Epileptic Seizure Prediction Using a Hybrid EEGNet Model with Integrated RMS, Variance, Line Length, and Hjorth Parameters

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Abstract

Accurate prediction of epileptic seizures using electroencephalogram (EEG) signals is critical for improving patient outcomes, especially in patients with drug-resistant epilepsy.The preictal state,which immediately precedes seizure onset,exhibits complex and subtle signal patterns that are often difficult to detect due to inter-patient variability.This study proposes an enhanced seizure prediction model that extends the EEGNet convolutional neural network by integrating key time-domain features, specifically Root Mean Square (RMS), Variance, Line Length, and Hjorth Parameters. These features capture essential characteristics of the EEG signal, such as amplitude fluctuations, signal variance and temporal complexity, which tend to change before seizure onset.The model was trained and validated on the CHB-MIT scalp EEG dataset using a stratified Train-Test split. The proposed approach achieved an average sensitivity of 91.9% and specificity of 95.8%,indicating improved predictive accuracy and robustness.These results highlight the effectiveness of integrating specific time-domain features with the EEGNet architecture in enhancing seizure prediction performance and supporting real-time clinical applications.

Keywords:EEG signals, Preictal state, Interictal state, EEGNet,Deep learning, RMS,Line Length, Variance, Hjorth parameters, CHB-MIT dataset.

1. Introduction

Epilepsy is a neurological condition characterized by recurrent seizures resulting from abnormal and excessive electrical discharges in the brain. These electrical activities are captured using electroencephalogram (EEG) recordings, which involve placing electrodes on the scalp to monitor brain signals. EEG remains an essential tool for identifying and analyzing seizure events.

Seizures are typically accompanied by symptoms such as involuntary movements, impaired motor control, and altered consciousness, all of which negatively affect patients' quality of life [1]. According to the World Health Organization, around 70 million people worldwide are affected by epilepsy, with nearly one-third of these individuals exhibiting resistance to anti-epileptic treatments[2].Predicting seizures in advance is important because it allows patients to take preventive steps and get timely treatment,potentially reducing the severity and frequency of seizures[3] .Traditionally, seizure prediction depended on observing physical signs and manually analyzing EEG recordings, which was often slow and lacked accuracy. However,recent progress in areas such as using deep learning technologies, continuous EEG analysis, and wearable technology has led to more accurate and faster seizure detection, promoting improved patient safety[4].Brain activity during a seizure can be categorized into three phases.

1) The interictal phase is the period between seizures, typically marked by normal brain activity with possible minor irregularities.
2) The preictal phase occurs before a seizure starts. During this phase, the brain's electrical activity changes that can warn us a seizure occurs.
3) The ictal phase is the seizure period, marked by sudden rhythmic spikes in temporal regions spreading to frontal areas, followed by high-amplitude spike-and-wave discharges lasting about 30 seconds.

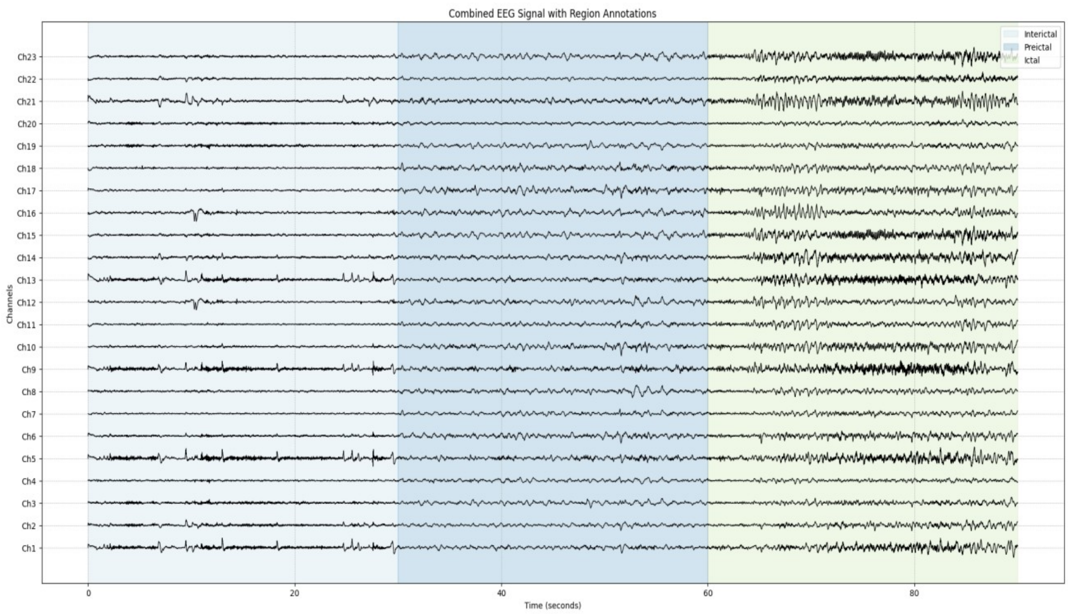

Fig-1: EEG Signal Visualization of Interictal , Preictal and Ictal States Across 23 Channels Over Time

