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ORIGINAL

Advanced Predictive Framework for Early Detection and Classification of Psychiatric Conditions Using EEG Data

Marco predictivo avanzado para la detección precoz y la clasificación de afecciones psiquiátricas mediante datos de EEG

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ABSTRACT

Psychiatric illnesses, such as depression, generalized anxiety disorder, and schizophrenia, tend to be characterized by mild neurophysiological markers that make early diagnosis difficult. The greatest limitation of present diagnostic approaches is the failure to detect such mild brainwave anomalies with good accuracy, especially during the early stages of the disorders. This research presents a new predictive model for the early classification and diagnosis of psychiatric diseases from Electroencephalogram (EEG) signals. The framework employs the use of the Archerfish Hunting Optimizer Tuned Spiking Neural Network (AHO-SNN). This hybrid approach combines the computational effectiveness of an evolution-inspired optimizer with spiking neural networks' (SNNs) temporal processing ability. The AHO algorithm is used to fine-tune the SNN's synaptic weights in order to make the SNN more sensitive to neural oscillations and cortical pathologies related to psychiatric disorders. The projected AHO-SNN results are precision 94 %, f1-score 94 %, accuracy 96 %, and recall 92 %. The outcomes reveal that the AHO-SNN approach obtains high diagnostic precision, separating psychiatric patients from healthy controls based on the patterns of neural activity, for instance, theta and alpha band anomalies. The technique has enormous potential to support improved early psychiatric diagnosis, facilitating timely interventions and customized treatment strategies. Future research will center on integrating multimodal biomarkers and real-time monitoring to further enhance diagnostic accuracy and increase clinical utility.

Keywords: Electroencephalogram (EEG); Early Detection; Psychiatric Disorders; Real-Time Diagnostic; Clinical Practice.

RESUMEN

Las enfermedades psiquiátricas, como la depresión, el trastorno de ansiedad generalizada y la esquizofrenia, tienden a caracterizarse por marcadores neurofisiológicos leves que dificultan el diagnóstico precoz. La mayor limitación de los enfoques diagnósticos actuales es la incapacidad para detectar estas anomalías leves de las ondas cerebrales con buena precisión, especialmente durante las primeras fases de los trastornos. Esta investigación presenta un nuevo modelo predictivo para la clasificación y el diagnóstico precoz de enfermedades psiquiátricas a partir de señales de electroencefalograma (EEG). El marco emplea el uso de la Red Neuronal de Spiking Sintonizada con el Optimizador de Caza Archerfish (AHO-SNN). Este enfoque híbrido combina la eficacia computacional de un optimizador inspirado en la evolución con la capacidad de procesamiento temporal de las redes neuronales con picos (SNN). El algoritmo AHO se utiliza para ajustar los pesos sinápticos de la SNN con el fin de hacerla más sensible a las oscilaciones neuronales y a las patologías corticales relacionadas con los trastornos psiquiátricos. Los resultados proyectados de AHO-SNN son precisión 94 %, puntuación f1 94 %, exactitud 96 % y recuperación 92 %. Los resultados revelan que el enfoque AHO-SNN obtiene una alta precisión diagnóstica, separando a los pacientes psiquiátricos de los controles sanos basándose en los patrones de actividad neuronal, por ejemplo, anomalías en las bandas theta y alfa. La técnica tiene un enorme potencial para apoyar la mejora del diagnóstico psiquiátrico precoz, facilitando intervenciones oportunas y estrategias de tratamiento personalizadas. La investigación futura se centrará en la integración de biomarcadores multimodales y la monitorización en tiempo real para mejorar aún más la precisión diagnóstica y aumentar la utilidad clínica.

Palabras clave: Electroencefalograma (EEG); Detección Precoz; Trastornos Psiquiátricos; Diagnóstico en Tiempo Real; Práctica Clínica.

