Al-Qadisiyah JournalFor Engineering Sciences 19 (2026) 001 – 009

Contents lists available at: http://qu.edu.iq

Al-Qadisiyah Journal for Engineering Sciences

Journal homepage: https://qjes.qu.edu.iq

Research Paper

Emotion recognition using brain computer interface by adopting optimized feature selection approach for EEG signal

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ARTICLE INFO

Article history:
Received 30 October 2025
Received in revised form 11 March 2026
Accepted 00 mmmm yyyy

keyword:
EEG
BCI
Adaptive Notch filter
MABC with inertia weigh
SVM Classifier

ABSTRACT

For Brain Computer Interface (BCI) applications, this research suggests an ideal feature selection framework for Electroencephalography (EEG)-based emotion recognition. In order to improve signal quality, EEG signals are first preprocessed using an adaptive notch filter to reduce power-line interference and artifacts. Then, in order to capture discriminative emotional patterns, time–frequency features, frequency domain, and time-domain are extracted. A Modified Artificial Bee Colony algorithm with inertia weight (MABC-IW) is used to choose the best subset of features that minimizes dimensionality and maximizes classification performance in order to handle feature redundancy and overfitting. A Support Vector Machine (SVM) is employed to categorize the chosen features. The suggested MABC-IW–SVM framework works better than traditional feature selection techniques, according to experimental assessment carried out in MATLAB with classification accuracy of 94%, precision of 91%, recall of 100% and F1-score of 95%. The suggested method reduces the feature set while increasing accuracy when compared to the baseline SVM without optimization. These findings demonstrate that the suggested optimum feature selection approach greatly improves the ability to recognize emotions from EEG signals.

1. Introduction

A mechanism called BCI uses the brain's output route to transmit requests and signals to the outside world [1]. BCI systems frequently fall into one of two categories. These two types of BCI are non-invasive and invasive. Due to their accessibility and versatility in recording brain signals, non-invasive BCI technologies are preferred by the majority of Asian nations [2]. In a BCI structure, there are 4 stages. Interaction with the computer, signal acquisition, pre-processing, and classification [3]. Several non-invasive techniques, including EEG [4], Near-Infrared Spectroscopy (NIRS) [5], functional Magnetic Resonance Imaging (fMRI) [6] and Magnetoencephalography (MEG) [7], are employed for collecting brain data. Due to its outstanding temporal accuracy, security, and simplicity of usage, EEG is a highly popular signal acquisition technique. The installation of 10–20 conventional electrodes is utilized to capture EEG signals. ECG has non-stationary characteristics and low spatial resolution. Clinical testing facilities generally use fMRI technology. However, despite having excellent temporal and spatial resolution, it is more expensive to set up. In the data acquisition process, time delay is greater. Low temporal resolution of NIRS technology may slow down conversion rates. However, being less expensive, it performs substantially less well than EEG-based BCI. The magnetic signals produced by electrical activity are recorded utilizing MEG technology. Among all non-invasive technologies, the ECG provides less temporal resolution, and it is safety and easy method. Table 1 represents the various rhythm of brain. Since EEG signals are influenced by muscle movement, eye blinks, external interference, and individual variations in neurophysiology, they are inherently noisy and changeable, which lowers the consistency and dependability of emotion identification models. It is difficult to preserve the quality of raw EEG data outside of controlled lab settings, and pre-processing techniques by themselves are unable to completely remove all artifacts without perhaps deleting useful neurological signals. Owing to the non-stationary nature of EEG, models trained on one set of settings or people may not generalize well to others, resulting in inter-subject variability and decreased applicability in real-world scenarios. Furthermore, a large number of publicly accessible EEG datasets are unbalanced and relatively small, which introduces bias and restricts the model's performance on unknown data from various populations or recording configurations. Following acquisition, the signals need to be pre-processed. The acquired brain signals are typically affected by noise and distortions. Visual blinks, eye movements, and heartbeat are artifacts. Along with these, brain impulses are also disorganized due to muscle movement and power line interference. Common Average Referencing (CAR), Frequency Analysis, Principal Component Analysis (PCA), Common Spatial Patterns (CSP), Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are all utilized to eradicate Artifacts [8–11].

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https://doi.org/10.30772/qjes.2026.166722.1797

Nomenclature

EEG	Electroencephalography	v_{ij}	New candidate solution
BCI	Brain-Computer Interface	x_{ki}	Random neighbouring solution
SVM	Support Vector Machine	y_i	Class label
$MABC$	Modified Artificial Bee Colony	b	Bias term
PSD	Power Spectral Density	$k(x_i, x_i)$	Kernel function
DE	Differential Entropy	D	Problem dimension
$RASM$	Rational Asymmetry	P	Signal power
$STFT$	Short-Time Fourier Transform	H	Entropy
PCA	Principal Component Analysis	x_{ij}	Current solution
ICA	Independent Component Analysis	x_{best}	Global best solution
CSP	Common Spatial Pattern	*Greek Symbols*	
CAR	Common Average Referencing	α	Scaling factor
GA	Genetic Algorithm	φ	Random perturbation parameter
DWT	Discrete Wavelet Transform	β	Scaling factor
x_i	Input feature vector	μ	Mean value
ω	Weight vector	*Subscripts*	
$f(x)$	Decision function	$xxix$	Index of sample
N	Number of samples	j	Dimension index
f_s	Sampling frequency (**Hz**)	k	Neighbour solution index
E	Energy of signal	max	Maximum value

However, the aforementioned techniques have some drawbacks, including that several calculations are needed for decomposition. The computation of averages and head coverage are complicated by finite sample density and insufficient head coverage, and the accuracy of classification is impacted by electrode location changes.

