Knowledge-Based Systems 303 (2024) 112270

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Efficient predefined time adaptive neural network for motor execution EEG signal classification based brain-computer interaction

Jose N N [a,*], Deipali Gore [b], Vivekanandan G [c], Nithya E [d], Nallarasan V [e], Krishnakumar K [f]

[a] Department of IT Consultant/Architect Regent Strategic Solutions, India
[b] Department of Computer Engineering, PED Modern College of Engineering, Pune, Maharashtra, India
[c] Department of Computer Science and Engineering Sri Sairam Institute of Technology, Chennai, India
[d] Department of IT, Sri Sairam Engineering College, Chennai, India
[e] Department of Networking and communications, School of computing, SRM Institute of Science and Technology Kattankulathur, Chengalpattu, India
[f] Department of Programming, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, India

ARTICLE INFO

Keywords:
Bitwise arithmetic optimization algorithm
Efficient predefined time adaptive neural network
EEG signals
Publicly available EEG datasets
Robust M-type error-state Kalman Filters
Signed cumulative distribution transform

ABSTRACT

Nowadays, Electroencephalogram (EEG) devices that do not require invasive procedures get more attraction. Brain-Computer Interface (BCI) systems use EEG analysis to identify users' mental states, cognitive shifts, and stimuli-induced reactions. The Motor Execution (ME) paradigm is a vital control paradigm that holds great significance in this framework. In this manuscript, an Efficient Predefined Time Adaptive Neural Network for EEG-Based Brain-Computer Interaction in Motor Execution Classification (EPTNN-BCI-EEG) is proposed. Initially, the input signals are collected from EEG Dataset. The input signals are preprocessed using Robust M-Type Error-State Kalman Filter (RMESKF) to remove the artifacts and baseline signals. Then, the pre-processed signals are given to Signed Cumulative Distribution Transform (SCDT) for feature extraction. SCDT is used to extract Spatial and temporal features. Afterward, Efficient Predefined Time Adaptive Neural Network (EPTNN) is used to classify the EEG gender and signal, such as Audio/Video and Male/Female. In General, EPTNN does not expose any adoption of optimization systems to determine optimal parameters to classify the EEG gender and signal. Hence, Bitwise Arithmetic Optimization Algorithm (BAOA) is proposed to optimize the EPTNN. The proposed EPTNN-BCI-EEG approach is implemented in MATLAB and the performance metrics, such as Recall, Accuracy, Root Mean Square Error (RMSE), F1-score, Specificity, ROC, Computation time are assessed. The performance of EPTNN-BCI-EEG approach provides 17.82 %, 28.95 %, and 19.2 % higher accuracy, 24.38 %, 34.53 %, and 18.78 % higher recall, 26.7 %, 24.2 %, and 32.7 % higher specificity when analysed with the existing methods.

1. Introduction

An interface that communicates directly by a machine and brain impulses is called brain-computer interface (BCI). BCI interprets how central nervous system functions converts it into artificial output enhances, restores, and replaces natural CNS's output, changing the CNS's on-going interactions with internal/external surroundings [1]. BCI systems have recently gained a lot of attention because of its various applications that is vital to people's daily lives, especially for physical limitations and mental health issues. By controlling brain waves during human-computer interactions, one can enhance modelling, research, assistance, security, entertainment, and identification [2,3]. Wheelchairs and other helpful apps for individuals with mobility impairments can also be supported by it. Furthermore, brain-computer interfaces (BCIs) have applications in the healthcare industry since they are an effective technology that enables people to communicate by outside world using their own thoughts, which machine can identify as patterns [4]. In several significant domains, such as automotive drones and robotics, these tasks are carried out with the aid of external devices. These ideas have distinct brain patterns that scalp electrodes record, and computers use algorithms to apply the signals [5]. Through the interaction of brain activity measures, BCI assists in managing applications. It categorises to manage tools, like computer games, spelling apps, and creative expression. Lastly, it offers behaviour feedback [6,7]. The brain signals play a vital role in the occurrence of every emotion, including alertness, comfort, focus, and concern [8]. Brainwaves may be tracked

* Corresponding author.
E-mail address: profjosennita@gmail.com (J.N. N).

https://doi.org/10.1016/j.knosys.2024.112270
Received 4 June 2024; Received in revised form 18 July 2024; Accepted 24 July 2024
Available online 25 July 2024

by an EEG, which also describes neural oscillation of membrane potential and post-synaptic action potential rhythms. This technique uses electroencephalogram (EEG) analysis to track electrical activity in the brain and assess voltage variations derived from the ionic field at intervals between brain neurons [9,10]. When viewed from a clinical perspective, the EEG graph represents the brain's continuous electrical activity as recorded over time by various scalp electrodes [11]. EEG is a BCI non-invasive brain wave measurement method [12,13] which is frequently used in conjunction with other signal processes like Positron Emission Tomography, MRI. It is more practical than Electrocorticography that requires direct evaluate to brain tissues, is used in all contemporary BCI applications [14]. When utilized, analysed by healthy participants for investigate, applications, EEG requires inexpensive, portable equipment that is easy to obtain and provides a high time resolution signal [15]. A non-invasive method called scalp electroencephalography (EEG) gathers the electrical fields the brain produces and reflects the activity that underlies it [16]. EEG is frequently utilized in neuroscience and as a basic diagnostic tool for a number of neurological conditions [17]. EEG is frequently utilized in BCI systems, in which the subject's objectives are converted EEG signals as set of appropriate commands, allowing brain to communicate directly by external device [18]. EEG is generally well tolerated by patients, widely available, reasonably priced, and simple to use [19]. Sadly, it also has a few significant drawbacks. The capacity of DL to generalize even in the presence of complicated inputs is one of its biggest potentials [20].

Accurately classifying EEG signals in Motor Execution (ME) tasks for Brain-Computer Interface (BCI) systems presents significant challenges due to artifact contamination, limited task generalizability, and high computational requirements. Existing methods often fail to effectively remove artifacts, generalize across different tasks beyond gender classification, or operate efficiently in real-time scenarios. This research aims to address these shortcomings by developing an advanced EEG signal classification model that enhances artifact removal, improves task versatility, and optimizes computational efficiency. By overcoming these challenges, the goal is to advance BCI technology, enabling more reliable and real-time interaction between users and external devices based on their neural activity patterns.

In this work, a signal processing model is proposed to categorize data from fourteen EEG channels that are utilized to record the responses of nine human brain neurons. The proposed approach contains three stages: signal preprocessing under RMESKF, feature extraction under SCDT, and classification under (EPTNN). Feature extraction is the key process which determines the significant classes of brain signals and dimension reduction. The aim of this paper is to design and implement the better model for feature extraction and classification of BCI signals as well as propose an optimized EPTNN classification method depending on both (ME) movement left/right hand with Audio/video (A/V) stimuli.

The key contributions of this research are summarized as below,

- Introducing an efficient EPTNN-BCI-EEG model that combines signal processing, feature extraction, classification algorithms to accurately categorize EEG signals from several channels during ME tasks.
- Combining Automatic EEG artifacts SCDT and EPTNN to improve feature extraction and classification, resulting in better performance than previous models.
- Identifying key multimodal elements in multichannel EEG data to depict specific mental processes associated with ME tasks, thus increasing comprehension of brain responses during motor execution.
- Developing evaluation models using Audio/Video (A/V) and Male/Female (M/F) stimuli to exhibits efficacy, flexibility of EPTNN-BCI-EEG method in a variety of categorization scenarios.
- Showing that the proposed EPTNN-BCI-EEG model outperforms regards classification accuracy, performance metrics.

Remaining part of this paper is organized as below: segment 2 portrays the literature review, the proposed approach is designated in segment 3, results with discussion are exemplified in segment 4, and conclusion is given in segment 5.