INTRODUCTION

Early detection and classification of mental illness must occur in order to treat and intervene effectively. Electroencephalography (EEG) became the ideal method of testing neural activity of most mental illnesses because it is a non-surgical test; it provides excellent temporal resolution, and is able to detect brainwave patterns corresponding to cognition and emotional status.[1] The conventional diagnosis procedures rely heavily on subjective judgments and clinical check-ups, leading to delays in diagnosis and treatment plan inconsistencies.[2]

EEG is a straightforward neurophysiological technique that makes use of head probes to evaluate the brain's electric signals.[3] It records brain wave patterns generated by the activity of neurons, providing valuable insight into cognitive processes, sleep disorders, epilepsy, and neurological disease.[4] EEG is commonly used in medical diagnosis, brain-computer interfaces, and mental state exploration, as it allows excellent temporal resolution for monitoring brain activity in real time.[5]

A broad spectrum of mental health conditions that affect emotion, thought, and behavior are referred to as psychiatric issues. These conditions can affect daily functioning and general health. These illnesses, which include depression, anxiety disorders, schizophrenia, and bipolar disorder, originate in intricate relationships among biological, genetic, environmental, as well as psychological variables. Advances in neuroscience as well as psychology have advanced diagnosis and treatment through the integration of medicine, psychotherapy, and lifestyle modifications.[6] Treatment of psychiatric illnesses is paramount to breaking the stigma, promoting early intervention, and enhancing mental health care procedures to enhance the quality of life for individuals suffering from these conditions.

Early diagnosis and typification of psychiatric disorders with EEG data take advantage of sophisticated signal processing and methodologies to detect patterns of neural activity related to mental illness. EEG offers a painless and low-cost means to record brain function, allowing early diagnosis and intervention. Researchers categorize disorders like depression, schizophrenia, and anxiety by analyzing EEG signals, enhancing diagnostic accuracy and tailored treatment. The goal of this research is to present a sophisticated predictive model for the early identification and classification of psychiatric disorders by EEG signals.

A Machine Learning (ML) approach was applied to evaluate EEG information from numerous channels for the diagnosis of schizophrenia, which provided superb accuracy, sensitivity, and specificity.[7] The approach performed better while compared to other signal decomposition methods based on computational efficiency, while performance differs with larger datasets and other patient conditions.

The ML focused on the need for biomarkers to make distinctions between Bipolar Disorder (BD) and Major Depressive Disorder (MDD) at the early depression phase.[8] The method investigated widespread ML algorithms applicable in brain image classification, highlighting the investigation that classified MDD from MRI data, as well as predicting treatment outcomes. The process also examines complications, possible areas, and limits in creating successful biomarkers in depression.

The research assessed ML methods using Deep Learning (DL) and Support Vector Machine (SVM) methods that were conducted to investigate the feasibility of employing EEG data for assessment of stress.[9] Eleven subject-dependent approaches were completed, combining EEG data of persons with ASD and neurotypical brains. The models combined traditional brain-computer interface (BCI) techniques with DL models. Long ShortTerm Memory (LSTM) and a two-layer Recurrent Neural Network (Two-layer RNN) effectively and accurately categorized mental stress conditions. The methodology established the potential for real-time stress assessment and adaptive intervention through closed-loop respiration modulation.

EEG and ML methods were used to examine cognitive deterioration following Deep Brain Stimulation (DBS) in Parkinson's disease (PD).[10] Extreme cognitive scores were classified using a Random Forest (RF) model with feature selection. The classifier effectively distinguished cognitive performance, while occipital Peak Alpha Frequency (PAF) showed lower accuracy. Predicted class probabilities correlated negatively with cognitive

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function, suggesting EEG's potential for cognitive profiling in DBS screening, though broader validation is needed.

EEG-based functional connectivity metrics combined with DL were explored for classifying cognitive workload levels.[11] EEG information collected from contributors completing the n-back mission was analyzed to extract Mutual Information (MI), Phase Locking Value (PLV), and Phase Transfer Entropy (PTE). Subject-specific classifiers involving Convolutional-LSTM (Conv-LSTM), Convolutional Neural Networks (CNNs), and LSTM performed effectively in classification. The results, indicating great accuracy in subject-specific categorizations, demonstrate the effectiveness with which functional connectivity measures are integrated with DL for cognitive workload evaluation.

