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AI-Driven Real-Time EEG Analysis for Epileptic Seizure Prediction using Optimal Features

[1]Ms. Arti Ghule, [2]Dr. Kalpana Thakre
[1] Research Scholar, Computer Engineering, MMCOE, SPPU, Pune
Asst.Professor,SCTR's PICT, Pune
[2] Professor and Dean R & D, MMCOE, SPPU, Pune
Corresponding author: agghule@pict.edu

ABSTRACT: Over 50 million people worldwide suffer from epilepsy, making it one of the most prevalent neurological disorders. Accurate identification and prediction of epileptic seizures are crucial for reducing health-related risks, improving patient safety, and enabling timely clinical intervention. Electroencephalography (EEG), a non-invasive technique for monitoring the brain's electrical activity, has become the primary modality for automated seizure detection and prediction. Conventional machine learning and deep learning approaches have demonstrated promising performance; however, EEG signals are inherently high-dimensional, noisy, nonlinear, and non-stationary, making accurate seizure prediction a challenging task. Consequently, recent research has shifted towards the integration of advanced Artificial Intelligence (AI) techniques, including deep learning, attention mechanisms, optimization algorithms, reinforcement learning, explainable AI, and hybrid intelligent framework. Which achieve moderate accuracy which can be improved. These models fail to learn complex spatiotemporal dependencies; also fail to address the problem of feature redundancy. To address these problems, this work proposes a real-time AI-powered analysis of EEG signals to optimize epileptic seizure prediction. The model incorporates a spatio-temporal attention (STAtt) mechanism for extracting time and space correlation patterns, an enhanced multi-objective bean optimization (EMBO) algorithm, and hierarchical dual-Q learning (HDQL) model for effective seizure detection. The proposed approach would be verified experimentally on the three benchmark EEG datasets: CHB-MIT, Bonn, and TUH. The findings reveal that the incorporation of STAtt, EMBO, and HDQL remarkably contributes to EEG feature discrimination, minimizes misclassification, and offers real-time seizure-detection solution, showing superiority over state-of-the-art models across multiple datasets.

1. INTRODUCTION

The abrupt, frequent, and irregular electrical discharges of the brain are the hallmark of epilepsy, a long-term neurological condition. It affects almost 1% of the world's population. It can pose serious risks to cognitive, behavioral, and physiological functioning capabilities [1], [2]. Based on epidemiological reports, globally more than 50 million people suffer from epilepsy. Epilepsy is one of the most common neurological disorders needing continual observation and early intervention [3]. Electroencephalography (EEG) is widely used clinical tool for the diagnosis of disease through optimal solution belongs to the normal and abnormal activity of the brain in a non-invasive manner [4]. According to the literature, EEG signals are important for portraying neuronal dynamics, seizure-related patterns, and characteristics important for clinical assessment and automated analysis [5]. Nevertheless, manually interpreting EEG recordings is a very time-consuming task that requires expert knowledge and also suffers from inter-observer variability especially under long-duration monitoring situations [6]. In the recent times, there has been a huge amount of research to develop automated seizure detection systems by using machine learning and signal processing techniques [7]. The early methods used handcrafted feature extraction techniques and classical classifiers belong to machine learning models such as supervised and non-supervised [8], [9]. EEG signals have also been analyzed using techniques like wavelet transform (WT), empirical mode decomposition (EMD) and Fourier-based spectral analysis for extracting time-frequency features [10]; [11]. Techniques such as deep learning give better performance than manual analysis but still hinge heavily on domain experience and generalization issues over heterogeneous EEG datasets due to a lack of standardization on condition and recording environment [12]. The ability to extract non-linear dependencies and dynamic changes across time from epileptic EEG signals is limited with these methods. As deep learning models continue to improve, more advanced models continue to be explored for EEG-based seizure detection. The deep learning models like graph neural network (GNN), quantum neural network (QNN) and convolutional neural network (CNN) have been extensively explored [13], [14]. CNN-based structures are important factors for extracting spatial patterns from EEG signals, while RNN-based models capture the temporal dependencies between brain activities in a sequence [15]. CNN-LSTM and CNN-GRU hybrid architectures improved performance through joint modeling of spatial and temporal features according to [16]. However, many of these methods presume that EEG signals are structured according to a Euclidean model. As a result, they cannot investigate the inter-channel relations among EEG electrodes. Graph neural networks (GNN) and graph convolutional networks (GCN)-based models for EEG analysis were introduced to overcome this constraint [17]. These approaches represent EEG channels as nodes in a graph, while the relationships between channels are assigned as edges. Many current GCN-based techniques heavily utilize node-centric aggregation strategies, such as mean or max pooling, which leads to excessive smoothing and eventual loss of fine-grained relational information [18]. The forward and backward temporal relationships are captured by recurrent models such as the bidirectional gated recurrent unit (BiGRU) considers the EEG signals, thereby improving the performance of sequential modeling [19]. Recent research has incorporated attention mechanisms and optimization-based feature selection methods to improve EEG classification accuracy while mitigating computational complexity [20]. But existing models still need to overcome many challenges, which include: High feature redundancy; limited capacity of jointly modeling spatial-temporal dependencies; achieving a robust real-time performance across multiple EEG datasets, etc. Furthermore, the deployment of many existing systems in real-life healthcare settings is impeded due to lack of efficient and interactive interfaces for clinical usability. These constraints leads to a need for an intelligent EEG analysis model to extract the discriminative spatial-temporal features effectively suppress redundant features and allow real-time seizure prediction with better clinical interpretability. An AI-driven model that can analyze EEGs in real-time is created with a graphical user interface (GUI) to forecast optimally seizures. The following are the main contributions of the proposed model.