Table 1. Different rhythms of the brain.

Rhythm	Amplitude μv	Frequency range, Hz	State of mind
DELTA	20-200	Up to 4	Deep sleep
ALPHA	20-50	8-13	Relaxed Awareness
BETA	5-30	13-30	Alert, active attention and thinking
GAMMA	≤ 5	≥ 31	Consciousness mechanism
THETA	≥ 20	4-8	Drowsiness, emotional stress and sleep in adults

These issues are overcome by using the Adaptive Notch Filter. It is effective for signals and Artifacts when spectra coincide. The most important features of the brain signals are obtained after getting free of noise data from the signal improvement phase. Techniques like Adaptive Auto Regressive Parameters (AAR) [12], PCA [13], ICA, Wavelet Transformations (WT), Genetic Algorithms (GA) and Wavelet Packet Decomposition (WPD) are employed to derive features from EEG signals [14–18]. But these methods have poor time localization, which leads to inappropriate performance for all applications; defining the depiction's characteristics for EEG signals is challenging, and it is also not relevant to signals that are not stationary [19]. Therefore, in this research work, a novel MABC algorithm is proposed with inertia weight, which effectively selects the optimal features. The signals are divided into numerous classes employing different classifiers following feature selection [20]. There are many kinds of classifiers, including nearest neighbor classifiers and nonlinear Bayesian classifiers [21]. However, it has a high level of complexity and fails to generate an accurate prediction of the appropriate class probability [22]. Random forest [23] offers maximum accuracy and is robust to noise, but it necessitates more memory. An Adaptive neural decision tree [24] benefits from the learning capacity of a neural network, though it makes the implementation more difficult. The K-nearest neighbor [25] is easy to implement, and its identification period is very slow. With the implementation of an SVM classifier, the above issues are solved. Furthermore, it is used to expand the properties of the linear model used to predict human emotions from brain signals. Hence, an SVM classifier method is employed to diagnose human emotion utilizing a BCI system. Initially, the input signals are pre-processed with the support of an adaptive notch filter to minimize artifacts from the input signals. Then, using the MABC algorithm with inertia weight, the best features are chosen from the domains of time-frequency, time, and frequency features. Finally, the SVM Classifier efficiently performs emotion detection based on the emotion model. The proposed approach applies a MABC with inertia weight to pick the most informative features from the EEG data, unlike other approaches that pick features based on separate feature scoring that miss complex interactions among features and leave redundant data that impacts performance. Optimized feature selection searches the search space more clearly and predicts a subset that enhances accuracy. When incorporated with SVM, it results in more reliable emotion recognition than traditional approaches. Therefore, the integration of the MABC algorithm with inertia weight for optimal feature selection, which improves classification performance when combined with SVM, makes the presented work new as opposed to relying solely on generic statistical features. The method differs from studies that merely extract and categorize common features without using targeted selection to increase accuracy and generalization because of this optimization stage.

2. Proposed system description

In general, EEG signals provide more information about emotional processes and actions. Research on EEG-based emotion recognition also has significant benefits for improving the user experience and functionality of BCIs, as EEG is commonly used in BCIs. Figure 1 illustrates a new MABC with inertia weight and SVM classifier for effective emotion recognition using a BCI system.

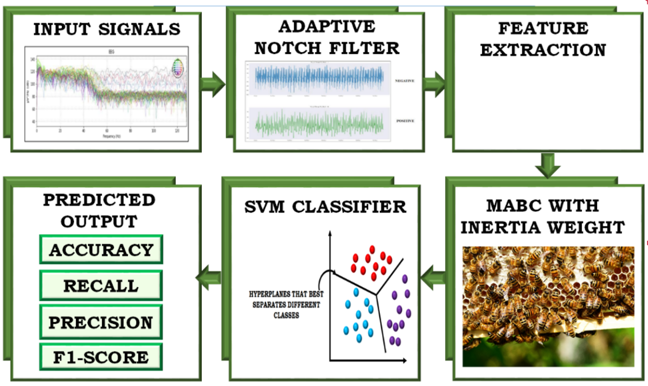

Figure 1. Block diagram of the proposed system indicating the process flow from input to the output.

In the beginning stage, the obtained input signals are pre-processed using an adaptive notch filter. In this stage, the filter removes power line noise from EEG signals. By using a feature extraction method, the signals' most discriminating properties are identified. Following this, using the MABC algorithm with inertia weight, the best features are chosen from the domains of time and frequency. At last, the SVM classifier recognizes signals dependent on the emotion model. The primary contribution of this SVM is to estimate the data and identify the pattern of emotion accurately. Enhancing real-time emotion identification with EEG-based systems is important because, in contrast to behavioral inputs like speech or facial expressions, EEG offers direct, high temporal resolution access to neural activity, allowing for quicker and more precise tracking of emotional changes. In assistive technologies, gaming, and online learning, real-time emotion recognition can improve human–computer communication by permitting systems to dynamically adjust to user reactions. It also has significant ramifications for mental health monitoring, since non-invasively identifying minute emotional changes can help with early interventions and individualized treatment. These applications are pushed toward responsive, useful deployment in real-world scenarios with the aid of advancements in optimized feature selection and classifier performance, as demonstrated in the proposed study. These enhancements aid in resolving present issues with latency, dependability, and usefulness in EEG-based affective computing systems.