METHOD

EEG-based prediction frameworks have been demonstrated to be crucial for the early diagnosis and categorization of mental disorders. The AHO-SNN model enables accurate classification, while the AHO method optimizes synaptic weights. By distinguishing neurological irregularities, the classification improves diagnostic accuracy and predictive stability. The overall flow is illustrated in figure 1.

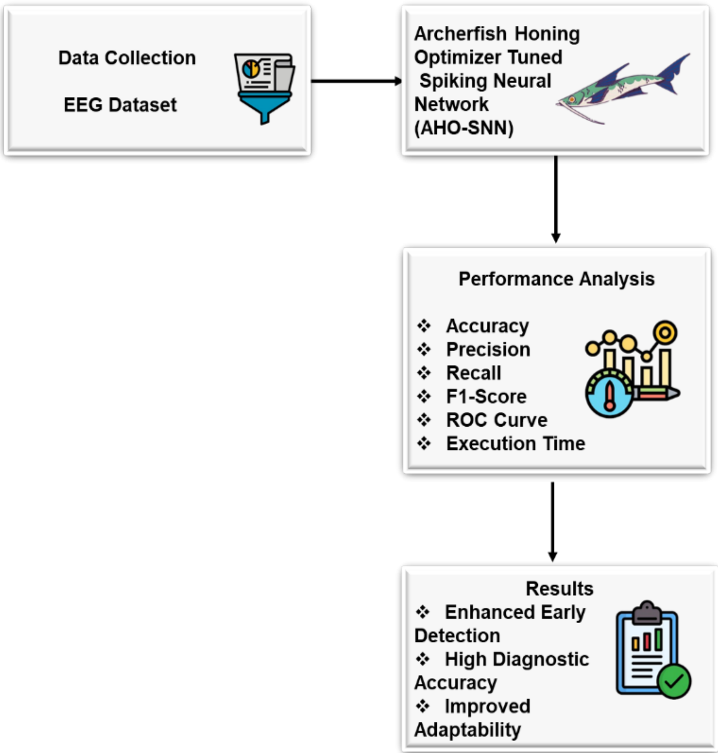

Figure 1. Proposed Flow

Data Collection

EEG data for the investigation was extracted from the EEG Dataset for Schizophrenia on Kaggle (https://www.kaggle.com/datasets/shashwatwork/eeg-psychiatric-disorders-dataset?utm_source=chatgpt.com).

A psychiatric disorder is a mental illness determined by an expert in mental health that significantly impairs the individual's thoughts, moods, and/or behavior, increasing their risk of impairment, suffering, dying, or loss of liberty. Furthermore, those symptoms must be more severe than normal in response to a distressing occurrence, including natural sadness, following the death of a family member.

Archerfish Hunting Optimizer Tuned Spiking Neural Network (AHO-SNN) for Psychiatric Disorder Classification

The proposed AHO-SNN approach combines an Archerfish Hunting Optimizer (AHO) with Spiking Neural Networks (SNNs) to enhance the identification of mental diseases using EEG data. By recovering synaptic weights, the AHO approach reduces the susceptibility of the SNN to brain oscillations, especially anomalies in the theta and alpha bands. Early detection and individualized planning for therapy are made possible by the technique's recovery of diagnostic accuracy.

Spiking Neural Network (SNN)

After the data collection process, the data has been sent as input to the SNN technique. EEG signals are analysed using the SNN, by taking advantage of its ability to efficiently produce time dependent structures.

The method isolates spike trains and decodes EEG signals to mimic the operation of organic neurons. Spiking neuron models, such as the Izhikevich Model (IM), Hodgkin-Huxley (HH), Integrate-and-Fire (IF), and Spike Response (SR), are commonly utilized for EEG-based psychological classifications. The representations' ability to replicate the feasibility of computation and biological neuron function differs.