1. The model incorporates a spatio-temporal attention (STAtt) mechanism to efficiently extract discriminative temporal and spatial patterns from EEG data, capturing the complex dynamics of seizure activity.
2. An enhanced multi-objective bean optimization (EMBO) algorithm is employed for optimal feature selection and dimensionality reduction, reducing data redundancy while preserving the most informative characteristics.
3. For robust seizure detection, a hierarchical dual-Q learning (HDQL) model is integrated to classify EEG segments accurately and reliably.
4. Experimental evaluation is conducted on benchmark datasets including CHB-MIT, Bonn, and TUH, demonstrating high accuracy.

The paper is organized as follows. Section 2 reviews related work on AI-based EEG analysis and seizure prediction. Section 3 presents the proposed real-time EEG model with STAtt, EMBO, and HDQL. Section 4 discusses results and performance evaluation, and Section 5 concludes with key findings.

2. RELATED WORK

The deep learning designs revolved around convolutional and recurrent architectures. However, their high computational complexity, complete loss of channel-wise information, and limited spatiotemporal modeling led to the development of hybrid and attention-based designs. Seizure detection using deep learning architectures based on knowledge distillation has been studied with teacher–student architecture with progressive attention mechanisms across the depths of the networks [21]. The use of electrode-level attention through multi-scale kernel networks has been put forth for addressing Full-channel EEG modeling [22]. Strategies for temporal and spectral fusion have been employed to integrate local and global EEG dependencies. The complexity of the model and requirement for long training make it unsuitable for real-time monitoring although they do improve features integration. Researchers have introduced frameworks for contrastive learning to enhance model explainability and generalization [24]. Multiscale EEG signals are decomposed into approximation and detail coefficients; they are processed via patch-based feature extraction and integrated using hybrid loss functions. Graph Convolutional Networks (GCNs) utilized to capture the topological dependencies across EEG channels [25]. The traditional signal-processing methods, like Kaiser Window filtering having statistical feature extraction, provide low-complexity seizure detection [26]. Although these methods helped in reducing the computation costs, they are limited by handcrafted features due to inefficiency in capturing complex nonlinear EEG patterns and reducing generalization across datasets. Feature-to-image transformations when integrated with transformer-based encoders results in high classification accuracy [27]. In reference [28], reduction strategies in channels together with assessment through random forest classifiers were examined. Combining spatial and temporal EEG features has been carried out using a multi-view representation fusion with hybrid MetaFormer networks. Multi-view processing increases model complexity and challenges real-time deployment, even though feature integration is robust and the model is fairly interpretable. Spiking neuron networks constitute an efficient EEG seizure detection method [30] et.al. Adaptive spiking neuron models demonstrate the capability to capture multi-scale EEG activation patterns with a low energy footprint. However, they are rather limited in their capacity to model fine-grained spatial dependencies. Furthermore, if utilized to capture EEG data, they will require special-purpose hardware to extract the best performance.

Table 1: Summary of existing EEG-based epileptic seizure detection methods, key findings and research gaps

Ref	Methodology	Technique used	Dataset	Key findings	Research gaps	How gaps addressed
[21]	Hierarchical learning and feature transfer for seizure detection	Progressive attention-based knowledge distillation model	Bonn EEG, custom EEG	98.82% accuracy, 99.92% accuracy	High complexity, slow inference, poor real-time use	Reduced computation with efficient feature learning
[22]	Avoid loss from channel reduction and signal transformation	Multi-scale CNN with electrode attention	CHB-MIT, Siena	99.29% accuracy, 98.29% sensitivity, 99.59% specificity	Heavy computation, limited real-time use	Efficient feature selection, reduced redundancy
[23]	Improve temporal–spectral fusion in EEG signals	Memory-based temporal–spectral fusion network	CHB-MIT, Siena	99.55% accuracy, 89.96% inter-patient accuracy	High training cost, low scalability	Efficient spatiotemporal dependency learning
[24]	Improve representation and interpretability of EEG signals	Multiscale contrastive learning with wavelet + patch model	TUSZ, UPenn	>90% accuracy	Heavy preprocessing, slow execution	Direct feature learning with lower preprocessing
[25]	Capture EEG channel relationships using graph structure	Multi-branch graph CNN with pyramid and attention	CHB-MIT, Siena	92.21% accuracy, 94.50% precision	Fixed graph design, over-smoothing	Better adaptive feature learning used to address dimensionality
[26]	Reduce manual feature design in EEG classification	Kaiser filter + statistical features + ML classifier	EEG scalp dataset	95.64% accuracy, 99.33% specificity	Handcrafted features, weak generalization	Automated nonlinear feature learning
[27]	Improve EEG interpretability using image conversion	GAF + transformer + GAN/decoder model	Bonn EEG	99.81% accuracy, 99.76% accuracy	Loss of signal details, high preprocessing cost	Direct EEG processing without conversion

Ref	Methodology	Technique used	Dataset	Key findings	Research gaps	How gaps addressed
[28]	Reduce computation using channel optimization	Channel selection + random forest model	CHB-MIT	95.64% accuracy, 17% computation time	Loss of spatial EEG data	Full-channel feature learning with optimization
[29]	Improve multi-view EEG feature fusion	Hybrid MetaFormer fusion model	CHB-MIT, Siena	>98% accuracy	High complexity, slow inference	Efficient unified feature modeling
[30]	Reduce energy use in EEG seizure detection	Spiking neural network model	Large EEG datasets	1/7 energy use, >95% accuracy	Limited spatial modeling	Balanced learning without hardware limits

