International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 6, December 2023, pp. 6891~6903
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i6.pp6891-6903

Survey analysis for optimization algorithms applied to electroencephalogram

Ekram Hakem, Dhiah Al-Shammary, Ahmed M. Mahdi
Department Computer Science, College of Computer Science and Information Technology, Universitas of Al-Qadisiyah, Diwaniyah, Iraq

Article Info

Article history:

Received Nov 9, 2022
Revised May 15, 2023
Accepted May 23, 2023

Keywords:

Classification
Electroencephalogram data
Machine learning algorithms
Optimization algorithms
Particle swarm optimization

ABSTRACT

This paper presents a survey for optimization approaches that analyze and classify electroencephalogram (EEG) signals. The automatic analysis of EEG presents a significant challenge due to the high-dimensional data volume. Optimization algorithms seek to achieve better accuracy by selecting practical features and reducing unwanted features. Forty-seven reputable research papers are provided in this work, emphasizing the developed and executed techniques divided into seven groups based on the applied optimization algorithm particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), grey wolf optimizer (GWO), Bat, Firefly, and other optimizer approaches). The main measures to analyze this paper are accuracy, precision, recall, and F1-score assessment. Several datasets have been utilized in the included papers like EEG Bonn University, CHB-MIT, electrocardiography (ECG) dataset, and other datasets. The results have proven that the PSO and GWO algorithms have achieved the highest accuracy rate of around 99% compared with other techniques.

Corresponding Author:

Ekram Hakem
Department Computer Science, College of Computer Science and Information Technology, Universitas of Al-Qadisiyah
Diwaniyah, Iraq
Email: com21.post1@qu.edu.iq

1. INTRODUCTION

An electroencephalogram (EEG) signal is the most common way to diagnose changes in brain cells [1]. EEG signals contain a vast amount of data [2]–[4], and visual diagnosis of them by neurophysiologists is more prone to error, time-consuming, and complex. An EEG records the brain's electromagnetic Activity, which can reveal crucial details about various brain disorders like epilepsy and eye issues [5]. On the scalp, electrodes are employed.to determine EEG data. It identifies and monitors neurological disorders like sleep apnea and epilepsy [6]. The most prevalent neurological condition affecting people is epilepsy, marked by recurrent seizures [7]. Many studies and research endeavors, including gaming, neuromarketing, and many others, employ EEG signals [8]. As a result, many researchers have suggested various optimization and machine learning techniques to analyze and classify the EEG signal with high accuracy to protect people's health and early detection of brain diseases [9]. EEG analysis is crucial for identifying epileptic seizures and monitoring sleep disorders [10]. These signals are complex, noisy, nonlinear, and nonstable [11]. As a result, recognizing and discovering information relating to the brain is a difficult task [12]. Furthermore, the Automated analysis of EEG signals faces many problems due to the high dimensional data volume [13]. Moreover, optimization algorithms seek to obtain better accuracy by reducing the number of features and exploiting the excellent search space within appropriate time intervals [3], [14].

2. MOTIVATION

Recently, the number of researchers analyzing the EEG signal has increased due to its importance in discovering and diagnosing brain diseases [15]. EEG is a complex network of billions of neurons whose data are interconnected, producing thousands of features per second [16]. It constitutes a burden on machine learning algorithms in the classification of EEG as they suffer greatly from high features rate and several undesirable features [17]. Therefore, optimization algorithms strive to select the optimal features for better exploration and exploitation [18]. However, efficient feature extraction and reduction of data dimensions can improve Complexity, processing time, and memory storage. Optimization algorithms suffer from many limitations, which can have summed up in two steps. First, the problem of optimal local stagnation results from a need for more diversity to discover new solutions and extract essential features from previous iterations. Second, it takes much processing time, and the convergence rate of many iterative processes is low [19].

3. SURVEY STRATEGY AND EVALUATION

The thirty proposed optimization techniques for EEG signal enhancement are divided into seven groups (particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), bat algorithm (BA), grey wolf optimizer (GWO), firefly algorithm (FA), and other optimizer approaches). These are the most common techniques applied in evolutionary algorithms (EA). This survey analyzes the problem and proposed solutions, evaluates performance using some metrics, and analyzes the best results. A critical statement is shown for each approach. These studies focus on using some measures to assess performance, such as precision, recall, accuracy, and F1-score. Technically, compare and evaluate the best results within their groups.

Furthermore, the best accuracy for all techniques within the same group has been calculated and compared with other improvement groups. The PSO and GWO groups have reached the highest accuracy level. Moreover, most researchers ignored the evaluation of processing time, so the system's performance in most techniques could have been clearer [20].

3.1. Particle swarm optimization

Satapathy *et al.* [21] have focused on the problem of detecting epileptic seizures in patients based on EEG analysis and classification. An accurate analysis of these signals may be critical for the early detection of many diseases of the human brain. This proposal uses a radial basis function neural network (RBFNN) to classify the EEG signal. Furthermore, the mean square error (MSE) is optimized using the modified PSO algorithm. PSO modification aims to overcome the slow search problem and find the optimal solution. Some measures are computed for evaluation, including accuracy, precision, recall (true positive (TP), false negative (FN), false positive (FP), true negative (TN)), and F1-score. Two EEG datasets are utilized one is an epileptic seizure for the EEG dataset determination, and the other is eye condition prediction for the EEG dataset. This paper has achieved a high accuracy of 99% compared with other methods. The proposed model achieved high-precision classification results but ignored the careful performance analysis regarding processing time and complexity.

Jamali-Dinan *et al.* [22] have focused on detecting patients with temporal lobe epilepsy (TLE), the prevalent form of focal epilepsy. This paper applies a new method for optimizing particle swarm, and Minkowski weighted k-means to determine the aspect of temporal lobe epilepsy. K-means it suffered from noisy features. To address this problem, weighted k-means of optimization using Minkowski distance. Generally, it is sensitive to the initialization assembly, therefore. PSO allows the user to avoid local stagnation and maintain the advantages of PSO and mobile water kit (MWK) methods. The proposed model the evaluated by computing the accuracy metric only. Furthermore, Silhouette criteria are applied to scale the better cluster number. They have been used as standard datasets with previously named sets selected from the UCI Machine Learning Repository. This method can identify epilepsy with 82.3% and 93.6% accuracy. This research could have evaluated the model's performance, as it adopted the accuracy measure only and ignored many criteria, such as processing time and complexity.

Another study by Sun *et al.* [23] discussed the problem of EEG signals and how they can easily be affected by noise that impacts the intelligent diagnosis of diseases. To reduce noise affecting EEG signals and improve the accuracy of feature extraction. This paper proposes using a wide, deep echo state network with several parallel reservoirs instead of a single reservoir. EEG signals are trained to distinguish between noisy and noise-free EEG features. However, uniform search particle swarm optimization (UPSO) is used to optimize the reservoir parameters of a wide deep echo state network. The proposed model is evaluated by comparing the signal-to-noise ratio (SNR); root means square error (RMSE), and nonlinear features. The high the SNR value, the better the filtering impact. The model takes relatively less time. The dataset used in this paper is obtained from the physical website. Experiments are applied to the dataset electrocardiography (ECG) and electromyography (EMG). SNR results of ECG noise are one dB=23.14416873 and RMSE with one dB=0.040621086. The results of this research were unclear and lacked many measures, such as accuracy. Moreover, this method performed relatively poorly in removing noise in some data types, such as ECG.