The process follows the equation (1):

$$D_n \frac{cu}{cs} = J(s), \nu \leftarrow \nu_{rest} \approx When\ \nu \geq \nu_{jg} \quad (1)$$

Where:
J(s)-represents the input current.
v_{jg}-is the firing threshold.
v-denotes the membrane potential.
D_n-represents the membrane capacitance.

A spike is released when the potential reaches v_{jg} returning it to its resting condition v_{rest}.

The Leaky Integrate-and-Fire (LIF) hypothesis, which presents a decay factor that restricts the indefinite accumulation of potential, has been included to enhance temporal patterns. The governing equation is (2):

$$S_{leak} \frac{cu}{cs} = [U(s) - \nu_{rest}] + q_n J(s), \nu \leftarrow \nu_{rest} \approx When \approx \nu \geq \nu_{jg} \quad (2)$$

Where:
q_n-is the membrane resistance
S_{leak}= q_n D_n is the membrane time constant.

This model improves spike-based feature extraction, enabling effective psychiatric condition classification.

By utilizing SNN, the system efficiently processes EEG signals with reduced computational cost while preserving biologically plausible neuron dynamics. This enhances classification accuracy by capturing temporal dependencies in EEG data.

Archerfish Hunting Optimizer (AHO)

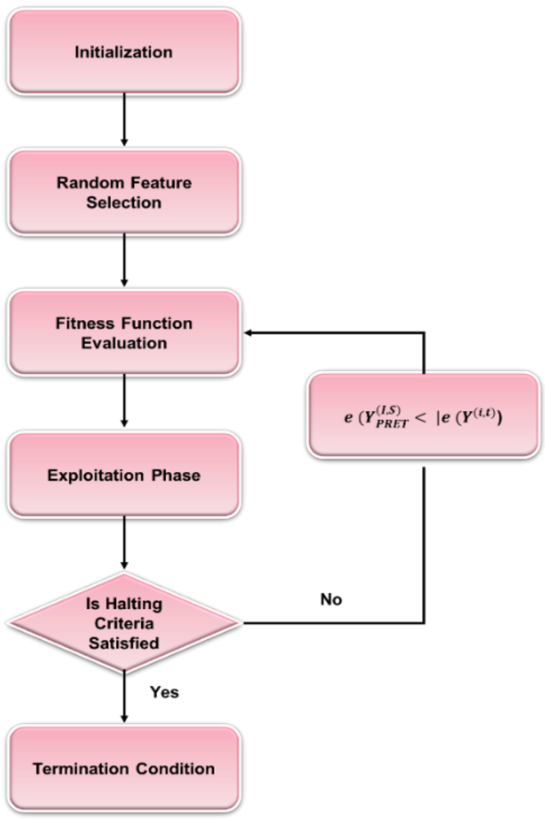

Figure 2. Flowchart for AHO

The Archerfish Hunting Optimizer (AHOA) is a nature-inspired metaheuristics system that appropriates the unique hunting behaviours of archerfish, such as shooting and jumping, identifies the most significant traits while eliminating unnecessary ones. The performance enhances feature selection by sustaining optimal stability between exploration and exploitation. The flowchart is given in figure 2.

Step 1: Initialization

The feature-selection strategy begins by establishing a searching space, with each possible solution indicating an assortment of characteristics. The initial population comprises several archerfish, each located within feature space. The location of archerfish is represented in equation (3):

$$Z^{(b,a)} = \left(\lambda_1 \times y_1^{max} - y_1^{min} + y_c^{min}\right) + y_1^{min}, .., \lambda_c \times (y_c^{max} - y_c^{min}) \quad (3)$$

Where:
c denotes the dimensionality of the feature space.
$Z^{(b,a)}$ is the current position of the archerfish.
y_1^{min} and y_c^{max} describe the feature selection boundaries.
λ is a random variable uniformly distributed ranging from 0 and 1.

Step 2: Random Feature Selection

Each archerfish randomly selects a subset of features for evaluation. The selection process is guided by the problem-specific constraints and hyperparameter tuning to ensure diversity among solutions.