2. Literature review

Several research works have suggested in the literature associated to deep learning based BCI-ME EEG Signal; a few recent works are reviewed here,

Elsayed et al. [21] have suggested a DL method for BCI-ME EEG signal classification. Where, identifying key multisensory aspects of multi-channel EEG indicate certain mental processes using dual evaluation methods: Audio/Video, Male/Female. ERPs (electro cortical signals) were measured, recorded utilizing EEG after otherwisethrough psychological, motor, sensory events. The DBN was utilized independently to two methods, yielding higher classification rates in Motor Execution (ME). It provides higher accuracy, but lower recall.

Ieracitano et al. [22] have suggested novel explainable ML method for EEG-depend BCI systems. It examines interpretability of deep CNNs to acquire deeper insights into hidden activation process of cortical sources through hand sub-movements. Specially, an occlusion sensitivity analysis was performed to determine that cortical regions commonly involved in categorization method. It reached high recall and high RMSE.

Medhi et al. [23] have suggested efficient EEG signal classification method for BCI utilizing hybrid DL. A hybrid deep learning architecture was presented for efficient EEG signal analysis. The design efficiently chose and applied CNN filters to extract key multi-domain features. To improve system efficiency, superfluous features were eliminated using feature reduction techniques. Real-time EEG recordings from the PhysioNet bio signal collection were used. It provides low RMSE and low F1-score.

Zhu et al. [24] have suggested DL methods for EEG-depend BCI utilizing motor imagery. The five recently suggested MI-EEG deep classification methods: EEGNet, Shallow & Deep ConvNet, MB3D, ParaAtt were chosen and tested on two publicly available databases containing 42 and 62 human individuals. EEGNet produced greater outcomes at lower training costs depending on the parameters tested. It provides high F1-score, but lower specificity.

Abenna et al. [25] have suggested motor imagery depend BCI: enhancing EEG classification utilizing Delta rhythm with Light GBM algorithm. A new strategy for increasing the quality of EEG motor imagery classification systems was applied to the BCI competition IV 2a, 2b, PhysioNet EEG-MI datasets. It employs band pass filter to eliminate any unwanted signals before increasing prediction with the understanding that adding a PSO optimizer to parameters of LightGBM classifier provides for best, most stable categorization of EEG data. It reached high specificity, but low ROC.

Bagherzadeh et al. [26] have suggested EEG-based emotion recognition utilizing ensemble DL techniques and fusion of brain effective connectivity maps. Emotion identification was a significant task in many applications, including human-computer interaction, mental health detection. It seeks to increase accuracy and resilience of emotion recognition by merging several effective connectivity approaches, pre-trained CNNs, and LSTM. It attains higher ROC and more computing time.

Meng et al. [27] have suggested EEG-based BCI for suspecting backdoor attacks. The narrow period pulses for poisoning attacks on EEG-depend BCIs, making adversarial attacks easier to implement. The backdoor key was used to classify test samples into the attacker's stated target class. The solution differs from earlier ones by not requiring synchronization of the backdoor key with EEG trials, making it simple to execute. The backdoor attack strategy revealed serious security vulnerability for EEG-based BCIs. It provides low computing time and low Accuracy.

Recent studies in deep learning-based EEG signal classification for ME tasks within BCI systems highlight advancements and persistent challenges. One study introduced a method focusing on multi-channel EEG analysis using dual evaluation methods, achieving superior classification rates but with limitations in recall accuracy. Conversely, another study suggested an explainable machine learning approach using deep CNNs to interpret cortical activation during hand sub-movements, demonstrating high recall but encountering challenges in RMSE. Evaluation of multiple deep learning methods for motor imagery-based BCI highlighted performance variability across datasets, suggesting challenges in generalization. Integration of ensemble DL techniques with effective connectivity maps for emotion recognition from EEG

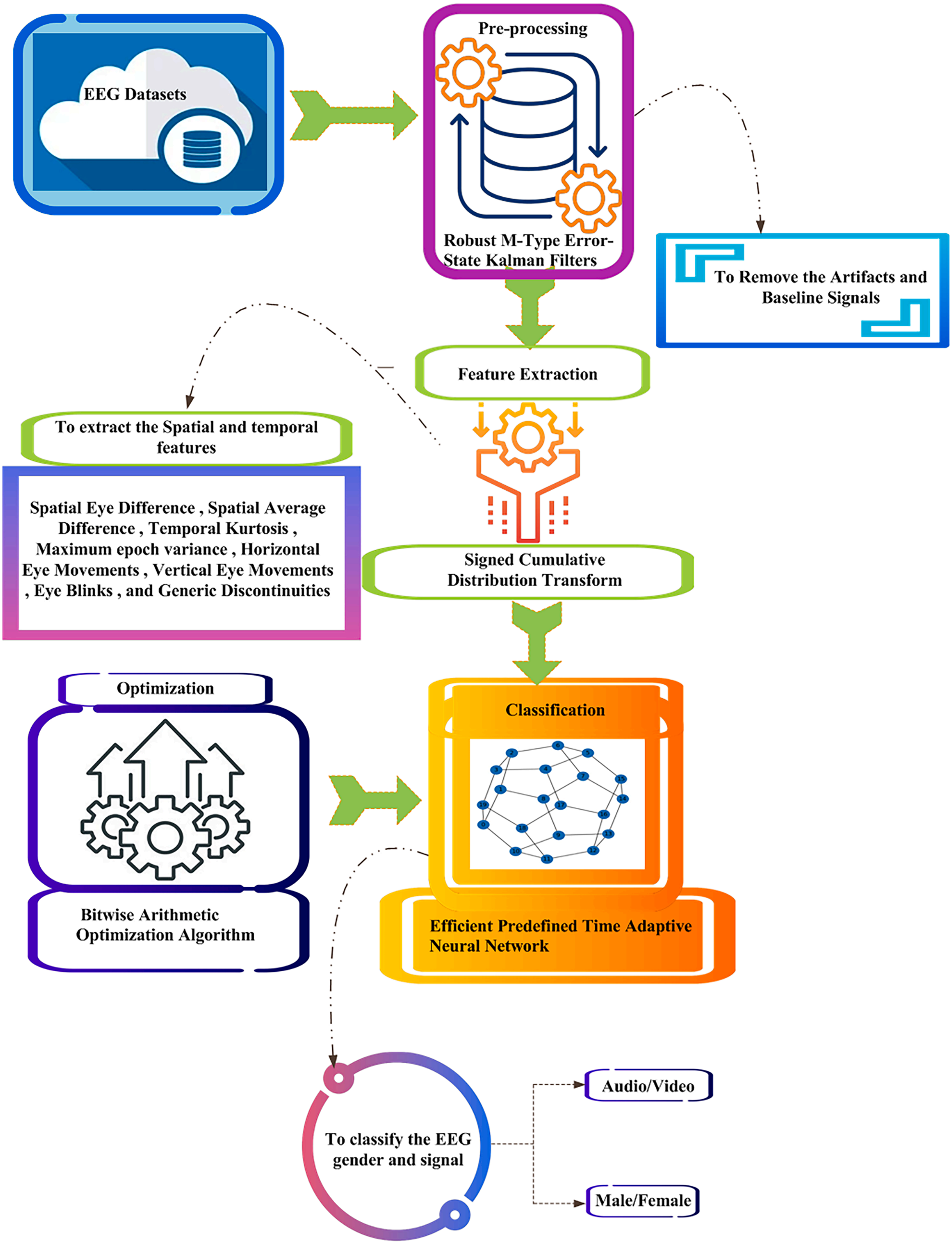

Fig. 1. Block diagram for proposed EPTNN-BCI-EEG method.

showed improved accuracy but increased computational complexity. Identification of vulnerabilities in EEG-based BCIs to backdoor attacks revealed critical gaps in security measures and data integrity. The literature underscores the need for advancements in generalizability across BCI tasks, effective artifact handling, improved computational efficiency, and better balance between interpretability and performance metrics to enhance the reliability and applicability of deep learning models in BCI systems.