2.1 Model of Emotion

The discrete model and the dimensional model are the two fundamental models used to categorize emotions originally. According to discrete conceptions of emotion, the presence of different feelings is shown by coordinated patterns of physiological, neurological, and morphological expressive responses. Six fundamental emotions- joy, sadness, anger, contempt, fear, and surprise are listed by the discrete model to define emotion. The valence and arousal dimensions theory is the most widely used. Arousal describes the intensity of excitement from passive to active, and valence describes the range of human enjoyment from positive to negative. Due to its simplicity and potent capacity to accurately characterize emotion, the valence-arousal model has become extensively employed in EEG-based emotion identification. Following signal pre-processing, emotion-relevant EEG features are discovered and correlated with emotional states. These features are retrieved from the time, frequency, and time-frequency domains, which is explained clearly in forth coming section.

2.2 Feature extraction

2.2.1 Features of frequency domain

Power characteristics associated with various frequency bands used in rhythms of EEG are identified in the frequency phase during a frequency-domain analysis. In some frequency bands, the combined value of three power features are computed as follows.

- **Features of Power Spectral Density (PSD):** PSD, which has been used to explain the distribution of signal shifts in frequency when unpredictable vibrations produce power, is an efficient response time series for frequency features index. In this analysis, the 4 bands power is alpha $(8-14Hz)$, gamma $3(0-50Hz)$, theta $(4-8Hz)$ and beta $(14-30Hz)$ are estimated as the characteristics.
- **Features of Differential Entropy (DE):** Among the more significant frequency aspects that is effective in recognising emotions is DE. Applying DE to generate characteristics in four frequency bands is comparable to applying PSD.
- **Features of Rational Asymmetry (RASM):** The proportions of the DE of various combinations of electrodes with hemispheric asymmetry are referred to as RASM, which is a modification of DE.

2.2.2 Features of time-Frequency domain

When using time-frequency approaches to analyse an unsteady signal, dynamical changes are taken into consideration to reveal new information.

2.2.3 Wavelet coefficient features

The Short-Time Fourier Transform (STFT) by which the Wavelet Transform (WT) is derived. It fixes STFT's faults and evolves into the best tool for signal time-frequency analysis and processing. WT is used to determine the signal's characteristics and estimates, which correspond to both low and high frequencies accordingly. One of the techniques that is widely utilized in the analysis of EEG signals is the Discrete Wavelet Transform (DWT). A series of low-pass and high-pass filters is reduced out till the required frequency band is attained. In this research, the gathered EEG signal is initially minimized to $128Hz$, and then 5 frequency bands are generated from the DWT's 'db4' detailed decomposition. These bands ranged in frequency from 4 to $128Hz$. D5 is particularly broken into the theta band $4-8Hz$, D2 into the gamma $32-64Hz$, 1 into high gamma value of band $64-128Hz$, D4 into the alpha band $8-16Hz$ and D3 into the beta band $16-128Hz$, D. The final stage to determine the energy and entropy for each frequency range using Eq. 1 and 2.

$$ENT_j = -\sum_{k=1}^{N}\left(D_j(k^2)\right) \times log\left(D_j(k)^2\right) \tag{1}$$

$$ENG = \sum_{k=1}^{N}\left(D_j(k^2)\right) \tag{2}$$

Here the number of wavelet coefficients is k, and $j = 1,2,3,...etc$, is the stage of wavelet decomposition. Consequently, the following is the signal's composition vector of wavelet features, Eq. 3.

$$FV_{wavelet} = \left[ENT_j, ENG_j\right] \tag{3}$$

The most important step before classification is feature selection. It is primarily utilized to minimize any redundant features and choose an informative subset. Without affecting classification accuracy, it is produces a classification issue with fewer dimensions [26]. The delta (up to $4Hz$), alpha (8–13Hz), theta (4–8Hz), beta (13–30Hz), and lower gamma bands (30–60Hz) correspond to known physiological brain rhythms. Beyond this range, particularly above about 60–80Hz, a large portion of the recorded activity tends to be dominated by noise, such as muscle (EMG) artifacts and environmental interference rather than genuine neural oscillations. In EEG research, it is usual practice to concentrate on frequencies up to about 60Hz because scalp EEG is significantly suppressed at higher frequencies and because it is challenging to distinguish higher bands from noise without intrusive recordings or extremely high-density arrays. Such high-frequency components over $60Hz$ are less reliably captured by normal EEG settings and are frequently eliminated in emotion recognition because they compromise feature quality. In this research, a new modified ABC with inertia weight approach is proposed to determine the most desirable feature combination from various dimensions. The detailed description of the proposed MABC with inertia weight is explained as follows.

2.3 Feature selection using modified MABC with inertia weight

The ABC algorithm's searching expression approach is essential to its effectiveness. In particular, a randomly generated solution is employed in Eq. 4 and only a single dimension is modified. This supports the method's diversification behaviour but has a detrimental impact on its intensification behaviour. As a result, although the technique has a good chance of escaping local optimal spots, early convergence still exists. As an outcome, while ABC shows promise, particularly in multimodal situations, it merges poorly in many other kinds of problems.

