CIT. Journal of Computing and Information Technology, Vol. 33, No. 2, June 2025, 109–122
doi: 10.20532/cit.2025.1005997

EEG Signal Classification Using Bayesian-Optimized Neural Networks in IoMT Systems

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The Internet of Medical Things (IoMT) consists of interconnected devices and applications that enable real-time collection, transmission, and analysis of medical data for healthcare applications. This study utilizes medical data from the publicly available BCICIV2a dataset rather than data collected directly from individuals or medical institutions. With advancements in neuroinformatics and intelligent computing, the classification of electroencephalography (EEG) signals has become increasingly important, particularly for detecting and predicting epilepsy. However, existing EEG classification methods often suffer from low accuracy, high computational complexity, and slow processing. To address these challenges, this study proposes an EEG classification approach utilizing a Backpropagation Neural Network (BPNN) enhanced with Bayesian optimization. This method enhances the identification and prediction of epileptic seizures by utilizing IoT-enabled EEG data. Performance evaluation on the BCICIV2a dataset demonstrates that the proposed model achieves an accuracy of 93.21%, outperforming conventional techniques. The results indicate that this approach enhances efficiency and accuracy in EEG signal processing, contributing to real-time medical diagnostics. The integration of IoMT with advanced neural networks represents a significant advancement in medical informatics and telemedicine, providing promising directions for future research and clinical applications.

ACM CCS (2012) Classification: Computing methodologies → Artificial intelligence → Machine learning → Machine learning approaches → Neural networks

Computer systems organization → Embedded and cyber-physical systems → Embedded systems → Internet of Things.

Keywords: Back Propagation Neural Network (BPNN), Bayesian optimization algorithm, Seizure, Internet of Things, Electroencephalogram

1. Introduction

The Internet of Medical Things (IoMT) refers to devices and applications connected through a network for gathering and exchanging real-time medical data needed for different medical purposes. Core applications of IoMT are:

a) real-time patient monitoring;

b) self-administered rehabilitation;

c) tracking medication effects;

d) medical supply and inventory tracking.

The advantages of IoMT include improved accessibility, better treatment because of timely health interventions, and potential reductions in both cost and the need for in-person clinical visits [1].

Recent advances in artificial intelligence, bionics, and brain science has made EEG-based information processing and control emerge as a promising industrial application domain that has significant potential to improve the life quality of the elderly and people with disabilities. EEG signals, created by electrical brain activity, can be acquired through wearable cranial sensors. Such signals are used to monitor individual mental health, as well as for diagnosing neuropsychological illnesses. Elderly and disabled people could use particular devices that gather EEG data for creating control signals via motor imagination, therefore, they could handle household appliances and other devices remotely using their thoughts. Current studies show that EEG signals have various features in various states that could be recognized and classified using machine learning (ML) techniques [2].

ML techniques are suitable for analysis of complex EEG data, playing an important role in signal processing, feature extraction, and classification. First, machine learning approaches such as adaptive filters are employed to reduce noise and improve signal quality [3]. Then, temporal, frequency, and spatial information are extracted using techniques like principal component analysis (PCA) and wavelet transform. Next, algorithms like Support Vector Machine (SVM) and deep neural networks (CNN and LSTM) are used to classify or discover patterns, such as epilepsy diagnosis or brain state prediction. This combination of machine learning with EEG in applications such as BCI, neurological disease detection, and rehabilitation is critical for improving diagnosis and quality of life [2].

It is assumed that a specific wearable EEG device, for example, Emotiv Insight, is used to collect the EEG data of one user through motor imagination in an IoT application scenario. These devices capture EEG signals during tasks such as motor imagery, where users imagine specific movements. The collected data is then transmitted to IoT-enabled applications for real-time processing and analysis [4].

The gathered data is transferred to the related terminal for classification and identification. After that, an appropriate action is performed based on the outcome of identification, like handling TV program switching and setting air conditioner temperature, *etc.* If a hospital wishes to use the patient's EEG data to predict the risk of epilepsy, this task may be delegated to the prediction service provider (such as a cloud service). So, such a process might show information based on the patient. Accurate prediction in such cases requires appropriate machine learning algorithms [5].

Advancements in science and technology have expanded the application of EEG signal analysis across various domains, including intelligent information systems, rehabilitation medicine, and other interdisciplinary fields. The inherent complexity of EEG signals presents various obstacles and conflicts for EEG data analysis methods. These obstacles include a low signal-to-noise ratio, which makes it difficult to identify relevant brain activity from background noise. Furthermore, the high dimensionality of EEG data might cause computational inefficiencies, as processing huge amounts of data necessitates substantial CPU resources. Finally, the existence of untidy or irregular noise complicates the filtering process, as typical noise removal approaches may not be efficient in dealing with the different and unpredictable types of noise seen in EEG recordings. These difficulties make it difficult to accurately analyze and interpret EEG data using standard identification and analysis techniques

To address these limitations, this research proposes the use of Bayesian Optimization Algorithm (BOA) to enhance the performance of neural networks trained via backpropagation (BP) [7]. While BP remains a foundational method for training neural networks, it often suffers from slow convergence and susceptibility to local minimum. In recent years, many researchers have studied how to avoid falling into local minimum, how to set optimal initial weights, optimal learning rates [6], and momentum, how to find optimal NN architectures using pruning and construction techniques, sophisticated optimization techniques, and adaptive activation functions.

