Before applying the ResNet features to GRU-BGWO, the data are normalized by subtracting the mean, dividing by the standard deviation, and then scaling to a range of 0 to 1 by adding 0.5.

Furthermore, we evaluate the performance of ResNet features across the delta, theta, alpha, beta, and gamma frequency bands. Figure 6 illustrates the average accuracy of various classifiers across these five frequency bands, highlighting that the gamma and beta bands perform better than the others. The findings suggest a stronger correlation between beta and gamma oscillations of brain activity than other frequency bands.

Table 3 offerings the average accuracies are demonstrating that GRU-BGWO outperforms other classifiers, especially for low individual frequency features. In addition, it is necessary to analyse the classification accuracy for each classifier, as shown in Figure 7, which depicts the average accuracies across the five frequency bands.

Table 3. Accuracy of frequency bands

Classifier	Alpha (%)	Delta (%)	Theta (%)	Beta (%)	Gamma (%)	Total (%)
SVM	60.70	59.90	62.26	71.45	65.32	65.03
KNN	60.21	53.83	65.96	72.58	47.02	74.02
GRU	75.32	77.10	63.26	87.87	77.87	76.19
GRU-BGWO	95.36	87.33	86.28	94.97	96.32	91.45

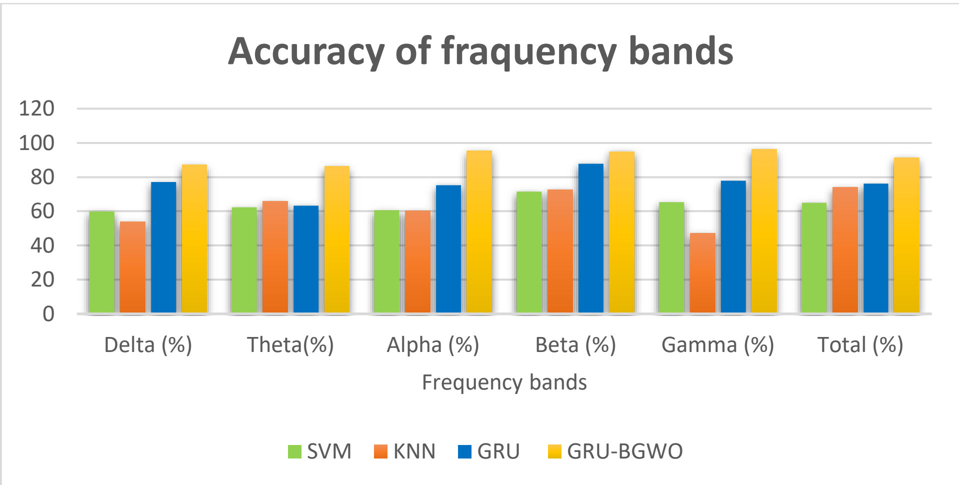

Figure 7. The average accuracy of each classifier across all five and all other frequency bands.