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{kj}\right) \tag{4}$$

Some more recent research employed the most suitable solution available rather than choosing at random variables in their search formulae to prevent premature convergence. In other investigations, modified searching expressions with simultaneous changes to several dimensions have also been presented. Both methods speed up convergence when the issue type and dimension have modified, but they become stuck at local optimal points. Depending on the issue category, it appears that the diversification and intensification behaviours of the ABC algorithm ought to happen at various rates, but this rate is unknown at the beginning of algorithm execution. The proportion of these two behaviours has to be determined when the method executes using an adaptive search equation. To solve this problem, the paper suggests a new ABC technique that incorporates an adaptive search equation. The M-ABC [27] with inertia weight algorithm utilises an adaptive search equation selection approach rather than Eq. 4 in the traditional ABC algorithm. The first of the equations that follow is used in the suggested search method to account for each dimension of the solution, Eq. 5, 6 and 7:

$$X_{i,j} = \omega X_{i,j} + rand(-\delta, +\delta)\left(X_{i,j} - X_{k,j}\right) \tag{5}$$

$$X_{i,j} = \omega X_{i,j} + rand(-\delta, +\delta)\left(X_{i,j} - X_{best,j}\right) \tag{6}$$

$$X_{i,j} = \omega X_{i,j} \tag{7}$$

When $x_{best,j}$ represents the current best solution at dimension and ω is the inertia weight. The scaling factor ratio that regulates the magnitude of the disturbance is represented by the real numbers j and d, both of which are positive. Since it uses a random solution, the initial of these Eq. 5 contributes to the diversification characteristic. The second Eq. 6, on the other hand, helps with the intensification characteristic because it uses the optimal response. Therefore Eqs. 5 and Eq. 6 are employed in some dimensions, while the other dimensions remained identical. A probabilistic selection rule determines the frequency of use of these three solutions in the generation of each candidate solution. The chance of selecting each search equation hk is determined in accordance with the rule as follows, Eq. 8.

$$\theta_k = \frac{S_k}{\sum_{m=1}^{3} S_m} \tag{8}$$

The effective score of a search equation is represented here by s_k. For each search equation, the success score is initially assigned a value larger than zero at the beginning of the procedure. The utilization ratio of each equation employed in the newly proposed solution (v_i) that outperforms the reference solution (x_i) is contributed to the success score in the following manner, Eq. 9.

$$S_k = S_k \times \gamma + r_k \times D \tag{9}$$

If r_k is the frequency with which the appropriate search equations Eqs. 5, 6 7, are used, and c is the resultant decay coefficient, D is the problem dimension. In order to find an improved solution, the search equation i is therefore utilized in $r)kD$ dimensions. Additionally, the c coefficient is employed to eliminate the previous attractive but deceptive performance values. A search equation is capable of producing excellent outcomes at the beginning of the method's iteration process, but does not yield excellent findings afterwards. The chosen probability of a search formula reduces exponentially by the c coefficient as the frequency of application of the search equation in a workable solution decreases. As a result, c encourages the exploration of new parts of the search space and helps prevent premature convergence.

2.3.1 Employed Bee Phase

The employed bee phase [10] of the ABC is an initial iterative process in which engaged bees in the dance zone communicate food source details to the observer bees. The observer bees then decide which food sources to choose and keep in mind based on the quantity of nectar they contain or $f(x_i)$, which is the fitness function of the problem that needs to be optimized, Eq. 10.

$$V_{ij} = \omega X_{ij} + \varphi_{ij}(X_{ij} - X_{kj}) \tag{10}$$

It regulates when the current food source affects the development of the upcoming one. In this section, three different types of inertia weight are employed: inertia weight that increases dramatically, inertia weight that increases linearly, and inertia weight that decreases linearly. These variations are all adaptable based on the number of iterations. In Eq. 11, the exponential inertia weight is displayed.

$$\omega = exp\left(\frac{t}{t_{max}} - 1\right) \tag{11}$$

Here t denotes the current iteration and t_{max} denotes the maximum iteration. On the other hand, Eq. 11 is used to determine the linear inertia weight.

$$\omega = \left(\frac{t}{t_{max}} - 1\right)(\omega_{init} - \omega_{final}) + \omega_{final} \tag{12}$$

Figure 2 displays the rate of change for certain inertia weights. Small inertia promotes convergence and avoids premature convergence, while high inertia promotes exploration. The novel candidate food source is formed around the present solution, x_i, and a randomly chosen solution,x_k, where $k \neq i$ and is randomly chosen in the range of 1- SN, according to the second portion of Eq. 10. The ϕ_{ij} is a random value between one and one. In the presented system, to implement classification, the SVM classifier is employed.

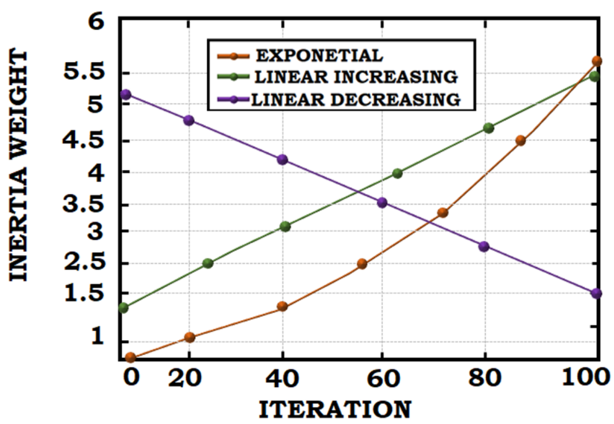

Figure 2. Rate of change of inertia weight with respect to the number of iterations.

2.4 Classification by SVM

SVM aims to identify a hyperplane for a specific two-class, independently divisible classification issue that divides the input space with the greatest possible margin, as revealed in Fig. 3.