In this study, we apply BOA to improve neural network training by effectively tuning hyperparameters, as an alternative to relying solely on traditional backpropagation (BP). The BOA offers substantial improvements over the traditional BP approach. BOA a probabilistic framework to explore the parameter space more efficiently, allowing it to avoid problems like becoming stuck in local minima. This technique also uses less data to discover the best parameters and is faster than BP, which involves more iterations and fine-tuning of the learning rate. Furthermore, BOA is better suited for more complicated models and deep neural networks, with lower sensitivity to initial parameter choices. As a result, BOA surpasses BP as the best alternative for difficult machine learning tasks, particularly in models with a large number of nonlinear features.

The proposed BO-optimized neural network (BOA-BPNN) offers several advantages:

1. it mitigates the risk of premature convergence;
2. it expands the global search capacity for better solutions;
3. it consistently outperforms conventional tuning methods, as demonstrated in Section 4.

The primary purpose of this study is to examine and optimize the classification of electroencephalogram (EEG) signals using the error backpropagation (BP) neural network on the Internet of Medical Things (IoMT) platform. This work aims to give a more efficient way to diagnose and anticipate disorders like epilepsy by utilizing EEG readings via wearable and IoT devices. The research gap in this subject encompasses the issues that existing EEG classification algorithms face, such as slow processing speeds, limited accuracy, and significant data complexity. The purpose of this study is to increase the accuracy of diagnosing and predicting diseases in real-world situations, as well as to provide methods for optimizing the processing of EEG signals in medical systems based on the Internet of Things.

The implications of this study could include reducing diagnosis time, improving the quality of medical services, and helping to make faster and more accurate decisions in medical care. This study can also contribute to scientific advances in the field of biological signal analysis and the development of new technologies in digital health.

The remainder of the paper is organized as follows. Section 2 describes the proposed methodology. Section 3 outlines the implementation of the BOA-BPNN framework. Section 4 presents the experimental setup and results. Section 5 concludes with a discussion of the findings and their implications.

2. Related Work

This section discusses comprehensive and extensive state-of-the-art on IoMT frameworks and medical data analysis with standard and advanced ML/DL models. Outlined papers focus on ML/DL techniques for interpreting monitoring data generated from wearable/medical sensors.

Li *et al.* [8] use wavelet transform integrated with four functions and an adaptive technique of threshold method for carrying out the ECG filtering and feature extraction. These two techniques, the wavelet transform and the thresholding method, are especially effective for processing EEG signals in Internet of Medical Things (IoMT) systems because they can analyze complicated signals more efficiently and isolate significant features from noise and interferences. After that, use the mechanism of BPNN for classifying and analyzing ECG. BPNN could apply various techniques of optimization. One of the most common issues in the design of machine learning models, particularly neural networks, is the presence of mistakes caused by poor design or parameter values. These errors typically result in a decline in model accuracy and efficiency due to poor parameter selection, such as the learning rate, number of layers, or other network characteristics. PSO can automatically optimize these parameters and eliminate unsuitable selections, lowering the likelihood of a poor design. For contemplating the defects, the optimization mechanism of PSO used is broad, also expected to increase the precision of the prediction outcome, decrease the errors incurred in testing because of flawed model design, and hinder the last ECG allocation. The experiments show that the PSO-optimized BPNN intelligent model has higher accuracy and classification outcomes than the conventional BPNN model.

Alqahtani *et al.* [9] propose applying binary classification for automatic epilepsy detection. Binary classification is often employed for epilepsy diagnosis since the primary purpose is to distinguish between two conditions: the presence or absence of an epileptic seizure. In such systems, the model is separated into two major categories. EEG signals of patients are pre-processed after being recorded. Based on the results of the feature extraction technique, the top features are selected for further analysis using a structured genetic algorithm.

Genetic algorithms are an evolutionary optimization technique commonly employed in feature extraction. These algorithms are modeled after the natural processes of selection, mutation, and reproduction in living organisms and can be used to address difficult optimization issues such as feature selection and extraction in machine learning and data processing. The EEG data are analyzed and classified as seizure-free or epileptic seizure-related using the support vector classifier, under the assumption of feature optimization. As a result, classifying EEG data is an excellent application for the proposed method. For shared calculation accelerating implementation aim, CEHOC (Chaotic Elephant Herding Optimization based Classification) is applied for grouping a broad dataset field.

One of the most important uses of CEHOC in classification is feature optimization. This method can extract relevant and crucial features from big, complicated data sets while removing irrelevant or harmful elements. This approach reduces the dimensionality of the data while improving the classification accuracy.

Ahmad *et al.* [10] provided a novel architecture that contains four schemes, like detection, feature fusion, and engineering, as well as a user IoT module for real-life early seizure prediction. In feature engineering, handicraft linear and nonlinear features were manually retrieved and passed through, while deep features were acquired via a residual module. The multi-feature fusion (handicraft + deep feature) was then combined in the feature fusion module to better characterize EEG signal fluctuation. Furthermore, an attention mechanism was included, allowing the model to concentrate on the most important channels or regions. The authors used BiLSTM for temporal attributes.