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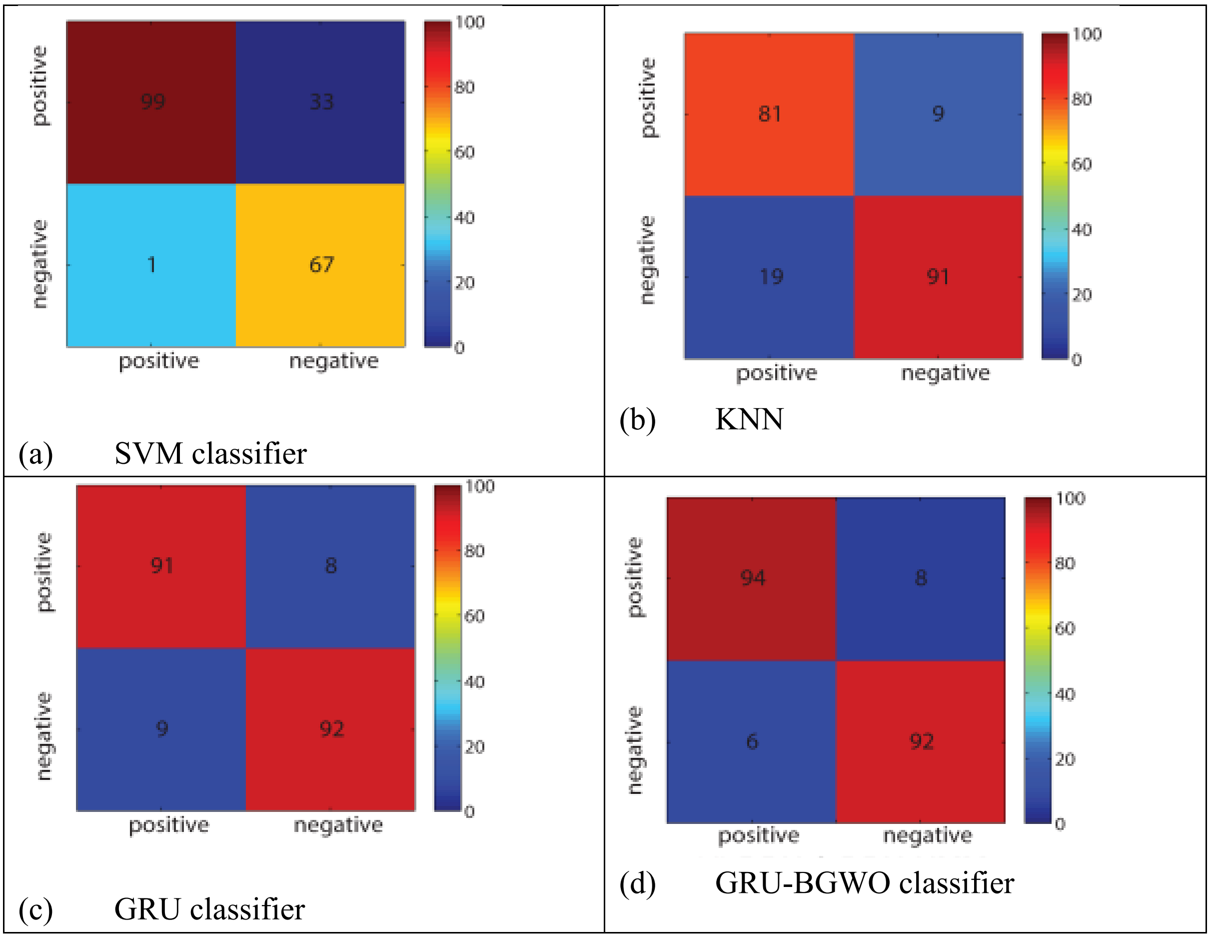

Figure 8 The confusion matrix of various classifiers for a single person in a trial experiment (numbers are displayed as percentages).

Numerous factors, such as the individuals' educational background, sociability, and actual evoked emotional state during the trials, may impact the categorization accuracy between the subjects. Figure 8 displays the confusion matrix of various classifiers for a single individual in a trial experiment.

5. Conclusion

In summary, this study successfully integrates sophisticated preprocessing, feature extraction, selection, classification, and optimization techniques to provide a thorough and novel framework for emotion recognition from EEG signals. By employing a low-pass filter, we enhanced the quality of EEG data, allowing for more accurate analysis. Using Higuchi's Fractal Dimension and Entropy as feature extraction methods provided valuable insights into the complexity and variability of emotional states. The application of ResNet-50 for feature selection significantly improved the model's performance by identifying the most relevant features. At the same time, the Gated Recurrent Units (GRUs) facilitated the effective classification of temporal patterns inherent in the EEG signals. Furthermore, incorporating Binary Grey wolf optimization (BGWO) led to optimized model parameters, enhancing overall classification accuracy. A DEAP dataset was used to evaluate the suggested methodology, and

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the GRU deep learning algorithm was used to accomplish classification. By lowering the complexity and dimension of the data, the feature extraction and selection phases enhanced model performance.

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