Detecting brain malignancies has been the focus of Deepa *et al.* [24]. It is critical for protecting human health, catching diseases, and treating certain cancers. This paper has proposed a solution for brain tumor detection. Firstly, a filtering algorithm performs the preprocessing to select important features. Second, to speed up the search process, modified PSO is used to segment the tumor portion of the image and then categorize it by the k-nearest neighbor (KNN) algorithm. The obtained accuracy is compared with the sensitivity, specificity, and error rate to evaluate this proposed approach. The dataset used in this paper is a set of magnetic resonance images (MRI) brain images obtained from a brain web database. An accuracy achieved by this method of 98.2 percent is the best result. Technically, the new model has outperformed other approaches. This research achieved high accuracy results, but compared to other methods the percentage of change in results was low. Moreover, this research should have addressed the calculation of processing time.

3.2. Ant colony optimization

Miao *et al.* [25] have discussed the high dimensional features pattern of the motor imagery EEG (MI EEG) classification. The authors have proposed a framework for cooperative optimization using adaptive multi-domain features to optimize the MI EEG feature pattern. The algorithms for random forests (RF) and composite kernel support vector machines (CKSVM) account for the potential and diverse local temporal–frequency and spatial channels. ACO is proposed to identify more channels and temporal frequency segments. The performance of the classifier is measured using a variety of performance formulas. The accuracy metrics evaluate the proposed model competition III dataset Iva, Hand MI dataset, and Finger MI dataset. The highest average accuracy is 90.85%. Researchers have failed to show some metrics as an accuracy scale is used only. Therefore, accurate performance metrics are considered to be insufficient.

Fernandez-Fraga *et al.* [26] have focused on reducing feature extraction by removing irrelevant data from EEG-acquired brain electrical signals to enhance brain-computer interaction (BCI) system performance. ACO algorithms have been proposed by the authors to obtain the main features of signals and detect events based on visual stimuli. The steady-state visual evoked potentials (SSVEP)-based BCI systems have an advantage over other BCI systems because they have a superior SNR and faster information transfer rate (ITR). The dataset used in this proposal is the original O1 and O2 signals from the EEG signals and the end outcome of combining them to create a signal reconstruction. Compared to unreconstructed calls, O1-ACO has an 82.76 more significant correlation in original O1-O2, obtaining an 86.2% better correlation of O2-ACO versus original O1-O2. This research lacks essential measures such as accuracy, processing time, and performance complexity, and the results of the proposal and dataset used must be clarified.

Alghawli and Taloba [27] has focused on diagnosing and detecting depression, considered one of the most common mental illnesses. The authors have proposed an improved ACO (IACO) technique to reduce the number of features by removing irrelevant or extraneous feature data. To differentiate between bipolar disorder (BD) and major depressive disorder (MDD), the support vector machine (SVM) loads the selected features and classification. Metrics are used to evaluate performance methods such as accuracy rate, Recall, and area under the curve (AUC) classification levels using various feature selection (FS) approaches. The dataset used BD Patients in comparison to MDD patients. This research has achieved an average accuracy of 80.18 compared to other approaches. ACO still needs to improve the practice algorithm's basic parameters, such as the possibility of falling into the Local optimum, the significant computational effort and system resources needed for the optimal answer, and the challenge of inventing the suggestive approach to achieve high efficiency.

3.3. Artificial bee colony

Satapathy *et al.* [28] mainly focused on detecting and classifying epileptic seizures vs. non-seizure patients. ABC and RBFNNs are proposed in this paper to detect epileptic seizure disorders in the human brain using EEG signal analysis. To evaluate the proposed method's performance, metrics such as accuracy, Recall, accuracy, MSE, and discrete wave transformation (DWT) technique were used to extract potential features from the signal. From the University of Bonn's publicly accessible sources, five sets of EEG data for epileptic seizure identification have been gathered. EEG data can be classified using a modified ABC algorithm, with the maximum degree of accuracy for epilepsy identification is 82.3. The proposed method did not achieve high results compared with other methods. Moreover, evaluation metrics such as time calculation and system complexity are lacking.

Alshamlan *et al.* [29] have discussed the issue of the high dimensionality of the microarray gene selection and cancer classification method. This paper addressed the A method based on ABCs for correctly identifying cancer microarray data. The SVM is used to evaluate the effectiveness of gene selection approaches for classification. To assess the efficacy of the suggested method using two criteria: the number of predictive genes utilized for cancer classification and the accuracy of the classification. The microarray dataset is used in leukemia and colon datasets in this paper. The best result of the colon dataset in terms of accuracy is 95.61, and the number of genes is 20. The best result of the leukemia dataset is an accuracy of 95.83 and several genes of 20. When using this algorithm with complex and high-dimensional data like the Microarray dataset, the ABC algorithm faces several challenging problems, particularly in processing efficiency.

Another research by Satapathy *et al.* [30] focused on the EEG classification problem, one of the Invasive techniques; they can discover numerous instances of brain diseases, including epileptic seizures and sleep disturbance. The ABC approach, which is utilized to improve the parameters required in the RBF network to categorize the EEG signal, was presented in this paper. Adaptive synthetic sampling (ADASYN) enhances the learning method for addressing the category imbalance issue in the EEG dataset. To assess the effectiveness of multi-quadric RBFNN classifiers on imbalanced and balanced EEG data using ADASYN. To evaluate the efficacy of multi-quadric RBFNN classifiers on imbalanced and balanced EEG data using ADASYN metrics such as accuracy, recall, and computing the mean square error. The Department of Epileptology at the University of Bonn provided these data. The best results are achieved by this proposal, with a high accuracy rate of 92%. The results and evaluations are limited and have shown accuracy only as a measure of assessment.

A recent study by Ahirwal *et al.* [31] focused on the problem of the noise that occurs in the EEG/filtering of event-related potentials (ERP), which is caused by hand or eye movement. The authors have proposed an adaptive noise-canceling (ANC) system that was developed using the ABC method tool to filter the EEG from ERP signals. ANC is implemented using the recursive least square (RLS) algorithm and the least mean square (LMS) algorithm. SNR in dB and mean value difference are used to measure the algorithms' performance. The squared error of the adaptive coil is examined in adaption time analysis using the mean and standard deviation (STD). The effectiveness of ERP, kurtosis(k), and skewness(s) values-statistical shape measurements are calculated. The Physio Net web database provided the information used in this study. While it is 2.2343 for the LMS approach, and 0.5565 for the RLS technique, the average SNR obtained with the ABC technique is closer to zero at 0.3095.

The results of this research are ambiguous due to the lack of measures such as accuracy and processing time. Miao *et al.* [32] have addressed the channel selection pattern by removing numerous channels and minimizing the computing overhead for the common spatial pattern (CSP) method. The MI EEG classification of optimum frequency bands and period channels. Technically, they are essential for extracting MI EEG features. This research uses the ABC algorithm to determine the frequency and time domain combinations that are globally optimal. Simultaneously, prior expertise in CSP feature extraction and classification is not required.

Moreover, it finds relatively optimal channels. To evaluate the performance was measured objectively using the cross-validation average classification accuracy. Moreover, fisher's linear discriminant criteria (FDC) channel reduction is calculated. This study has used three EEG datasets for evaluation; the BCI Competition III dataset IIIa, the BCI Competition III dataset Iva, and the BCI Competition I dataset. The algorithm achieved an average classification accuracy for the first dataset up to 89.45%, the second at 90.76%, and the third at 0.5336%. The scales are insufficient to assess performance as only the accuracy scale is used.