Zhao *et al.* [11] presented HybMED, which refers to the new neural signal processor that supports on-chip training of a hybrid neural network applying a composite direct feedback alignment-based paradigm. It is a neural network design and training approach that is particularly useful when developing hybrid neural networks. This paradigm in HybMED is especially effective for neural signal processing since it can train and adapt models in real time with greater accuracy. HybMED is appropriate for general-purpose health controlling systems of AIoMT. That develops usage of source as well as efficiency of the region by reconfigurable homogeneous core with heterogeneous data stream, also increases energy efficiency by exploiting sparsity at various granularities.

Kapoor *et al.* [12] presented an epileptic seizure prediction scheme with electroencephalogram (EEG) signal data collected via IoT. IoT data is gathered and pre-processed to remove artefacts from the input signal. Frequency signal bands like alpha, delta, gamma, theta, beta waves are created, from what attributes are required for classification, like statistical, spectral, features, wavelet, entropy-based attributes, logarithmic band power, and CPR are extracted. The extracted features are concatenated and used to pick the electrode, which is then executed using the suggested hybrid cuckoo finch optimization. Using random search tactics and evolutionary steps, this algorithm can quickly identify excellent parts of the search space and perform optimization at a high speed. At last, signals would be normalized and transferred to a deep CNN classifier that is optimally tuned with hybrid cuckoo finch optimization aid for grouping epilepsy seizures with improved performance. Hybrid cuckoo finch optimization combines local and global search, which improves classification model accuracy. This technique can find key elements in EEG data that would otherwise be lost in a broad search space, hence boosting seizure grouping accuracy.

Mary *et al.* [13] presented an ECG controlling system based on IoT, which applies a sensor of heart rate for collecting data and a smart hybrid classification mechanism for grouping data. ECG control became a broadly applied technique to diagnose cardiac issues. The present article provides WISE (wearable IoT cloud-based health controlling device), the single real-time individual health controlling device. For proposing real-time health control, WISE applies the implementation of BASN (sensor network of the body region). BASN Data are quickly sent to the WISE cloud, light wearable LCD might be integrated for presenting quick accessibility to real-life data. Such a hybrid scheme could control the ECG dataset class imbalance issue that would help IoT-based intelligent and suitable healthcare system improvement.

Nandy *et al.* [14] improved the novel architecture of IoMT for real-life EEG signal controlling and analyzing, applying the explainable AI (XAI) method known as, Intelligent Agent-based Bag-of-Neural Networks (IBoNN) scheme. The presented XAI method benefits over the present schemes of ML/DL is letting end-users know the whole logic about controlling signals analysis to decide nontransparently. The present model of IBoNN works given the sensor-related brain signal in the architecture of IoMT. Such sensors tend to get brain impulses. In gathering data, the human subject is stimulated with various signs/ voices. The scheme of IBoNN grouped controlling brain signals applying bag-of-neural networks and assigned an accurate solution from patients' EEG signals.

Wang *et al.* [15] integrates BP NNA with online measurement device given the IoT. This integration is critical due to its benefits in real-time data processing and predictive accuracy. The device can handle complex EEG data fast and reliably, allowing for more precise diagnosis of medical issues such as seizures. In comparison to a traditional online measurement device, a device combined with an AI mechanism is smart and flexible in processing and gathering data. The IOT device of MP online measurement related to BP NNA completes the set of parameters, analyzing, and showing via a layer of network transmission, an app, as well as perception. Main point refers to a layer of system app which adds BP NNA for optimizing real-life parameters of achievement, doing a process for parameter measurement time reduction.

Borhade and Nagmode [16] presented an efficient mechanism of optimization known as Modified Atom Search Optimization-based DNN for carrying out suitable seizure prediction with less time of calculation. Now, the classifier of DNN carries out seizure prediction by applying different hidden layers related to the hierarchy layer, given the optimally chosen attributes. The presented mechanism of Modified Atom Search Optimization is schemed by applying ASO as well as the Squirrel Search Algorithm. That should be noted that the presented MASO-based DNN was carried out soon and is suitable for seizure prediction, applying electroencephalogram signals.

Wang *et al.* [17] proposed a feature-level graph embedding method and combines the method with EEGNet; this new network is called EEG_GENet. The purpose of combining the EEGNet graph embedding method in the analysis of EEG signals is to improve the feature extraction capability and prediction accuracy. Specifically, time-domain features are obtained by convolving raw EEG signals for each electrode. Then, the adjacent matrix, conceptualized as a graph filter, performs graph convolution and uses the time-domain features to embed the topology information. This process can also perform multi-order graph embeddings. In addition, the adjacency matrix in this paper can adapt to different brain network connectivity for different subjects.

Various approaches for analyzing EEG and ECG signals have been offered in various research, each with its own set of advantages and drawbacks. For example, while wavelet transform and PSO optimization improve ECG analysis accuracy, they may not perform well with complicated EEG data. Furthermore, the employment of genetic algorithms and BiLSTM in epilepsy diagnosis improves accuracy; nonetheless, model complexities and real-time processing issues may impede wider adoption. This study aims to increase the accuracy and efficiency of EEG signal processing for seizure prediction by filling gaps in existing approaches and optimizing and integrating the models.