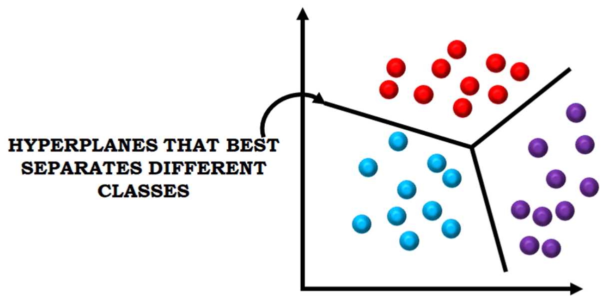

Figure 3. SVM classifier indicating hyperplanes separating different classes with greatest possible margin

The best hyperplane is discovered to be in the following order, Eqs. 13 and 14:

$$W \times X_i + b \geq +1, \quad if \quad y_i = +1 \tag{13}$$

$$W \times X_i + b \leq +1, \quad if \quad y_i = -1 \tag{14}$$

In normal hyper plane, the vector weight is denoted by $w.b$ is bias, x_i is the ith input vector $x \in R^N$, y_i is ith input's class labe $y \in (-1,+1)$ and w is the weight vector, two margins that are parallel to the ideal hyperplane lead to the discovery of the optimal hyperplane. Equation 15 is used to find margins.

$$W \times X_i + b \leq \pm 1 \tag{15}$$

Support vectors are the input vectors that establish the margins. If the issue isn't linearly separable, the input vectors ought to be subjected to a kernel function to make the issue linearly separable in the transformed space, Eq. 16.

$$K(x_i, x_j) = \varphi(x)\varphi(x_j) \tag{16}$$

A two-class linearly non-separable problem has the following solution, Eq. 17.

$$f(x) = sign\left(\sum_i a_i y_i \varphi(x)\varphi(x_i) + b\right) \tag{17}$$

With the employment of an SVM classifier, human emotions are effectively predicted with accuracy.

3. Result and discussions

Thus, using a BCI system with SVM classifier algorithm is used to identify human state of mind. To reduce Artifacts from the input signals, the adaptive notch filter is subsequently used to pre-process the input signals. Then, optimum characteristics from the time, time-frequency domain and frequency features are selected using the MABC algorithm with inertia weight. Lastly, utilising the emotions model, the SVM Classifier effectively detects emotions. The several stages of outcome presented below. Figure 4 represents the waveform for sampled frequency signal and Fig. 5 illustrates the preprocessed filtered waveform of filtered output of EEG signal. Figures 6 and 7 display the pre-processed signal representation of proposed system.

The final result displayed EEG signal waveforms that are smoothed. Preprocessing for the EEG signals includes artifacts elimination, filtering, epoch selection and signal averaging. While arousal indicates to an emotion's intensity or the effectiveness of the related emotional state, valence denotes the degree to which an emotion is positive or negative. Low arousal positive valence (Relaxed, Calm), High arousal positive valence (Happy, Excited), low arousal negative valence (Sad, Bored) and High arousal negative valence (Nervous, Angry) are all examples of Valence and arousal pairings that are converted into emotional states. Initially Artifacts like electro galvanic signals and motion artifacts are removed using an adaptive notch filter with a frequency, which is represented in Fig. 8. Here, an ICA approach is employed for eliminating the ocular artifacts. ICA decomposes EEG signals to maximise independent components, and those with eye activity are identified and removed. Twenty primary components have been employed for decomposing the EEG data. An EEG signal free of artifacts is recreated after the component showing eye activity has been eliminated. Figure 9 illustrates topographic EEG evaluation that is employed to show the spatial distribution of brain electrical activity. In order to best study the general resolutions and accuracy limits of EEG measurement configurations, the minimum norm estimation (MNE) gives the amount of information that truly exists in the data. Additionally, this strongly implies that the standard minimum norm solution is a useful technique whenever there is a lack of accurate a priori knowledge about source generators. The evoked response for each condition is developed for ideal cleaner epochs, as depicted in Fig. 10.

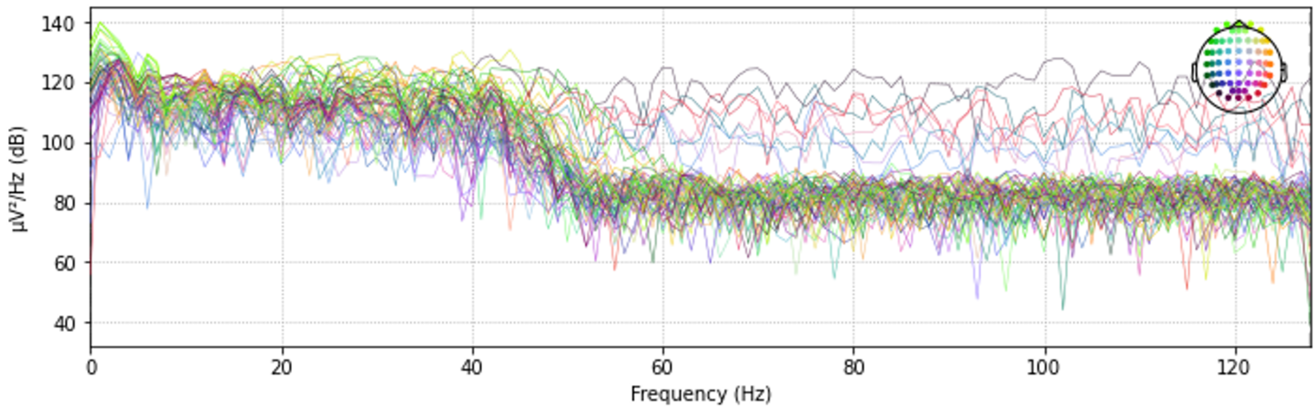

Figure 4. Sampled frequency-domain EEG signal illustrating spectral characteristics extracted for subsequent emotion recognition analysis.