3.4. Firefly algorithm

He *et al.* [33] has discussed the high-dimensional features pattern and complexity of emotion. However, the mechanism of pattern recognition used in EEG-based emotion recognition is a complex process. Using a new Firefly integrated optimization algorithm (FIOA) to identify emotions. The best feature selection, parameter setting, and classifier selection can all be accomplished simultaneously. Based on diverse emotion datasets EEG-based. To evaluate this research, many classification measures, including Recall, Precision, specificity, negative predictive value (NPV), and accuracy, are used the check the compared methods. Both Labe data and database for emotion analysis using physiological signals (DEAP) datasets have verified the FOIA. The best result accuracy (ACC) of Labe data is 92%, and DEAP datasets are 86% with less feature number comparison with PSO binary and F.A. binary. This method has achieved high accuracy with fewer features. However, the researchers still need to calculate the processing time.

The optimal selection of EEG electrodes and features (EFS) for efficient classification has been addressed by Lahiri *et al.* [34]. This research has presented a self-adaptive variant of the Firefly algorithm (SAFA) proposed to improve individual targets by effectively balancing computational accuracy and run-time complexity. Some measures, such as recall, precision, and average error rate, are evaluated. Moreover, Mobility gives a ratio of the standard deviation of the EEG signal's slope to the standard deviation of the initial signal amplitude. At the same time, Activity measures the EEG signal's squared standard deviation or variance. Complexity indicates the frequency shift. The suggested approach uses a training dataset Tc (used for classifying different cognitive tasks). The best results in this proposed Recall are 83.9196, a precision of 94.6017, and an average error rate of 99.8625. There needs to be a clear dataset used in this paper. Therefore, the results of this research need to be more accurate.

Attia *et al.* [35] have discussed EEG signals to determine epilepsy and epileptic seizures, which is a complex problem. This paper has presented a new method using the autoregressive model (AR) in the process of feature extraction and FA to get the best model order (P). The FA algorithm's goal function is the Akaike information criterion's (AIC) lowest residual variance. A SVM classifier is used to classify epileptic seizure signals. Accuracy, recall, and precision have evaluated performance. Allergy describes the precision as a correct ratio of positive and negative divided by the total number of cases. A true positive ratio is as specific as a true negative ratio. The Bonn EEG dataset is applied. It has been widely used in epilepsy and is available online. The suggested method can classify data with an average accuracy, sensitivity, and specificity of 98.0%, 100.00%, and 96.0%. In this publication, the researchers have produced excellent results. The processing time scale, however, is separate from this article.

Sharaf *et al.* [36] have focused on using EEG signals to find epileptic seizures. By reducing the original features and producing a reduced compressed package. The authors have proposed a Firefly optimization algorithm due to a feature selection and the vast quantity of retrieved features. A random forest classifier is developed to categorize and forecast seizures and seizure-free cases. To evaluate performance, some criteria, such as precision, recall, accuracy (ACC), F-score, receiver operating characteristics (ROC), and Matthew's correlation coefficient (MCC), are used. The University of Bonn acquired the standard data collection used in this inquiry. The method has achieved an accuracy of 99%, precision of 97%, Recall of 98%, F-score of 98%, and MCC of 95%. Although high classification accuracy of 99% was attained using this method, the results are not compared with those from other approaches.

3.5. Bat algorithm

Kumar *et al.* [37] have addressed the problem of autism spectrum disorder (ASD). It is a diverse neurodevelopmental disturbance that impacts the enhancement curve in many attitude domains and involves the weakness of social communication, perceptual, and language abilities. This paper analyzes the signals EEG that can detect ASD in children. Firstly, EEG signals are investigated in the dataset. The Kalman filter's processing has already exposed this signal. Finally, the variable mode decomposition is used to achieve signal analysis. The hybrid Bat algorithm with ANFIS classifier (HBA-ANFIS) is used to classify data. The proposed model is evaluated using a variable mode decomposition technique (VMD). Different characteristics are extracted from the analysis signal, including wavelet entropy, approximation entropy, relative wavelet entropy, root mean square (RMS), Hurst exponent, correlation dimension, principal component analysis (PCA), kurtosis, and skewness. Calculations are made for F1-score, accuracy, precision, and recall. These features are then classified by the HBA and ANFIS classifiers. The signal is then categorized as either a standard or an autistic instance. The dataset used in the paper comprises only EEG signals. The accuracy obtained from the proposed is 98%; the precision value is 97% for the proposed method. The Recall for the proposed technique is 0.97, higher than all the other methods. Due to the absence of processing time, this paper's performance cannot be easily assessed.

Bablani *et al.* [38] have proposed developing a system for identifying deception using a test known as the "concealed information test" can be achieved by identifying relevant channels and removing irrelevant channels from the EEG signal classification. The SVM parameters are improved, and the EEG channels are determined to boost the performance of the deceit identification system. This proposal has applied the non-performing channels eliminated using binary BAT. This paper uses performance measurement for some metrics, such as accuracy, specificity, sensitivity, and G-measure. Citizenship Law dataset is applied in the proposed model. The average accuracy of the system increased from 94.11% to 96.8%. It was unclear how well the model performed because the evaluation missed the time measure for encoding and decoding.

Another research by Dodia *et al.* [39] detecting lies by acquiring and preprocessing EEG brain signals. Furthermore, features are extracted, and the optimal feature set is selected from the EEG. This paper has provided a system that combines the short-time Fourier transform (STFT) approach for feature extraction, the binary bat algorithm for feature selection, and the extreme learning machine (ELM) for classification. The performance measures accuracy, precision, and Recall are used to evaluate the lie detection system performance. These performance measures are the primary metrics for the classifiers. 600 EEG recording samples from the experiment were used, of which 540 were used for training and 60 for testing. The proposed lie detection system yields an accuracy of 88.3%. Results from the system have been significant. Although this research has achieved good results, the performance measures must be revised and compared with other techniques. However, the performance of the system could be clearer.

Mujeeb *et al.* [40] have focused on the problem of big data, which includes a high amount of information that needs to be organized and stored. The authors have proposed map reduce framework MRF-based optimization is used to deal with extensive imbalanced data classified using deep belief network (DBN). The adaptive E-Bat algorithm that has been suggested has been applied in the feature selection process. To evaluate the effectiveness of the proposed E-Bat DBN adaptive approach using the accuracy and true positive rate (TPR) metrics. The results of this research are analyzed using six standard datasets obtained from the standard datasets of the UCI device repository, including breast cancer, hepatitis, Indian diabetes Pima, heart disease, Poker Hand, and SUSY data. This research has achieved a high accuracy of 89.98% and a higher TPR of 0.9144. The measures used in this paper need to be revised, as accuracy is the only applied metric.

3.6. Grey wolf optimizer

Karasu and Saraç [41] have discussed the problem of power quality (PQ) disturbances in the modern electric network, such as high and low voltage. Moreover, continuous control by measurement can be complex and take a long time. The researchers have proposed a novel method to merge the two-dimensional Reisz transform (2D-RT). The statistical and image-based feature collection representing P.Q. disturbances is extracted in the signal processing stage, and 1D signals are converted into 2D signals. Each 2D signal is transformed using the 2D-RT technique, yielding 12 2D matrices, which are then used to categorize PQ disturbances using the multiobjective grey wolf optimizer (MOGWO) using the KNN method. To assess the suggested study. The mathematical mean, harmonic mean, geometric mean, standard deviation, skewness, and kurtosis values are extracted as statistical features. Image properties are removed, including contrast, homogeneity, and total compromise-the best result of the proposed with 99.26% accuracy. When compared to alternative alternatives, the suggested approach has produced excellent outcomes. However, past studies have produced results with higher overall accuracy. Additionally, this article lacked time processing.