3. Proposed Method

In this paper, we present the multi-scheme BOA-BPNN for improving the precision of EEG diagnosis. The flowchart for the proposed method is illustrated in Figure 1.

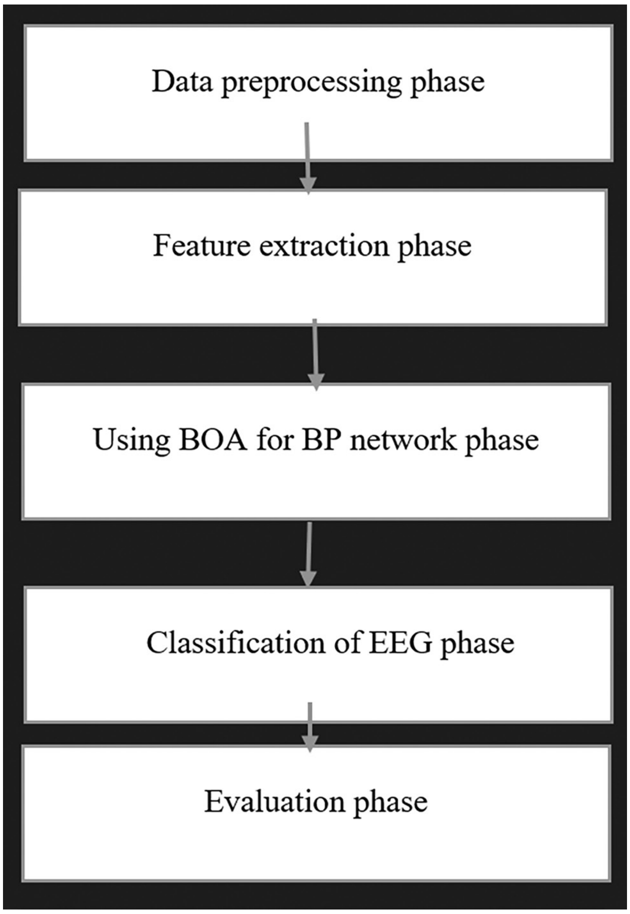

Figure 1. Flowchart of the Proposed System.

3.1. Preprocessing of Data

Cross-validation [18] is a widely used technique for evaluating model generalization and mitigating overfitting during training. In this study, we applied 5-fold cross-validation to assess the performance of the proposed neural network model. The dataset was partitioned into five equal subsets; in each iteration, four subsets (80%) were used for training, while the remaining subset (20%) served as the test set. This process was repeated five times, and the average performance across all folds was reported to ensure a robust evaluation of the model's predictive capability.

3.2. Feature Extraction

Adaptive Auto-regressive (AAR): The characteristics of a signal are represented by the AAR parameters or estimators. There is no trend in the signal that it models. AAR is frequently used in conjunction with an EEG signal to forecast or filter brain activity. That is, AAR parameters can be used to build models that describe the short-term and long-term properties of an EEG signal. Autoregressive models extract the signal's characteristics from past values and accurately predict its future state.

$$Y_t = a_{1,t} * Y_{t-1} + a_{2,t} * Y_{t-2} + \ldots + a_{p,t} * Y_{t-p} + E_t \quad (1)$$

The $a_{1,t}, \ldots, a_{p,t}$ are AAR estimators in Equation (1). The auto-regressive model's order is represented by p. Et is the random or white noise. It is otherwise called the expectation mistake. With a more modest mistake estimate, the EEG signal is depicted more precisely by the AAR model. EEG signals are dynamic and temporal, which means that their features change with time. AR and AAR models use estimators (model coefficients) to account for temporal changes and instantaneous dependencies between signal values throughout time. In this study, the RLS (Recursive Least Squares) adaptation of AR models has been utilized for highlight extraction [19].

3.3. Neural Network of BP

Rumelhart and McClell introduced the BP neural network in 1986. It is one of the most extensively used and successful neural networks. Training the network mainly consists of two steps, which are negative signal error as well as positive signal transmission. As the positive signal broadens, data arrives at the input layer and is propagated through hidden layers, layer by layer, and finally transferred to output layer.

When actual output layer outcome varies from desired outcome, it changes to reversal error transferring step, error reversal transferring is exchanged layer by layer to the layer of outcome using several path kinds, every layer function error provides entire parts, so getting every part error signal layer, such signal of error like the stable amount based on every part right base.

Network of BP includes an input layer as well as one or more hidden layers plus ad output layer. Network learning progress contains 2 units, 1 unit refers to transferring info of input on the straight side, also the other refers to transferring error on the opposite side. In a straight function, info of the input is transferred to the hidden layers from layer of input layer to the output layer. When the output layer outcome varies greatly outcome of output, the error of the output would be computed, error would be sent to the opposite side. The weights among each layer would be changed to minimize the error. Then the network is said to be rehearsed for the given data or application. The 3-layer form, as illustrated in Figure 2, is the typical BP neural network form.

