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Multi-Task EEG Signal Classification for Emotion Recognition and Epilepsy Detection Using Intelligent Learning Models

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Abstract

Electroencephalography (EEG) provides rich information and a representation of brain activity for intelligent healthcare applications. This study proposes a framework for automated emotion recognition and epileptic seizure classification using machine learning (ML) and deep learning (DL) techniques. The framework was tested on three EEG datasets to cover areas of anomaly detection, multi-class emotion recognition, and binary seizure prediction. EEG signals were first normalized and then segmented into fixed-length windows depending on each participant's recording traits, thus maintaining subject-specific temporal patterns. Models' evaluation was done with properly separated training and testing data to guarantee a trustworthy performance assessment. For emotion recognition, the model based on Gated Recurrent Units (GRU) obtained 96% accuracy on the test data, whereas ensemble learning with Random Forest got 98%, thereby proving its excellent discriminative power on structured EEG features. Anomaly detection without supervision through Histogram-Based Outlier Score (HBOS) was able to detect the abnormal single-channel EEG segments accurately. In seizure classification, a convolutional neural network (CNN) trained on log, scaled time, frequency spectrograms yielded 95. 75% accuracy with an AUC of 0. 996 on the test dataset, thus successfully differentiating interictal and preictal states. The findings confirm that ML models provide robust and computationally efficient performance on engineered EEG features, whereas DL models effectively capture complex temporal and spectral representations across multiple EEG analysis tasks.

Keywords: Epilepsy–Seizure Detection, EEG Signals, Machine Learning, Emotion Recognition, Deep Learning, Convolutional Neural Networks

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1. Introduction

Electroencephalography (EEG) signal analysis has been integrated into brain-computer interfaces [1] for controlling wheelchairs and other machinery for people with disabilities. Additionally, EEG analysis has been used in controlling autonomous vehicles [2]. Beyond machinery control, EEG can analyze human emotional expressions, enabling recognition of emotions in affective computing [3]. It also plays a key role in detecting various brain-related disorders, such as those caused by sleep irregularities [4], epilepsy [5], depression [6], and Alzheimer's disease [7]. Moreover, EEG analysis has applications in biometric identification [8] and monitoring driver fatigue to improve road safety [9]. Epileptic seizure analysis typically involves seizure detection—identifying ictal events from normal background activity—or seizure prediction, which distinguishes preictal states from interictal baseline activity. Seizures can be classified as binary (e.g., preictal vs. interictal) or multi-class (interictal, preictal, ictal, postictal). In this study, the task is framed as a binary classification, differentiating preictal segments, which occur before seizure onset, from interictal

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baseline EEG activity, using time–frequency representations.

EEG signals are highly non-stationary, characterized by rapid temporal fluctuations, low signal-to-noise ratio (SNR), and susceptibility to artifacts. Their spatial–temporal complexity makes reliable pattern extraction challenging, particularly for affective computing and seizure analysis tasks [10]. The conventional methods of manual processing of the signal through neurologist evaluation and signal processing, which could be done through Fast Fourier Transform and Band Pass Filtering, involve so much manual feature extraction and basic statistical processing [11]. The said conventional methods are regarded as less efficient in terms of serving their purpose of recognizing complex patterns in the signals; therefore, not appropriate in this study for emotion recognition and seizure detection. The machine learning (ML) and deep learning (DL) methods could potentially make good feature extraction from the raw and processed EEG signals [12]. Hence, the improvement of accuracy and overall efficiency of the classification task applied to various EEG problems could thus be achieved with the help of the efficiency of the said advanced methods.

Convolutional Neural Networks (CNNs) refer to layers of DL models that hierarchically and spatially learn features automatically through convolutional filters. By converting EEG signals into time-frequency spectrograms, it not only visualizes the electrical neural activity in 2D, but it also enables CNNs to pinpoint seizure-related spectral changes more accurately.