Step 3: Fitness Function Evaluation

The performance of each selected feature subset is assessed using an objective function that optimizes classification accuracy and minimizes redundancy. The fitness function is defined as equation (4):

$$Fitness\ Function\ =\ Optimizing[\text{selecting features of NSL} - \text{KDD dataset}] \quad (4)$$

This ensures that only the most informative features are retained for subsequent classification tasks.

Step 4: Archerfish Jumping and Shooting behaviors

Archerfish employ two distinct strategies for hunting: shooting and jumping, which are adapted for feature selection.

Jumping behavior

Jumping is a more energy-intensive process but provides a higher probability of capturing prey. The position of an archerfish is updated based on the Euclidean distance between the prey (optimal feature subset) and its current position (equation 5):

$$Z^{(b,a+1)} = Z^{(b,a)} + f^{-\left\|z_{prey}^{b,a} - Z^{(b,a)}\right\|_2} (Z_{Prey}^{(b,a)} - Z^{(b,a)}) \quad (5)$$

Where:
$Z^{(b,a)}$ is the current position of the archerfish.
$Z^{(b,a+1)}$ is the updated position.
$z_{prey}^{(b,a)}$-$Z^{(b,a)}$ represents the best feature subset.
f is a random learning coefficient.

Shooting behavior

Shooting is a more precise but less exhaustive process. Archerfish adjust their positions based on refraction effects at the air-water interface while targeting prey. The new feature selection is determined as follows in equation (6):

$$(Z_{Prey}^{(b,a)} =\ Z^{(b,a)} + (0, \dots \frac{d^2}{2m} \times sin^2\theta \dots 0 + \varepsilon) \quad (6)$$

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Where:
m represents motion due to gravity.
$\sin^2\theta$ accounts for air resistance.
d^2 is the attractiveness ratio for a specific feature subset.
ε denotes refraction effects.

Step 5: Balancing Exploration and Exploitation

The optimization process alternates between exploitation (fine-tuning the optimal solution) and exploration (looking for a variety of possibilities). The exploitation phase, known as swinging on the water surface, ensures that archerfish focus on local refinement to prevent premature convergence, equation (7):

$$y_n^{new2} = \{y_n(s) + q\left(1 - \frac{s}{S}\right).(2q-1)y_n(s) \quad (7)$$

Where:
q is a random exploration parameter.
s represents the present iteration.
S denotes the maximal repetition count.

The position is updated using equation (8):

$$y_n(s+1) = \begin{cases} y_n^{new2}, if P(y_n^{new2}) \leq P(y_n) \\ y_n(s)\ else \end{cases} \quad (8)$$

Where:
$P(y_n)$ signifies the fitness value of the candidate resolution.
$P(y_n^{new2})$ denotes the fitness value of the new solution.

Step 6: Termination and optimal Feature selection

Until such a termination condition is met, such as reaching convergence or the number of iterations, the stage goes on. Once selected with caution, the ultimate set of best features can be used for model prediction or classification.

By efficiently eliminating redundant and unnecessary features, the AHOA-based feature selection approach enhances model performance in classification problems. AHOA improves computational performance, preserves a better balance between exploration and exploitation, and achieves a better selection accuracy compared to other optimization algorithms.

The AHO-SNN approach utilizes the Archerfish Hunting Optimizer to fine-tune the synaptic weights of SNNs for better detection of faint neurophysiological markers that are indicative of psychiatric diseases. This maximizes the classification performance and early diagnosis ability, and facilitates more efficient differentiation between controls and patients and lower diagnostic uncertainty. This integration increases the computational efficiency and enables real-time analysis, making it a strong instrument for early psychiatric diagnosis and also for individualized treatment planning.

RESULTS

The aim of the research is to enhance a state-of-the-art prediction system using EEG data for early identification and classification of psychiatric disorders. Testing was conducted using Python 3.11.4 on a high-performance computer with 64 GB RAM and an AMD Ryzen 5900X CPU running Windows 11, resulting in more effective estimation and reliable model analysis. The strategy proposed makes use of the Archerfish Hunting Optimizer Tuned Spiking Neural Network (AHO-SNN), in which the AHO algorithm enhances the synapse weight to enhance the model's response to neurophysiological fluctuations.