BPNN progress is basically shared in 2 steps for the scheme of NN, along with just 1 hidden layer. The first step is signal forward propagation that goes via the hidden layer from layer of input layer to the output layer. The second step refers to the BP of error, from output layer to the hidden layer, and finally to the input layer,. Set the hidden layer weights and bias to the layer of output layer, weights, and input layer bias to the hidden one. The learning mechanism of BP sets the weight with a negative gradient, which is a side where the operation quickly decreases. BPNN learning progress is illustrated in Figure 1. The amount of weight is modified using Equation (2).

$$x_{k+1} = x_k - a_k g_k \tag{2}$$

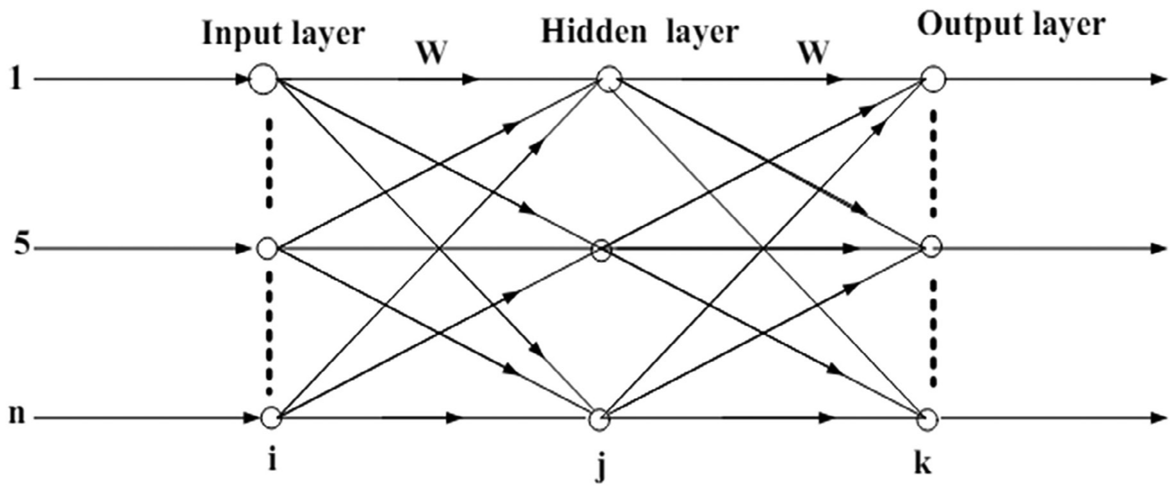

Figure 2. Structure of Back Propagation.

That x_k is a matrix of threshold and weight, g_k is the operation gradient, and a_k is the rate of learning. Analyzing derivation process is analyzed in the following. Describe x_i as a vector of the input layer, y_j as a vector of the hidden layer, zl as a vector of the output layer, ωji as a vector of weights between the hidden and input layer, and νlj as a vector of weights between the output and hidden layer. While the vector of prospect output is t1, the hidden and output layer outcome vector is as in Equations (3) and (4):

$$y_i = f(\Sigma_i\, w_{ji}\, x_i - \theta_j) = f(\mathrm{net}\, j), \quad \mathrm{net}\, j = \Sigma_i\, w_{ji}\, x_i - \theta_j \tag{3}$$

$$z_1 = f(\Sigma_i\, v_{lj} y_j - \theta_1) = f(\mathrm{net}\, l), \quad \mathrm{net}\, l = \Sigma_j\, v_{lj} y_i - \theta_1 \tag{4}$$

After that, error among certain as well as desired output amounts is presented as Equation (5):

$$E = \frac{1}{2}\sum_l \left(t_l - f\left(\sum_j v_{lj} f\left(\sum_j w_{ji}\, x_i - \theta_j \right) - \theta l \right) \right) 2 \tag{5}$$

BPNN designing progress is as follows:

1. Pre-process data.
2. Assign network layers number, aim errors, BPNN learning speeds, and training times.
3. Train BPNN on training data.
4. Applying data of test kind for testing the scheme of the NN model, then finally take the predicted amount.
5. Compare and analyze the actual and predicted amounts achieved in the last stage.

Bayesian optimization refers to the iterative mechanism that is broadly applied in issues of hyperparameter optimization. Bayesian optimization is an appropriate alternative for optimization issues where the objective function is nonlinear, expensive, or time-consuming. Unlike classic hyperparameter optimization approaches such as grid or random search, which typically require several evaluations of the objective function, Bayesian optimization employs probabilistic models to forecast and reduce the number of evaluations needed. This strategy effectively manages uncertainty in predictions and updates the model based on available facts. Instead of searching in the hyperparameter space at random or systematically, Bayesian optimization can be steered to the target areas with the least amount of assessment. As a result, in issues that demand expensive assessments, such as building complicated machine learning models, Bayesian optimization is more efficient than classic hyperparameter optimization methods.

That contains two main units, the surrogate model and the acquisition task. The surrogate model aims is set whole presently monitored points in the objective task. After that surrogate model prediction share is achieved, and the task of acquisition is used for assigning the next point for being assessed, which could decrease iterations number as well as the assessment price. Bayesian optimization sometimes confirms Gaussian process (GP) as a surrogate model for objective function design because of the GP model's tractability as well as flexibility. GP refers to the multidimensional Gaussian process development on the immortal stochastic process in dimension, which is specialized in tasks of covariance as well as mean. Typical BO tasks of achievement contain confidence limit, desired, and probability development.