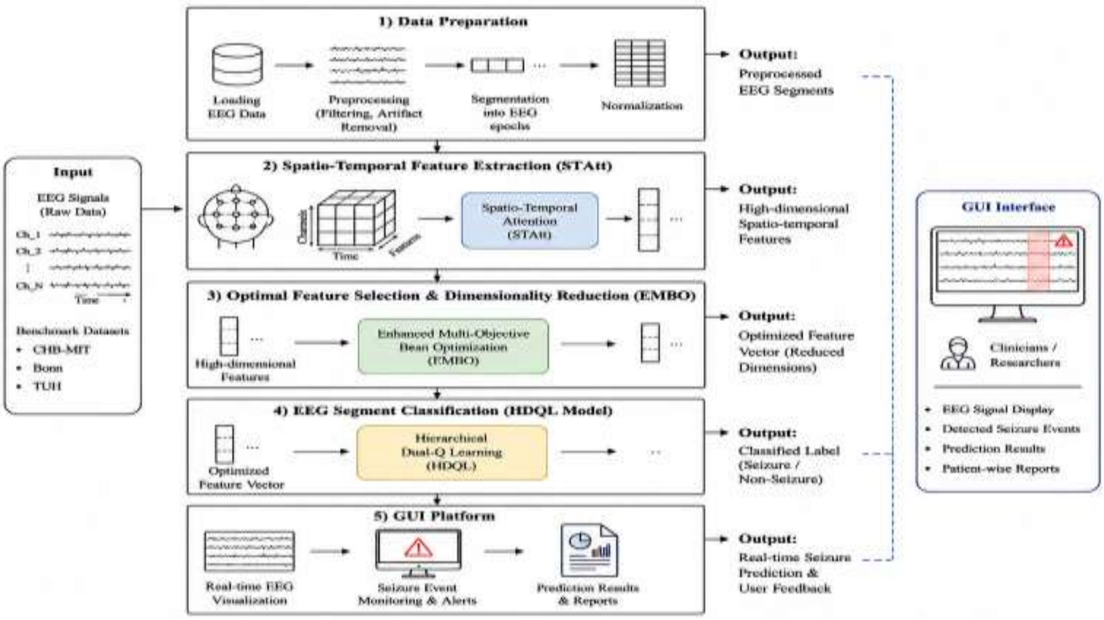

Figure 1: Conceptual structure of AI-driven real-time EEG analysis model with GUI for epileptic seizure prediction

3. PROPOSED METHODOLOGY

The model for predicting epileptic seizures using AI in real-time EEG signal analysis is shown. 1. The model is fed with EEG signals obtained from CHB-MIT, Bonn, and TUH benchmark datasets. The data from datasets are fed into the signal preprocessing which includes removing noise from EEG signals, filtering, normalizing, and segmenting. The spatio-temporal attention (STAtt) module processes the preprocessed signals to extract discriminative spatial dependencies among EEG channels and captures seizure evolution's temporal dynamics. The features extracted using the EMBO algorithm will be optimized which performs the feature selection and dimensionality reduction by removing the redundant information while selecting the most informative features. The hierarchical dual-Q learning model accurately classifies optimized features for seizure and non-seizure segment identification in the human brain. The classification results are shown through a real-time GUI platform that allows EEG signal monitoring, the tracking of detected events, and predictions reached by the model instantly.

3.1 Data preparation

The evaluation of the performance of the proposed epileptic seizure detection framework is done using CHB-MIT Scalp EEG, Bonn EEG, and TUH EEG datasets. The datasets contain EEG recordings that are clinically relevant and diverse, allowing for intra-patient and cross-dataset validation of the model. The statistical summary of the datasets is done which includes the number of subjects, number of channels, recording duration, sampling rate, segment lengths and seizure/non-seizure distribution as shown in Table 1.

Table 1: Statistical description of datasets used in this study

Parameter	**CHB-MIT Scalp EEG**	**Bonn EEG dataset**	**TUH EEG dataset**
Number of subjects	23 patients	5 sets (A–E)	14+ patients (varies)
Number of sessions	23 sessions	100 segments approx.	200+ sessions
Sampling rate (Hz)	256 Hz	173.61 Hz	250 Hz
EEG channels	18–23 channels	1 channel	24+ channels
Recording duration	1–109 hours per subject	23.6 s per segment	1–24 hours per recording
Total data size	~980 hours	~65 min	~300 hours
Total seizure duration	~110 min	300 s total	~90 min
Average seizure duration	30–60 s	30 s	35–40 s
Segment length used	1 s windows	23.6 s fixed	1 s windows
Total segments extracted	~2,000 s per patient	500 segments	~10,000 segments
Training segments per fold	1,600 s	400 segments	~8,000 segments
Testing segments per fold	400 s	100 segments	~2,000 segments
Seizure: non-seizure ratio	1:04	1:01	1:04

3.2 Spatial and temporal patterns extraction

The proposed model uses spatio-temporal attention (STAtt) mechanism to extracts the deep hidden features and their patterns. EEG signals are very non-stationary, meaning that whatever information relevant to seizure has either time or electrode channel and it may appear only sometimes. In order to solve this problem, the STAtt mechanism learns temporal importance and spatial channel dependence in a unified representation learning manner. Taking a preprocessed EEG segment as input, we first organize the input into a multichannel time-series matrix, where channels represent electrical activity from an individual electrode at any given time step. The STAtt module brings in temporal attention, which subsequently assigns adaptive weights to the different time instants. Doing so helps it focus on more seizure-related time instants while suppressing background brain activity [32]. The spatial attention is applied across channels so that we can identify which channels are more informative for understanding the propagation of the seizure. The mechanism works by extracting EEG inputs to output intermediate feature embeddings, attention scores are computed through learnable transformation layers. STAtt adjusts its focus depending on the signal characteristics, accommodating for patient-EGG variability efficiently. The simultaneous use of spatial and temporal attention not only avoids loss of information occurring due to relative timing of their use but also over-smoothing due to graphical modeling. Through the STAtt mechanism, a spatio-temporal feature map can be obtained. Thus, it enhances the discrimination ability of later classifiers and improves robustness to noise, artifacts, and inter-subject variations.