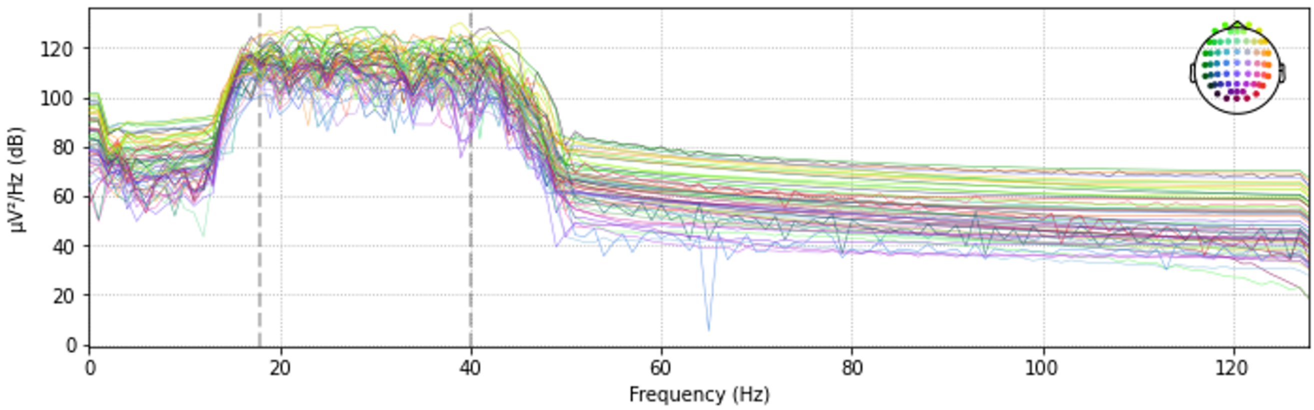

Figure 5. Filtered EEG signal after adaptive notch filtering for effective removal of noise.

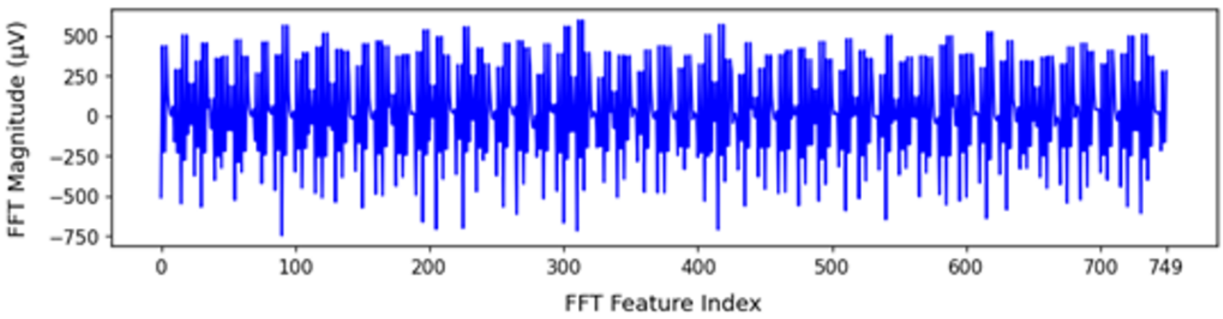

Figure 6. Negative emotion EEG signal pre-processed using an adaptive notch filter to suppress power-line interference.

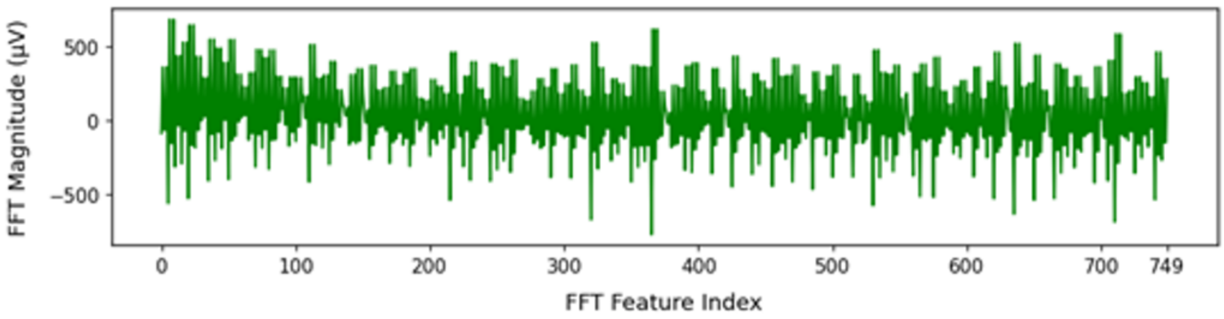

Figure 7. Positive emotion EEG signal pre-processed using an adaptive notch filter to suppress power-line interference.