The main contributions of this work are outlined below:

- Multi-objective EEG framework: A single comprehensive system that resolves the anomaly detection, multi-class emotion recognition, and binary seizure prediction problems simultaneously, through consistent preprocessing and validation strategies.
- Log-scaled spectrogram transformation: EEG segments are being converted into log-scaled time-frequency representations, thus allowing the CNN classifier to better differentiate seizure and non-seizure patterns.
- Integration of unsupervised detection: Using Histogram, Based Outlier Score (HBOS) for finding abnormal EEG segments before the supervised classification step.
- Comparative evaluation: The paper systematically compares the robustness and computational efficiency of ensemble learning models and DL architectures.

2. Literature Review

Electroencephalography (EEG) emotion recognition and neurological disorder classification have evolved from the initial use of handcrafted features to the application of DL models. At the beginning, researchers utilized decomposition methods like Empirical Mode Decomposition (EMD), Intrinsic Mode Functions (IMFs), and Variational Mode Decomposition (VMD) to extract frequency components in ER experiments [13]. While such techniques are effective in making the results understandable, they significantly increase the computation load and are highly reliant on manual extraction of entropy and fractal features. The combination of the Random Forest (RF) method with Info Gain (IG) feature selection [14] yielded a more robust performance, but classical machine learning (ML) methods still have a hard time modeling long-range temporal dependencies.

In order to model sequential dynamics, researchers proposed the use of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). LSTM-based networks outperformed ordinary RNNs in terms of temporal learning [16] and [17]. By means of evolutionary optimization, the integration of Multilayer Perceptron (MLP) and Adaptive Boosted LSTM (AB, LSTM) highly impacted the result accuracy through network structure and boosting methods [15]. Nevertheless, these methods are mostly focused on ER; thus, task generalization is a challenge.

For neurological applications, CNNs have been widely adopted due to their ability to learn hierarchical spatial–spectral representations. A lightweight CNN with Monte Carlo Dropout (MCD)

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uncertainty modeling improved seizure prediction reliability [20]. Despite strong spectral learning capability, CNN-based models are typically implemented as standalone classifiers without anomaly-aware preprocessing.

Recent research emphasizes hybrid and multiview deep architectures. Hybrid Quantum Deep Learning (HQDL) improved ER through quantum-inspired feature mapping [21], while multiview DL frameworks using Discrete Wavelet Transform (DWT) and Multivariate Empirical Mode Decomposition (MEMD) enhanced schizophrenia diagnosis [22]. Although these systems increase in representational diversity, they introduce high architectural complexity and computational overhead. Overall, current literature reveals three main gaps:

- Predominance of single-task frameworks (ER or seizure prediction only).
- Limited unified evaluation of ensemble ML and DL under consistent preprocessing.
- Scarce integration of unsupervised anomaly detection before classification.

To address these limitations, the proposed framework integrates ensemble ML, recurrent temporal models, CNN-based spectral learning, and Histogram-Based Outlier Score (HBOS) anomaly detection within a unified multi-objective EEG pipeline for both multi-class ER and binary seizure prediction.

3. Materials and Methods

This research proposes a single EEG signal analysis framework using ML techniques in solving two key tasks: automated emotion recognition and epilepsy seizure classification. First, the raw EEG signals are preprocessed through normalization, segmentations, and transformations into informative representations such as statistical features and time–frequency spectrograms. Emotion recognition will involve classical ML classifiers and recurrent deep learning models to capture both discriminative and temporal patterns from brain signals. Seizure classification uses a deep CNN to analyze spectrogram-based EEG images to learn the spatial-frequency characteristics of epileptic activity. The framework makes use of supervised learning, adopting robust training-test splits and optimization strategies in order to ensure generalization.

3.1 First Task: Automated Emotion Recognition

The First Task, Automated Emotion Recognition, will employ two different and complementary EEG datasets in order to successfully model and classify human emotions. The DEAP-EEG dataset [23] will enable the extraction of multi-channel raw EEG data, which can be used for the detection of irregular patterns in the human brain using HBOS, an unsupervised method for anomaly detection.

The second dataset is the EEG Brainwave Dataset. will have directly labeled positive, neutral, and negative emotions regarding the classification and will have optimal and balanced frequency-domain attributes for either traditional or deep learning approaches [24]. The proposed deep approach using a GRU Neural Network will manage the temporal dependencies of the EEG signal with the ultimate goal of achieving optimal classification success rates, and at the same time, being able to converge and learn successfully. Traditional classification approaches using various machine learning algorithms will be employed as a comparison method to ensure the robustness and validity of the proposed ensemble classification approach.