3. Proposed method

This section discusses about the proposed EPTNN-BCI-EEG technique. The block diagram of the proposed EPTNN-BCI-EEG is represented in Fig. 1. This figure comprises dataset, pre-processing, feature extraction, classification, and optimization. Recently, Non-invasive Electroencephalography (EEG) technologies are gaining popularity. BCI systems use EEG analysis to determine user's mental state, cognitive state changes, response to events. ME is an extremely significant control paradigm. EPTNN-BCI-EEG model classifies signals from fourteen EEG channels using nine patients' brain neurons. This study identified key multisensory features of multiple channel EEG that indicate some mental processes based on dual different evaluation methods (audio/video), (male/female).

3.1. Data acquisition

Initially signals are collected from Publicly Available EEG Datasets [28].The dataset consists of EEG recordings from 109 subjects utilizing 64-channel EEG setup based on the 10–10 Electrode placement system. Each subject engaged in a task where they imagined moving their right or left hand on target appearance on corresponding side of screen. Trials with no target were marked as rest intervals. Task involved imagining opening and closing the first until target invisible on the screen with all trial lasting 4 secs emulated by inactivity period. In average, 150 EEG trials were obtained from all user, with a roughly equal distribution of left, right or rest labels. The signals are given to the pre-processing segment.

3.2. . Pre-Processing using robust M-Type error-state Kalman filter (RMESKF)

In this section, Pre-Processing Using RMESKF [29] is discussed. RMESKF is used to remove the artifacts and baseline signals. Pre-processing using RMESKF provides significant advantages across various applications. It excels in enhancing data quality by effectively filtering noise and artifacts, thereby improving signal accuracy and reliability for subsequent analysis. RMESKF's robustness against uncertainties and its ability to adapt to dynamic signal characteristics make it suitable for real-time processing scenarios in fields such as healthcare, robotics, and environmental monitoring. Its integration into complex systems is seamless due to its minimal computational overhead, ensuring efficient operation without compromising performance. The purpose of RMESKF is to provide exact and reliable state estimation in dynamic situations. Their breakthroughs have a substantial impact on various applications comprising navigation, autonomous cars, robotics, where precise system state estimate is vital to success. This is given in equation (1),

$$C(X, Y) = E[k(X, Y)] \tag{1}$$

here, $X, Y$is defined as random variable; E denotes the energy level; k denotes the kind of distribution and C denotes join distribution. Kalman function is common used EEG labelled in equation (2),

$$k(x,y) = G_{\alpha,\beta}(x,y) = \exp(-|e/\beta|^{\alpha}) \tag{2}$$

here, $k(x, y)$represents baseline signal; $x\,and\,y$represents signals of$X\,and\,Y$; αdenotes shape parameter; βimplies bandwidth; G implies state Kalman function and $e$specifies true function of$x - y$. Then the join distribution of random variable is defined by removing the artifacts. This is given in equation (3),

$$C(X, Y) = \sum_{i=1}^{l} \beta_i^{\alpha} C_{\alpha,\beta_i}(X_i,\ Y_i) \tag{3}$$

where $X, Y$is defined as random variable;C denotes join distribution;X_i, $Y_i$implies initialization of random signal; αrepresents shape parameter,β denotes baseline signal. The join distribution is not available and only samples N can be obtained. It is given in equation (4),

$$C_{\alpha,\beta_i}(X_i,\ Y_i) = \frac{1}{N}\sum G_{\alpha,\beta_i}(x_i(k),\ y_i(k)) \tag{4}$$

here X, Y as random variable; $k$as kind of distribution, C denotes join distribution; G represents Gaussian density function; αimplicates shape parameter; $\beta$is represented by the kernel bandwidth; N denotes the only sample function and $X_i,\ Y_i$is defined as the initialization of random variable. Here RMESKF has removed the artifacts and baseline signals that is articulated in equation (5),

$$J_{GL}(X, Y) = \sum_{i=1}^{l} \beta_i^{\alpha}\left(1 - C_{\alpha,\beta_i}(X_i, Y_i)\right) \tag{5}$$

here J_{GL} is defined as generalized loss; $X, Y$is defined as random variable; C denotes join distribution; αrepresents shape parameter; βrepresents kernel bandwidth and $X_i,\ Y_i$is defined as the initialization of random variable. Finally, RMESKF has removed the artifacts and baseline signals. The pre-processed signals are given to Feature extraction phase.

3.3. . Feature extraction using signed cumulative distribution transform (SCDT)

In this section, Feature Extraction Using Signed Cumulative Distribution Transform (SCDT) [32–34] is discussed. SCDT is used to extract spatial, temporal features, such as Spatial Eye Difference, Spatial Average Difference, Vertical Eye Movements, Temporal Kurtosis, Maximum Epoch Variance, Horizontal Eye Movements, Eye Blinks, and Generic Discontinuities. SCDT for feature extraction offers a number of significant benefits for data processing and analysis. It is useful for extracting complex patterns and dynamics since it can capture both temporal and spatial changes in data. Because SCDT is resistant to noise and unpredictability, the retrieved features have more reliable and more correctly reflect the underlying qualities of the data. Through the preservation of pertinent information and dimensionality reduction of feature space, SCDT enhances computing efficiency and facilitates further analytic activities. Adaptable to diverse data formats and harmonious with an array of machine learning techniques, SCDT facilitates improved performance indicators including precision and accuracy in categorization. SCDT is a potent technique for reliable, understandable, and effective feature extraction in a variety of domains, such as biomedical signal processing, time-series analysis, and image processing. First, transform is defines sample image by arbitrary mass is defined in Eq. (6).

$$I(s) = \begin{cases} (I*(s), \|I\|_{M1}, & if\,I \neq 0 \\ (0, 0), & if\,I = 0 \end{cases} \tag{6}$$

where $\|I\|_{M1}$ is the $_{M1}$ norm of image I and $I*$is the CDT; obtaining outer borders of provided fingerprint image. Dilation filled in missing pixel of fractured ridge while adding pixels to objects' boundaries. After performing this operation, object expanded its areas, shrunk a single hole, narrowed space among two sections. It is shown in equation (7)

$$I(t) = \|I^{+}\|_{M1}\left((I^{+})^{*-1}(t)\right) - \|I^{-}\|_{M2}\left((I^{-})^{*-1}(t)\right) \tag{7}$$

where $I(t)$ denotes the image at certain dimension$t$, I^{+} and I^{-} denotes two regions in the image and $M1, M2$ is the norm of two image gap. After dilation, fingerprint image is smoothed using complement operation of dilation. By extracting the inner boundaries of fingerprint edge, it resulted in reduction of size. As a result, it utilized to eliminate noisy connections among dual items. Then undesirable pixels were ejected, which sharpened the fingerprint image. It is shown in equation (8),

$$\widehat{I}_h = \left(h^{-1}\circ(I^{+}), \| I^{+} \|_{M1}, h^{-1}\circ(I^{-}) \| I^{-} \|_{M2}\right) \tag{8}$$

where h^{-1} denotes the inner boundary of the image and $\widehat{I}_h$ shows the size of extracted images. The Spatial Eye Difference of the extracted result concentrates showing high quality output image. In each extracted features, SED evaluates the difference in spatial distribution of EEG signals recorded from different electrodes that indicate eye movements exhibited in equation (9),

$$SED = \sqrt{\sum\nolimits_{i=1}^{n} (e_{i1} - e_{i2})^2} \tag{9}$$

where e_{i1} and e_{i2} denotes EEG signals recorded from electrode i in different conditions. SAD assesses average difference in EEG signal amplitude across numerous electrodes and is commonly used to detect changes in brain activity. It is given in equation (10),

$$SED = \frac{1}{n}|e_{i1} - e_{i2}| \tag{10}$$

where n implicates total number of samples. TK assesses the peakedness or flatness of the distribution of EEG signal values across time, revealing information regarding signal variability. It is given in equation (11),

$$TK = \frac{1}{N}\sum\nolimits_{t=1}^{N} \frac{(x_i - \mu)^4}{\sigma^4} \tag{11}$$

where μ represents vertical amplitude, σ represents frequency, x_i represents signal values. MEV measures the maximum variance of EEG data over epochs, which indicates signal variability over time. It is given in equation (12)

$$MEV = \max(\mathrm{var}(e1), \mathrm{var}(e2), ..., \mathrm{var}(en)) \tag{12}$$

where en is the value within each epoch, $\mathrm{var}(en)$ as the variance for that epoch. HEM detects the horizontal displacement of the eyes, which is commonly observed by changes in EEG signals across electrodes near the eyes. It is given in equation (13)

$$HEM = \frac{Total\ horizontal\ eye\ movement\ distance}{Total\ time} \tag{13}$$