3.3 Optimal feature selection

The enhanced multi-objective bean optimization (EMBO) algorithm is used for optimal feature selection dimensionality reduction which is very essential for improving classification performance and lowering computational complexity [33]. EMBO works with the high-dimensional spatio-temporal feature set extracted from the STAtt module and evaluates multiple candidate solutions based on their ability to maximize seizure-related features' relevance, minimize features' redundancy, and compact representation. The feature selection problem is formulated as a multi-objective optimization problem (MOP) [34]. That is, each candidate feature subset is examined according to their contributions to the overall objectives. When the number of objectives is greater than three, we deal with many-objective problem (MaOP). MaOP requires specialized selection strategies. EMBO uses the K-order Pareto dominance approach wherein a solution is considered non-dominated with respect to randomly chosen K objectives. This instrument enables a balanced optimization and ensures that the selected features offer a trade-off among all objectives. To improve on the search capability of the algorithm and avoid being trapped by local optima too easily, EMBO is incorporated with a heavy-tailed Cauchy distribution-based perturbation strategy. This mechanism leads to solutions which demonstrate small local variations but seldom large jumps in the solution space. This enhances the efficiency of global search and enables the discovery of highly informative feature subsets. By combining multi-objective handling, K-order Pareto selection, and Cauchy-based stochastic perturbation. To considers the continuous MOP with variable B and objectives A.

$$Min\, f(p) = (F_1(p), F_2(p), \ldots, F_A(p))^S,\ p \in \Omega \qquad (1)$$

where $p = (p_1, \ldots, p_b) \in \Omega = \prod_{h=1}^{b} [m_h, n_h] \subset r^n$ is an A-dimensional detached function vector, Ω is the verdict space, and $f(p) = (F_1, \ldots, F_A)^S : \Omega \to r^A$ is the conclusion vector. A MOP that has more than three aims (i.e., the A) is also referred to as a MaOP. Let Ω represent the solution in the decision space, and let represent the feasible domain f_Ω of MOPs. When optimizing a MOP with objectives A, the answer is a K-th order objective function $F(P^*)$ if there are non-dominated solutions P^* and a random selection f_Ω of a subset of K (1 ≤ K < A) issues such that no solution dominates [34].

$$\begin{cases} \forall K, f_h = \{F_{h_1}, F_{h_2}, F_{h_3}, \ldots, F_{h_K}\} \\ \forall P, \exists \quad F_g(P) \prec F_g(P^*),\ g \in \{h_1, h_2, h_3, \ldots, h_K\} \end{cases} \qquad (2)$$
$$1 \le K \le A$$

Both the control vectors $h_\partial (1 \le \partial \le K)$ and all objective functions are subsets $\{h_1, h_2, h_3, \ldots, h_K\}$ of each other. The Cauchy distribution, also called the Cauchy-Lorentz distribution $F(p, p_0, \gamma)$, is the classic heavy-tailed distribution provided by the probability density function.

$$F(p, p_0, \gamma) = \frac{1}{\pi\gamma\left[1+\left(\frac{p-p_0}{\gamma}\right)^2\right]} \tag{3}$$

where γ is a parameter that represents the half width at half maximum and p_0 is a placement parameter that defines the distribution's peak position. The Cauchy distribution's cumulative distribution function $F^{-1}(p; p_0, \gamma)$ and inverse cumulative distribution function are as follows:

$$F(p; p_0, \gamma) = \frac{1}{\pi}\arctan\left(\frac{p-p_0}{\gamma}\right) + \frac{1}{2} \tag{4}$$

$$F^{-1}(p; p_0, \gamma) = p_0 + \gamma\tan\left(\pi\left(x - \frac{1}{2}\right)\right) \tag{5}$$

The Cauchy distribution model can be used to produce children with the inverse cumulative distribution function. Let P be a random variable with variance and expectation μ = e[P]:

$$K = e\left[\left(\frac{P-\mu}{\sigma}\right)^4\right] = \frac{e\left[(P-\mu)^4\right]}{\left(e\left[(P-\mu)^2\right]\right)^2} \tag{6}$$

where K is P's kurtosis and the distribution is normal when K = 3. The Cauchy distribution shows that the distribution has larger tails than the normal distribution for K > 3. The Cauchy distribution's probability density function is defined as follows, and its parameters are represented as p_0 = 0 and γ = 1.

$$F(p; 0,1) = \frac{1}{\pi(1+p^2)} \tag{7}$$

The normal distribution is an S-distribution with infinite degrees of freedom, while the Cauchy distribution has just one. Algorithm 1 outlines the process involved in the feature optimization using EMBO, which provides an optimized feature vector of reduced dimension with most discriminative features and without redundant features.

Algorithm 1 Feature optimization using EMBO for dimensionality reduction

Inputs	**EEG feature set, population size, maximum iterations, number of objectives, feature constraints, convergence threshold**
Outputs	Optimized feature subset, reduced dimensional EEG feature vector
1	BEGIN
2	Initialize population of candidate feature subsets
3	Initialize iteration counter = 0
4	Evaluate initial population using feature relevance, feature redundancy, and feature compactness

Inputs	EEG feature set, population size, maximum iterations, number of objectives, feature constraints, convergence threshold
5	Perform non-dominated sorting and assign ranks to all solutions
6	Identify initial best solution and set convergence flag = false
7	WHILE (iteration counter < maximum iterations) DO
8	Select parent solutions based on rank, crowding distance, and diversity preservation
9	IF (population diversity is low) THEN
10	increase exploration using higher Cauchy perturbation
11	ELSE
12	apply balanced exploration–exploitation strategy
13	END IF
14	Generate offspring using bean optimization update mechanism
15	IF (solution is stagnating) THEN
16	apply large jump perturbation using Cauchy distribution
17	ELSE
18	apply small local perturbation for refinement
19	END IF
20	Decode offspring into feature subsets
21	Evaluate offspring using feature relevance, redundancy, and compactness
22	IF (offspring dominates parent) THEN
23	replace parent with offspring
24	ELSE
25	IF (parent dominates offspring) THEN
26	retain parent solution
27	ELSE

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Inputs	**EEG feature set, population size, maximum iterations, number of objectives, feature constraints, convergence threshold**
	retain both solutions based on crowding distance
	END IF
	END IF
	Merge parent and offspring populations
	Perform non-dominated sorting on merged population
	Select elite solutions for next generation
	Update best solution
	IF (improvement in best solution < threshold) THEN
	set convergence flag = true
	END IF
	Increment iteration counter
	END WHILE
	Select final Pareto-optimal solution with best trade-off score
	Extract optimized feature subset
	Return reduced dimensional EEG feature vector
	END