Performance Evaluation

The efficiency of the suggested technique is assessed in this research employing accuracy, precision, f1-score, recall, execution time, and Receiver Operating Characteristic (ROC) curve. The proposed AHO-SNN framework demonstrates high accuracy in detecting and classifying psychiatric disorders using EEG signals.

Accuracy: Accuracy is the measure of the general correctness that the AHO-SNN framework demonstrates in categorizing psychiatric disorders using EEG signals. It is calculated as the number of subject cases correctly identified, whether healthy controls or psychiatric patients, divided by the total predictions made. This is intended to bring an overall assessment of performance concerning the model. If accuracy is above average or high, the framework is assumed to be a very useful one, aiding detection of the psychiatric misclassified high conditions with less number of errors, as defined in equation (9).

$$Accuracy = \frac{\text{TN+TP}}{\text{TN+TP+FN+FP}} \quad (9)$$

Precision: The precision of evaluating the classifier expresses the ratio of correctly identified instances of schizophrenia compared to all instances that are considered to be psychopathological. It describes how much the model can be trusted to prevent false positives. High precision indicates that the framework assures that healthy subjects are not misclassified as having mental disorders. Hence, higher precision indicates that the AHO-SNN model effectively minimizes the rate of false diagnosis, thereby increasing the degree of confidence in the diagnosis. The precision is calculated as follows in equation (10):

$$Precision = \frac{truepositive}{\text{falsenegative+true positive}} \quad (10)$$

Recall: It assesses the proportion of actual instances correctly identified to get a sense of the system's psychiatric disease recognition capability. It is important so that the patients with psychiatric illnesses are not missed. The goal of recall-power measurement is to reduce false negatives, which is critical for early diagnosis. A large value of recall indicates the system's sensitivity to subtle neurophysiological markers, thus improving the accuracy of early detection, as given in equation (11).

$$Recall = \frac{true\ positive}{false\ positive+true\ positive} \quad (11)$$

F1-Score: It measures recall and precision to deliver a complete assessment of the strategy's diagnostic effectiveness. It represents the balanced average of precision and recall. The purpose is to provide an overall assessment of classification reliability. A high F1-score in the AHO-SNN framework indicates that it maintains strong predictive power while minimizing both types of errors, as defined in equation (12).

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

Table 1 and figure 3 show the results for accuracy, precision, recall, and f1-score. The findings of the proposed AHO-SNN technique are 96 % in accuracy, 94 % in precision, 92 % in recall, and 94 % in f1-score.

Table 1. Numerical outcomes of the proposed method

Metrics	Values (%)
Accuracy	96
Precision	94
Recall	92
F1-score	94

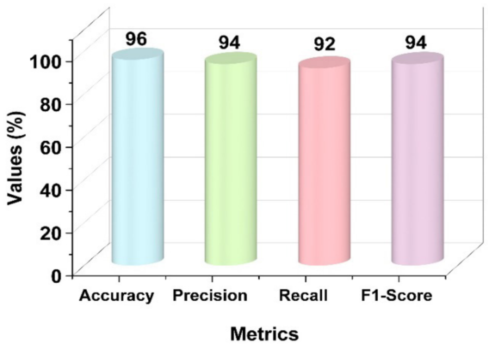

Figure 3. Graphical representation of proposed outcomes

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ROC Curve: To assess the AHO-SNN method's classification performance in the detection of psychiatric conditions based on EEG signals, the ROC curve is being utilized. It compares the True Positive Rate (TPR) against the False Positive Rate (FPR) at several limits. The outcomes of the ROC are presented in figure 4. It demonstrates the model's effectiveness, with AUC quantifying performance. The higher AUC indicates better discrimination, validating the model's reliability for classification tasks.