Vertical Eye Movements (VEM) is the displacement of the eyes along the vertical axis, which allows people to change their gaze vertically within the visual environment. It is given in equation (14),

$$VEM = \frac{V}{T} \tag{14}$$

where V denotes set of indices with discontinuities, T is the threshold for determining a discontinuity. Eye blinks (EB) are short, involuntary closures of the eyelids that usually last a fraction of a second. They require the fast contraction and relaxation of the orbicularis oculi muscles. It is given in equation (15)

$$EB = \frac{Number\ of\ blinks}{Time\ period} \tag{15}$$

Generic Discontinuities (GD) in EEG data are abrupt changes, spikes, or irregularities in recorded electrical activity of brain that cannot be attributed to specific physiological events or known artifacts. The spatial and temporal features are given in equation (16)

$$\widehat{I}_h = \left(\frac{h^{-1}\circ(I^{+}) + \lambda}{\varpi}, \| I^{+} \|_{M1}, \frac{h^{-1}\circ(I^{-}) + \lambda}{\varpi} \| I^{-} \|_{M2}\right) \tag{16}$$

where λ denotes the extracted statistical features andϖ denotes the variable in transform domain. Finally, SCDT extracted the spatial and temporal features. The extracted features are given to EPTNN for classifying EEG gender and signal.

3.4. . Classification using efficient predefined time adaptive neural network (EPTNN)

In this section, Classification using Efficient Predefined Time Adaptive Neural Network (EPTNN) [30,31] is discussed. EPTNN is used to classify the EEG gender and signal such as Audio/Video and Male/Female. There are several significant benefits to classifying using EPTNN. It performs exceptionally well in real-time adaptation, dynamically modifying to shifting temporal fluctuations and data patterns to guarantee excellent prediction accuracy and precision. Low-latency applications can benefit from EPTNN's computational efficiency, which allows it to analyze massive amounts of data fast and with minimum resource use. Furthermore, because of its adaptive nature, generalization is improved, overfitting hazards are decreased, and performance on new datasets is improved. The main purpose of EPTNN is to improve the neural networks' capabilities by increasing its efficiency, flexibility, and performance in time-constrained circumstances, allowing for the construction of responsive and intelligent systems for real-world deployment. Adding event-triggered mechanism is articulated in equation (17),

$$S(h) = -\lambda_{et}(h)\Phi_{et}(F(h)) \tag{17}$$

where S is the rate of change of a quantity over time, (h)represents variable at time$h$,λdefines parameter controls rate of change, Φ_{et} defines parameter controls rate of change, Φ_{et}defines the state variable and$F(h)$ denotes activation function. EPTNN simplifies computations using present time steps, lowering training complexity and resource overhead. Its adaptive nature enables continuous learning and adjustment, ensuring relevance in dynamic data contexts. The signals are categorized from fourteen EEG channels to record the functioning reactions brain neurons of nine subjects. By this, the researchers identified relevant multisensory features of multi-channel EEG. Event-triggered EPTNN model includes measurement error is shown in equation (18),

$$\varepsilon(h) = P_{et}(h) - P_{dp}(h) \tag{18}$$

where, $\varepsilon(h)$is utilized to quantify the mistake and the value of $\varepsilon(h)$is determined by the difference between $P_{et}(h)$and $P_{dp}(h)$. The EEG gender for classifying is defined in equation (19),

$$r_{et}(h) = r_{dp}\left(y_{f+1}\right) \tag{19}$$

where r_{et} signifies convergence rate, (h)signifies variable at time$h$,r_{dp} represents stochastic time intervals and $y_f$represents transmission range. A smaller threshold reduces measurement error and increases triggering frequency, but bigger threshold leads to larger measurements error and reduced triggering frequency. Thresholds might be fixed or relative, depending on their relationship to the trigger situation. Each type has unique advantages and drawbacks. EEG signals classification as Audio/Video is labelled in equation (20),

$$\gamma = \sigma\left|r_{dp}\left(y_{f+1}\right)\right| + \eta_2 \tag{20}$$

where η_2 is used to provide a lower limit forγ, r_{dp}specifies rate of change in another quantity and σ specifies inversely proportional to time. Furthermore, EPTNN resource optimization features make it ideal for deployment on edge devices, extending its reach into resourceconstrained situations. Particularly, its resistance to data increases its utility, allowing for successful data processing even in adverse settings. EPTNN has classified the EEG gender and signal expressed in equation (21),

$$r_{et}(h)r_{dp}(h) \geq 0 \tag{21}$$

where r_{et}implies the convergence rate, (h)implies variable at time$h$ andr_{dp}implicates rate of change in another quantity. Finally, EPTNN classified the EEG gender and signal. Due to its convenience, pertinence, AI-depend optimization approach is taken into account in EPTNN classifier. The BAOA is employed to enhance EPTNN optimum parameters(h, γ). Here BAOA is employed for turning weight with bias parameter of EPTNN.

3.5. Optimization using bitwise arithmetic optimization algorithm

In this section, Bitwise Arithmetic Optimization Algorithm (BAOA) [29] is discussed to enhance weights parameters$(h, \gamma)$of proposed EPTNN. Because BAOA relies on bitwise operations, it has excellent computing efficiency and facilitates speedier optimization procedures, among other benefits. It guarantees consistent outcomes by exhibiting strong performance in a wide range of intricate optimization tasks. Because of its simplicity and ease of implementation, BAOA is accessible for a wide range of applications and reduces mistakes. Because of its adaptability, it can handle discrete and continuous variables with ease, making it appropriate for various tasks. Because of these benefits, BAOA is an effective and adaptable approach for resolving challenging optimization issues in a variety of fields. The stepwise procedure for BAOA is described below,

Step 1: Initialization

The BAOA initialization step includes defining parameters and constraints, selecting appropriate bit representations for numbers, initializing variables, such as masks and shifts, preparing input data as needed, selecting optimization strategies, and validating the setup through testing. Cluster node formation is expressed in equation (22),

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1,i} & \cdots & r_{1,n} \\ \vdots & \ddots & \vdots & \cdots & \vdots \\ r_{i,1} & \cdots & r_{j,k} & \cdots & r_{i,n} \\ \vdots & \cdots & \vdots & \ddots & \vdots \\ r_{M,1} & \cdots & r_{M,i} & \cdots & r_{M,n} \end{bmatrix} \tag{22}$$

where Rrefers number of routes, $r$is the candidate solution, m *and* $n$is the route attributes.

Step 2: Random Generation

Input parameters are formed randomly. Based on their specific hyper parameter conditions, the optimal progressive value is selected.

Step 3: Fitness Function

Generate random solution from the initialization. It is assessed by equation (23),

$$Fitness\ Function = optimize\ (h, \gamma) \tag{23}$$

where $h$is for increase accuracy and $\gamma$is for decrease computation time.