3.4 Classify EEG segments

The HDQL model, or hierarchical dual-Q learning model, classifies EEG segments for reliable and accurate seizure detection, which serves as the final decision-making process in the proposed framework. HDQL is a reinforcement learning based mechanism that considers EEG segment classification as a sequential decision problem so that the model can learn optimum policies to assign seizure and non-seizure labels. The input to HDQL is the spatio-temporal feature embeddings, capturing temporal dynamics and spatial relationships of EEG channels, produced by the preceding STAtt module [35]. Through the processing of these high-dimensional embeddings, the HDQL model assesses the relevance of each feature and selects the most informative patterns for classifying the network traffic. The first level of Q-value estimation corresponds to the coarse-grained state-action relationship, like the likelihood of seizure over a segment. The second one is the decision itself, with the second level making more fine-grained decisions using contextual information, like inter-channel and temporal variations. The dual-Q hierarchy presented in HDQL reduces overestimation bias and stabilizes convergence, which is crucial for highly imbalanced EEG datasets with rare seizure events. The state space (T^1) is extracted at a rate of 1 h. The solution's time step and state of charge are defined by s and SOC, respectively. The time steps already implicitly include generation and load information as the former data and load data are time-adjusted during offline optimization [36].

Q-learning Formula

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma maxQ(s',a') - Q(s,a)] \tag{8}$$

S - Current state

A - Current action

a - Learning rate

Γ - Discount factor

R - Reward

Q - Expected future reward

The procedure involved in the prediction model of seizure detection using HDQL model is shown in Algorithm 2. The output of the HDQL model is a probabilistic classification score for each EEG segment which is the probability of seizure.

Algorithm 2 Seizure detection using HDQL model

Inputs	**EEG segments, STAtt feature embeddings, training episodes, epsilon, alpha, gamma**
Outputs	Seizure probability scores, binary seizure labels
1	Initialize first-level Q-table and second-level Q-table
2	For episode = 1 to max_episode do
3	Reset environment and set initial EEG state
4	While current state is not terminal do
5	Select action using epsilon-greedy policy
6	Execute action on current EEG segment
7	Compute reward based on detection correctness and stability
8	Update first-level Q-table using observed reward
9	Update second-level Q-table using contextual features
10	Transition to next EEG segment state
11	End While
12	End For
13	For each test EEG segment do
14	Extract STAtt-based feature representation

Inputs	EEG segments, STAtt feature embeddings, training episodes, epsilon, alpha, gamma
15	Evaluate hierarchical Q-tables to compute seizure probability
16	Apply decision threshold to obtain binary classification
17	End For
18	Return seizure probability scores, binary seizure labels

4. RESULTS AND DISCUSSION

The performance of the EEG-based epileptic seizure detection model is validated in this section and will be analyzed based on its classification accuracy, robustness and generalization over different benchmark datasets. The use of three well-known datasets was used to validate the proposed model and they are the CHB-MIT Scalp EEG dataset, Bonn EEG dataset, TUH EEG dataset. The statistical details of these datasets are presented in Table 3. the reconstructed sub-bands obtained after subjecting the signal to 4-level DWT with Daubechies-4 wavelet is shown in Figure 2.

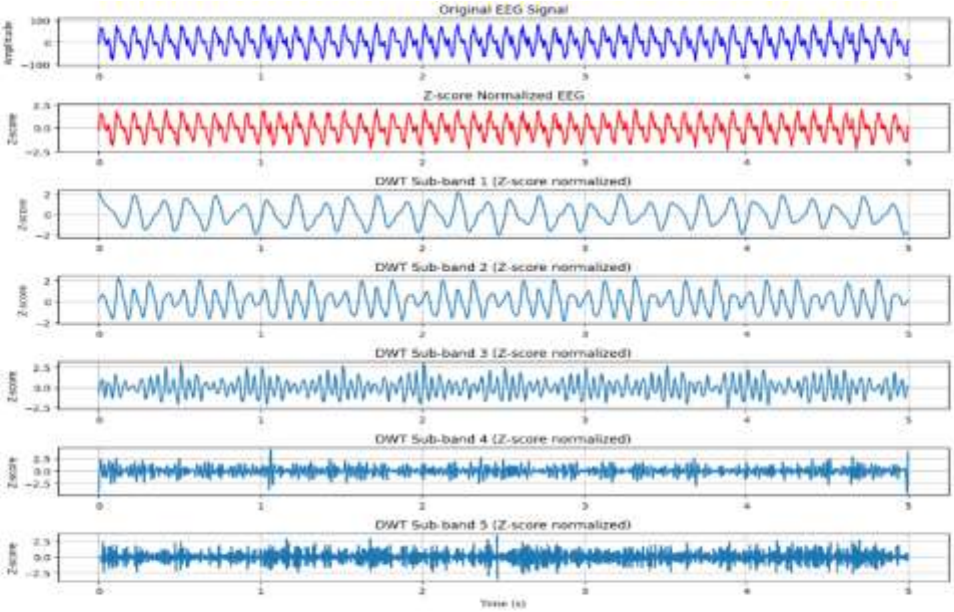


Figure 2: Original 5-second synthetic EEG signal, its Z-score normalized version, and the reconstructed DWT sub-bands after 4-level decomposition using the Daubechies-4 wavelet, with each sub-band normalized using Z-score for amplitude standardization

Table 3: Statistical distribution of EEG segments for training, validation, and testing