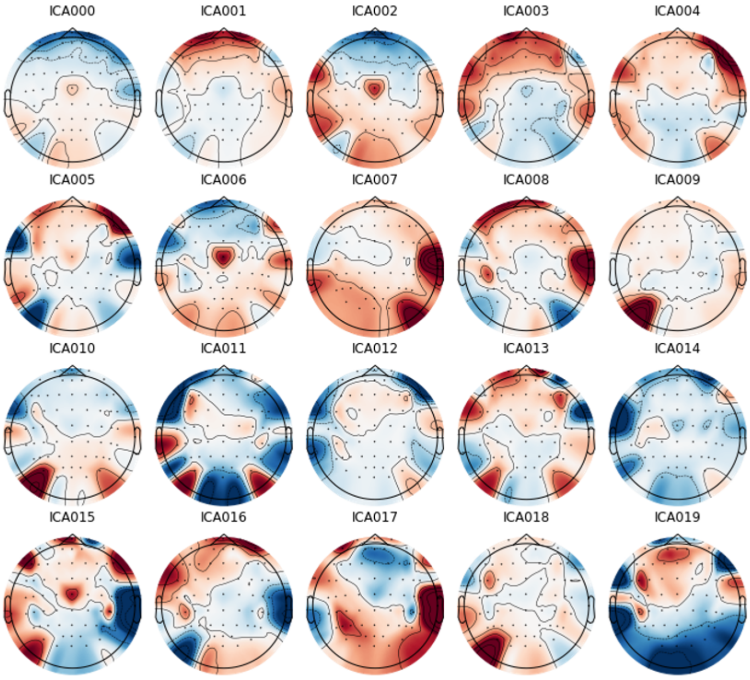

Figure 8**.** Detection and identification of EEG artifacts using ICA for improved signal quality.

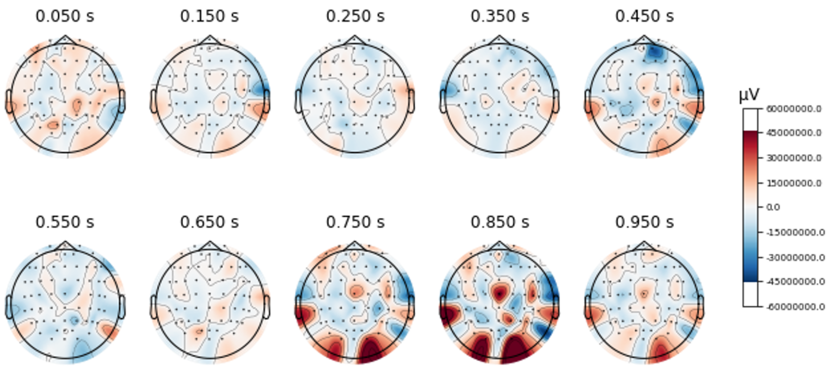

Figure 9**.** Topomap representations illustrating the spatial distribution of EEG activity across different scalp regions.

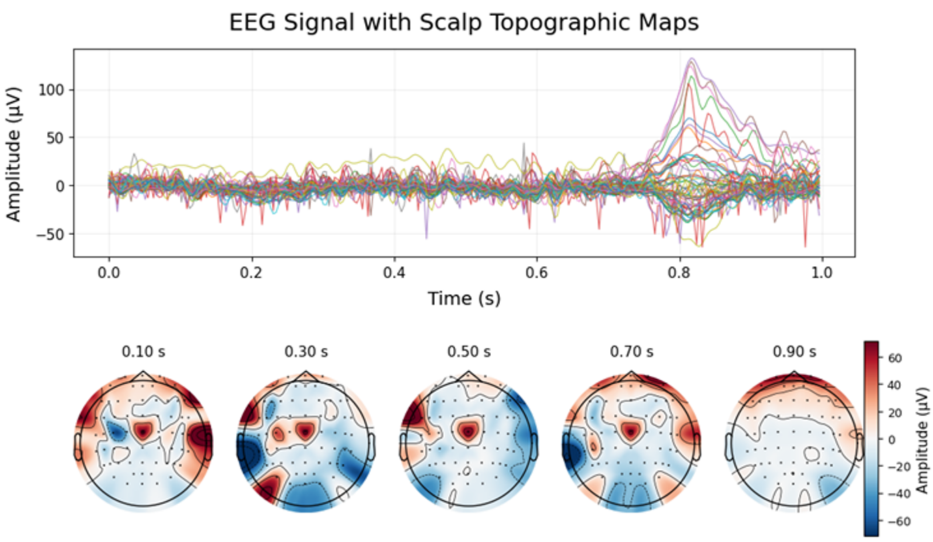

Figure 10**.** Evoked response obtained from clean EEG epochs, illustrating time-locked neural activity associated with emotional stimuli.

Figure 11 represents the confusion matrix of SVM. Here, the 11 false negatives indicate instances where a target emotion exists but is unpredicted. Likewise, 0 false positives denote that the model does not generate false alarms, which is useful for averting redundant interventions based on misread signals. Nevertheless, the occurrence of more false positives than true positives for class 1 indicates the recall is impaired owing to the class imbalance or subtle facial features. These outcomes imply that the system is reliable if it triggers a prediction and susceptible to significant emotional states. Table 2 denotes the results the or SVM classifier using the EEG signal for human emotion detection. The recommended SVM accomplishes the classification precision of 94% and it is observed that SVM obtains the maximum accuracy in contrasted to other approaches. Table 3 represents the analysis of the proposed SVM with different classifiers, for example, KNN [28], DBN [29] and MLP [30] and the corresponding plots are represented in Fig. 12.

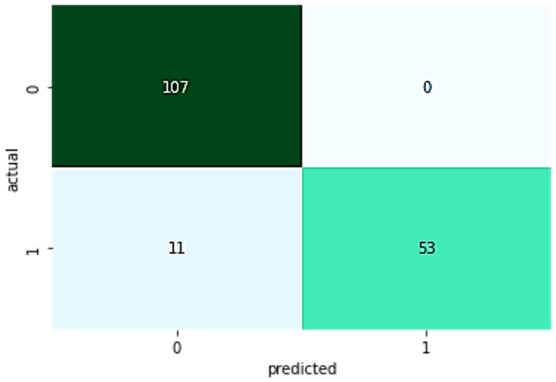

Figure 11**.** Confusion matrix illustrating the classification performance of the proposed EEG emotion recognition model.