Step 4: Determine the best solution for optimizing$h$

BAOA focuses exploitation search in promising areas to discover best answer. Each cluster head provides a fitness rating based on a variety of factors, including distance to other cluster heads, energy level, and network traffic. The overall health score is optimized through bitwise arithmetic operations, with the goal of minimizing energy usage and increasing the life span of the network. The BAOA technique allows for value modifications, unlike the usual BAOA approach that relies on fixed values. Cluster head selection can be expressed in the given equation (23),

$$ERY = \left(\left(1 - \frac{h_{current}}{h_{\max}}\right) \times h\right) \tag{23()}$$

where, $ERY$is the adaptive theta function, φtheta scale factor, $h_{current}$ represents the current iteration and $h_{\max}$indicates maximum iterations. In proposed BAOA, it used a single modulus (%) operator rather thantwo for exploration search. BAOA first generates many solutions to detect best one solution is given in equation (24),

$$h = best(E_l)\%/2(EMPO \times (VA_l - WA_l) \times ERY + WA_l) \tag{24}$$

where p^{th}solution at $h_{current}$ on l^{th}location is represented as $E_{p,l}(h_{current} + 1)$, $E$the parameter is utilized to form the cluster head selection, E_l in l^{th}location is considered $best(E_l)$, $EMPO$is the exploration based math probability, $ERY$is the adaptive theta function, VA_l *and* WA_lrepresents the upper, lower values of search space onl^{th} place.

Step 5: Update the location for optimizingγ

The suggested BAOA improves convergence and search mechanisms, resulting in a better balance between exploitation compared to the original BAOA. The proposed BAOA also uses the bitwise operator to regulate the exploitation phases. The bitwise function connects theERY, EMPO functions, resulting in a balanced exploitation search with a single adaptable parameter. Routing selection in given in equation (25),

$$\gamma > ERY\&(bitwise\,AND)\,M > EMPO \tag{25}$$

where, ERY Helps choose whether to do global or local searches, $M$is the parameter is used to form the routing, $EMPO$Controls the range of possible solutions at the levels,$bitwise\,AND$is the bit wise and operator andφtheta scale factor. Update the location can be described as given in equation (26),

$$EMPO(h_{current}) = \left(1 - \frac{h_{current}{}^{1/ERY}}{h_{\max}{}^{1/ERY}}\right) \tag{26}$$

where ERY helps to choose whether to do global or local searches, $EMPO$ controls range of possible solutions at levels, $h_{current}$ represents the current iteration and $h_{\max}$indicates maximum iterations.

Step 6:Termination

The weight parameter values $(h, \gamma)$of generator from EPTNN is enhanced with help of BAOA, iteratively repeat the step 3 until fulfil the halting criteria $R = R + 1$. Then EPTNN classify the EEG gender and signal with higher accuracy by lessening the computing time.

4. Result with discussion

The experimental outcomes of EPTNN-BCI-EEG method are discussed in this section. The implementation work is done in MATLAB with PC, 16 GB of RAM, Core i7 CPU by using the performance metrics, like recall, accuracy, RMSE, F1-score, specificity, ROC, computation time. The outcomes of EPTNN-BCI-EEG method are analysed with existing methods, like EEG signal classification (DL-BCI-EEG), a new explainable machine learning method for EEG-based brain-computer interface systems (ML-BCI-EEG) and EEG signals (DL-BCI-EEGS) respectively.

4.1. Performance metrics

This study aims to Efficient Predefined Time Adaptive Neural Network for EEG-depend BCI in Motor Execution Classification by EPTNN-BCI-EEG approach. The proposed technique is validated by the mentioned metrics. This is a main task to diagnose and classify the disease. To analyse the performance, the confusion matrix is essential to compute the performance measures.

- True Positive (TP): The classifier appropriately identifies both the presence of a particular EEG signal and the correct gender.
- True Negative (TN): The classifier appropriately identifies both the absence of a particular EEG signal and no gender difference.
- False Positive (FP): The classifier incorrectly identifies a particular EEG signal or gender difference when there is none.
- False Negative (FN): The classifier incorrectly identifies the presence of a particular EEG signal or gender difference when it exists.

4.1.1. Accuracy

It is calculated as the ratio of count of samples accurately categorized by the scheme with total count of samples using equation (27),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{27}$$

*TP*signifies true positive, *TN* signifies true negative, *FP* symbolizes false positive, *FN* signifies false negative.

4.1.2. Recall

It computes predictions made by correct number of positive predictions create by total positive forecasts by equation (28),

$$recall = \frac{TP}{(TP + FN)} \tag{28}$$

4.1.3. Specificity

Specificity weighs efficiency of method on unique class by similar to likelihood that positive sample is true. It is computed by equation (29),

$$Specificity = \frac{(TN)}{(FP + TN)} \tag{29}$$

4.1.4. F1-Score

The performance equation is provided and the evaluation parameter of F1-score is analysed by equation (30),

$$F1 - Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{30}$$

4.1.5. Root mean square error

It is a standard metric for assessing accuracy of predictive method, particularly in context of regression research. It calculates the average magnitude of errors between projected and actual values using equation (31),

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \widehat{x}_i)^2} \tag{31}$$

where $n$denotes number of data points, x_i refers observed values and $\widehat{x}_i$ refers the predicted data.

4.1.6. ROC

ROC can be stated as the ratio among changes in single variable comparative to equivalent change in another graphically, the rate of change represents slope of line. It is determined by equation (32)

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + TP} \right) \tag{32}$$

4.2. . Comparative performance analysis

The simulation outcomes of EPTNN-BCI-EEG method are portrayed in Figs. 2–7. The EPTNN-BCI-EEG approach is analysed with existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS models.

Fig. 3 depicts accuracy analysis. It is determined as ratio of correctly classified examples to total occurrences in dataset, which is usually reported as a percentage. High accuracy in EEG analysis shows that the model is competent at discriminating between different brain states or tasks based on retrieved parameters. In this context, the proposed EPTNN-BCI-EEG method attains 27.84 %, 39.12 %, 17.29 % higher accuracy for Audio/Video; 26.55 %, 37.12 %, 19.24 % higher accuracy for Male/Female compared to the existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

Fig. 4 depicts sensitivity estimation. In EEG signal processing and classification, sensitivity is the proportion of true positive events accurately classified as positive by method. High recall in EEG analysis suggests that the model is effective in capturing and properly classifying relevant EEG patterns or events, such as specific brain states or activities. In this context, EPTNN-BCI-EEG technique attains increases of 20.88 %, 36.12 %, 21.89 % higher Sensitivity for Audio/Video; 24.88 %, 35.44 %, and 22.65 % higher Sensitivity for Male/Female analysed with existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

Fig. 5 portrays specificity assessment. Specificity, also known as true negative rate, is an important parameter in classification tasks that assesses a methods ability to properly detect negative instances in dataset. Specificity in EEG signal processing and classification refers to the fraction of true negative events that the model properly recognizes as such, EEG patterns or events, lowering false alarms and improving classification accuracy. In this context, EPTNN-BCI-EEG method achieves increments of 24.38 %, 34.53 %, and 18.78 % higher Specificity for Audio/Video; 25.22 %, 30.46 %, and 20.29 % higher Specificity for Male/Female analysed with existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

Fig. 6 depicts F1-score assessment. F1-score is a statistic often used in classification problems to balance precision and recall. In EEG signal processing and classification, a high F1-score implies that meaningful EEG patterns were captured well while decreasing false detections, hence improving brain signal interpretation. In this context, EPTNN-BCI-EEG method achieves increments of 24.38 %, 34.53 %, and 18.78 % higher F1-score for Audio/Video; 28.9 %, 26.6 %, and 30.2 % higher F1-score for Male/Female analysed with existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

Fig. 7 depicts RMSE analysis. In EEG signal processing and classification, RMSE is the average error magnitude between predicted and real EEG signal values. Lower RMSE values suggest that forecasts are closer to true values, implying more accuracy in assessing EEG signal properties. Reduced RMSE allows researchers to improve the precision of EEG signal processing, resulting in more effective utilization of brain-controlled devices and better user experiences. In this context, EPTNN-BCI-EEG method achieves increments of 34.5 %, 24.3 %, and 19.7 % lower RMSE for Audio/Video; 28.4 %, 19.6 %, and 27.9 % lower RMSE for Male/Female compared to the existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

Fig. 8 depicts ROC analysis. It is a graphical representation often used to evaluate effectiveness of binary classification algorithms, such as those used in EEG data processing. A larger area under the ROC curve exemplifies that the classification model is better distinguishing among positive and negative cases. In this context, EPTNN-BCI-EEG technique attains 17.82 %, 28.95 %, 17.82 % higher ROC evaluated to the existing DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS models.