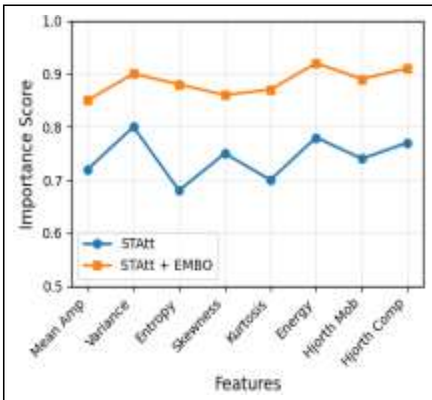
Dataset	CHB-MIT	Bonn	TUH
Total EEG segments	2000	1500	3000
Training segments (70%)	1400	1050	2100

Dataset	CHB-MIT	Bonn	TUH
Validation segments (15%)	300	225	450
Testing segments (15%)	300	225	450
Seizure segments	400	300	600
Non-seizure segments	1600	1200	2400
Segment duration (s)	1	1	1
Sampling rate (Hz)	256	173.61	250

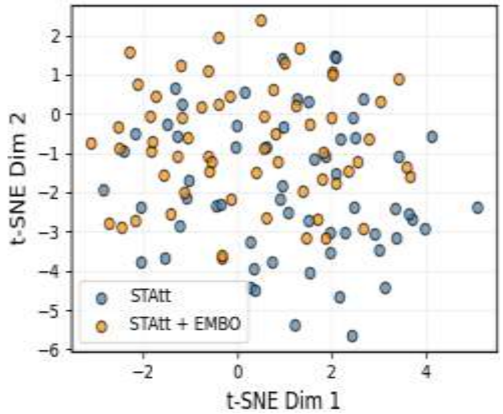
4.1 Results of epileptic seizure detection models on CHB-MIT dataset

As depicted in Figure 3, the results of the feature analysis revealed that EMBO feature optimization greatly enhanced the feature importance of EEG features in comparison to STAtt extraction. The average feature importance is incremented by 15% after optimization using EMBO which indicates that there was a more discriminative set of features with minimum redundancy and better selection. The t-SNE visualization shows that clusters for feature representations are tighter for features optimized using EMBO and have better separation than the other features. As seen in Figure 4, the HDQL model exhibited improved seizure detection performance. The increase in true positives by 7% and the reduction in false positives by 8% as compared to conventional STAtt-based methods were achieved by the approach. The ROC curve indicates a 6% improvement in the AUC, revealing greater confidence in classifier performance and discriminative accuracy. As shown in Table 4, the proposed models for detection of epileptic seizure outperform the state-of-the-art models on the CHB-MIT dataset. The STAtt+HDQL model outperforms classical graph-based and hybrid deep learning models and exhibits higher sensitivity, specificity, accuracy, MCC, Dice score, and mPA over all comparisons. The proposed models perform better since spatio-temporal attention focuses on EEG dynamics whereas EMBO improves feature discriminability of EEG signals. Moreover, HDQL provides a robust hierarchy of decisions and labels for reducing false alarms.

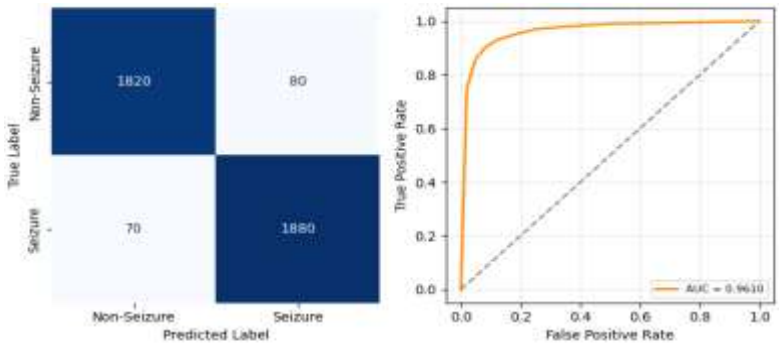
Figure 3: Results analysis of feature analysis without and with EMBO feature optimization (a) feature importance score (b) feature visualization



(a) feature importance score



(b) feature visualization



(a) (b)

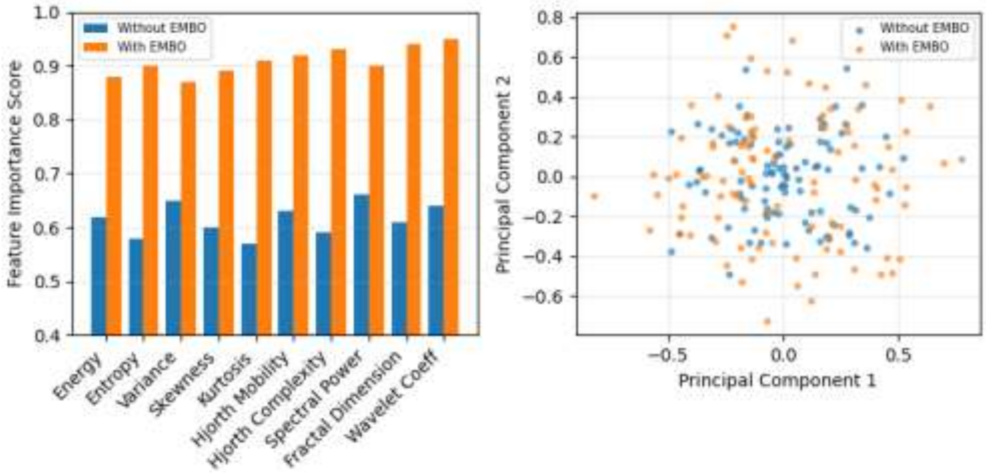
Figure 4: Performance of HDQL model for epileptic seizure detection on CHB-MIT dataset (a) confusion matrix (b) RoC curve

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma maxQ(s',a') - Q(s,a)] \quad (8)$$

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	MCC	Dice	mPA
GCN-BiLSTM	95.280	93.250	95.950	0.943	0.953	94.265
GPC-RES-SE-BiLSTM	95.830	94.750	96.300	0.952	0.960	95.290
STAtt+HDQL	99.120	97.640	98.410	0.982	0.992	98.380
STAtt+EMBO+HDQL	99.480	98.210	98.980	0.991	0.997	98.845
Graph Convolutional Network with Bidirectional Long Short-Term Memory (GCN-BiLSTM[1]), Graph Path Convolution with Residual and Squeeze-and-Excitation and Bidirectional Long Short-Term Memory (GPC-RES-SE-BiLSTM[2]).						