Jaffino *et al.* [42] have focused on discovering and analyzing epileptic seizure diseases by monitoring people's brain activity using EEG signals to identify the usual signals and signal epileptic seizures. To accurately identify epileptic seizures in brain waves, this is addressed by using GWO-based on a deep recurrent neural network (RNN) technique. Statistical parameters are computed to evaluate the proposed approach, such as precision, Recall, and accuracy, as performance measures for this paper. The research's application dataset is taken from the University of Bonn. This method has achieved results with an accuracy of 93.4%. Although this research has presented results with high accuracy compared with other methods, the researchers still need to calculate the processing time and Complexity of the system, which leaves ambiguity in the efficiency of this system.

Another recent study [43] has performed research focusing on taking EEG/ERP as the input signal for accurate adaptive noise cancellation. It might be generated due to movements like eyeball, hand movement, or heart signals. ERP is too Weak signals combined with EEG with a meager SNR. GWO and other gradient-based approaches to reduce the noise of the EEG signal and swarm techniques with an adjustable filter are used to cleanse the EEG signal. To evaluate the method, the analysis of ERPs is achieved. Ensemble averaging (EA) is one technique for identifying and removing the noise component from EEG readings. Wavelet denoising is an algorithm that also uses the discrete wavelet transform. Furthermore, adaptive filter and applied quality metrics mean and SNR. This paper uses the EEG/ERP data signal to analyze and implement the proposed method. The best results of this proposed approach are the Maximum SNR of 3.204 was attained, and the lowest correlation value was 0.0689. Additionally, it is predicted that the typical mean value is 0.00093. This research has achieved high results by reducing the noise emitted by the EEG. However, a large group of different techniques is used for improvement, and this has increased the complexity of the system and taken longer processing time.

3.7. Other optimizer approaches

Baldominos and Ramon-Lozano [44] have discussed the problem of epilepsy seizures as a vital neurological condition that causes seizures with a severe probable impact on human health. This paper has described a seizure detection system based on energy. That is applied over EEG signals. This method includes various parameters that have an essential impact on the detection performance. Genetic algorithms (GAs) are used to optimize these parameters. The proposed model is evaluated by computing the FP and FN rates per hour and TP. The investigation has significant accuracy with a low false positive rate for some patients. A public dataset accessible via Physio Net is the CHB-MIT Scalp EEG database. With an average of 0.39 false positives every 24 hours, the approach is better than previous methods at detecting very few false positives. One of the disadvantages of this research is that the results are ambiguous, and the measurements need to be completed.

Shon *et al.* [45] focused on detecting emotional stress state and feature selection using EEG signals. In this article, the KNN classifier and GA-based feature selection is used to assess stress based on analyzing EEG signals. The proposed model is evaluated by computing the accuracy only. The DEAP, an open-source EEG dataset, was used to assess this paper. The obtained classification accuracy with the EEG dataset was up to 71.76%. This research needs metrics such as computing processing time, error rate, and complexity.

Another research by Abdi *et al.* [46] discussed the difficulty of choosing a channel for EEG-based biometric person identification. This article has proposed an approach to a multiobjective binary using the cuckoo search algorithm (MOBCS-KNN) to identify people by selecting the best EEG channels. Moreover, EEG-based biometric person identification using the KNN classifier. Five measures are used to evaluate their proposed model: channels selected, accuracy ratio, precision, F-score, and recall. In this study, the performance is assessed using a common EEG motor imagery dataset. With an accuracy of 93.86 percent, the best results can be obtained. The time metric that made it unclear for the model's efficacy to be evaluated in this article must be included.

Pratiwi *et al.* [47] have focused on discovering epileptic seizures, a mental illness that impacts the brain. Epilepsy can be confirmed by EEG classification. Their proposed model analyzes EEG signals using a hybrid cuckoo search and neural network for epilepsy classifications. Moreover, the multi-layered perceptual (MLP) weight is the cuckoo search method optimizes. Technically, two measures are computed for evaluation: MSE and accuracy. The Epilepsy Center at the University of Bonn provided the EEG data utilized in this work. The proposed methods have resulted in an MSE of 0.001 and an accuracy of 90.0%. This research achieved high-accuracy results. However, it needed some critical measures of processing time and complexity.

The problem of feature extraction and selection to process the tri-axial acceleration data loggers data and resolve the issue of the imbalanced dataset and measurement noise has been discussed by Yang *et al.* [48]. This research describes the feature extraction, choice, and application of the K-NN method to categorize the behavior of sharks using the data gathered by ADLs. In this paper, performance measurement is achieved by applying metrics such as recall, precision, and F1-score and calculating training time. Tri-axial acceleration data recorders were used to gather the dataset ADLs. This research has achieved a high precision of 94%. It needs clarity of the system's performance in terms of complexity.

Mo and Zhao [49] have addressed classifying BCI using electroencephalography for motor imagery. This article proposed a SVM that improved by crediting a new bioinspired magnetic bacteria optimization algorithm. To produce a high-performance classifier for brain-computer interfaces using electroencephalography for motor imaging BCI. Technically, in the evaluation of the performance of this proposal, accuracy criteria were applied for classification. This research shows the efficacy of the suggested strategy using the BCI competition IV dataset II-a. This paper has achieved an accuracy of 67.3611. This paper needs more than many vital metrics to assess the system's performance.

4. ANALYSIS AND EVALUATION

Three important measures have optimization to assess the outcomes of the optimization techniques achieved by researchers: accuracy, precision, recall, and F1-score [50]. Most research has focused on measuring accuracy, an essential component of the optimization process. Typically, all publications are grouped into their primary optimization method: PSO, ACO, ABC, GWO, Bat, Firefly, and others. The accuracy result is displayed in seven tables. Table 1 shows the accuracy of the PSO group with their tools. Technically, the accuracy of the results obtained by all publications grouped with PSO optimizer started from 93.6% to 99%. However, several classification algorithms and tools used in the preprocessing process were used in this research.

Moreover, all studies that utilized an ACO optimizer have demonstrated potential results accuracy ranging from 80.18% to 90.85%, as presented in Table 2. Furthermore, all ABC-based research has generated high accuracy results ranging from 82% to 95%, as shown in Table 3. Moreover, studies based on Firefly optimizer have demonstrably displayed a significant accuracy range from 92% to 99%, as presented in Table 4. As shown in Table 5, the high accuracy results for the Bat optimizer group are 98%. For the GWO optimizer group, accuracy best results are 99.26% shown in Table 6.

The accuracy result reported in Tables 1 to 7 is visually represented by bar chart figures for a precise visual analysis in Figures 1 to 7. Figure 1 shows the accuracy result by particle swarm optimization. Figure 2 shows the accuracy result by ACO optimization. Figure 3 shows the accuracy result by ABC optimization. Figure 4 shows the accuracy result of Firefly optimization. Figure 5 shows the accuracy result of Bat optimization. Figure 6 shows result accuracies by GWO optimization. Finally, Figure 7 shows the resultant accuracy of the other optimizer approaches group. To have a precise comparison for all the included optimizers, the average of all the extracted accuracy is computed and compared as shown in Figure 8. PSO, Firefly, and GWO have shown the highest accuracy, above 99%. Then, Bat has shown the second-best accuracy with 98%. ACO has shown a demonstrated average accuracy of around 90%.