Fig. 9 portrays computation time analysis. Computation time is an

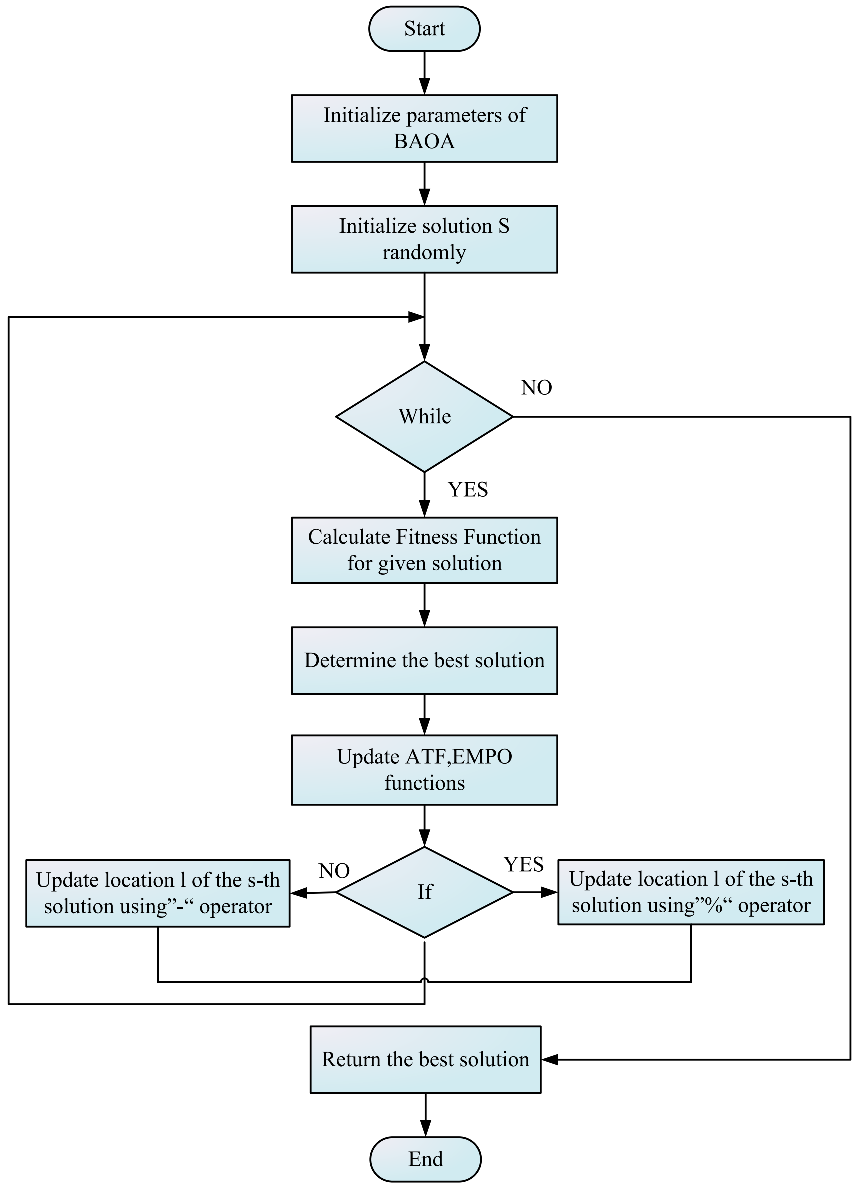

Fig. 2. Flowchart of BAOA for optimizing EPTNN.

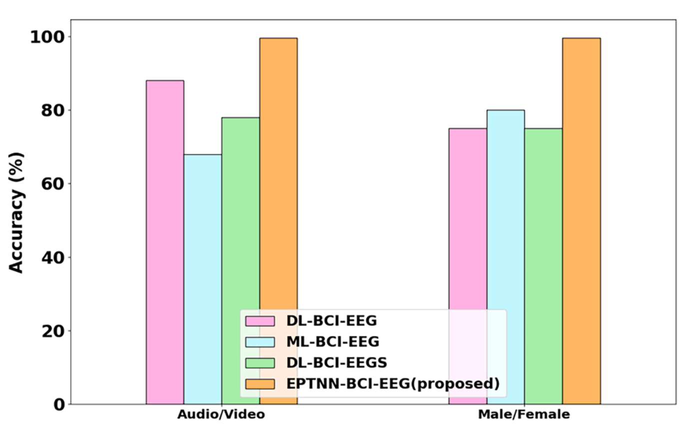

Fig. 3. Accuracy estimation.

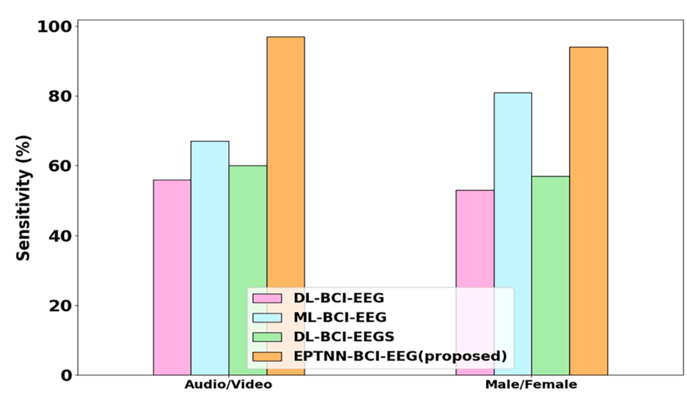

Fig. 4. Sensitivity estimation.

important consideration in EEG data processing and categorization, as it affects the efficiency and practicality of algorithms used in BCI systems. The time it takes to process EEG data, extract features, and classify

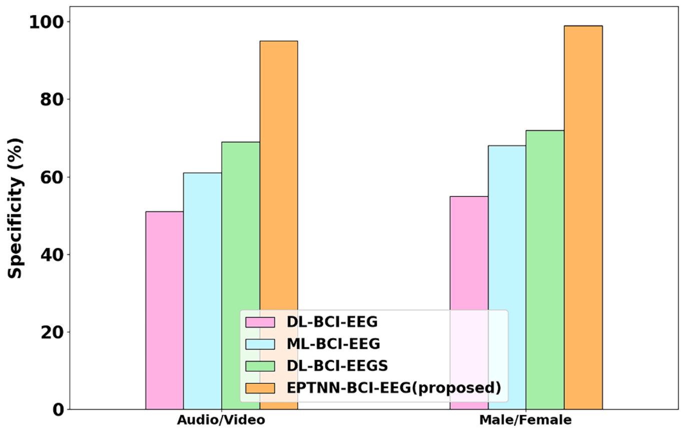

Fig. 5. Specificity assessment.