Like the hyperparameter-tuning method based on the model, the mechanism of BO designs validation collection performance conditional abilities while hyperparameters are chosen by applying surrogate tasks. Against random/ grid looks, the mechanism of BO follows the whole historical assessments. So, prevent computations' wasting for assessing the worst hyperparameters. Furthermore, the task of achievement finds the most satisfactory hyperparameter for evaluation in the next iteration. The presented scheme uses the approaches of the BO mechanism for finding optimum BPNN hyperparameters. The mechanism of BO obtains greater efficiency of tuning in a shorter time of assessment.

3.4. Basic BPNN Weights and Thresholds Optimization

We used the BOA method with defined agents to optimize important BPNN parameters such as initial weight sets, threshold changes, and overall framework optimization. This strategy improved BPNN's performance by speeding up convergence, enhancing parameter adjustment, and increasing the model's precision. Therefore, the optimized scheme of BPNN would possess two global BOA mechanism optimization capabilities as well as local BP mechanism search capability.

The proposed method uses BOA to fine-tune the BPNN's initial weight sets and bias thresholds. The search space for the initial weights was set to 1.0, 1.0–1.0, 1.0–1.0, 1.0, and for the biases as −0.5, 0.5–0.5, 0.5–0.5. The optimization technique sought to reduce the mean squared error (MSE) on the training data. BOA was constructed with a population size of 30 and 50 iterations. The Expected Improvement (EI) acquisition function drove the selection of new candidate solutions. This design allowed for fast exploration of the parameter space and convergence to optimal initialization settings.

4. Experimental Setup and Development

4.1. Classification Models

Optimization module given the BO-mechanism straightly related to precision as well as rate of convergence. Although, embedded scheme is better than present schemes like [10], [17] due to its ability to smoothly integrate the optimization process into the system architecture. This integration takes advantage of the Bayesian Optimization mechanism's characteristics to improve precision and speed of convergence. The mentioned schemes are assigned as schemes of benchmark schemes because of structural resemblances with the evolved scheme. The structural resemblances between the benchmark schemes and the developed scheme are most likely due to common underlying frameworks, techniques, or approaches. These resemblances can be used to compare and benchmark products.

4.2. Dataset

The BCI Competition IV 2a dataset (BCICIV2a dataset [20]) is used to assess the suggested network. For motor imagery decoding, the BCI Competition IV 2a Dataset is widely utilized in the literature. This dataset is frequently used to examine how well various decoder models for motor imagery EEG signals function. The EEG signals were captured by twenty-two electrodes at a sampling rate of 250 Hz. The waveforms had a frequency range of 0.5 Hz to 100 Hz. There are nine individuals in the dataset. Two sessions were recorded for every subject, with 288 four-second trials of four motor imagery (left hand, right hand, both feet, and tongue) in each session. Based on the competition's published results, five of the nine subjects (subjects A01, A03, A07, A08, and A09) with the best data quality are chosen from the dataset. The training and testing sets are 2592 trials $x \in R^{22\times1125}$, with testing occurring in the second session following training in the first [21].

In this paper, we choose subjects A01, A03, A07, A08, and A09 from the BCI Competition IV-2a dataset. These patients were chosen for their generally excellent data quality, low levels of artifacts, and consistent trial designs. Furthermore, these specific subjects have been extensively studied in earlier studies, allowing for more credible benchmarking and fair comparison with existing methodologies.

4.3. Performance Evaluation

The efficiency of the classifier can be measured using the rate of true positives (TP), false positives (FP), and accuracy (AC), which are determined using Equations (6), (7), and (8), respectively.

$$TP = TP/(TP + FN) \tag{6}$$

$$FP = FP/(FP + TN) \tag{7}$$

$$AC = (TP + TN)/(TP + FN + FP + TN) \tag{8}$$

TP: This metric calculates the proportion of correctly detected positive instances among all real positive cases. It indicates the classifier's capacity to discover relevant occurrences, which directly affects its sensitivity or recall.

FP: This statistic computes the percentage of wrongly detected positive instances among all genuine negative instances. It emphasizes the classifier's susceptibility to false alarms while demonstrating its accuracy in discriminating between positive and negative cases.

AC: This statistic measures the proportion of correctly classified occurrences (both positive and negative) out of the total number of instances. It provides a generic measure of the classifier's performance, however, it may be less useful in imbalanced datasets.

True positive shows aim specimens fetched collection as aim units, False-negative does not show any specimen fetched to non-aim specimens, False positive shows non-aim components fetched to aim components, lastly, true negative shows non-aim specimens.

In addition to accuracy, we use Precision, Recall, and F1-Score as performance metrics to fully evaluate the proposed model's classification performance. These measures are commonly employed in classification tasks, especially when dealing with imbalanced datasets.