3.2 Second Task: Epilepsy-Seizure Classification

This task will explore the viability of using intracranial EEG as a method of forecasting the onset of seizures in patients [25]. A CNN model will be developed on log-scale spectrograms obtained from the preictal and interictal phases. On one hand, the high-resolution EEG recordings contain information that gives the model insight into the possible phases of seizures. On the other hand, using spectrograms can help the CNN model capture characteristics of time-frequency observations, thus boosting its forecasting results in the case of an accident.

4. Results

This paper assesses the proposed framework by conducting experiments using various benchmark EEG datasets for emotion recognition as well as seizure classification tasks. The effectiveness of the used ML and DL algorithms will be demonstrated using various quantitative parameters.

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4.1 EEG Dataset (EEG-Emotion-classification)

The dataset consists of the raw values of the EEG signals, which were obtained by the use of 32 scalp electrodes. Every row in the dataset portrays a specific channel, and the columns illustrate the samples of the EEG signals. Once the dataset was uploaded, it was systematically analyzed as follows:

- Although Independent Component Analysis (ICA) is commonly used for ocular and muscular artifact removal, it was not adopted in this study due to two reasons: (1) the utilized benchmark datasets were pre-cleaned and artifact-minimized, and (2) ICA introduces subject-dependent component selection, which reduces reproducibility. Instead, Z-score normalization was applied to stabilize feature scale while preserving discriminative signal variance.
- The raw EEG data is segmented into fixed-length intervals of 0.5 seconds based on the sampling frequency of 256 Hz.
- The segmented windows are reformed into a feature matrix, where each segment symbolizes an individual sample of the EEG signal.
- To create the training set, a total of 2,016 EEG segments, consisting of 128 samples, is created.
- Detection of irregular patterns using an unsupervised HBOS method. For a sample $x = (x_1, x_2, \ldots, x_d)$, the HBOS score is computed by Eq (1):

$$HBOS(x) = \sum_{j=1}^{d} \log\left(\frac{1}{p_j(x_j)}\right) \quad (1)$$

Where $p_j(x_j)$ represents the probability density estimate for the value x_j in the feature j, and is calculated as the ratio of the number of samples within the corresponding histogram box to the total number of samples.

Samples with HBOS scores above a predefined percentile threshold were flagged as anomalous and excluded before supervised training. Binary classification results were analyzed on segmented training data. The trained classifier generated binary predictions, where class 1 represented anomalous segments and class 0 represented normal segments. The model demonstrated clear separation between the two classes across consecutive EEG windows, indicating that the extracted statistical features preserved sufficient discriminative structure for anomaly identification.

The classification boundaries were consistent across segments, suggesting stable model convergence during training. Fig. 1 illustrates the temporal EEG segments after preprocessing and HBOS-based anomaly detection.