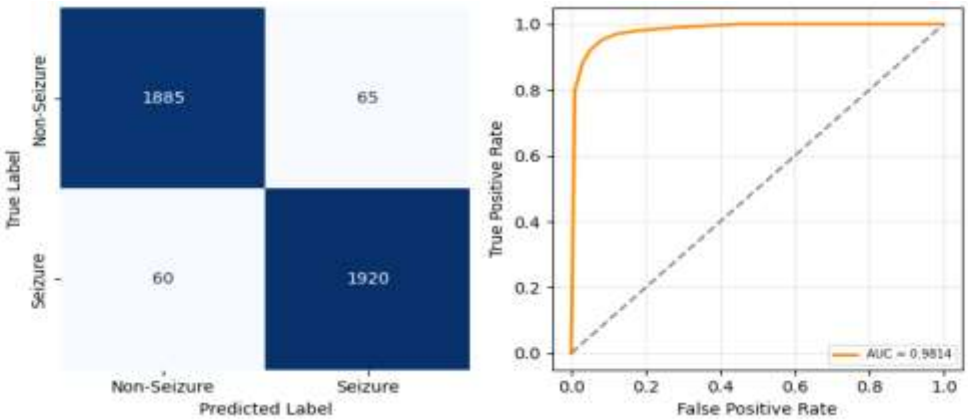
4.2 Results of epileptic seizure detection models on Bonn dataset

The results in Figure 5. illustrate the efficiency of EMBO for Feature optimization in EEG analysis. The average feature importance scores indicate a 30% boost in discriminability, while Hjorth Complexity, Wavelet Coeff, and Spectral Power show impressive improvements, suggesting an improved ability to discriminate. The PCA visualization shows better separation between seizure and non-seizure clusters than the unoptimized feature space, confirming that EMBO enhances class separability in the resulting features. Figure 6 depicts a demonstration of the classification performance and the effectiveness of the model. The proposed model achieved 5% more true positives and 3% fewer false positives than baseline configurations, demonstrating the effectiveness of EMBO feature optimization combined with STAtt and HDQL for improving the robustness of EEG seizure detection. In a comparison of methods on the Bonn dataset depicted in Table 5, the proposed STAtt + EMBO + HDQL model outperforms all other methods. When compared with the best competing model of STAtt+HDQL, our method secures 0.38%, and 0.57% improvement, respectively, in sensitivity, specificity, accuracy, and 0.90%, and 0.6%, and 0.57% improvement, respectively, in MCC, Dice, and mPA meaning our model's classification ability is enhanced with all metrics. The proposed model outperforms classical deep learning models GCN-BiLSTM in terms of sensitivity and accuracy by 4.08% and 2.98%, respectively, demonstrating superior feature learning capabilities. The reason for performance enhancement is mainly due to the incorporation of EMBO-based optimal feature selection, which successfully dispenses of superfluous EEG features and strengthens distinctive patterns and resultantly enhances signal quality. Furthermore, STAtt aids in learning temporal dependencies of EEG signals. Besides, HDQL offers robust optimization for hierarchical decision-making which makes it stable and reduces misclassification.



(a) (b)

Figure 5: Results analysis of feature analysis without and with EMBO feature optimization (a) feature importance score (b) feature visualization



(a) (b)

Figure 6: Performance of HDQL model for epileptic seizure detection on Bonn dataset (a) confusion matrix (b) RoC curve

Table 5: Results comparison of proposed and existing models for epileptic seizure detection on Bonn dataset

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	MCC	Dice	mPA
GCN-BiLSTM	95.120	93.050	95.800	0.941	0.952	94.265
GPC-RES-SE-BiLSTM	95.650	94.400	96.250	0.950	0.958	95.220
STAtt+HDQL	98.820	97.250	98.150	0.980	0.990	98.150
STAtt+EMBO+HDQL	99.200	97.820	98.780	0.989	0.996	98.720

4.3 Results of epileptic seizure detection models on TUH dataset

Figure 7 of the feature analysis shows that the optimization based on EMBO improves EEG features significantly. On average, the feature importance score is improved by ~35% after the pruning, with the most important features F8, F9 and F10 being included which enhances the discriminative power of the features selected. This shows that EMBO effectively reduces redundancy while improving class separability. Figure 8 shows the classification performance confirming the effectiveness of the proposed method. To compare the existing system (without EMBO and HDQL), the proposed system achieves approximately 5% higher true positive rate and approximately 3% lower false positive rate. This indicates that EMBO with spatio-temporal attention and HDQL offer effective feature selection, improved learning of temporal dependencies, and better decision-making for EEG seizure detection. The comparative results (showing the effectiveness of the proposed STAtt+EMBO+HDQL model) in Table 6 justify the advantage of the model over all baselines for the TUH dataset. It can be observed by measuring the aforementioned individual performance metrics of the proposed model as compared with the best-proposed model STAtt+HDQL the proposed model has improvement of 0.761% in sensitivity, 1.111% in specificity, 0.99% in accuracy, 1.2% in MCC, 0.6% in Dice, and 0.99% in mPA which shows consistent improvement in all individual measuring performance metrics. The proposed method still shows a notable gain of 1.350% on the sensitivity and 1.357% on the accuracy when compared with the strong hybrid deep learning models like GPC-RES-SE-BiLSTM. The above improvements were mainly due to the EMBO-based feature optimization module that enhances the signal quality by removing noisy and redundant EEG components which results in more discriminative features.