Precision measures the fraction of accurate positive predictions among all positive predictions made by the model. It reflects the model's accuracy in predicting a sample as positive.

$$\text{Precision} = \text{TP}/(\text{FP} + \text{TP}) \qquad (9)$$

Recall (also known as sensitivity or true positive rate) is the proportion of true positives properly detected by the model among all actual positive cases.

$$\text{Recall} = \text{TP}/(\text{FN} + \text{TP}) \qquad (10)$$

The F1-score is the harmonic mean of precision and recall, resulting in a single statistic that balances both.

$$\text{F1} - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (11)$$

4.4. Result Analysis

First, every classifier mentioned previously is applied to confirm training feature subsets independently. Classifiers apply 5-fold cross-validation to assess performance. Table 1 shows the classifiers' classification outcomes for Fs. The receiver operator curve (ROC) that is defined later here is applied in quantifying the outcome of the classifier. The ROC curve is crucial because it provides a full evaluation of a classifier's performance by displaying the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) at various classification thresholds. ROC shows that instances were organized to raise the sequence given the desired performance of the learner. All instances will be sequentially tagged and processed, and the current instance, along with the previously

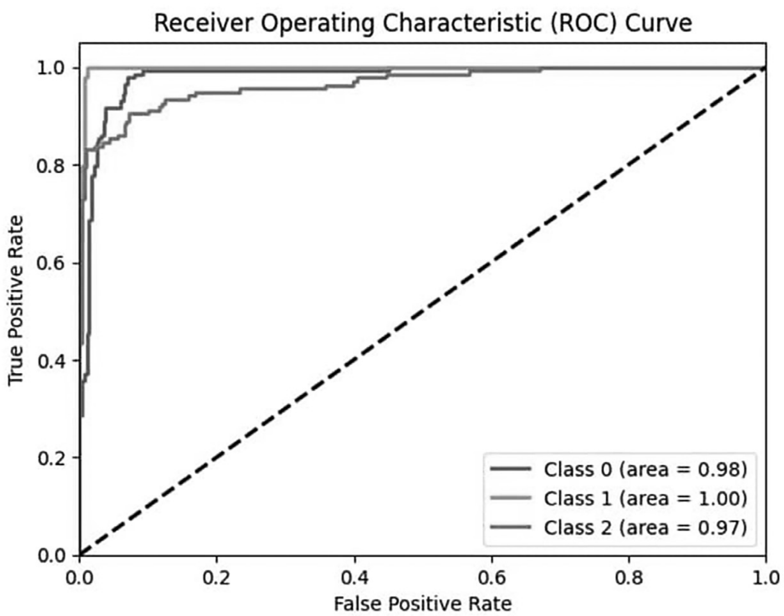

Figure 3. ROC curve area for proposed method.

marked instances, will be used to estimate the remaining untagged instances. Amounts of Tr and Fr are calculated and shown in vertical and horizontal dimensions, relatively Figure 3.

The ROC curve results in Figure 3 show that the suggested model has good discriminative performance. The AUC values for classes 0 through 2 are 0.98, 1.00, and 0.97, respectively. These numbers demonstrate the model's exceptional ability to distinguish across classes, with an AUC of 1.00 indicating perfect classification for class 1. The model's near-perfect AUC scores indicate that it strikes a compromise between sensitivity and specificity, making it extremely dependable for classification in EEG-based motor imagery tasks.

Figure 4 shows the confusion matrix of the proposed method. We can see that the proposed method has a high rate of FP and FN. The confusion matrix demonstrates that the suggested technique has high false-positive (FP) and false-negative (FN) error rates in several classes. Specifically, 140 samples from class "0" are correctly classified, with no samples from other classes misdiagnosed as this class (FP=0), but three samples from class "0" are misclassified into other classes. (FN). For class "1", the model's performance has been significantly improved, with 145 examples predicted correctly and only three samples categorized incorrectly. The performance in class "2" is poorer; although 113 samples were correctly recognized, 20 samples were mislabeled as other classes (FN), and three samples from other classes were also mislabeled as class "2." These findings demonstrate that the model is particularly weak in recognizing class "2". The confusion matrix (Table 1) demonstrates that class "2" has a greater misclassification rate, with 20 false negatives and 3 false positives. This is mainly due to data imbalance, as class "2" has fewer training samples compared to other classes. Additionally, feature overlap between class "2" and other classes adds to the categorization difficulty. To boost performance, future research could use data augmentation and enhanced feature selection to better differentiate this class. Table 1 displays the comparative accuracy of the proposed method versus various benchmark methodologies.