Table 1. Accuracy result for PSO optimizer group

References	Methods	Dataset	Accuracy (%)
Satapathy *et al.* [21]	PSO+RBFNN	Epileptology, University of Bonn	99%
Jamali-Dinan *et al.* [22]	PSO+MWK-means	TLE, MEG, and DTI	93.6%
Deepa *et al.* [24]	PSO+KNN	MRI	98.2%

Table 2. Accuracy result for ACO optimizer group

References	Methods	Dataset	Accuracy (%)
Miao *et al.* [25]	ACO+RF+CKSVM	III dataset Iva, Hand MI and Finger MI	90.85%
Alghawli and Taloba [27]	IACO+SVM	MDD+BD	80.18%

Table 3. Accuracy result for ABC optimizer group

References	Methods	Dataset	Accuracy (%)
Satapathy *et al.* [28]	ABC+RBFNN	Five sets of EEG signals	82.3%
Alshamlan *et al.* [29]	ABC+SVM	leukemia and colon	95.83 %
Satapathy *et al.* [30]	ABC+ADASYN	Epileptology, University of Bonn	92%
Miao *et al.* [32]	ABC	BCI Competition III Dataset Iva, BCI Competition III Dataset IIIa, and BCI Competition I Dataset	89.45%

Table 4. Accuracy result for Firefly optimizer group

References	Methods	Dataset	Accuracy (%)
He *et al.* [33]	FIOA	Labe data	92%
Lahiri *et al.* [34]	SAFA	training dataset Tc	94%
Attia *et al.* [35]	FA+SVM	The Bonn EEG	98.0%
Sharaf *et al.* [36]	FA+RF	University of Bonn	99%

Table 5. Accuracy result for Bat optimizer group

References	Methods	Dataset	Accuracy (%)
Kumar *et al.* [37]	HBA–ANFIS	Only EEG signals	98%
Bablani *et al.* [38]	Binary BAT+SVM	CIT dataset	94.11% 96.8%
Dodia *et al.* [39]	BBAT+ STFT	600 EEG recording samples	88.3%
Mujeeb *et al.* [40]	E-Bat DBN	Including breast cancer, hepatitis, Indian diabetes Pima, heart disease, Poker Hand, and SUSY data	89.98%

Table 6. Accuracy result for GWO optimizer group

References	Methods	Dataset	Accuracy (%)
Karasu and Saraç [41]	MOGWO+KNN	PQ disturbances	99.26%
Jaffino *et al.* [42]	GWO+RNN	'University of Bonn	93.4%

Table 7. Accuracy result for other optimizer approaches group

References	Methods	Dataset	Accuracy (%)
Baldominos and Ramon-Lozano [44]	GA	CHB-MIT Scalp EEG	
Shon *et al.* [45]	GA+KNN	DEAP	71.76%
Abdi *et al.* [46]	MOBCS-KNN	standard EEG motor imagery	93.86%
Pratiwi *et al.* [47]	Hybrid cuckoo research	the University of Bonn	90.0 %
Yang *et al.* [48]	KNN	ADLs	94%
Mo and Zhao [49]	Magnetic bacteria+SVM	BCI Competition IV dataset II- a	67%

