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Deep Hybrid Neural Network for Automated Epileptic Seizure Detection from EEG Signals using MATLAB

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Abstract: Epilepsy is a long-term neurological disorder marked by recurring seizures resulting from irregular neuronal activity in the brain. Prompt and precise identification of epileptic events from electroencephalogram (EEG) signals is essential for successful clinical diagnosis. This study introduces a Deep Hybrid Neural Network framework that combines Convolutional Neural Networks (CNN) with the Aquila Optimizer (AO) for the automatic detection of epileptic seizures utilizing EEG data in MATLAB. The suggested system initially converts EEG signals into time–frequency spectrograms through Short-Time Fourier Transform (STFT), allowing the CNN to capture advanced spatial–spectral characteristics. The AO algorithm further improves these features by tuning hyperparameters and choosing the most distinguished feature subsets, thereby boosting classification accuracy and decreasing computational overhead. The Bonn University EEG dataset was used to evaluate the model through a 5-fold cross-validation method, attaining an average accuracy of 95.62%, where per-class sensitivity and specificity surpassed 97%. Comparative evaluation showed that the CNN–AO hybrid surpassed traditional classifiers in terms of accuracy and convergence reliability. These findings demonstrate the effectiveness of the proposed hybrid framework for automated epileptic seizure detection and suggest its potential suitability for future real-time and wearable healthcare applications following further deployment-oriented validation.

Index Terms: Epilepsy, EEG, Deep Learning, Hybrid Neural Network, Aquila Optimizer, MATLAB

1. Introduction

Epilepsy is a neurological disorder due to which over 50 million people are affected worldwide. It can be identified by sudden, recurrent seizures due to excessive and synchronous neuronal discharges in the brain. Electroencephalography is the most reliable non-invasive method for monitoring epileptic activity by recording brain electrical potentials over the period. The EEG recordings reviewed by neurologists manually is time-consuming and prone to human error, thereby increasing the demand for automated and reliable seizure detection systems. EEG classification has widely been performed by traditional machine learning techniques, including SVM, k-NN, and Decision Trees. While most of these methods depend on handcrafted statistical and spectral features, their performance is often constrained by noise sensitivity and variability of the datasets. By contrast, deep learning models, especially CNNs, have demonstrated exceptional capability in automatic discriminative feature extraction from raw EEG data. However, CNNs often face such problems as over-fitting, suboptimal tuning of hyperparameters, and redundancy in extracted features while processing small biomedical datasets. This paper proposes a Deep Hybrid Neural Network framework that couples CNN-based deep feature extraction with the Aquila Optimizer for adaptive feature selection and parameter optimization. First, raw EEG signals are transformed into time-frequency spectrograms using the STFT, which allows for effective spectral-temporal representation. After that, the AO algorithm further refines CNN-extracted features by filtering and thus saving only the subsets which contain crucial information. The CNN-AO hybrid model was applied on the Bonn EEG dataset and showed accurate and reliable classification performance, proving that it can provide a robust and efficient real-time epileptic seizure detection system.

The main contributions of this work are summarized as follows:

- Development of a unified STFT–CNN–AO framework for automated multi-class EEG seizure classification.
- Transformation of EEG signals into spectrogram representations to jointly capture temporal and frequency-domain seizure characteristics.
- Integration of Aquila Optimizer for adaptive feature refinement and hyperparameter optimization, reducing feature redundancy and improving learning efficiency.
- Evaluation of the proposed framework on four EEG states (Healthy Eyes Open, Healthy Eyes Closed, Interictal, and Seizure) using a 5-fold cross-validation strategy.
- Comparative analysis of AO-based optimization against BDFA to demonstrate improved convergence behaviour and feature-selection effectiveness.

2. Literature Review

Automated epileptic seizure detection from EEG signals has evolved significantly in recent years. The increasing availability of deep-learning techniques has enabled automatic feature extraction directly from EEG recordings, thereby reducing dependence on manual feature engineering. Convolutional Neural Networks (CNNs) have emerged as one of the most widely adopted architectures for EEG-based seizure detection due to their ability to learn hierarchical representations from raw signals and time-frequency images. Acharya et al. [1] demonstrated the effectiveness of deep CNNs for automated seizure detection and reported significant improvements over conventional classifiers. However, CNNs primarily focus on local feature extraction and often struggle to capture long-range temporal dependencies present in EEG signals. Furthermore, their performance may deteriorate when trained on relatively small biomedical datasets, leading to overfitting and reduced generalization.