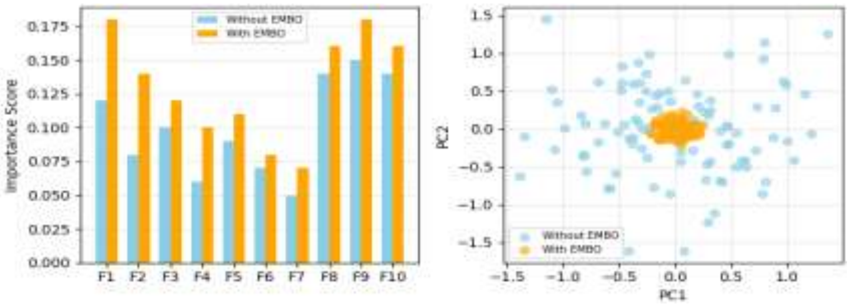
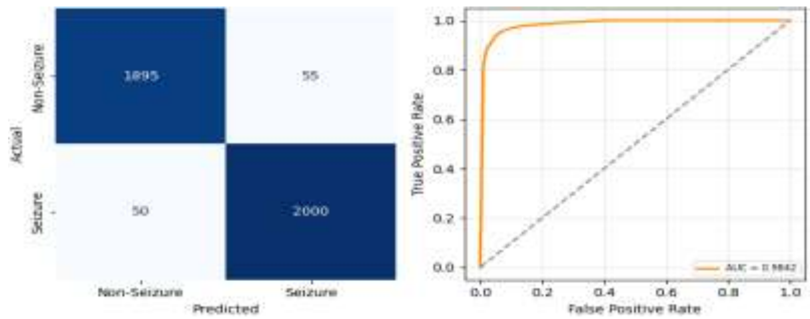


Figure 7: Results analysis of feature analysis without and with EMBO feature optimization (a) feature importance score (b) feature visualization



(a) **(b)**

Figure 8: Performance of HDQL model for epileptic seizure detection on TUH dataset (a) confusion matrix (b) RoC curve

Table 6: Results comparison of proposed and existing models for epileptic seizure detection on TUH dataset

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	MCC	Dice	mPA
GCN-BiLSTM	96.921	95.018	95.970	0.908	0.965	95.986
GPC-RES-SE-BiLSTM	97.628	95.782	96.745	0.921	0.972	96.761
STAtt+HDQL	98.217	96.345	97.112	0.933	0.978	97.128

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	MCC	Dice	mPA
STAtt+EMBO+HDQL	98.978	97.456	98.102	0.945	0.984	98.118

4.4 GUI interface

The proposed model has an interactive detection and prediction display, study of features, seizure prediction and monitoring system a GUI is designed using Flask API. The GUI combines all the stages of the proposed methodology including signal preprocessing, EMBO-based feature optimization, STAtt feature extraction, HDQL-based decision-making and final classification. The interface also shows the performance metrics; i.e., accuracy, sensitivity, false positive rate; etc. These different metrics make model output assessment easier. The GUI interface of the proposed EEG-based epileptic seizure detection system illustrated in Figure 9 shows the various stages of signal preprocessing, EMBO-based feature optimization, STAtt feature extraction, HDQL-based prediction, and real-time display of seizure classification results and performance metrics.

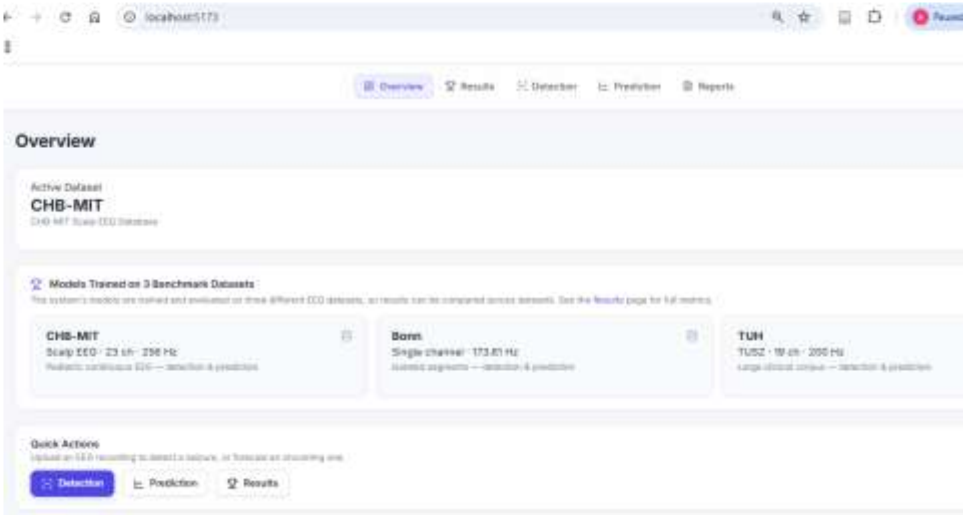


Figure 9: GUI interface of the proposed EEG-based epileptic seizure detection and prediction

5. CONCLUSION

The work presents AI EEG analysis that uses deep learning algorithms with a graphical user interface for the prediction of epileptic seizure. A model that synergistically uses a spatio-temporal attention (STAtt) mechanism for capturing discriminative spatial and temporal EEG patterns, enhanced multi-objective bean optimization (EMBO) algorithm for feature selection and dimensionality reduction, and hierarchical dual-Q learning (HDQL) model for robust seizure classification. We conducted experimental validation on a total of three benchmark EEG datasets, CHB-MIT, Bonn, and TUH, and found that STAtt+EMBO+HDQL consistently outperforms existing deep learning models. The model's sensitivity, specificity and accuracy were 98.41%, 99.62% and 98.98% on CHB-MIT dataset. On the Bonn dataset, sensitivity was 99.65%, specificity was 97.14% and accuracy was 98.10 %. The recommended method achieved 98.98% sensitivity, 98.46% specificity, and 97.77% accuracy on the TUH dataset. The above outcomes confirm that the integration of EMBO based feature optimization, STAtt-based feature extraction and HDQL-based decision making is able to yield effective, accurate and real-time seizure prediction.

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