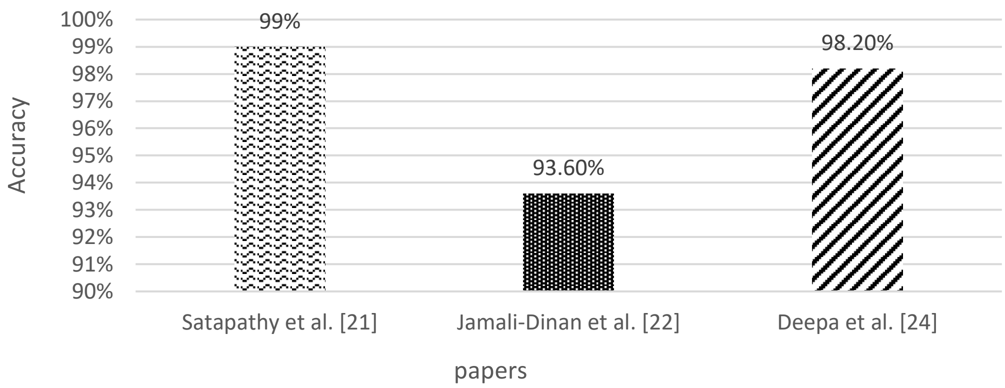

Figure 1. Accuracy result for PSO optimizer group

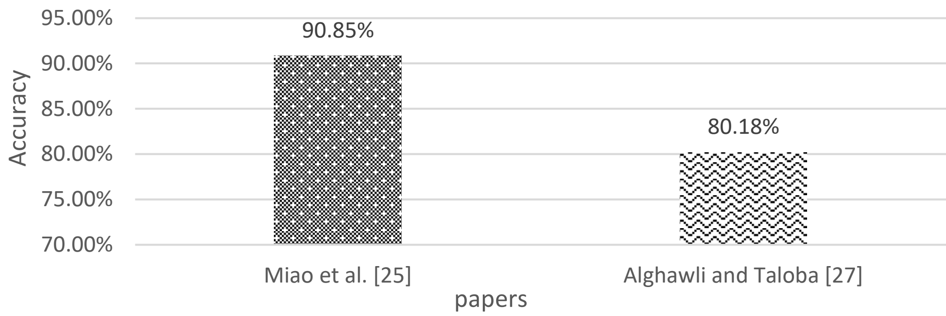

Figure 2. Accuracy result for ACO optimizer group

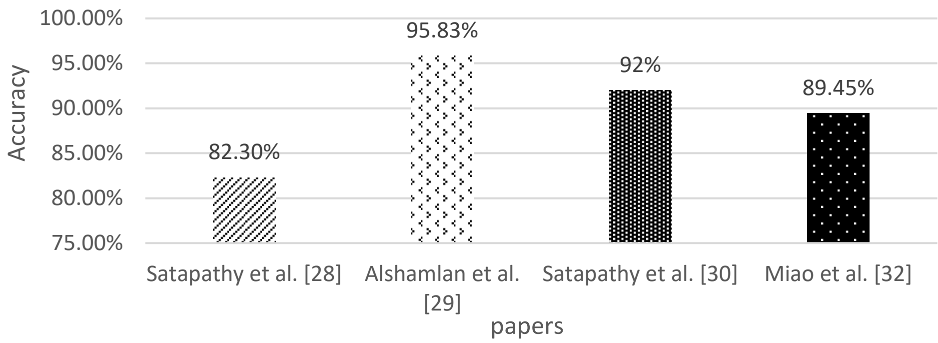

Figure 3. Accuracy result for ABC optimizer group

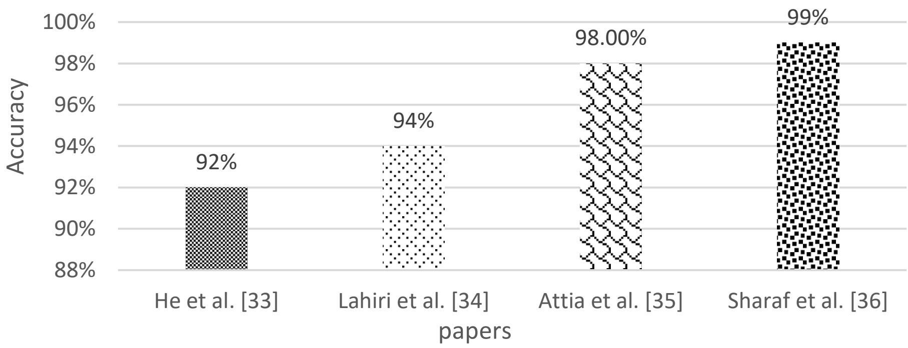

Figure 4. Accuracy result for Firefly optimizer group

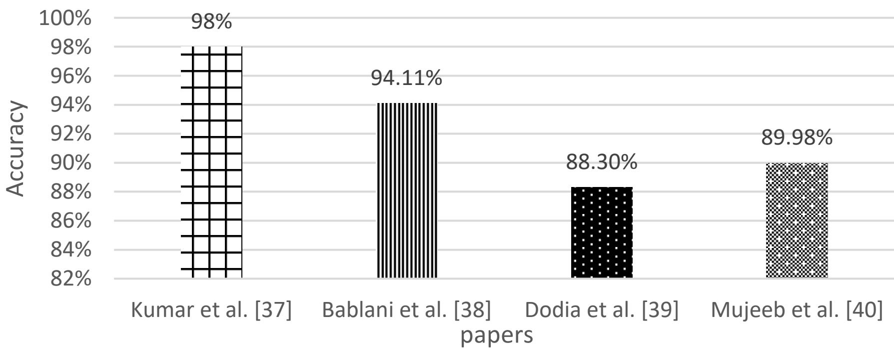

Figure 5. Accuracy result for Bat optimizer group

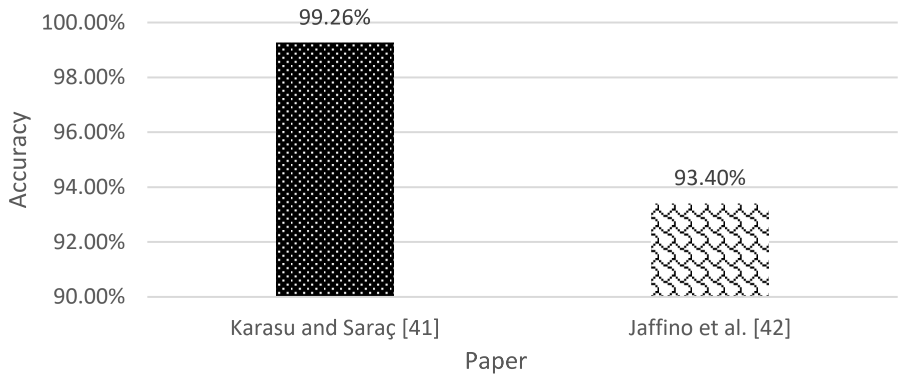

Figure 6. Accuracy result for GWO optimizer group

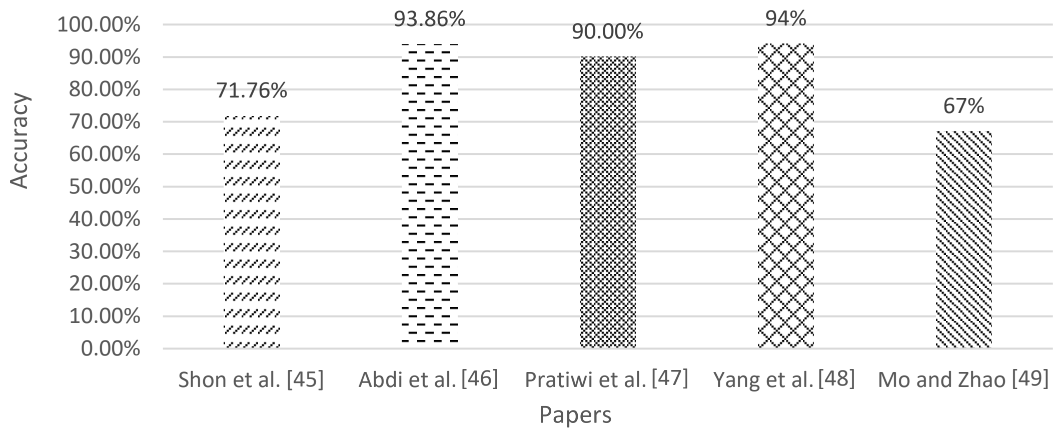

Figure 7. Accuracy result for other optimizer approaches group

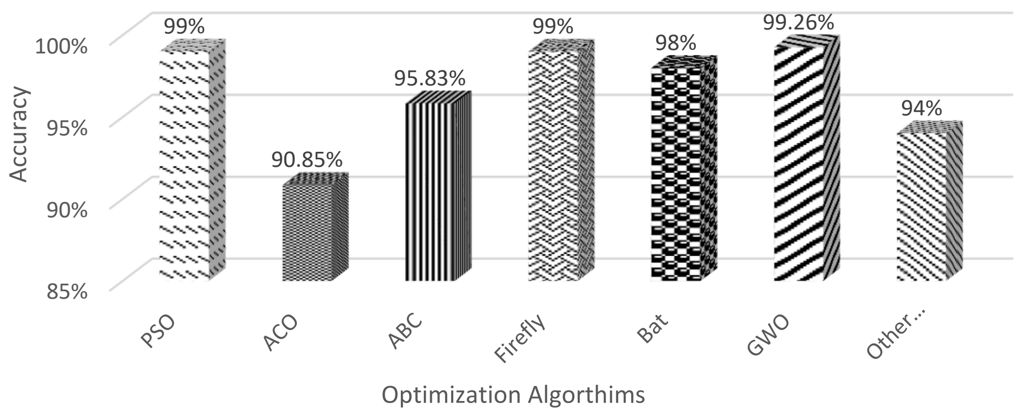

Figure 8. Average accuracy with several optimization algorithms

5. CONCLUSION

In conclusion, this research has provided the thirty most effective techniques for EEG signal optimization that were discussed and analyzed. All approaches are divided into seven groups based on the primary optimization strategies proposed (PSO, ACO, ABC, GWO, Bat, Firefly, and other optimizer approaches). The main measures for this research analysis are the evaluation of accuracy, precision, recall, and F1-score. However, the system performance analysis and the processing time of all papers still need to be included. Generally, all optimization groups have shown extraordinary accuracy abilities. PSO and GWO approaches have outperformed.

REFERENCES

[1] A. A. Al-hamzawi, D. Al-Shammary, and A. H. Hammadi, “A survey on healthcare EEG classification-based ML methods,” in *Mobile Computing and Sustainable Informatics*, 2022, pp. 923–936. doi: 10.1007/978-981-19-2069-1_64.

[2] M. K. Hussain, B. M. Alshadeedi, and R. Hejeejo, “Optimized Kalman filters for sensorless vector control induction motor drives,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, pp. 17–27, Feb. 2023, doi: 10.11591/ijece.v13i1.pp17-27.

[3] Y. Tashtoush, R. Obeidat, A. Al-Shorman, O. Darwish, M. Al-Ramahi, and D. Darweesh, “Enhanced convolutional neural network for non-small cell lung cancer classification,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, pp. 1024–1038, Feb. 2023, doi: 10.11591/ijece.v13i1.pp1024-1038.

[4] M. Baniyounis, S. Z. Salah, and J. A. Ghaeb, “Machine learning for prediction models to mitigate the voltage deviation in photovoltaic-rich distributed network,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, pp. 55–68, Feb. 2023, doi: 10.11591/ijece.v13i1.pp55-68.