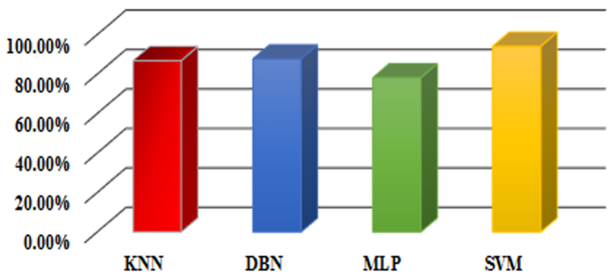

Figure 12**.** Accuracy analysis demonstrating the classification effectiveness of the proposed EEG-based emotion recognition model.

Table 2**.** Accuracy analysis demonstrating the classification effectiveness of the proposed EEG-based emotion recognition model.

Classes	F1-score	Recall	Precision
0	0.95	1.00	0.91
1	0.91	0.83	1.00

Table 3**.** Comparative analysis of the proposed model with existing EEG-based emotion recognition methods.

Classifier	KNN [28]	DBN [29]	MLP [30]	SVM
Accuracy	86.75 %	87.62 %	78.11%	94%

From the obtained results, it is clear that the suggested classifier achieves the highest accuracy of 94% for predicting human emotions. The SVM classifier is compared with KNN [31] and RF [32] in Fig. 13, which reveals the SVM classifier has the recall of 100%, highlighting the performance enhancement in forecasting human emotions. The suggested approach is unique in that it selects the most informative EEG features using a MABC, which has been demonstrated to increase classification accuracy and decrease the number of features required when compared to using all features. By concentrating on the most pertinent signal features, Meta heuristic feature selection has been shown to dramatically improve performance and efficiency in a variety of brain signal classification tasks. In contrast to conventional approaches that carry out feature selection inefficiently or not at all, it improves generalization and reduces computational cost when paired with SVM. It adaptively explores feature subsets, permitting the classifier to more precisely recognize subtle emotional states.

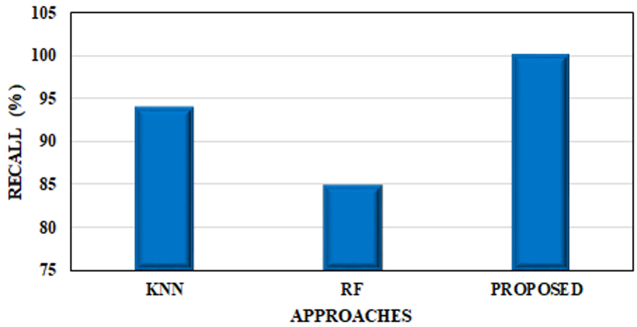

Figure 13**.** Recall analysis demonstrating the ability of the proposed model to correctly identify emotional classes.

4. Conclusion

Emotion recognition dependent on physiological signals, particularly EEG signals, has gained popularity as an analytical area in the past few years due to the constant advancement of BCI technology. But it has also become more crucial for comprehending to extract significant features from EEG data so that classifiers are able to correctly recognise emotions. Therefore, in this work presents an SVM-based technique for EEG signal emotion identification. Extracting features from the pre-processed EEG signal that requires initially taking into consideration the frequency, time and time-frequency domain that are all correlated to emotion. The innovative Modified ABC with inertia weight feature selection approach is utilised to minimise the dimensions of the features. The next step is to train an SVM classifier for precise emotion prediction using the optimised feature sets. Finally, it has been demonstrated that the suggested method works well for identifying emotions, with an excellent average precision reaching up to 94%. The efficacy of the developed approach is much better than other existing approaches. Future research should examine multimodal techniques that combine EEG with additional physiological signals such ECG, GSR, EMG, or audio visual cues. In order to detect subtle emotional patterns more reliably, researchers can also look into deep learning and advanced fusion algorithms that develop shared representations across modalities. Classification performance may be further improved by combining physiological signals with environmental or behavioural information (such as speech or facial expressions).

Authors' contribution

Conceptualization: Kalakonda Jyothsna Data Curation: Kalakonda Jyothsna Methodology: Viswaprakash Babu, B. Chempavathy, Dinesh Kumar Budagam, M. J. D. Ebinezer, V. Pujari, Kalakonda Jyothsna Project administration: Viswaprakash Babu, B. Chempavathy, Dinesh Kumar Budagam, M. J. D. Ebinezer, V. Pujari Supervision: Viswaprakash Babu, B. Chempavathy, Dinesh Kumar Budagam, M. J. D. Ebinezer, V. Pujari Validation: Viswaprakash Babu, B. Chempavathy, Dinesh Kumar Budagam, M. J. D. Ebinezer, V. Pujari Writing-original draft: Kalakonda Jyothsna Writing-review & editing: Viswaprakash Babu, B. Chempavathy, Dinesh Kumar Budagam, M. J. D. Ebinezer, V. Pujari, Kalakonda Jyothsna

Declaration of competing interest

The authors declare no conflicts of interest.

Funding source

This study didn't receive any specific funds

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article:
Alakonda Jyothsna, Viswaprakash Babu, B. Chempavathy, Dinesh Kumar B., M. J. D. Ebinezer, and V. Pujari, (2026). 'Emotion recognition using brain computer interface by adopting optimized feature selection approach for EEG signal', Al-Qadisiyah Journal for Engineering Sciences, 19(5), pp. xxx- 009.
https://doi.org/10.30772/qjes.2026.166722.1797