Accurately identifying different stages of brain activity, particularly the preictal phase, is essential for advancing seizure prediction methods. Seizure prediction typically involves classifying EEG signals into either the preictal or interictal phase [5]. This process requires analyzing EEG data to extract features that can effectively capture the distinguishing characteristics of these two states. Once relevant features are obtained, machine learning or deep learning models are employed to classify the signals accordingly. Numerous approaches have been proposed in the literature, leveraging both time-domain and automatically learned features to improve the accuracy and reliability of seizure prediction systems.

Ibrahim et al. [6] proposed a seizure prediction method using 1D-CNNs applied to EEG signals decomposed into frequency bands via MODWT, achieving 82% sensitivity with a false positive rate of 0.058 on the CHB-MIT dataset and 85% sensitivity with a false positive rate of 0.19 on the AES dataset, without relying on manual feature extraction. Similarly, Toraman [7] utilized pre-trained 2D-CNN models such as ResNet, DenseNet, and VGG19 to classify spectrogram images of 5-second EEG segments from the CHB-MIT dataset, achieving an accuracy of 91.05% by recognizing preictal and interictal states.

Ben Messaoud and Chavez [8] developed a seizure prediction approach using a Random Forest classifier trained on 25 extracted features—encompassing time-domain, spectral, and correlation attributes from 15-second EEG segments of the CHB-MIT dataset, achieving a sensitivity of 82.07%. Similarly, Xu, Yang, and Sawan [9] enhanced seizure prediction performance by augmenting the CHB-MIT dataset with synthetic preictal signals generated through a DCWGAN-based GAN, resulting in a tenfold increase in training data and a rise in prediction accuracy from 73.0% to 78.0%.

Usman, Khalid, and Aslam [10] proposed a method titled Epileptic Seizures Prediction Using Deep Learning Techniques, based on the CHB-MIT dataset. EEG signals were preprocessed using Short-Time Fourier Transform (STFT), followed by feature extraction using CNNs and classification using a Support Vector Machine (SVM). Their approach achieved 92.7% sensitivity and 90.8% specificity.Hu et al.[11] proposed a method for epilepsy prediction using a hybrid Transformer model integrated with transfer learning, based on the CHB-MIT dataset. By utilizing a combination of EEG rhythm features, the model achieved a sensitivity of 91.7%.

Several studies have demonstrated that deep learning models, including pre-trained CNNs and hybrid architectures,can achieve high prediction accuracy, while traditional methods offer simpler and faster solutions.However,balancing high accuracy with low computational cost remains a key challenge,particularly for real-time seizure prediction systems.

In this work, EEG signals are analyzed to identify the most discriminative features that distinguish between preictal and interictal brain states. We select four key Time-domain features such as root mean square (RMS), variance, line length, and Hjorth complexity are used to capture essential characteristics of signal dynamics. These time domain features are integrated into an EEGNet-based convolutional neural network(CNN),which is designed to perform both feature extraction and classification. The hybrid model enables accurate prediction of seizure onset by leveraging both learned and time-domain representations of the EEG data. Section 2 describes the dataset used in this study, Section 3 outlines the methodology, Section 4 presents the results and discussion, and Section 5 provides the conclusion.

2. DataSet Access

The CHB-MIT database used in this work was collected from Children's Hospital Boston, contains EEG recordings from 24 pediatric patients with drug-resistant seizures.It includes 664 files with 198 seizures, mostly recorded using 23 channels at a 256 Hz sampling rate following the International 10-20 system. Each recording lasts between one to four hours.For analysis, recordings are divided into segments focusing on the preictal period, defined as the 30 minutes before a seizure. This segmentation helps in efficient processing and feature extraction. The publicly available dataset on PhysioNet is widely used for developing seizure prediction and detection algorithms [12].

3. Methodology

This section presents the methodology of H-EEGNet, a dual-branch architecture that combines deep learning representations with time-domain features.The first branch employs EEGNet to extract convolutional spatiotemporal features directly from raw EEG signals. Simultaneously, the second branch derives time-domain features from the same input segments. Outputs from both branches are concatenated and passed through fully connected layers to perform the final classification.