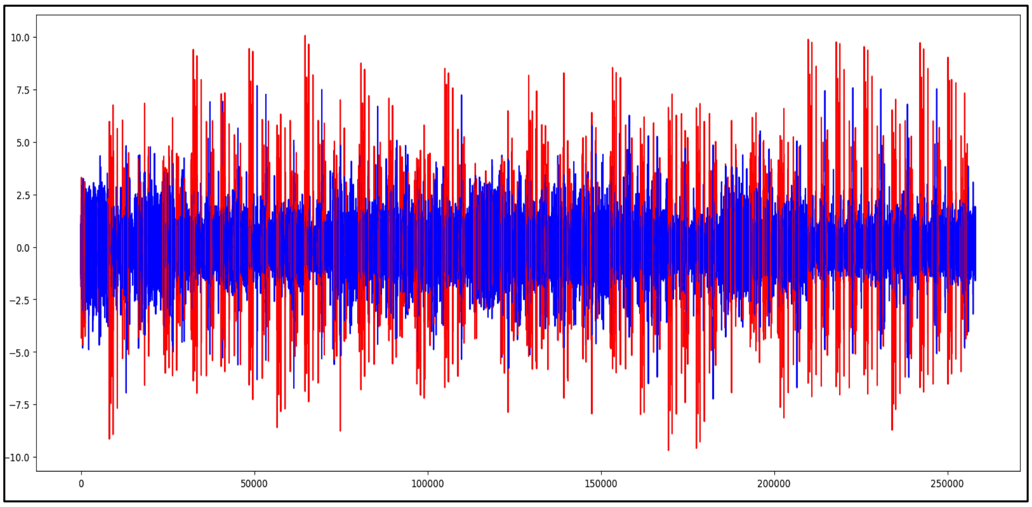

Fig. 1 HBOS-based anomaly detection on segmented EEG signals from the EEG dataset (blue: normal, red: anomalous).

4.2 EEG Brainwave Dataset (Feeling Emotions)

The second dataset from Kaggle enhances emotion recognition by offering EEG signals labeled clearly. The classes of emotion are well-balanced: 708 positive, 708 negative, and 716 neutral emotions, totaling 2132. These would thus be helpful in

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unbiased learning and reliable performance assessment.

The preprocessing stage starts by encoding the emotion labels into their numerical equivalents, as ML and DL algorithms can only process numerical data. It then separates the EEG feature matrix from the class labels to ensure a proper distinction between inputs and outputs. Standardization is then applied to the EEG features using z-score normalization; this allows the reduction of scale variations and helps improve model convergence. The encoded labels are further changed by one-hot encoding to support multi-class emotion classification. Finally, the processed data are divided into training and testing sets to enable model evaluation without bias.

In the classification of emotion, a deep learning model-based GRU [27] is used to capture temporal dependencies in EEG features. In Fig.2, the model structure includes an input layer where the feature vector expands into a dimension to adapt for sequential processing. Stacked GRU layers are employed to learn complex temporal patterns in brainwave signals, and their outputs are flattened into a single feature vector. Finally, a softmax output layer performs multi-class classification to predict neutral, positive, or negative emotional states.

Model: "functional_6"

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 2548)	0
lambda_6 (Lambda)	(None, 2548, 1)	0
gru_9 (GRU)	(None, 2548, 512)	791,040
flatten_6 (Flatten)	(None, 1304576)	0
dense_6 (Dense)	(None, 3)	3,913,731

Total params: 4,704,771 (17.95 MB)
Trainable params: 4,704,771 (17.95 MB)
Non-trainable params: 0 (0.00 B)
None

Fig. 2 Architecture of the proposed GRU-based DL model for EEG-based emotion recognition.

The model was trained for 10 epochs on preprocessed EEG data, with validation used to monitor performance. The model showed steadily increasing accuracy and decreasing loss, indicating effective learning of emotional patterns. Fig. 3 displays the training and validation loss curves, while Fig. 4 shows the accuracy curves, both confirming stable convergence.

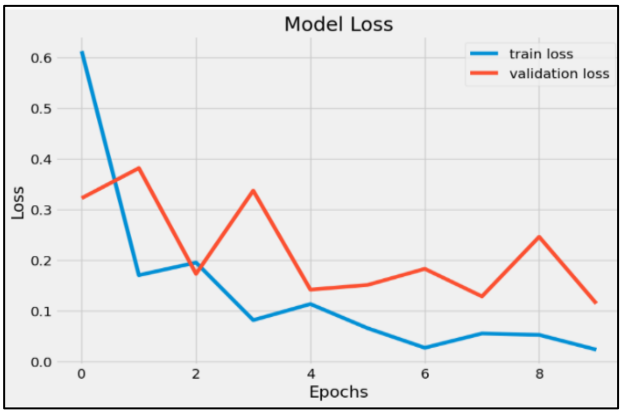

Fig. 3 Training and validation loss of the GRU model over 10 epochs.