To address temporal modelling challenges, recurrent architectures and hybrid deep-learning models have been explored. Tsiouris et al. [2] employed LSTM networks for seizure prediction, while Raghu et al. [3] utilized transfer-learning-based CNN models for multi-class seizure classification. Although these approaches improved temporal representation and classification performance, they generally required increased computational resources and longer training durations. More recently, CNN–BiLSTM frameworks have been proposed to jointly capture spatial and temporal information from EEG signals. While these hybrid models improve classification accuracy, they often introduce higher model complexity and parameter redundancy. Recent research has increasingly focused on attention-based and transformer-based architectures. Zhao et al. [4] proposed a Hybrid Attention Network for epileptic EEG classification, demonstrating improved feature discrimination through attention-guided learning. Similarly, Wang et al. [5] developed a channel-weighted transformer feature-fusion framework for seizure prediction, while Lian and Xu [6] introduced a Graph Transformer Networkfor epileptic EEG classification. However, they require large-scale training datasets and considerable computational resources, limiting their applicability to smaller datasets.

Graph-based learning approaches have also gained considerable attention because EEG recordings naturally exhibit spatial relationships among electrode channels. Raeisi et al. [7] proposed a spatiotemporal graph attention network for neonatal seizure detection, whereas Hu et al. [8] introduced an iterative gated graph convolutional framework for epileptic seizure classification. More recently, Xiang et al. [9, 15] proposed a synchronization-based graph spatiotemporal attention network. Although graph-based approaches effectively model spatial dependencies, their performance often depends on graph construction strategies and computationally expensive optimization procedures. Several recent studies have attempted to combine transformer architectures with graph learning and attention mechanisms. Zhu et al. [10] proposed a multidimensional Transformer framework integrated with recurrent neural networks for seizure prediction. Yan et al. [11] developed a Dynamic Temporal-Spatial Graph Attention Network to address limitations associated with fixed-topology graph models, while Xu et al. [12, 15] combined Graph Attention Networks and Transformer architectures for seizure detection. Despite achieving encouraging performance, these advanced architectures require extensive computational resources, large datasets, and sophisticated model tuning procedures.

Consequently, a significant challenge remains in developing EEG seizure-classification systems that simultaneously achieve high accuracy, reduced feature redundancy, computational efficiency, and robust generalization. Moreover, many recent studies focus primarily on binary seizure versus non-seizure classification rather than clinically meaningful multi-class categorization involving healthy, interictal, and ictal EEG states. Motivated by these limitations, the present work proposes the unified STFT–CNN–AO framework.

3. Description

This paper combines biomedical signal processing and deep learning, along with optimization techniques, to develop a hybrid STFT–CNN–AO framework for automated epileptic seizure detection based on EEG signals. Unlike conventional EEG classification approaches that rely primarily on handcrafted features or standalone deep-learning models, the proposed framework combines time-frequency signal representation, deep hierarchical feature learning, and adaptive optimization within a single pipeline. The objective is not only to improve classification accuracy but also to reduce feature redundancy and enhance convergence efficiency during model training. It starts with the preprocessing of an EEG, that is, Electroencephalogram signal, which contains voltage fluctuations resulting from periodic brain activity. Since EEG is a dynamic signal, it is transformed into a time–frequency domain, using Short-Time Fourier Transform. Using this technique, the signal is divided into multiple short, overlapping windows, for acquiring temporal and spectral information. The resulting spectrograms study and visualize energy changes across the frequency bands, thereby drawing insights from the seizure activity patterns.

The spectrograms are then classified using a Convolutional Neural Network, a deep learning framework that is ideal for pattern recognition and image-based classification tasks. The CNN learns hierarchical features—low-level features like edges and frequency bursts; high-level features including complex rhythmic patterns comparable to that of seizures, giving an optimal classification accuracy. To further improve the efficiency of the proposed model, an Aquila Optimizer (AO) algorithm has been included for better feature selection and hyperparameter optimization. Inspired from the hunting behaviour of the Aquila eagles, AO balances exploration-exploitation allowing the model to select the best subset of features as training parameters. This reduces redundancy, accelerates convergence, and enhances overall classification performance.

The final output of the hybrid CNN model returns class probabilities of the EEG segments corresponding to healthy, interictal, and seizure states. This framework has been built and executed using the MATLAB Deep Learning Toolbox. The combined usage of the STFT, CNN, and AO shows great compatibility between signal processing and Deep Learning, delivering a promising framework for automated epileptic seizure detection and other neurodiagnostic applications. Future studies may investigate its deployment in real-time monitoring environments.

4. Data Description

This work focuses on experimental analysis based on the publicly available Bonn University EEG dataset, used to raise the benchmarks of automated epileptic seizure detection. The data were collected from healthy volunteers and epilepsy patients at the Department of Epileptology, University of Bonn, Germany. It provides a standardized dataset, free from artifacts suitable for validation of any kind of signal processing or classification model.

The dataset consists of five subsets labelled as A, B, C, D, and E, each containing 100 single-channel EEG recordings of 23.6 seconds in length, sampled at 173.61 Hz. Each recording contains 4097 data points and has been pre-filtered with a band-pass filter between 0.5 and 40 Hz, thus eliminating noise and power-line interference.