A. Data Preprocessing

The CHB-MIT scalp EEG dataset [12],which includes recordings from 24 subjects, was preprocessed to extract labeled preictal and interictal segments suitable for classification using the proposed H-EEGNet architecture. The preprocessing pipeline was developed using the MNE-Python library,which provides tools for reading and processing multichannel EEG signals stored in EDF format.

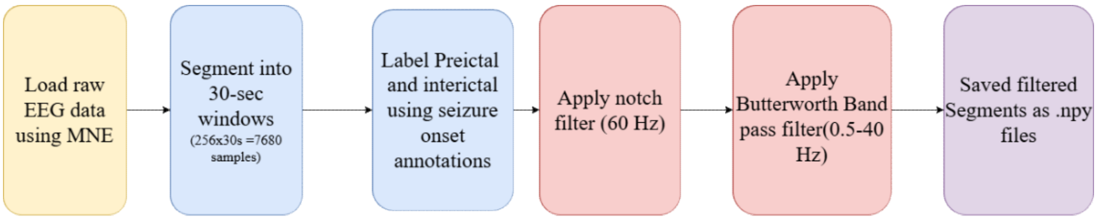

Fig 2:Work flow for EEG Data Preprocessing and Labeling for Preictal and Interictal State Classification

The complete preprocessing workflow is illustrated in Figure 1, outlining the core stages: loading raw EEG data, segmenting it into 30-second windows, labeling segments based on seizure onset annotations,applying filtering, and saving the processed data as structured NumPy files.

Each raw EEG recording was segmented into non-overlapping 30-second windows, corresponding to 7,680 samples at a 256 Hz sampling rate. Segments falling within the 30-minute window prior to a seizure onset were labeled as preictal, while those outside preictal, ictal, and postictal periods were labeled as interictal. Seizure annotations provided in the dataset guided the accurate identification of these intervals. A 10-minute postictal buffer was applied following each seizure to prevent contamination from residual seizure activity. Additionally, only seizures with at least 2 minutes of valid preictal duration were considered, ensuring sufficient data for reliable classification.

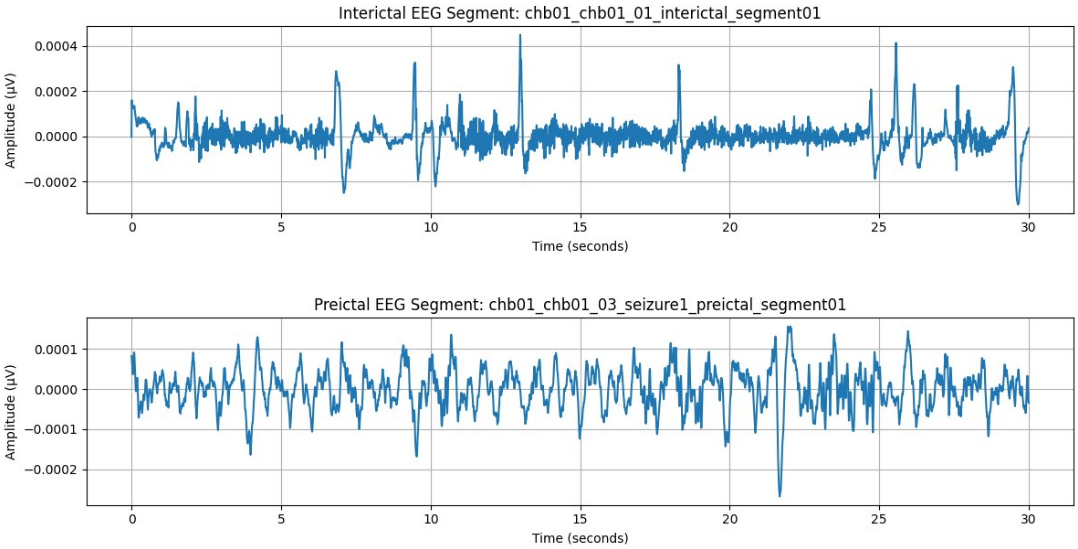

Fig 3: Comparison of EEG signal segments in interictal and preictal states

Figure 3 provides a side-by-side view of typical interictal and preictal EEG segments to show how the brain's activity changes over time. The interictal segment looks calm and steady, with low-amplitude signals that reflect normal brain function.On the other hand, the preictal segment shows small but noticeable changes and greater signal variability features that may indicate the early onset of a seizure.These distinct signal characteristics justify the classification of preictal and interictal segments as separate classes, as they represent fundamentally different patterns in neural activity.