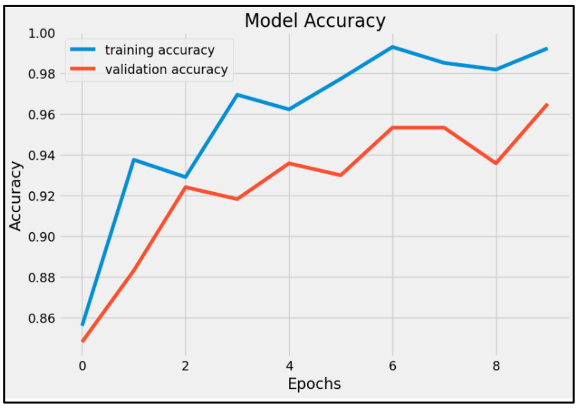

Fig. 4 Training and validation accuracy of the GRU model over 10 epochs.

After the completion of the training phase, the model underwent testing on an unseen test dataset, which helps to measure its capability in a real-world environment. According to the outputs, the classification accuracy of the model is nearly 96%, which is solid evidence of the effectiveness of the proposed methodology. Prediction and ground truth emotion labels are highly correlated; thus, the recognition of the three states has been done correctly. The confusion matrix, which is encapsulated in Table 1, serves to illustrate the fact that the correct classification rates were high and only a small number of misclassifications were made in every emotion category.

Table 1: Confusion matrix of the GRU-based emotion recognition model.

Actual \ Predicted	**“Neutral”**	**“Positive”**	**“Negative”**
“Neutral”	150	3	0
“Positive”	2	135	5
“Negative”	0	5	127

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To gauge the efficacy of various classical ML classifiers in the realm of emotion recognition through the utilization of EEG features, an assessment was conducted. As demonstrated in Table 2, due to stringent independence assumptions, which do not neatly correspond to the complex nature of the EEG, Gaussian Naive Bayes had quite a low accuracy. On the contrary, both SVM and Logistic Regression were above 96% accuracy, and their performance was strong and consistent for all emotion types. The Decision Tree, when compared with linear models, had a bit less generalization, but its results were still quite close to the competitors. The Random Forest (RF) achieved the highest accuracy of 98%, thus verifying the advantage of ensemble learning for reliable EEG-based emotion classification.

Table 2: Comparison of ML classifiers for the EEG brainwave dataset.

Model	Accuracy	Macro-Precision	Macro-Recall	Macro-F1-score
Gaussian Naïve Bayes	0.65	0.64	0.64	0.62
Support Vector Machine (Linear Kernel)	0.96	0.96	0.96	0.96
Logistic Regression	0.97	0.97	0.97	0.97
Decision Tree	0.95	0.95	0.95	0.95
RF	0.98	0.98	0.98	0.98
LSTM (GRU)	0.96	0.96	0.96	0.96

4.3 American Epilepsy Society Seizure Prediction Challenge Dataset

The second task, Epilepsy-Seizure Classification, will be focused on predicting seizure onset, utilizing the intracranial EEG (iEEG) data from the Kaggle American Epilepsy Society Seizure Prediction-Challenge, more specifically from the "Patient 1" folder. Additionally, the dataset will be divided into 10-minute epochs sampled at high sampling rates (up to 5000 Hz), which will be annotated as either preictal or interictal, while the preictal recordings will be extended up to one hour before seizure onset. To perform feature extraction, EEG recordings will be cut into one-second (5000 samples) epochs, followed by transformation to respective spectrograms depicting time-frequency patterns, which will be logarithmically scaled, serving as discriminative patterns to be utilized differently between the interictal state (baseline) and preictal seizure patterns. Time–frequency representations were generated using the Short-Time Fourier Transform (STFT) with a Hamming window of 256 samples, 50% overlap, and an FFT size of 512. The magnitude spectrum was logarithmically scaled to enhance discriminative spectral features and stabilize dynamic range.

The extracted spectrogram features were combined with their corresponding labels and carefully organized before model training. To prevent data leakage, patient-wise separation was enforced, and the training and testing sets were split chronologically to ensure no temporal overlap between preictal and interictal segments; additionally, no segments from the same continuous recording block were shared across splits, and normalization parameters were computed solely from the training data and then applied to the test set independently. The final dataset consisted of 21,000 training samples and 600 testing samples, where spectrograms were reshaped into four-dimensional tensors suitable for CNN input, and labels were one-hot encoded for efficient classification.