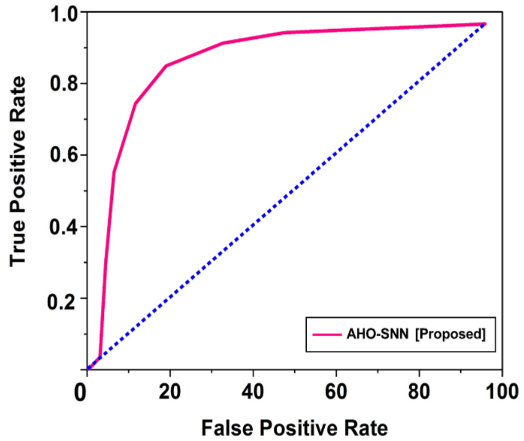

Figure 4. Graphical representation of ROC

Execution Time: It denotes the computational efficiency of AHO-SNN in processing EEG signals toward psychiatric disorder classification, which represents time for feature selection, training a model, and classifying the EEG data. It illustrates processing time and analyzes processing speed performance and real time applicability. The findings of execution time are displayed in figure 5. The results indicate an optimized and real execution time at which speed/accuracy balance for effective early diagnosis is achieved.

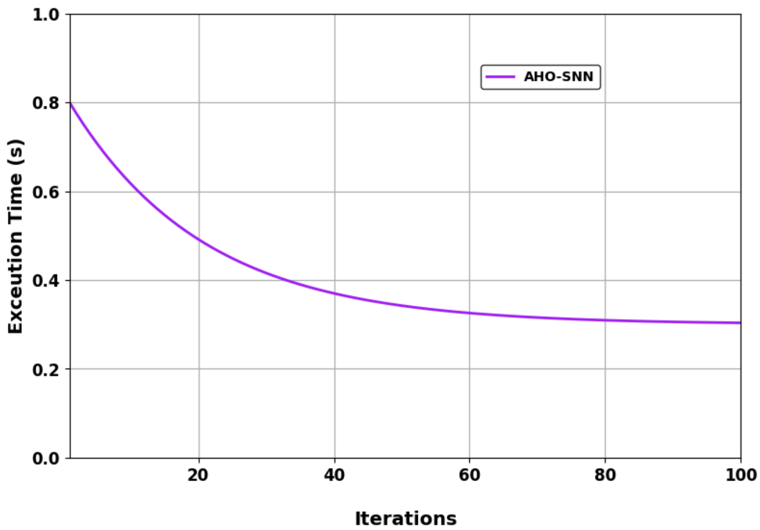

Figure 5. Graphical representation outcomes of execution time

DISCUSSION

The suggested AHO-SNN framework efficiently improves early psychiatric disorder detection by leveraging EEG signals. The AHO-SNN model demonstrated superior classification performance by effectively capturing subtle neurophysiological markers associated with psychiatric disorders. The integration of the AHO with SNNs enhances synaptic weight adjustments, improving sensitivity to understate neurophysiological markers. Investigational results establish high diagnostic accuracy, especially in distinguishing healthy individuals from those with psychiatric conditions based on theta and alpha band anomalies. The model's ability to capture these neural patterns allows for early intervention, addressing a critical restriction in conventional diagnostic methods. Despite its effectiveness, integrating multimodal biomarkers and real-time monitoring might further improve diagnostic precision and flexibility. Future developments may include combining additional physiological and behavioral data to enhance classification outcomes and develop the technique's clinical relevance for personalized treatment strategies.

CONCLUSIONS

The carried-out AHO-SNN framework correctly improves the early detection and category of psychiatric problems utilizing EEG indicators. By leveraging the AHO to pleasant-song synaptic weights, the technique will increase sensitivity to neural oscillations, allowing accurate version among healthful people and people with psychiatric situations. The numerical findings of the proposed method are accuracy of 96 %, recall of 92 %, precision of 94 %, and f1-score of 94 %. The AHO-SNN model demonstrated greater accuracy in identifying small neurophysiological indicators. The method holds giant capacity for advancing psychiatric analysis, permitting earlier intervention and customized remedy techniques. Future research will focus on combining multimodal biomarkers and real-time tracking to similarly improve diagnostic precision and clinical applicability, ensuring a greater, complete and adaptable framework for mental health evaluation.

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None.

CONFLICT OF INTEREST

Authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

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