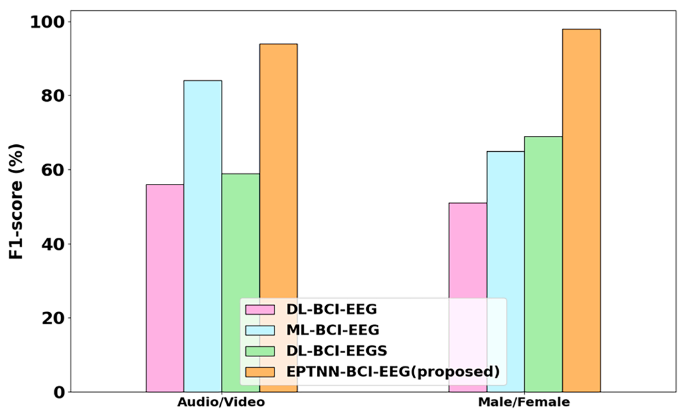

Fig. 6. F1-score assessment.

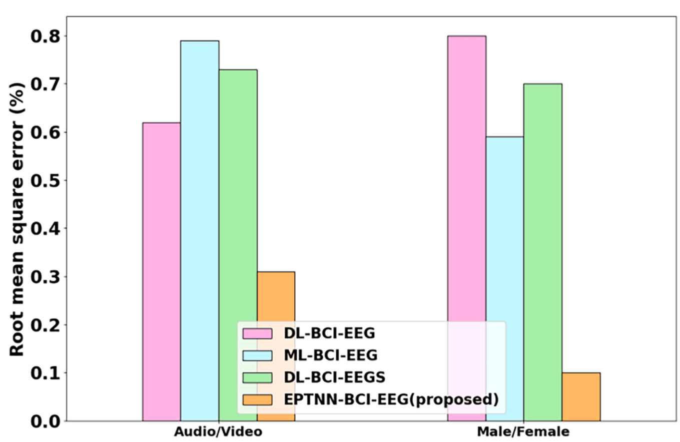

Fig. 7. RMSE analysis.

signals has an impact on BCI applications' real-time performance, which affects user experience and system responsiveness. In this context, EPTNN-BCI-EEG technique attains 33.22 %, 27.5 %, 18.2 % lower computing time are analysed with existing methods DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively.

4.3. Discussion

The results obtained from the Efficient Predefined Time Adaptive Neural Network for EEG-Based Brain-Computer Interaction in Motor

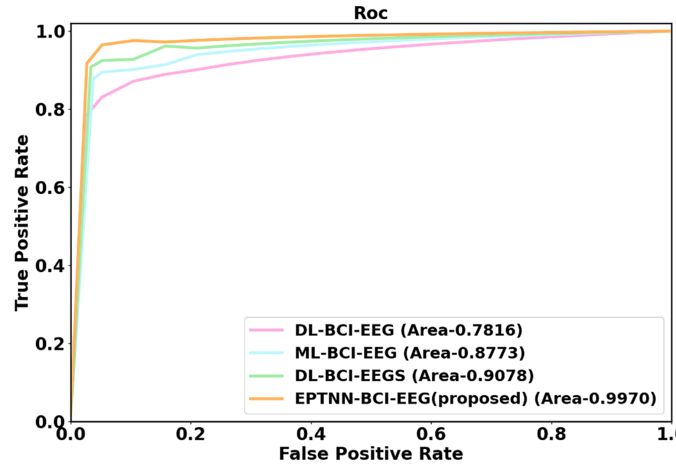

Fig. 8. ROC analysis.

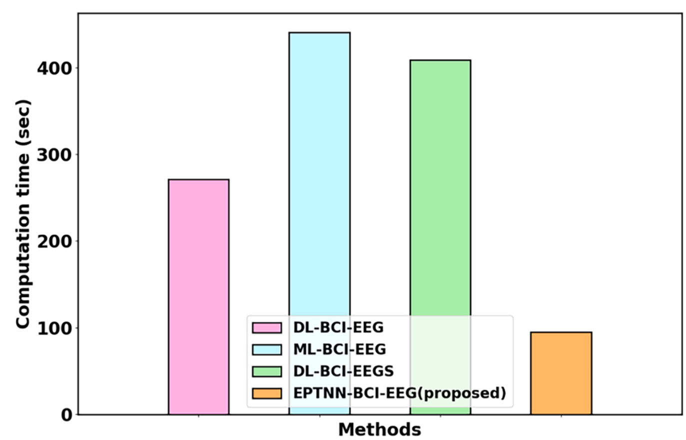

Fig. 9. Computation time analysis.

Execution Classification (EPTNN-BCI-EEG) indicate significant improvements over existing methods. The suggested method demonstrated its resilience and effectiveness in identifying motor execution (ME) tasks from EEG signals by achieving improved accuracy, recall, and specificity. These gains may be ascribed to the Bitwise Arithmetic Optimization Algorithm (BAOA) for neural network parameter optimization and the SCDT for thorough feature extraction. The improved performance measures imply that EPTNN-BCI-EEG is capable of accurately capturing the intricate temporal and spatial characteristics of EEG data, which are essential for classification. The intrinsic variability in EEG data is handled via EPTNN's dynamic flexibility, which increases its dependability for practical uses. With the help of BAOA optimization, the neural network is guaranteed to function as efficiently as possible, cutting down on calculation time without sacrificing classification accuracy. Compared to previous methods, such as the DL method by Elsayed et al. [21] the explainable ML approach by Ieracitano et al. [22] and the hybrid DL architecture by Medhi et al. [23], the proposed EPTNN-BCI-EEG demonstrates superior performance across multiple metrics. This indicates that the integration of advanced feature extraction and optimization techniques can significantly enhance the capabilities of EEG-based BCI systems.

5. Conclusion

In this section, Efficient Predefined Time Adaptive Neural Network for EEG-based BCI in Motor Execution Classification (EPTNN-BCI-EEG) was successfully executed. The EPTNN-BCI-EEG is executed in MATLAB.

The EPTNN-BCI-EEG is used to classify the EEG gender and signal. Evaluating the performance of approach, the results highlight distinct improvements and achieving 34.5 %, 24.3 %, and 19.7 % lower RMSE, 17.82 %, 28.95 %, 17.82 % higher ROC, 33.22 %, 27.5 %, 18.2 % lower Computing time are compared with existing methods like DL-BCI-EEG, ML-BCI-EEG and DL-BCI-EEGS respectively. There are several issues with the proposed EPTNN-BCI-EEG model that need to be resolved. First off, there is no diversity in EEG databases, which limits the model's applicability to different groups and circumstances. The computing needs of the model make real-time implementation difficult and require effective optimization. The emphasis on classifying people based on their gender may create biases and restrict application to other activities. Furthermore, in noisy or unstructured conditions, the model's performance can deteriorate, and there might not be any established methods for training and assessment.

Future research should concentrate on broadening the dataset range to incorporate a variety of situations, demographics, and sample sizes to overcome these constraints and enhance the generalizability and robustness of the method. It is imperative to enhance the model for real-time applications by means of either more efficient hardware or algorithmic improvements. Improving adaptive filtering strategies and sophisticated artifact removal procedures will lessen the influence of lingering artifacts. It will be more versatile if the model's categorization range is expanded to encompass different cognitive and mental states other than gender. Practical value will increase with the incorporation of adaptive learning mechanisms for ongoing real-time learning and modifications. To guarantee uniformity and comparability between investigations, consistent procedures for model training, assessment, and reporting should be established. Furthermore, putting the model to the test in chaotic or noisy settings will help identify its shortcomings and real-world applicability, which will guide future improvements.

Funding

None.