The proposed CNN architecture consists of several convolutional blocks that help learn hierarchical time-frequency features from the spectrograms of the EEG signals. The blocks consist of convolutional layers followed by batch

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normalization, max-pooling, and dropout to improve the process of feature extraction and prevent overfitting. The network further consists of fully connected layers to perform the task of classification. The architecture of the CNN-based seizure classifier is shown in Fig. 5.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 256, 22, 32)       320
_________________________________________________________________
batch_normalization (BatchNo (None, 256, 22, 32)       128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 256, 22, 32)       9248
_________________________________________________________________
batch_normalization_1 (Batch (None, 256, 22, 32)       128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 128, 11, 32)       0
_________________________________________________________________
dropout (Dropout)            (None, 128, 11, 32)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 128, 11, 64)       18496
_________________________________________________________________
batch_normalization_2 (Batch (None, 128, 11, 64)       256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 128, 11, 64)       36928
_________________________________________________________________
batch_normalization_3 (Batch (None, 128, 11, 64)       256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 5, 64)         0
_________________________________________________________________
dropout_1 (Dropout)          (None, 64, 5, 64)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 64, 5, 128)        73856
_________________________________________________________________
batch_normalization_4 (Batch (None, 64, 5, 128)        512
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 64, 5, 128)        147584
_________________________________________________________________
batch_normalization_5 (Batch (None, 64, 5, 128)        512
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 2, 128)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 32, 2, 128)        0
_________________________________________________________________
flatten (Flatten)            (None, 8192)              0
_________________________________________________________________
dense (Dense)                (None, 256)               2097408
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 514
=================================================================
Total params: 2,386,146
Trainable params: 2,385,250
Non-trainable params: 896
```

Fig. 5 CNN architecture for EEG-based seizure classification.

The CNN model was trained using the Adam optimizer with an initial learning rate of 1e-4 and a Reduce LR On Plateau scheduler to adaptively decrease the learning rate when validation loss plateaued. The training set comprised 21, 000 EEG spectrogram samples, out of which 600 samples were set aside for validation. The learning rate was gradually lowered according to the performance, which helped in better convergence and avoiding overfitting. Fig. 6 shows the learning rate schedule for all 30 epochs, demonstrating how it was faded depending on the changes in the validation loss.

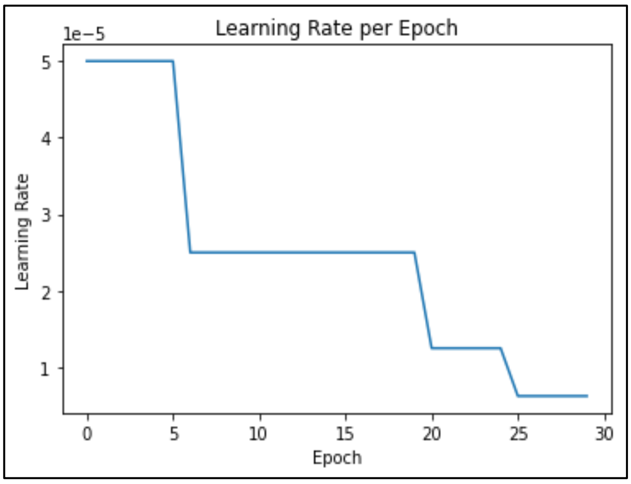

Fig. 6 Learning rate schedule per epoch during CNN model training.

The trained CNN model achieved a test loss of 0.122 and a high accuracy of 95.75% on the held-out EEG spectrogram data. As shown in Fig. 7, a confusion matrix shows a strong distinction between interictal and preictal states. Additionally, the model's predictive ability was assessed using the ROC curve, yielding an AUC of 0.996, which indicates excellent discrimination.

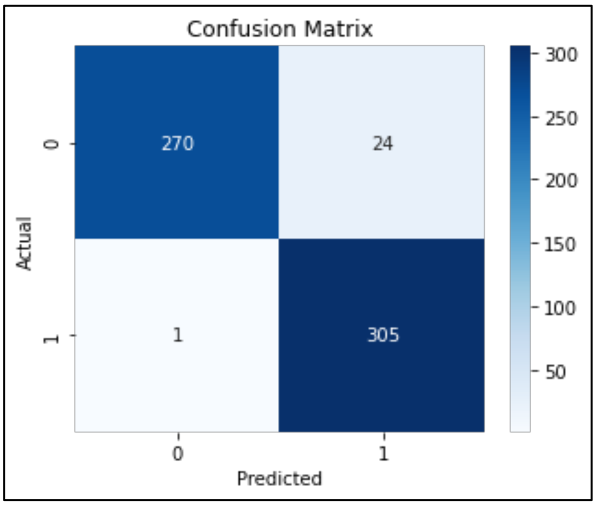

Fig. 7 Confusion matrix for CNN-based seizure model.

4.4 Discussion

The results demonstrate the effectiveness of the proposed methods that use EEG signal analysis:

- For EEG-emotion-classification, the unsupervised HBOS model successfully identified abnormal EEG segments, showing clear visual separation between normal and anomalous activity.