To enhance signal quality, the preprocessing pipeline applies a 60 Hz notch filter to remove power line interference. It then uses a 4th-order Butterworth bandpass filter (0.5–40 Hz) to retain frequency components relevant to seizure dynamics, including the delta, theta, alpha, and beta bands [10]. These filtering steps effectively suppress artifacts while preserving physiological EEG rhythms that are essential for accurate predictive modeling.

A notch filter at 60 Hz with a quality factor of 30 removes power-line noise:

$$y(t) = \mathrm{filtfilt}(b_{notch}, a_{notch}, x(t))$$

where b_{notch} and a_{notch} are coefficients of an IIR notch filter, and x(t) is the input signal.

A 4th-order Butterworth bandpass filter(0.5–40 Hz) isolates delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz) bands:

$$y(t) = \mathrm{filtfilt}(b_{bp}, a_{bp}, x(t))$$

The filter coefficients b_{bp} and a_{bp} were normalized by the Nyquist frequency (fs/2=128 Hz). After filtering, the pipeline saved each segment as a.npy file with in structured directories organized by preictal and interictal classes.It also recorded metadata including subject ID, filename, segment number, start and end times, segment type, and file paths into a Pandas DataFrame, which was exported to a CSV file to support traceability and model training reference.

This preprocessing pipeline effectively transformed continuous EEG recordings into a structured,labeled dataset containing N_p preictal and N_i interictal segments. Each segment was stored in the shape (C,7680) where C≈23 represents the number of EEG channels.

B. EEGNet Model Architecture

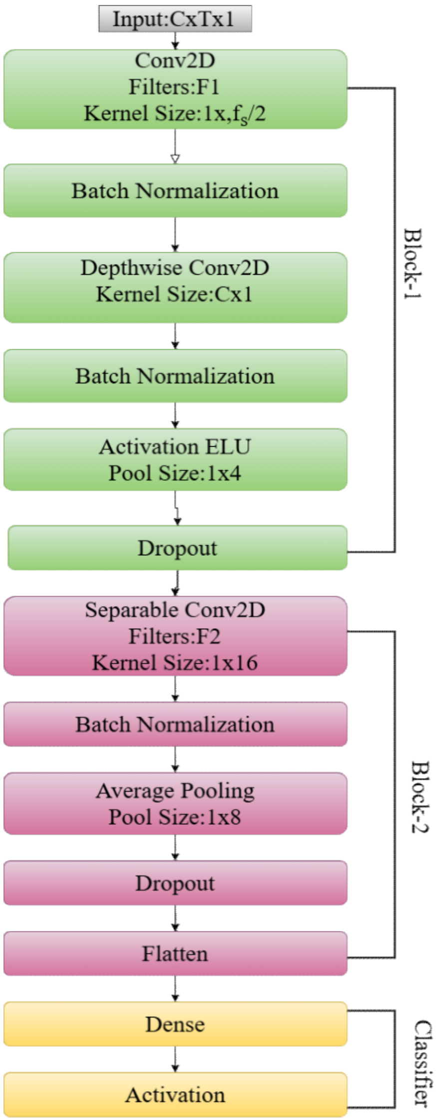

Fig 4: Architecture of the standard EEGNet

EEGNet is a compact CNN architecture designed for EEG-based applications, using depthwise and separable convolutions to efficiently capture temporal and spatial features while minimizing trainable parameters. Its lightweight design supports real-time use without sacrificing performance and has shown strong generalization in various BCI tasks. In this study, EEGNet serves as the backbone of the hybrid seizure prediction model, extracting spatiotemporal features from raw EEG segments. These features are combined with handcrafted time-domain features to enhance classification. This integration balances computational efficiency with predictive accuracy. The model architecture as shown in Figure 4.

The model comprises three main blocks, described as follows:

Block 1: Conv2D and DepthwiseConv2D Combination
This block starts with an input layer, followed by a standard Conv2D layer and a DepthwiseConv2D layer, each with batch normalization to stabilize training. Depthwise convolution reduces parameter count by connecting only to specific feature maps. In EEG processing, this combination allows the model to learn spatial filters aligned with each temporal filter. A depth multiplier controls the number of spatial filters per map. This design is inspired by the FBCSP algorithm for extracting spatio temporal features.

Block 2: Separable Convolution
This block applies separable convolution, consisting of a depthwise followed by a pointwise convolution. This approach reduces trainable parameters and decouples spatial from cross-channel feature learning. The depthwise step processes each feature map along the temporal axis, while the pointwise step merges them across channels. This enables efficient capture of multi-timescale feature representations for improved classification.