[5] Y. Paul, “Various epileptic seizure detection techniques using biomedical signals: A review,” *Brain Informatics*, vol. 5, no. 2, Dec. 2018, doi: 10.1186/s40708-018-0084-z.

[6] U. M. Diwekar, *Introduction to applied optimization*, vol. 22. Cham: Springer International Publishing, 2020. doi: 10.1007/978-3-030-55404-0.

[7] M. K. Siddiqui, R. Morales-Menendez, X. Huang, and N. Hussain, “A review of epileptic seizure detection using machine learning classifiers,” *Brain Informatics*, vol. 7, no. 1, Dec. 2020, doi: 10.1186/s40708-020-00105-1.

[8] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. Muller, “Optimizing spatial filters for robust EEG single-trial analysis,” *IEEE Signal Processing Magazine*, vol. 25, no. 1, pp. 41–56, 2008, doi: 10.1109/MSP.2008.4408441.

[9] E. Haselsteiner and G. Pfurtscheller, “Using time-dependent neural networks for EEG classification,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 4, pp. 457–463, 2000, doi: 10.1109/86.895948.

[10] C.-J. Lin and M.-H. Hsieh, “Classification of mental task from EEG data using neural networks based on particle swarm optimization,” *Neurocomputing*, vol. 72, no. 4–6, pp. 1121–1130, Jan. 2009, doi: 10.1016/j.neucom.2008.02.017.

[11] E. Dagdevir and M. Tokmakci, “Optimization of preprocessing stage in EEG based BCI systems in terms of accuracy and timing cost,” *Biomedical Signal Processing and Control*, vol. 67, May 2021, doi: 10.1016/j.bspc.2021.102548.

[12] N. Hazarika, J. Z. Chen, A. C. Tsoi, and A. Sergejew, “Classification of EEG signals using the wavelet transform,” *Signal Processing*, vol. 59, no. 1, pp. 61–72, May 1997, doi: 10.1016/S0165-1684(97)00038-8.

[13] M. R. Aziz and A. S. Alfoudi, “Feature selection of the anomaly network intrusion detection based on restoration particle swarm optimization,” *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 5, pp. 592–600, Oct. 2022, doi: 10.22266/ijies2022.1031.51.

[14] A. Singh, “An overview of the optimization modelling applications,” *Journal of Hydrology*, vol. 466–467, pp. 167–182, Oct. 2012, doi: 10.1016/j.jhydrol.2012.08.004.

[15] S. T. George, M. S. P. Subathra, N. J. Sairamya, L. Susmitha, and M. Joel Premkumar, “Classification of epileptic EEG signals using PSO based artificial neural network and tunable-Q wavelet transform,” *Biocybernetics and Biomedical Engineering*, vol. 40, no. 2, pp. 709–728, Apr. 2020, doi: 10.1016/j.bbe.2020.02.001.

[16] W. Tu and S. Sun, “A subject transfer framework for EEG classification,” *Neurocomputing*, vol. 82, pp. 109–116, Apr. 2012, doi: 10.1016/j.neucom.2011.10.024.

[17] D. Al-Shammary, A. L. Albukhnefis, A. H. Alsaeedi, and M. Al-Asfoor, “Extended particle swarm optimization for feature selection of high-dimensional biomedical data,” *Concurrency and Computation: Practice and Experience*, vol. 34, no. 10, May 2022, doi: 10.1002/cpe.6776.

[18] Ş. Öztürk, R. Ahmad, and N. Akhtar, “Variants of artificial bee colony algorithm and its applications in medical image processing,” *Applied Soft Computing*, vol. 97, Dec. 2020, doi: 10.1016/j.asoc.2020.106799.

[19] Y. Jiao, T. Zhou, L. Yao, G. Zhou, X. Wang, and Y. Zhang, “Multi-view multi-scale optimization of feature representation for EEG classification improvement,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 12, pp. 2589–2597, Dec. 2020, doi: 10.1109/TNSRE.2020.3040984.

[20] X. Zhu, C. Guan, J. Wu, Y. Cheng, and Y. Wang, “Expectation-maximization method for EEG-based continuous cursor control,” *EURASIP Journal on Advances in Signal Processing*, vol. 2007, no. 1, Dec. 2006, doi: 10.1155/2007/49037.

[21] S. K. Satapathy, S. Dehuri, and A. K. Jagadev, “EEG signal classification using PSO trained RBF neural network for epilepsy identification,” *Informatics in Medicine Unlocked*, vol. 6, pp. 1–11, 2017, doi: 10.1016/j.imu.2016.12.001.

[22] S.-S. Jamali-Dinan *et al.*, “A combination of particle swarm optimization and minkowski weighted K-Means clustering: Application in lateralization of temporal lobe epilepsy,” *Brain Topography*, vol. 33, no. 4, pp. 519–532, Jul. 2020, doi: 10.1007/s10548-020-00770-9.

[23] W. Sun, Y. Su, X. Wu, X. Wu, and Y. Zhang, “EEG denoising through a wide and deep echo state network optimized by UPSO algorithm,” *Applied Soft Computing*, vol. 105, Jul. 2021, doi: 10.1016/j.asoc.2021.107149.

[24] G. Deepa, G. L. R. Mary, A. Karthikeyan, P. Rajalakshmi, K. Hemavathi, and M. Dharanisri, “Detection of brain tumor using modified particle swarm optimization (MPSO) segmentation via haralick features extraction and subsequent classification by KNN algorithm,” *Materials Today: Proceedings*, vol. 56, pp. 1820–1826, 2022, doi: 10.1016/j.matpr.2021.10.475.

[25] M. Miao, W. Zhang, W. Hu, and R. Wang, “An adaptive multi-domain feature joint optimization framework based on composite kernels and ant colony optimization for motor imagery EEG classification,” *Biomedical Signal Processing and Control*, vol. 61, Aug. 2020, doi: 10.1016/j.bspc.2020.101994.

[26] S. M. Fernandez-Fraga, M. A. Aceves-Fernandez, J. C. Pedraza-Ortega, and S. Tovar-Arriaga, “Feature extraction of EEG signal upon BCI systems based on steady-state visual evoked potentials using the ant colony optimization algorithm,” *Discrete Dynamics in Nature and Society*, vol. 2018, pp. 1–19, Jun. 2018, doi: 10.1155/2018/2143873.

[27] A. Saif Alghawli and A. I. Taloba, “An enhanced ant colony optimization mechanism for the classification of depressive disorders,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–12, Jun. 2022, doi: 10.1155/2022/1332664.

[28] S. K. Satapathy, S. Dehuri, and A. K. Jagadev, “ABC optimized RBF network for classification of EEG signal for epileptic seizure identification,” *Egyptian Informatics Journal*, vol. 18, no. 1, pp. 55–66, Mar. 2017, doi: 10.1016/j.eij.2016.05.001.