- Set A: EEG signals from healthy subjects with eyes open.
- Set B: EEG signals from healthy subjects with eyes closed.
- Set C: Interictal (non-seizure) activity recorded from the epileptogenic zone of patients.
- Set D: Interictal activity recorded from the opposite (non-epileptogenic) hemisphere.
- Set E: Ictal (seizure) activity recorded during epileptic episodes.

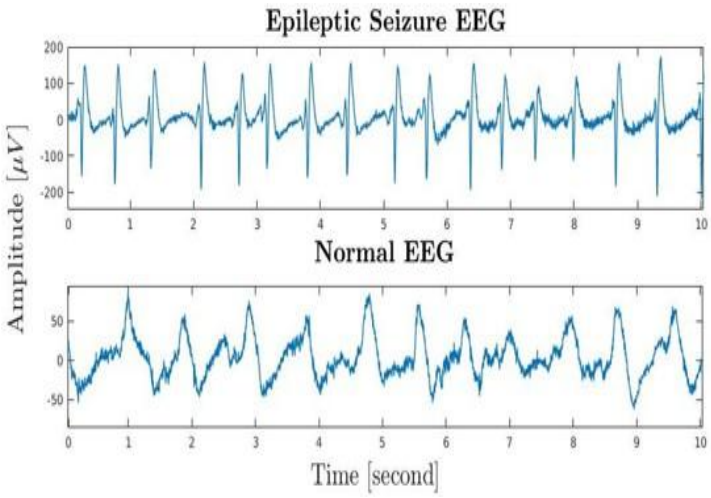

Fig 1. Wave Morphology of Epileptic Seizure EEG vs Normal EEG

4.1. Data Preprocessing

The EEG signals were pre-processed before feature extraction and model training:

- Normalizing Signals: All segments were normalized between 0 and 1 using min–max scaling to ensure a uniform distribution of input.
- Bandpass filtering: A 6th-order IIR filter (0.5–40 Hz) was implemented to remove low-frequency drifts and high-frequency noise while preserving the physiological EEG components.
- Segmentation and Labelling: Each 23.6-second segment of the EEG was then labelled with its class and stored in mat files.
- Data Balancing: Due to class imbalance, oversampling was a strategy used to ensure all classes contributed equally within the training dataset.

4.2. Dataset Statistics and Partitioning

The Bonn EEG dataset contains four subsets (A–D), each consisting of 100 or 200 EEG recordings, resulting in a total of 500 samples. The dataset is partitioned using an 80:20 hold-out strategy, where 80% of the samples are used for training and 20% are reserved for independent testing. All recordings have been utilized for feature extraction and classification. No oversampling or synthetic sample generation methods are applied. The original dataset distribution is retained throughout preprocessing and feature-selection stages.

For classifier training, data augmentation has been performed exclusively on the training subset after dataset partitioning. Augmented samples were generated by adding low-amplitude Gaussian noise to the normalized feature vectors. These augmented samples were combined with the original training data to improve model robustness and reduce overfitting. The testing data remained unchanged and contained only original EEG recordings, thereby preventing data leakage. Feature selection is subsequently performed using the Aquila Optimizer (AO), where the fitness of each candidate feature subset is evaluated using the mean classification accuracy obtained from a 5-fold cross-validated multi-class SVM classifier.

Table 1. Original class distribution of the Bonn EEG dataset prior to augmentation and feature selection

Class	Original Samples
Set A (Healthy Eyes Open)	100
Set B (Healthy Eyes Closed)	100
Set C (Interictal)	200
Set D (Seizure)	100
Total	**500**

5. Feature Extraction and Classification

5.1. Spectrogram-Based Feature Representation

EEG signals are inherently non-stationary and exhibit significant variations across both time and frequency domains. Consequently, conventional Fourier analysis alone is insufficient to capture transient seizure-related characteristics. To preserve temporal and spectral information simultaneously, each preprocessed EEG segment was transformed into a time-frequency representation using the Short-Time Fourier Transform (STFT), following the methodology adopted in [13]. The STFT divides the EEG signal into a series of short overlapping windows and computes the Fourier Transform within each window. This approach enables localized frequency analysis and allows seizure-related oscillatory activity to be observed over time. The mathematical representation of STFT is given by:

$$X(k,l) = \sum_{m=0}^{M-1} x[m + lH]w[m]e^{-j\left(\frac{2\pi km}{M}\right)} \quad (1)$$

where $X(k,l)$ denotes the STFT coefficient, $x[n]$ represents the discrete EEG signal, $w[n]$ denotes the analysis window function, M is the window length, H represents the hop size (overlap shift), k denotes the frequency-bin index, and l denotes the time-frame index.