Block 3: Classification
In the final stage, the extracted features are passed through a softmax activation function to perform multi-class classification. The softmax function is well-suited for EEGNet's multi-class framework, as it converts the output logits into class probabilities. For binary classification tasks, a sigmoid activation may be used as an alternative [14].

C. Hybrid Feature Extraction

1. Deep Spatiotemporal Feature Learning with EEGNet

In seizure prediction tasks, capturing evolving temporal patterns in EEG signals prior to seizure onset is critical for early detection. Let the input EEG segment be denoted by $X \in R^{cxt}$,where C represents the number of EEG channels and T denotes the number of temporal samples.

Convolutional neural networks (CNNs), particularly EEGNet-based architectures, are employed to extract discriminative features from these multichannel EEG segments.

Each local region (or input patch) of the signal, centered at location (u,v), is defined as $P_{u,v} \in R^{kh \times kw}$,where K_h and K_w,represent the spatial (channel) and temporal dimensions of the kernel, respectively.

Given a learnable convolutional kernel $K \in R^{kh} \times K^{wk}$,the output feature map $Z \in R^{H' \times W}$ is computed using the standard dot-product convolution as follows:

$$Z_{u,v} = \sum_{i=1}^{K_h} \sum_{j=1}^{K_w} P_{u,v}^{(i,j)} \cdot k^{(i,j)}$$

The convolutional operation is applied across the input EEG matrix to extract local temporal patterns within each channel and to capture cross-channel interactions that may indicate transitions from interictal (non-seizure) to preictal (pre-seizure) states. In this study, the initial layer employs temporal convolution filters of size 1×32 allowing the model to focus on short-term temporal dynamics within each EEG channel. Subsequent layers progressively integrate these localized features into higher-level representations that enhance the model’s ability to predict impending seizure activity.By modeling spatiotemporal dependencies in EEG signals, the architecture enables robust learning of early neural signatures associated with seizures an essential capability for real-time seizure prediction systems.

2.Integration of Time-Domain Features

To enhance EEGNet's ability to distinguish between seizure and non-seizure brain activity,a hybrid approach was implemented that combines deep patterns learned from raw EEG signals with meaningful time-based features known to capture important signal characteristics.EEGNet effectively learns complex patterns in EEG signals by using temporal convolutions, depthwise spatial filtering, and separable convolutions. These layers help the model capture how brain activity changes over time and across different EEG channels.

However, EEGNet does not directly extract statistical features that are often useful in detecting early signs of a seizure.As a result, it may miss fine-grained signal patterns that conventional methods are designed to highlight.To overcome this limitation, the model includes four key time-domain features: Root Mean Square (RMS), Variance, Line Length, and Hjorth parameters.These features describe the signal’s energy, variation, frequency, and shape.Incorporating these features into the model provides clear and meaningful information about the EEG signal, enabling the system to more effectively detect changes that occur prior to seizure onset.

Each selected time-domain feature serves a specific role in describing how the EEG signal changes over time.RMS measures the signal’s energy and tends to increase during preictal states because of higher brain activity.Variance shows how much the signal's amplitude varies from the average and helps detect instability and irregular patterns in brain activity.Line Length measures the complexity of the EEG waveform and can detect fast changes and sudden spikes, making it useful for identifying abnormal brain activity.The Hjorth parameters offer more detail about the signal: Activity shows the power, Mobility reflects the average frequency, and Complexity shows how the frequency changes over time. Together, they help describe how brain signals behave over time.

Time-domain features were extracted from 30-second EEG segments across all channels, resulting in a fixed-length statistical feature vector for each sample.The model applies Z-score normalization to standardize the feature values and ensure compatibility with the deep features produced by EEGNet. In parallel, the raw EEG signals were processed through the convolutional layers of EEGNet, producing a flattened feature vector $f_{EEGNet} \in Rd$, that captures learned patterns in the input data. The system then concatenates this vector with the normalized time-domain feature vector $f_{time} \in Rt$.The two vectors are concatenated to produce a combined feature representation:

$$f_{\text{concat}} = [\mathrm{f}_{\text{EEGNet}} \| \mathrm{f}_{\text{time}}] \in \mathbb{R}^{d+t}$$

where || denotes vector concatenation

The fused representation was passed through fully connected layers and a softmax classifier to distinguish between preictal and interictal states.This integration approach allowed the model to utilize both the complex features learned by deep neural networks and the descriptive statistical features extracted through time-domain analysis.By combining these integrated feature sets, the model achieved enhanced robustness, improved generalization across subjects, and greater sensitivity to early markers of seizure onset.Integrating time-domain features with EEGNet's learned representations was essential for developing a robust and clinically relevant seizure prediction system.