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- For the EEG emotion recognition dataset, the GRU-based deep learning model was able to capture temporal dependencies in brainwave signals; thus, it achieved a high classification accuracy of 96%, whereas classical ML models such as RF only reached 98% accuracy. Theoretically, GRU models are meant to capture temporal dependencies, but the segmented EEG windows (0. 5 seconds) provide very little long-range sequential information. Thus, the recurrent architecture might not be able to fully utilize its temporal modelling ability. On the other hand, RF gains from the statistical and frequency domain features that have been engineered to capture higher-order variance and nonlinear separability. Therefore, for short, feature, structured EEG segments, ensemble methods may give better results than deep temporal models by virtue of less overfitting and a better bias, variance trade, off.
- The CNN model trained on log, scaled, normalized spectrograms of EEG segments for the seizure prediction task obtained a very high-test accuracy of 95. 75% and an AUC of 0. 996, thus it was able to distinguish the interictal and preictal states quite accurately.

Across the three datasets, the ML and DL methods that were developed continually exhibited the capacity to extract highly functional temporal and spectral features; they were capable of performing both anomaly detection and classification tasks in EEG signal analysis.

Table 3: Comparative table based on the EEG Brainwave dataset.

Research	Best Results
Bird et al. [15]	MLP accuracy: 97.06%
Chowdary et al. [16]	LSTM accuracy: 97%
Priyadarshani et al. [17]	LSTM accuracy: 97%
Current Study	RF accuracy: 98%

Table 4: Comparative table based on the American Epilepsy Society Seizure Prediction-Challenge dataset.

Research	Best Results
Li et al. [20]	AUC of CNN: 0.903
Current Study	AUC of CNN: 0.996

Although recent models from 2024, such as quantum, assisted, and multiview architectures, have been able to report competitive performance, the CNN model proposed here has shown that it can achieve classification accuracy at a level that is comparable or even better, while it also has significantly lower computational complexity and implementation overhead. In contrast to hybrid frameworks that need feature fusion strategies or quantum simulation layers, the proposed solution can perform well with a simple end, to, end convolutional network. This indicates that carefully optimized CNN-based spectrogram learning can match advanced hybrid designs without the additional architectural and computational burden, making it more practical for real-time EEG emotion classification applications.

5. Conclusion

In this work, a comprehensive EEG framework that merges the advantages of both ML and DL approaches has been proposed for automated emotion recognition, as well as epilepsy seizure detection. Experimental outcomes have validated the efficacy of the proposed solution, with an accurate performance of 98% for the RF model in the case of emotion recognition, along with a 95.75% accuracy rate with an AUC of 0.996 for the CNN model in the case of seizure detection. The experimental outcomes have validated the efficacy of the proposed solution, which combines temporal, spectral, and time-frequency EEG signal characteristics. The proposed approach also showed robustness in handling both supervised and unsupervised learning tasks, including anomaly detection.

Future work will move from model training to rigorous validation and real-time application feasibility assessment. An excision study to remove the HBOS layer can also be conducted to determine its contribution to performance. Additionally, spectral power density (PSD) analysis should be performed to ensure that the 2014 EEG data meet modern signal quality standards and that the weights of the trained convolutional neural network are appropriate when applied to modern, high-impedance EEG sensors.

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Conflict of interest

"I, hereby, declare that there are no conflicts of interest regarding the publication of this manuscript".

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