Equation (1) results in a 1 × N matrix with N being N points of Fast Fourier Transform (FFT). Since N is an extensive data, it is reduced by calculating first-order statistics, thereby using it as feature vectors. These vectors include mean, variance, skewness, kurtosis, and entropy. The spectrogram is subsequently obtained by computing the squared magnitude of the STFT coefficients:

$$S(k,l) = |X(k,l)|^2 \quad (2)$$

where $S(k, l)$ represents the signal energy at frequency bin k and time frame l.

The generated spectrograms provide a two-dimensional representation of EEG activity, enabling the visualization of seizure-related frequency bursts and temporal transitions. These spectrogram images serve as inputs to the CNN for automatic feature extraction and classification.

5.2. CNN Feature Extraction

The spectrogram images generated using STFT were supplied as inputs to a Convolutional Neural Network (CNN) for automated feature extraction and classification. The proposed CNN architecture consists of two convolutional blocks followed by fully connected classification layers. The first convolutional layer employs 64 filters of size 3×3 with ReLU activation. Batch normalization is applied after convolution to improve training stability, followed by a dropout layer with a dropout probability of 0.3 to reduce overfitting.

The second convolutional block consists of 128 filters of size 3×3, followed by batch normalization, ReLU activation, and max-pooling. The extracted feature maps are flattened and passed through a fully connected layer containing 256 neurons. The final classification layer uses a Softmax activation function to estimate the posterior probability of each EEG class. The network parameters were optimized using the Adam optimizer with an initial learning rate of 0.001, mini-batch size of 32, and maximum training duration of 100 epochs.

Table 2. CNN Architecture and Training Parameters

Parameter	Value
Input Type	STFT Spectrogram
Conv Layer 1	64 Filters (3×3)
Activation Function	ReLU
Batch Normalization	Yes
Dropout Rate	0.3
Conv Layer 2	128 Filters (3×3)
Pooling Layer	Max Pooling
Fully Connected Layer	256 Neurons
Output Layer	Softmax
Optimizer	Adam
Learning Rate	0.001
Mini Batch Size	32
Epochs	100

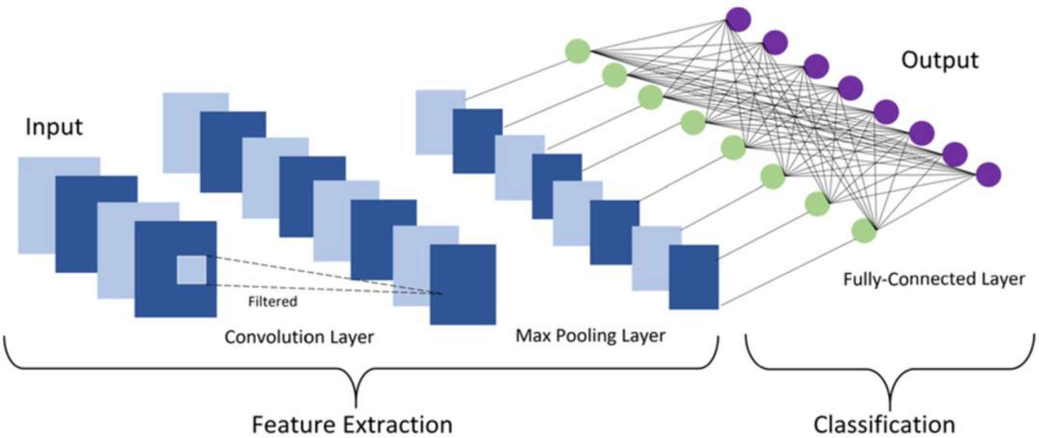

Fig. 2. CNN Feature Extraction and Classification Architecture

5.3. AO-Based Feature Optimization

The Aquila Optimizer (AO) is a population-based metaheuristic algorithm inspired by the hunting strategies of Aquila eagles. It employs adaptive exploration and exploitation phases to effectively search the solution space while avoiding premature convergence [14]. In the proposed framework, each candidate solution represents a subset of extracted EEG features, and the objective is to maximize classification accuracy while minimizing feature redundancy. During the expanded exploration phase, the position of each candidate solution is updated according to:

$$X_1(t+1) = X_B(t)\left(1 - \frac{t}{T}\right) + (X_{mean}(t) - X_B) \cdot rand \tag{3}$$

where the population mean position is defined as:

$$X_{mean}(t) = \frac{1}{M}\sum_{i=1}^{M} X_i(t) \tag{4}$$

where $X_B(t)$ denotes the global best solution obtained at iteration t, $X_{mean}(t)$ represents the mean population position, M is the population size, T is the maximum number of iterations, and $rand$ is a uniformly distributed random number in the interval $[0,1]$.