D.Proposed H-EEGNet Framework

The proposed extension of the original EEGNet architecture has been specifically adapted for seizure prediction using scalp EEG recordings. Its primary objective is to classify EEG segments as either preictal or interictal based on learned neural patterns. Although EEGNet has shown strong performance in general EEG-based classification tasks due to its ability to learn spatiotemporal representations from raw signals, its architecture is primarily designed for capturing spatial and temporal dependencies through convolutional layers. In seizure prediction, however, additional time-domain features such as signal variability, entropy, and complexity often contain crucial information that may not be fully recognized by convolutional operations alone. To overcome this limitation, the proposed approach incorporates both learned and time domain features to improve predictive performance, as shown in Figure 5.

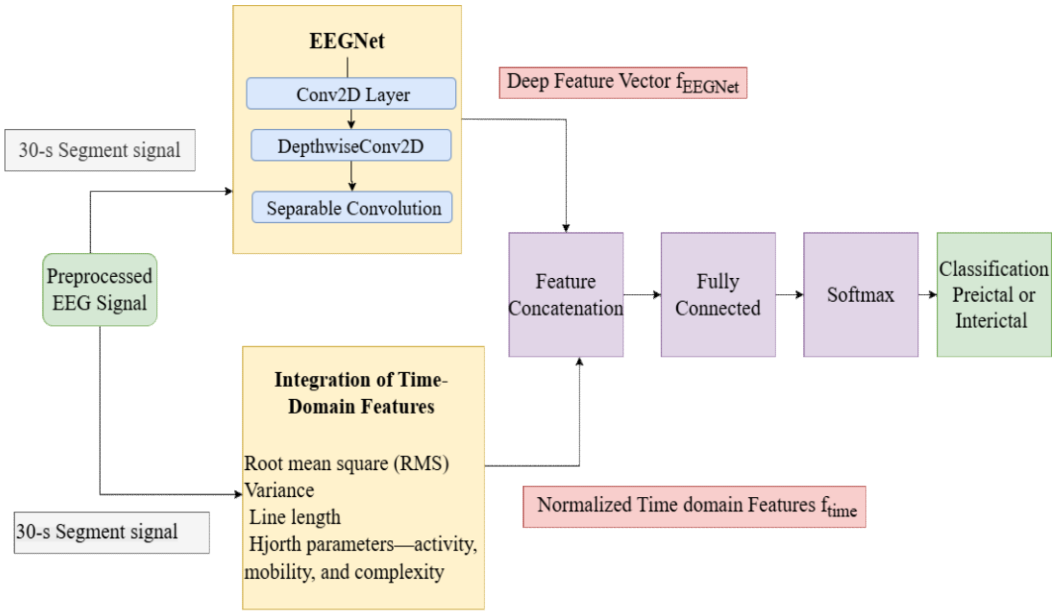

Fig 5: Flow diagram of the proposed method

In this framework each 30-second EEG segment is processed through two parallel branches.In the first branch, the raw EEG segment is fed into the EEGNet architecture, which applies temporal convolution, depthwise spatial filtering, and separable convolution. This sequence enables the model to learn frequency-related patterns and spatial dependencies across EEG channels, producing a deep feature vector f_{EEGNet} that encodes learned spatiotemporal representations.

Simultaneously, the second branch extracts time-domain features from the same EEG segment.These include Root Mean Square (RMS), variance, line length, and Hjorth parameters activity, mobility, and complexity.These features are established indicators of signal dynamics and are particularly effective for capturing the subtle irregularities often associated with seizure onset. The resulting time-domain feature vector is denoted f_{time}.The core enhancement in this framework lies in the fusion of both feature types at the feature level. The vectors f_{EEGNet} and f_{time} are concatenated to form a joint representation that captures both high-level learned features and low-level statistical properties.This combined vector is passed through one or more fully connected layers, followed by a softmax classifier that outputs the probability of the EEG segment belonging to either the preictal or interictal class.

This hybrid design modifies the original EEGNet architecture to better address the seizure prediction task by integrating time-domain features that capture meaningful EEG dynamics. These changes are based on the observation that preictal EEG signals often show small but consistent differences compared to normal brain activity.By combining these time-domain features with deep representations at the feature extraction stage, the model improves its accuracy and reliability in identifying early signs of seizure onset.