[29] H. Alshamlan, G. Badr, and Y. Alohali, “Microarray gene selection and cancer classification method using artificial bee colony and SVM algorithms (ABC-SVM),” in *Proceedings of the International Conference on Data Engineering 2015 (DaEng-2015)*, 2019, pp. 575–584. doi: 10.1007/978-981-13-1799-6_59.
[30] S. K. Satapathy, S. Mishra, P. K. Mallick, and G.-S. Chae, “ADASYN and ABC-optimized RBF convergence network for classification of electroencephalograph signal,” *Personal and Ubiquitous Computing*, vol. 27, no. 3, pp. 1161–1177, Jun. 2023, doi: 10.1007/s00779-021-01533-4.
[31] M. K. Ahirwal, A. Kumar, and G. K. Singh, “Adaptive filtering of EEG/ERP through bounded range artificial bee colony (BR-ABC) algorithm,” *Digital Signal Processing*, vol. 25, pp. 164–172, Feb. 2014, doi: 10.1016/j.dsp.2013.10.019.
[32] M. Miao, A. Wang, and F. Liu, “Application of artificial bee colony algorithm in feature optimization for motor imagery EEG classification,” *Neural Computing and Applications*, vol. 30, no. 12, pp. 3677–3691, Dec. 2018, doi: 10.1007/s00521-017-2950-7.
[33] H. He, Y. Tan, J. Ying, and W. Zhang, “Strengthen EEG-based emotion recognition using firefly integrated optimization algorithm,” *Applied Soft Computing*, vol. 94, Sep. 2020, doi: 10.1016/j.asoc.2020.106426.
[34] R. Lahiri, P. Rakshit, and A. Konar, “Evolutionary perspective for optimal selection of EEG electrodes and features,” *Biomedical Signal Processing and Control*, vol. 36, pp. 113–137, Jul. 2017, doi: 10.1016/j.bspc.2017.03.022.
[35] A. Attia, A. Moussaoui, and Y. Chahir, “Epileptic seizures identification with autoregressive model and firefly optimization based classification,” *Evolving Systems*, vol. 12, no. 3, pp. 827–836, Sep. 2021, doi: 10.1007/s12530-019-09319-z.
[36] A. I. Sharaf, M. A. El-Soud, and I. M. El-Henawy, “An automated approach for epilepsy detection based on tunable Q -wavelet and firefly feature selection algorithm,” *International Journal of Biomedical Imaging*, vol. 2018, pp. 1–12, Sep. 2018, doi: 10.1155/2018/5812872.
[37] N. S. Kumar, J. Mahil, A. S. Shiji, and K. P. Joshua, “Detection of autism in children by the EEG behavior using hybrid bat algorithm-based ANFIS classifier,” *Circuits, Systems, and Signal Processing*, vol. 39, no. 2, pp. 674–697, Feb. 2020, doi: 10.1007/s00034-019-01197-9.
[38] A. Bablani, D. R. Edla, D. Tripathi, S. Dodia, and S. Chintala, “A synergistic concealed information test with novel approach for EEG channel selection and SVM parameter optimization,” *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 11, pp. 3057–3068, Nov. 2019, doi: 10.1109/TIFS.2019.2913798.
[39] S. Dodia, D. R. Edla, A. Bablani, and R. Cheruku, “Lie detection using extreme learning machine: A concealed information test based on short-time Fourier transform and binary bat optimization using a novel fitness function,” *Computational Intelligence*, vol. 36, no. 2, pp. 637–658, May 2020, doi: 10.1111/coin.12256.
[40] S. Md Mujeeb, R. Praveen Sam, and K. Madhavi, “Adaptive exponential bat algorithm and deep learning for big data classification,” *Sādhanā*, vol. 46, no. 1, Dec. 2021, doi: 10.1007/s12046-020-01521-z.
[41] S. Karasu and Z. Saraç, “Classification of power quality disturbances by 2D-Riesz Transform, multi-objective grey wolf optimizer and machine learning methods,” *Digital Signal Processing*, vol. 101, Jun. 2020, doi: 10.1016/j.dsp.2020.102711.
[42] G. Jaffino, J. P. Jose, and M. Sundaram, “Grey wolf optimization with deep recurrent neural network for epileptic seizure detection in EEG signals,” in *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, Feb. 2021, pp. 1–5. doi: 10.1109/ICAECT49130.2021.9392541.
[43] “2019 6th International Conference on Signal Processing and Integrated Networks (SPIN) [Front cover],” *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2019, pp. 1-1, doi: 10.1109/SPIN.2019.8711790.*
[44] A. Baldominos and C. Ramon-Lozano, “Optimizing EEG energy-based seizure detection using genetic algorithms,” in *2017 IEEE Congress on Evolutionary Computation (CEC)*, Jun. 2017, pp. 2338–2345. doi: 10.1109/CEC.2017.7969588.
[45] D. Shon, K. Im, J.-H. Park, D.-S. Lim, B. Jang, and J.-M. Kim, “Emotional stress state detection using genetic algorithm-based feature selection on EEG signals,” *International Journal of Environmental Research and Public Health*, vol. 15, no. 11, Nov. 2018, doi: 10.3390/ijerph15112461.
[46] Z. Abdi Alkareem Alyasseri *et al.*, “EEG channel selection using multiobjective cuckoo search for person identification as protection system in healthcare applications,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–18, Jan. 2022, doi: 10.1155/2022/5974634.
[47] A. B. Pratiwi, A. Damayanti, and Miswanto, “Electroencephalography epilepsy classifications using hybrid cuckoo search and neural network,” 2017. doi: 10.1063/1.4991233.
[48] Y. Yang, H.-G. Yeh, W. Zhang, C. J. Lee, E. N. Meese, and C. G. Lowe, “Feature extraction, selection, and K-nearest neighbors algorithm for shark behavior classification based on imbalanced dataset,” *IEEE Sensors Journal*, vol. 21, no. 5, pp. 6429–6439, Mar. 2021, doi: 10.1109/JSEN.2020.3038660.
[49] H. Mo and Y. Zhao, “Motor imagery electroencephalograph classification based on optimized support vector machine by magnetic bacteria optimization algorithm,” *Neural Processing Letters*, vol. 44, no. 1, pp. 185–197, Aug. 2016, doi: 10.1007/s11063-015-9469-7.
[50] O. Caelen, “A Bayesian interpretation of the confusion matrix,” *Annals of Mathematics and Artificial Intelligence*, vol. 81, no. 3–4, pp. 429–450, Dec. 2017, doi: 10.1007/s10472-017-9564-8.

BIOGRAPHIES OF AUTHORS

Ekram Hakem has received a B.Sc. degree in Computer Sciences from the University of Al-Qadisiyah, Iraq in 2016. Currently, she is an M.Sc. student in College of Computer Science and Information Technology, University of Al-Qadisiyah, Iraq. She is interested in artificial intelligence and machine learning techniques. She can be contacted at email: com21.post1@qu.edu.iq.

Dhiah Al-Shammary has received his Ph.D. in Computer Science in 2014 from RMIT University, Melbourne, Australia. Dhiah is awarded as the best Ph.D. student and top publication during his Ph.D. period. He has several years of experience in both education and industry. His main industrial experience came from Silicon Valley-based companies working on security projects, including non-traditional and quantum-scale encryption. Dhiah has worked at several universities in Australia and Iraq like RMIT University and the University of Al-Qadisiyah. His research interests include performance modeling, Web services, compression, and encoding techniques, and distributed systems. Dhiah has several publications in the areas of improving the performance of web services and encoding techniques. He can be contacted at email: d.alshammary@qu.edu.iq.

Ahmed M. Mahdi has received his Ph.D. in applied mathematics and I.T. in 2020 from Szeged University, Hungary. Also, he received a Master's degree in number theory in 2013 from Szczecin, Poland. He has several years of experience in both education and industry. His research interests include number theory, numerical analysis, web services, compression and encoding techniques, and distributed systems. Ahmed has several publications in the areas of applied mathematics and IT. He can be contacted at email: ahmed.m.mahdi@qu.edu.iq and ahmediraqmath@gmail.com.