For feature optimization, the Aquila Optimizer was implemented using a population size of 20 candidate solutions and a maximum iteration count of 30. Each candidate solution was represented as a binary feature-selection vector. The fitness of each candidate solution was evaluated using the mean accuracy obtained from a 5-fold cross-validated multi-class Support Vector Machine (SVM) classifier. The fitness function is defined as:

$$Fitness = \frac{1}{K}\sum_{i=1}^{K} Accuracy \tag{5}$$

where K denotes the number of cross-validation folds and $Accuracy_i$ represents the classification accuracy obtained for the i^{th} fold.

To transform the continuous AO search space into a binary feature-selection problem, a sigmoid transfer function followed by thresholding is applied. Features associated with binary values greater than 0.5 were retained, whereas the remaining features were removed. This procedure reduces feature redundancy and improves classifier generalization. The optimization process was terminated when either the maximum number of iterations (30) was reached or no further improvement in the best fitness value was observed. The best-performing feature subset obtained at the end was subsequently used for evaluation.

The Aquila Optimizer (AO) demonstrates superior performance over the Butterfly-Dragonfly Algorithm (BDFA) in the EEG feature selection task, as evident from Fig. 3 and Table 3. Statistically, AO achieves around 42% higher final fitness than BDFA, confirming its robustness, stability, and suitability for EEG-based optimization problems.

Table 3. Comparison of Aquila Optimizer (AO) and Butterfly-Dragonfly Algorithm (BDFA)

Parameter	AO	BDFA
Optimization Phases	4 adaptive phases: exploration, exploitation, convergence, and adjustment	Two phases: exploration and exploitation
Convergence Speed	Rapid — stabilizes within ap-proximately 5 iterations	Slow — exhibits continuous de-cline after early iterations
Final Accuracy (Fitness)	0.72	0.30
Search Behavior	Balanced global–local search; avoids premature convergence	Premature convergence and poor local exploitation
Feature Selection Quality	Highly discriminative features with minimal redundancy	Suboptimal and less consistent feature subsets

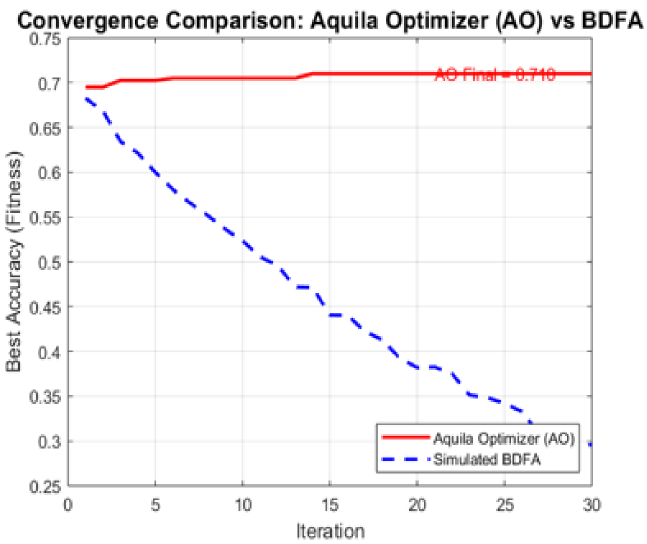

Fig. 3. Convergence Plot AO vs BDFA

6. Experiment

The performance of the proposed CNN-AO hybrid model was experimentally validated in a controlled MATLAB environment in detecting epileptic seizures from EEG signals. All experiments were implemented in the MATLAB 2024b environment, using its Deep Learning Toolbox and enabling GPU acceleration to reduce training and evaluation time. In these experiments, the hardware setup included an AMD Ryzen 5 processor 5600H with Radeon Graphics, running on Windows 11. To ensure accurate classification and avoid overfitting, the 5-fold cross-validation technique was employed. This involved distributing the dataset into five equal subsets, training four of them at a time in every fold and testing with the remaining one. The final accuracy is the mean of the folds. This made sure every data point was a part of training and testing to provide statistically sound performance estimation. The hyperparameters to be optimized included the model's learning rate, number of convolutional filters, and dropout ratio hence, Aquila Optimizer (AO) was applied. The network was trained using the Adam optimizer, renowned for rate adjustment capability in adaptive learning. The key hyperparameters used were:

- Optimizer: Adam
- Initial Learning Rate: 1×10^{-4}
- Batch Size: 32
- Epochs: 40

Early stopping has been used to avoid overfitting by stopping the training process when the validation loss did not change for six successive epochs. To increase sample diversity and robustness without disturbing EEG characteristics, data augmentation that included random rotation ±10°, translation ±5 pixels, and horizontal flipping has been performed. The proposed hybrid model has shown high and consistent accuracy across all folds, reflecting stable learning and excellent classification capability. The results also clearly elucidated that the CNN–AO model balanced the efficiency of learning against its accuracy.