4. Results and Discussion

The proposed hybrid seizure prediction model was implemented in Python using TensorFlow and Keras. EEG signals from the CHB-MIT dataset were segmented into 30-second non-overlapping windows and labeled as preictal or interictal. A stratified 80:20 train-test split ensured class balance,and time-domain features were standardized using z-score normalization.Deep and handcrafted features were fused via concatenation,followed by dense, dropout, and softmax layers for binary classification.The model was trained using the Adam optimizer with sparse categorical cross-entropy loss, incorporating early stopping, learning rate scheduling, and checkpointing.Class weights addressed dataset imbalance.Training used a batch size of 8 for up to 40 epochs, with 20% of training data used for validation.

4.1 Evaluation Metrics

Model performance was evaluated on both training and testing sets using accuracy, sensitivity and specificity derived from the confusion matrix. Accuracy measures the overall proportion of correctly classified instances across both classes. Sensitivity (also known as recall or true positive rate) evaluates the model's ability to correctly identify preictal segments, which is critical for seizure prediction. Specificity, on the other hand, quantifies the model's capability to correctly detect interictal segments, ensuring it avoids false alarms. Together, these metrics provide a balanced and comprehensive evaluation of the model's effectiveness in distinguishing between preictal and interictal EEG patterns.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Where:TP: True Positives (correctly predicted seizure/preictal)

TN: True Negatives (correctly predicted non-seizure/interictal)

FP: False Positives (incorrectly predicted seizure)

FN: False Negatives (missed seizure)

4.2 Performance Results

In this study, a total of 4,667 EEG segments were utilized, consisting of 2,287 preictal and 2,380 interictal samples. These were divided into training and testing sets using an 80:20 stratified split, resulting in 1,829 preictal and 1,904 interictal segments for training, and 458 preictal and 476 interictal segments for testing.This balanced distribution ensures representative exposure to both classes during training and evaluation, thereby reducing potential class imbalance bias.Model evaluation followed the same 80:20 partitioning strategy, where EEG segments from multiple patients were pooled and randomly divided. While this method provides a reliable estimate of overall model performance, it does not fully assess generalization to unseen patients.To address this, future work will adopt subject-wise evaluation strategies, such as leave-one-subject-out cross-validation.

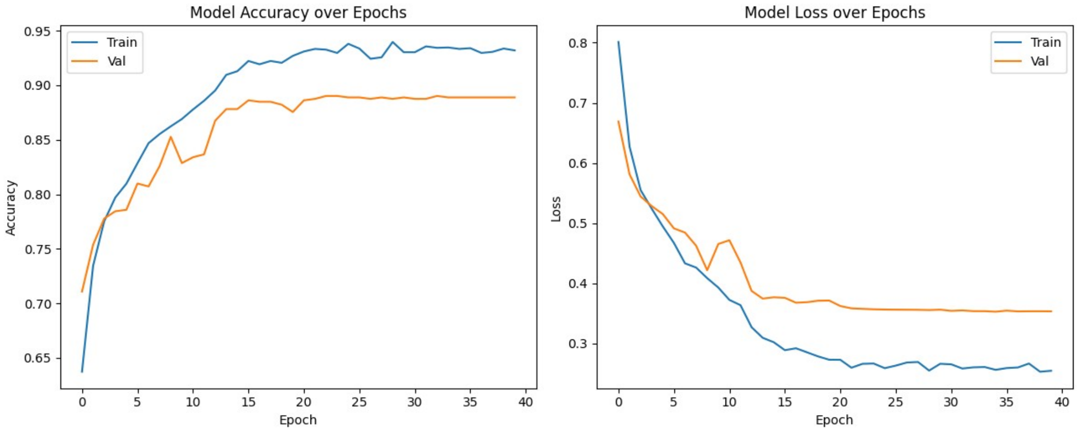

Fig 6: The progression of training and validation accuracy and loss over 40 epochs

As shown in Figure 6, the model achieved a training accuracy of 93.90% and a validation accuracy of 88.50% across 40 epochs.The training loss decreased from 0.8 to below 0.4, while validation loss stabilized after the 20th epoch, indicating effective convergence and no signs of overfitting.The confusion matrices depicted in Figure 7 further demonstrate the model's predictive performance.During training, the model correctly classified 1,826 interictal and 1,681 preictal segments, misclassifying 148 interictal and 78 preictal segments.In the testing phase, it correctly predicted 440 interictal and 403 preictal segments, with 55 interictal and 36 preictal segments misclassified.These results confirm the model's strong generalization ability and high predictive accuracy across EEG data.