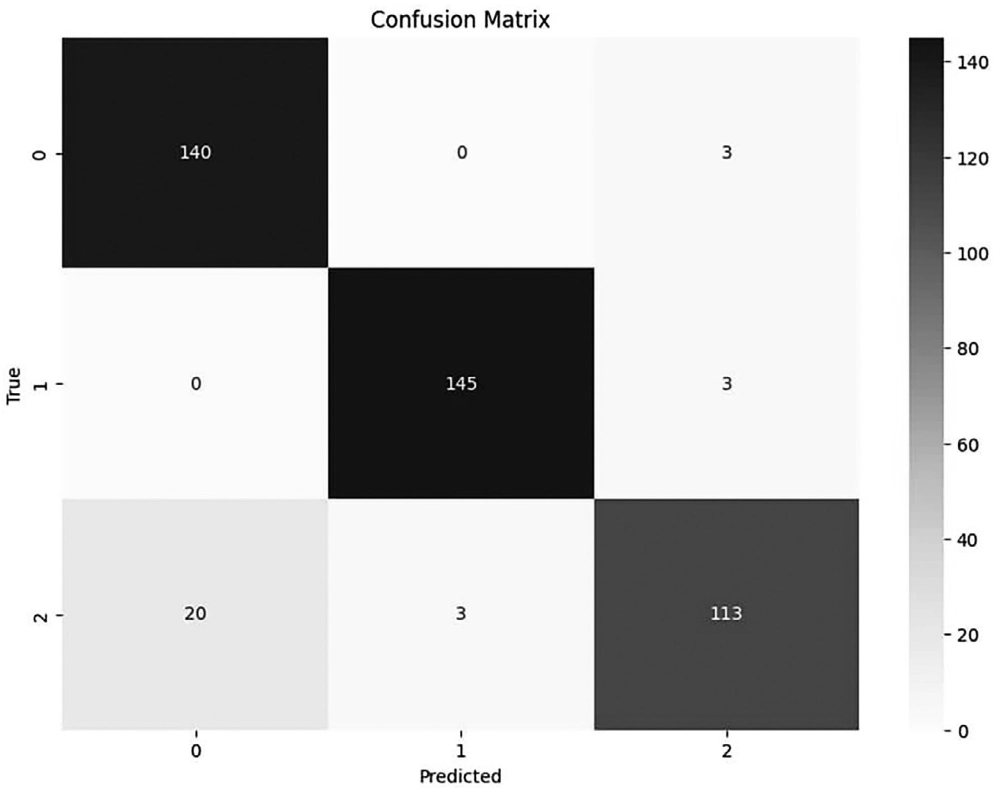

Figure 4. Confusion matrix for proposed method.

According to Table 1's results, the suggested approach performs better than the methods that were examined in terms of accuracy. The results demonstrate how well the BP neural network's optimization settings worked, as seen by the 13.64% increase in detection accuracy and other performance metrics over the other models.

The BP neural network's detection accuracy and overall performance improved by 13.64% after its settings were optimized. This optimization involved fine-tuning hyperparameters such as learning rate, number of hidden layers, and number of neurons in each layer, which assisted the network in better identifying hidden patterns in the data. Furthermore, improved training approaches like as adaptive learning rate and tuning methods (*e.g.*, L2 or Dropout) have helped to prevent overfitting and improve generalizability. Selecting useful features and eliminating noise from input data have also contributed significantly to network efficiency.

To achieve a fair and comprehensive comparison, we re-implemented and evaluated the baseline models proposed by Ahmad *et al.* [10] and Wang *et al.* [17] using the same dataset as our proposed method. The results in Table 1 show that our proposed strategy outperforms both baseline methods in all major metrics. Our model attained an accuracy of 93.21%, which outperformed Ahmad *et al.*'s 91.39% and Wang *et al.*'s 79.57%. In terms of precision, our technique achieved 99.1%, which is much greater than Ahmad *et al.*'s 90.8% and Wang *et al.*'s 78.2%, showing a far reduced false positive rate. Similarly, our model's recall was 93.6%, outperforming Ahmad *et al.*'s 91.0% and Wang *et al.*'s 76.5%, which reflects better identification of true positive samples. Finally, our model's F1 score of 96.2% demonstrates an excellent balance between precision and recall, outperforming Ahmad *et al.*'s 90.9% and Wang *et al.*'s 77.3%. These findings suggest that the re-implemented baseline models, which were tested under identical settings, demonstrated the higher performance and resilience of our proposed method.

To determine the statistical significance of the observed improvements, independent two-tailed t-tests were performed comparing the proposed method to the baseline models (Ahmad *et al.* [10] and Wang *et al.* [17]) based on accuracy and F1-score. The obtained p-values were less than 0.05, showing that the performance improvements are statistically significant and not attributable to random variation.

5. Conclusion

In summary, this study presents a neural network-based approach for EEG signal classification based on BPNN and BOA. The proposed architecture utilized the BOA mechanism to fine-tune the hyperparameters of BPNN, resulting in enhanced precision and improved performance. The proposed integration improves

Table 1. Comparative accuracy of the proposed method.

Techniques	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Ahmad *et al.* [10]	91.39%	90.8%	91.0%	90.9%
Wang *et al.* [17]	79.57%	78.2%	76.5%	77.3%
Proposed method	93.21%	99.1%	93.6%	96.2%

the accuracy, stability, and convergence of the current technique, all at the same time. The proposed BOA-BPNN achieved a high prediction accuracy of 93.21%, with consistent performance across different K-fold values. The benefits of the presented technique include faster convergence, easier implementation, robustness, high speed, and low complexity. Convergence speed refers to the speed at which the proposed technique achieves its optimal solution or intended accuracy throughout the training or optimization phase. In the context of optimization algorithms or machine learning models, it refers to how quickly the algorithm converges to the lowest loss or best parameters as compared to alternative methods. The BCI-CIV2a dataset, a benchmark dataset for EEG signal analysis, has been used to evaluate the performance of the proposed method. The proposed method outperformed the comparative methods in terms of accuracy, as demonstrated by a 5-fold cross-validation experiment. The proposed method improves accuracy and overcomes fundamental issues in EEG-based seizure prediction, such as detecting subtle patterns in brain activity and lowering false alarms. This development has the potential to dramatically improve the reliability of automated seizure prediction systems, hence increasing patient care and management in clinical applications.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This research work was not funded by any program.

Data Availability

The data used in this article are publicly available, and their sources are properly cited within the manuscript.

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Received: March 2025
Revised: June 2025
Accepted: June 2025

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