7. Analysis of Results

The proposed CNN-AO hybrid classifier was analysed for performance using multiple quantitative metrics along with comparative evaluations to establish its reliability, generalization, and robustness in classifying different states of EEG signals. The Bonn University EEG dataset was used to carry out the evaluation under a 5-fold cross-validation framework. This section discusses the observations based on the classification metrics, precision recall curve and the confusion matrix.

7.1. Metrics-Based Performance

The table below provides the names and formulas of the parameters.

Table 4. Performance Evaluation Metrics

Precision	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$
Recall	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
F1 – score	$\frac{2(\mathrm{Precision}\times\mathrm{Recall})}{\mathrm{Precision}\times\mathrm{Recall}}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$

The proposed CNN–AO hybrid classifier has performed consistently well on different evaluation metrics as shown in Table 5. Per-class sensitivity, specificity, and F1-scores obtained from the test runs indicate a very good discrimination between the four EEG states: Healthy, Healthy (Eyes Closed), Interictal, and Seizure.

Table 5. Detailed Per-Class Classification Performance

Class	Sensitivity	Specificity	F1-score
Healthy	0.975	0.9833	0.963
Healthy (Eyes Closed)	0.975	0.9917	0.975
Interictal	0.975	1.0000	0.987
Seizure	1.0000	1.0000	1.000

High sensitivity values ≈ 0.975–1.000 shown in Fig. 5, prove that the model is quite effective in identifying positive instances of each class, while specificity values ≈ 0.983–1.000 indicate the effective rejection of non-target samples. Confirmation of a strong balance between precision and recall is obtained, as evident from Fig. 4, with F1-scores ≥ 0.96 for all EEG categories. The Seizure class had perfect scores for the model: Sensitivity = 1.0, Specificity = 1.0, and F1 = 1.0, demonstrating its competency in the detection of epileptic events. The results obtained show that the proposed hybrid CNN–AO model uniquely identifies the spectral–temporal signatures of seizures. Conversely, flawless performance on the seizure category can also be partly attributed to the distinct traits of the Bonn dataset or the limited quantity of seizure samples.

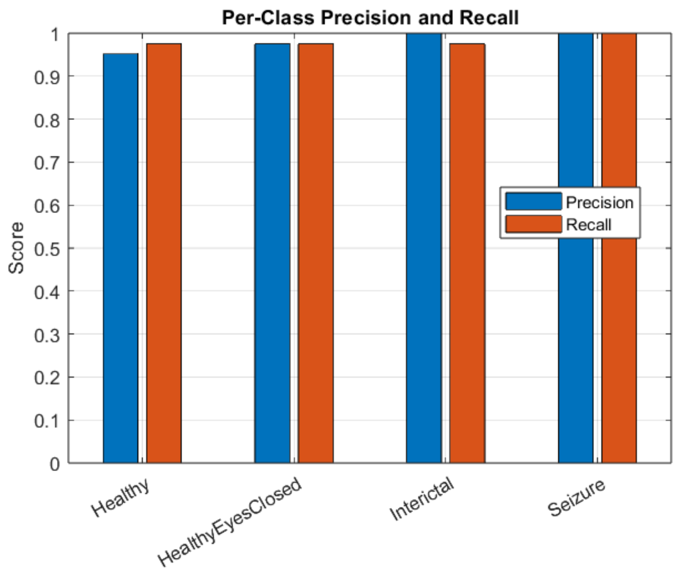

Fig. 4. Precision and Recall Analysis

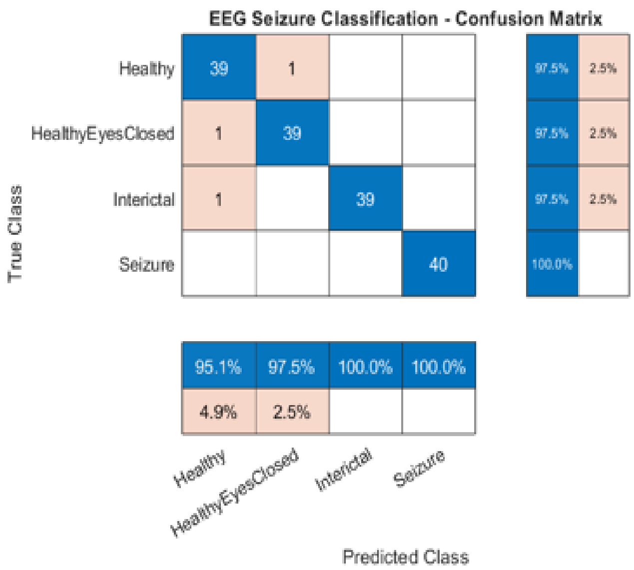

Fig. 5. Confusion Matrix of the Proposed CNN–AO Classifier

7.2. Cross-Validation Robustness

The proposed CNN–AO model achieved an average classification accuracy of 92.83%, demonstrating strong and consistent performance across all validation folds. The mean AUC value of 0.9968 indicates excellent discriminative capability between EEG classes, while the average Cohen's Kappa coefficient of 0.8925 reflects an almost perfect agreement between predicted and actual labels beyond chance. The relatively small variation in AUC across folds further confirms the stability and generalization capability of the proposed framework. The corresponding 95% confidence interval ranged from 92.08% to 99.16%.