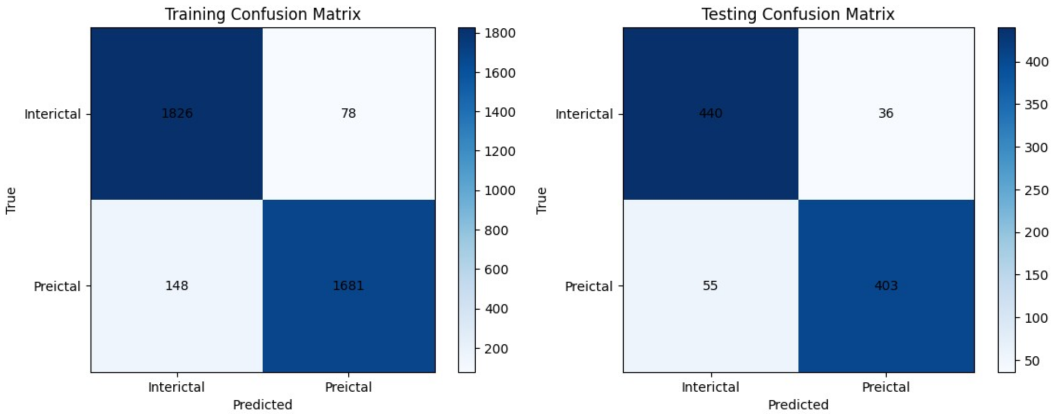

Fig 7 : Confusion Matrices for Training and Testing of the Seizure Prediction Model

4.3 Comparison with Previous Methods

While many earlier methods have explored the combination of deep learning with time-domain features, the approach adopted in this study presents a more cohesive and streamlined architecture. EEGNet is utilized both as a deep feature extractor and as the final classifier, eliminating the need for multiple, often redundant, processing stages.This compact design enhances computational efficiency without compromising performance. Additionally, meaningful handcrafted time-domain features such as root mean square (RMS), line length, and Hjorth parameters are directly integrated into the model. These features capture important statistical characteristics of the EEG signal, including amplitude, variability, and complexity. By combining these handcrafted features with the features learned by EEGNet, the model benefits from both domain-specific knowledge and data-driven learning. This dual-path strategy enhances the model's sensitivity to subtle preictal changes that precede seizures. Compared to previous multi-stage or overly complex frameworks, this method is simpler, faster, and more practical for deployment in real-time settings. It reduces the risk of overfitting and improves generalization across patients. Furthermore, the simplified architecture contributes to better interpretability, which is important for clinical applications. Overall, this hybrid approach achieves strong predictive performance while maintaining a lightweight and scalable design suitable for real-world seizure prediction tasks.

Comparison of Existing Techniques with Proposed Method

Reference	Model Used	Dataset	Parameter
Raza et al. [16]	EEGNet and NSL-EEGNet	Two-class MI (Graz dataset), Four-class MI (BCI Competition IV Dataset 2a)	Accuracy Two-class :76.07% Four-class:70.68%
Massoud et al.[17]	TCNN	Kaggle 2016 iEEG dataset	Accuracy = 60%, Sensitivity = 70 General AUC=0.75
Aslam et al. [18]	Custom CNN + LSTM (with handcrafted features)	CHB-MIT Scalp EEG (22 patients)	Accuracy: 94%, Sensitivity: 93.8%, Specificity: 91.2%
Toraman et al.[7]	Preictal Spectrogram + Pre-trained CNNs	CHB-MIT scalp EEG (20 cases)	Accuracy 91.05%
Messaoud et al.[8]	Random Forest Classifier	CHB-MIT scalp EEG (20 patients)	Sensitivity 82.07%
Usman et al.[10]	CNN + SVM Classification	CHB-MIT scalp EEG (24 subjects)	Sensitivity 92.7%, Specificity 90.8%
Proposed Method	EEGNet CNN model+RMS,Variance, Linelength and Hjorth Parameters features	CHB-MIT scalp EEG (24 subjects)	Sensitivity 91.9%, Specificity 95.8%

5.Conclusion

In this work,we developed a hybrid model for epileptic seizure prediction that combines key time-domain features with deep learning representations extracted using EEGNet.By integrating features like root mean square, variance, line length, and Hjorth parameters with spatiotemporal patterns learned from raw EEG data, the model effectively captured the subtle transitions from interictal to preictal states.We evaluated the model on the CHB-MIT scalp EEG dataset using an 80:20 train-test split, and it achieved high sensitivity and specificity,demonstrating strong predictive performance.Its efficient architecture and use of domain relevant signal characteristics make it well-suited for real-time seizure prediction in clinical applications.

Future work will explore subject-specific modeling, include additional features such as nonlinear dynamics and connectivity measures, and aim to deploy the model on wearable devices for continuous,real-world patient monitoring.

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