CRediT authorship contribution statement

Jose N N: Writing – original draft. **Deipali Gore:** Supervision. **Vivekanandan G:** Supervision. **Nithya E:** Supervision. **Nallarasan V:** Supervision. **Krishnakumar K:** Supervision.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

References

[1] J.H. Cho, J.H. Jeong, S.W. Lee, NeuroGrasp: real-time EEG classification of high-level motor imagery tasks using a dual-stage deep learning framework, IEEE Trans. Cybern. 52 (12) (2021) 13279–13292.
[2] F. Gurcan, N.E. Cagiltay, K. Cagiltay, Mapping human–computer interaction research themes and trends from its existence to today: a topic modeling-based review of past 60 years, Int. J. Hum. Comput. Interact. 37 (3) (2021) 267–280.
[3] X. Gu, Z. Cao, A. Jolfaei, P. Xu, D. Wu, T.P. Jung, C.T. Lin, EEG-based brain-computer interfaces (BCIs): a survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications, IEEE/ ACM Trans. Comput. Biol. Bioinform. 18 (5) (2021) 1645–1666.
[4] A. Kamble, P. Ghare, V. Kumar, Machine-learning-enabled adaptive signal decomposition for a brain-computer interface using EEG, Biomed. Signal Process. Control 74 (2022) 103526.
[5] P. Christodoulides, A. Miltiadous, K.D. Tzimourta, D. Peschos, G. Ntritsos, V. Zakopoulou, A.T. Tzallas, Classification of EEG signals from young adults with dyslexia combining a brain computer interface device and an interactive linguistic software tool, Biomed. Signal Process. Control 76 (2022) 103646.
[6] M. Nour, Ş. Öztürk, K. Polat, A novel classification framework using multiple bandwidth method with optimized CNN for brain–computer interfaces with EEG-fNIRS signals, Neural Comput. Appl. 33 (2021) 15815–15829.
[7] L. Wang, X. Huang, L. Ren, Q. Zhan, Signal analysis and classification of a novel active brain-computer interface based on four-category sequential coding, Biomed. Signal Process. Control 78 (2022) 103857.
[8] X. Geng, D. Li, H. Chen, P. Yu, H. Yan, M. Yue, An improved feature extraction algorithms of EEG signals based on motor imagery brain-computer interface, Alex. Eng. J. 61 (6) (2022) 4807–4820.
[9] M.K. Islam, P. Ghorbanzadeh, A. Rastegarnia, Probability mapping based artifact detection and removal from single-channel EEG signals for brain–computer interface applications, J. Neurosci. Methods 360 (2021) 109249.
[10] A.M. Roy, An efficient multi-scale CNN model with intrinsic feature integration for motor imagery EEG subject classification in brain-machine interfaces, Biomed. Signal Process. Control 74 (2022) 103496.
[11] K. Das, R.B Pachori, Electroencephalogram based motor imagery brain computer interface using multivariate iterative filtering and spatial filtering, IEEE Trans. Cogn. Dev. Syst. (2022).
[12] X. Meng, S. Qiu, S. Wan, K. Cheng, L. Cui, A motor imagery EEG signal classification algorithm based on recurrence plot convolution neural network, Pattern Recognit. Lett. 146 (2021) 134–141.
[13] P. Arpaia, F. Donnarumma, A. Esposito, M. Parvis, Channel selection for optimal EEG measurement in motor imagery-based brain-computer interfaces, Int. J. Neural Syst. 31 (03) (2021) 2150003.
[14] X. Wang, R. Yang, M. Huang, An unsupervised deep-transfer-learning-based motor imagery EEG classification scheme for brain–computer interface, Sensors 22 (6) (2022) 2241.
[15] G. Acampora, P. Trinchese, A. Vitiello, A dataset of EEG signals from a single-channel SSVEP-based brain computer interface, Data Brief 35 (2021) 106826.
[16] M. Varlı, H. Yılmaz, Multiple classification of EEG signals and epileptic seizure diagnosis with combined deep learning, J. Comput. Sci. 67 (2023) 101943.
[17] F. Hassan, S.F. Hussain, S.M Qaisar, Fusion of multivariate EEG signals for schizophrenia detection using CNN and machine learning techniques, Inf. Fusion 92 (2023) 466–478.
[18] O.S. Lih, V. Jahmunah, E.E. Palmer, P.D. Barua, S. Dogan, T. Tuncer, U.R. Acharya, EpilepsyNet: novel automated detection of epilepsy using transformer model with EEG signals from 121 patient population, Comput. Biol. Med. 164 (2023) 107312.
[19] M.T. Sadiq, H. Akbari, S. Siuly, Y. Li, P. Wen, Alcoholic EEG signals recognition based on phase space dynamic and geometrical features, Chaos Solit. Fractals 158 (2022) 112036.
[20] Z. Aslan, M. Akin, A deep learning approach in automated detection of schizophrenia using scalogram images of EEG signals, Phys. Eng. Sci. Med. 45 (1) (2022) 83–96.
[21] N.E. Elsayed, A.S. Tolba, M.Z. Rashad, T. Belal, S. Sarhan, A deep learning approach for brain computer interaction-motor execution EEG signal classification, IEEE Access 9 (2021) 101513–101529.
[22] C. Ieracitano, N. Mammone, A. Hussain, F.C Morabito, A novel explainable machine learning approach for EEG-based brain-computer interface systems, Neural Comput. Appl. 34 (14) (2022) 11347–11360.
[23] K. Medhi, N. Hoque, S.K. Dutta, M.I Hussain, An efficient EEG signal classification technique for brain–computer interface using hybrid deep learning, Biomed. Signal Process. Control 78 (2022) 104005.
[24] H. Zhu, D. Forenzo, B. He, On the deep learning models for EEG-based brain-computer interface using motor imagery, IEEE Trans. Neural Syst. Rehabil. Eng. 30 (2022) 2283–2291.
[25] S. Abenna, M. Nahid, A. Bajit, Motor imagery based brain-computer interface: improving the EEG classification using Delta rhythm and LightGBM algorithm, Biomed. Signal Process. Control 71 (2022) 103102.
[26] S. Bagherzadeh, A. Shalbaf, A. Shoeibi, M. Jafari, R. San Tan, U.R. Acharya, Developing an EEG-based emotion recognition using ensemble deep learning methods and fusion of brain effective connectivity maps, IEEE Access (2024).
[27] L. Meng, X. Jiang, J. Huang, Z. Zeng, S. Yu, T.P. Jung, D. Wu, EEG-based brain-computer interfaces are vulnerable to backdoor attacks. IEEE Trans. Neural Syst. Rehabil. Eng., 2024.
[28] https://openbci.com/community/publicly-available-eeg-datasets/ 2024.
[29] A. Bellés, D. Medina, P. Chauchat, S. Labsir, J. Vilà-Valls, Robust M-type error-state Kalman filters for attitude estimation, in: Proceedings of the 2023 31st European Signal Processing Conference (EUSIPCO), IEEE, 2023, pp. 840–844.
[30] Z. Qi, Y. Ning, L. Xiao, Z. Wang, Y. He, Efficient predefined-time adaptive neural networks for computing time-varying tensor moore–penrose inverse, IEEE Trans. Neural Netw. Learn. Syst. (2024).
[31] N. Talpur, S.J. Abdulkadir, E.A.P. Akhir, M.H. Hasan, H. Alhussian, M.H. A. Abdullah, A novel bitwise arithmetic optimization algorithm for the rule base optimization of deep neuro-fuzzy system, J. King Saud Univ. Comput. Inf. Sci. 35 (2) (2023) 821–842.

[32] A.H.M. Rubaiyat, S. Li, X. Yin, M. Shifat-E-Rabbi, Y. Zhuang, G.K. Rohde, End-to-end signal classification in signed cumulative distribution transform space, IEEE Trans. Pattern Anal. Mach. Intell. (2024).
[33] Y. Hu, Optimized multiscale deep bidirectional gated recurrent neural network fostered practical teaching of university music course, J. Intell. Fuzzy Syst. (2024) 1–14 (Preprint).
[34] N.E. Elsayed, A.S. Tolba, M.Z. Rashad, T. Belal, S. Sarhan, A deep learning approach for brain computer interaction-motor execution EEG signal classification, IEEE Access 9 (2021) 101513–101529.