A Wilcoxon signed-rank test was performed on the fold-wise accuracies obtained from five-fold cross-validation. The proposed CNN-AO model achieved an average accuracy of 95.62 ± 2.81%, compared with 87.33 ± 4.46% for the baseline CNN. Although the resulting p-value (0.0625) was slightly above the conventional significance threshold of 0.05, the proposed method demonstrated a substantial performance improvement of 8.29% points with a large effect size (Cohen's d ≥ 0.8), indicating strong practical significance. The limited number of cross-validation folds may have reduced the statistical power of the hypothesis test.

Table 6. Cross-Validation Performance of the Proposed CNN–AO Classifier

Fold	Accuracy (%)	Mean AUC	Cohen's Kappa
1	96.88	0.9954	0.9125
2	90.62	0.9942	0.7375
3	96.88	0.9994	0.9750
4	95.62	0.9985	0.9375
5	98.12	0.9964	0.9000
Mean ± SD	**95.62 ± 2.85**	**0.9968 ± 0.0021**	**0.8925 ± 0.0940**

7.3. Performance Evaluation

The robustness of the proposed CNN–AO classifier was further evaluated through training convergence analysis, ROC and Precision–Recall (PR) curves, and cross-validation statistics. Fig. 6. illustrates the training progress for a representative fold, where training and validation accuracy increased steadily while the loss rapidly decreased and stabilized, indicating effective learning and stable convergence without significant overfitting.

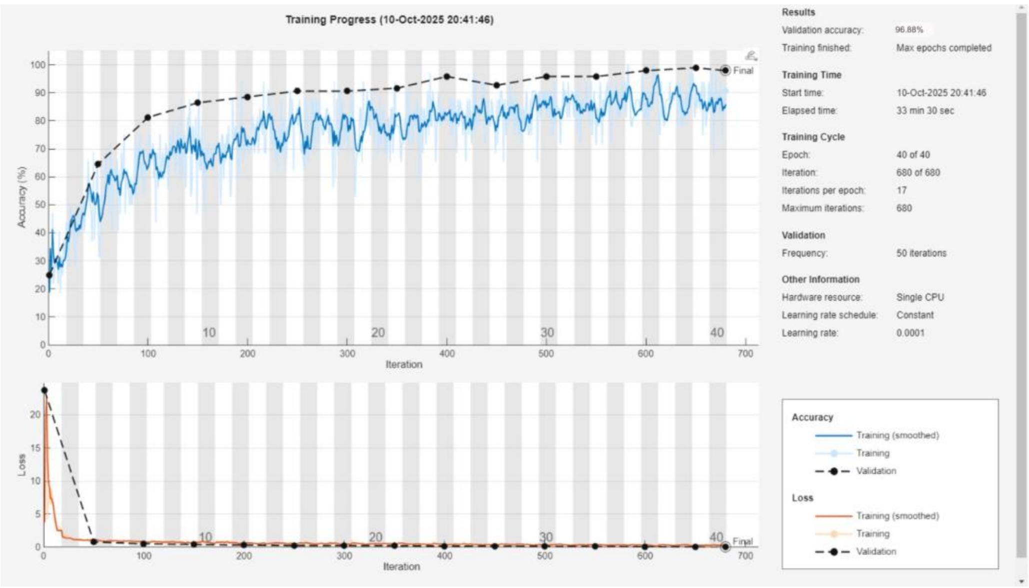

Fig. 6. Training progress of the proposed CNN–AO model for a representative cross-validation fold.

Fig. 7. presents the ROC curves for the four EEG classes. The corresponding AUC values of 0.9913, 0.9975, 0.9975, and 0.9934 demonstrate excellent discriminative capability and class separability. Similarly, Fig. 8. shows the PR curves, which achieved AUPRC values ranging from 0.9589 to 0.9708, confirming reliable classification performance across varying decision thresholds.

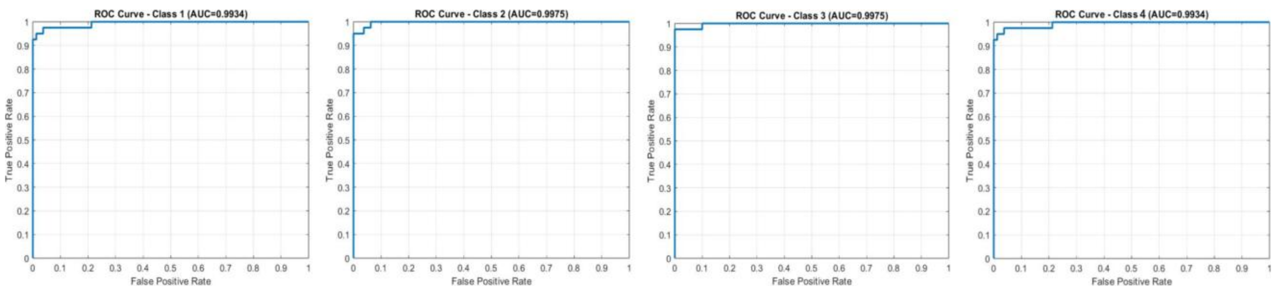

Fig. 7. ROC curves for a representative cross-validation fold.

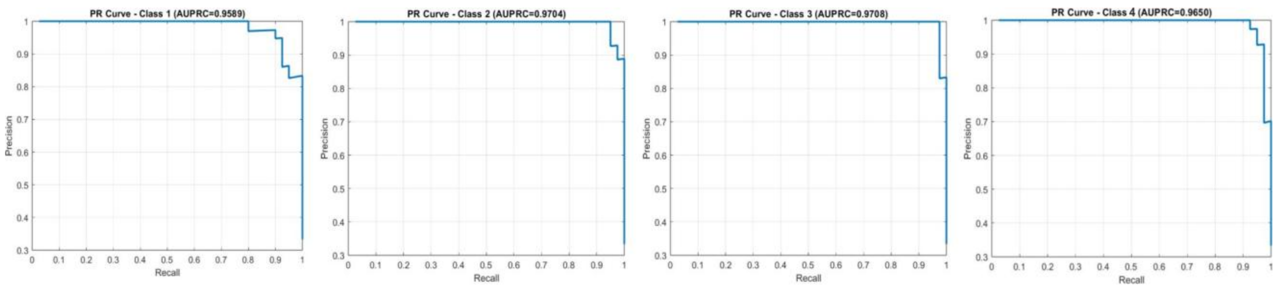

Fig. 8. PR curves for a representative cross-validation fold.

8. Conclusion

This paper presented a Deep Hybrid Neural Network framework that combines Convolutional Neural Networks (CNN) with the Aquila Optimizer (AO) for the automated detection of epileptic seizures through EEG signals. The novelty of this research lies in the integration of the robust feature-learning strength of CNNs with the adaptive optimization characteristics of AO to attain an effective balance among accuracy, computational efficiency, and model generalization. In contrast to traditional deep learning models that depend only on fixed architectures or manually adjusted parameters, the proposed hybrid system employs AO-guided feature optimization, improving feature selection efficiency and reducing redundancy in the learned representations.

Besides its algorithmic contributions, the framework demonstrates potential for future clinical and biomedical applications, such as seizure monitoring systems in hospitals, ICU observation platforms, and wearable neurodiagnostic technologies, subject to further clinical validation and hardware-level implementation. Additionally, the modular design of the proposed framework may facilitate future integration with edge computing and embedded healthcare platforms, supporting broader deployment across different medical environments. Overall, this study presents a hybrid deep learning and metaheuristic optimization framework for automated EEG-based seizure detection, highlighting the potential of combining signal processing, deep feature extraction, and intelligent optimization for neurological disorder classification and computational healthcare applications.

All the Declarations and Statements

Authorship contribution statement
Swati Chowdhuri: Conceptualization, Methodology, and Supervision. Reviewed and edited the manuscript, ensured clarity and coherence, and helped coordinate project milestones and deadlines
Tiyasha Mondal: Data Curation and Software Implementation. Proposed the research concept, designed the overall framework, performed preprocessing, and model implementation.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement
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 Declaration
This research did not receive any external funding.

Data Availability Statement
The EEG dataset used in this study is publicly available from the University of Bonn EEG Database: https://www.upf.edu/web/ntsa/downloads

Ethical Declarations
Not applicable. This study utilized publicly available anonymized EEG recordings and did not involve direct participation of human subjects or animals.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with language refinement, grammar correction and manuscript organization. The authors carefully reviewed, edited, and validated all generated content and take full responsibility for the final published manuscript.

Abbreviations
This manuscript uses the following abbreviations:

AI - Artificial Intelligence
AO - Aquila Optimizer
AUC - Area Under the Curve
AUPRC - Area Under the Precision–Recall Curve
CNN - Convolutional Neural Network
LSTM – Long Short Term Memory
DL - Deep Learning
EEG – Electroencephalogram
SD – Standard Deviation
FFT – Fast Fourier Transform
FPR - False Positive Rate
TPR - True Positive Rate
PR - Precision–Recall
ROC- Receiver Operating Characteristic
SVM - Support Vector Machine
TP – True Positive
FP – False Positive
TN – True Negative
FN – False Negative

Appendix A/B/C…, with appendix title
None.

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