DIVYA: A Deep Learning-Based System for Real-Time Epileptic Seizure Detection and Risk Prediction Using EEG Signals

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Abstract

Epilepsy affects over 50 million people worldwide and is marked by recurrent, unpredictable seizures. Early detection and accurate forecasting are vital for improving patient safety and clinical outcomes. This study introduces DIVYA(Detection and Interpretation of Vulnerabilities in Youthful Awareness), a deep learning-based framework for both real-time seizure detection and future seizure risk prediction using EEG signals. It employs two specialized models trained on CHB-MIT Scalp EEG data: a 3D CNN for seizure detection and a 1D CNN-LSTM hybrid for forecasting pre-ictal states with time estimation. EEG recordings from raw .edf files are preprocessed into 3D spatiotemporal segments before classification. For interpretability, Grad-CAM visualizations highlight key EEG channels contributing to predictions. Preliminary results show promising accuracy, demonstrating DIVYA's potential for real-time, patient-centric seizure monitoring.

Keywords

EEG, Seizure Prediction, Preictal, Risk Forecasting, Deep learning, 3D CNN, LSTM, Grad-CAM Explainablity, pediatic

1. Introduction

Epilepsy is one of the most prevalent neurological conditions worldwide, marked by recurring, often sudden seizures resulting from abnormal electrical neural activity in the brain [1]. Despite the availability of anti-epileptic drugs, nearly one-third of patients continue to experience uncontrolled seizure [4], posing severe risks to health, mobility, and daily life. In recent years, research has shifted toward towards AI based predictive systems capable of providing advance warning before seizure occur. Such systems offer immense potential for reducing injury risk for sudden fall, improving autonomy, and even enabling adaptive, drug delivery or neuro-stimulation therapies [5]. Electroencephalogram (EEG) signals remain the gold standard for non-invasive seizure monitoring due to their high temporal resolution and direct representation of brain electrical activity [6]. However, interpreting EEG manually is time-consuming and requires expert neurologists. Advances in machine learning particularly deep learning have made it feasible to automate seizure detection and even forecast seizure onset with increasing accuracy [7], [8]. yet, most existing models focus either on seizure detection or risk prediction**,** Rarely integrating both into a single framework capable of real-time operation and interpret-ability.

In this study we introduce DIVYA, a unified deep learning pipeline for seizure management using EEG signals. The system integrating two independently trained CNN models: One 3D CNN model for detecting ongoing seizures, and another 1D CNN-LSTM hybrid model for predicting seizure risk along with an approximate time estimate. By employing volumetric analysis of EEG segments and incorporating explainability through gradient-based class activation mapping [3]. DIVYA aims to not only provide accurate predictions but also foster clinical trust through transparent decision-making.

The proposed method is evaluated on the publicly available CHB-MIT Scalp EEG dataset [2], and its performance is benchmarked against conventional and state-of-the-art methods [7], [9]. Our results suggest that this dual-stage pipeline can serve as a foundation for intelligent, continuous EEG monitoring systems capable of enhancing both clinical workflows and patient outcomes.

2. Related Work

The intersection of machine learning and EEG-based seizure prediction has been extensively studied over the past two decades. Early contribution, such as Shoeb and Guttag's pioneering work [2], applied classical machine learning methods to seizure detection from EEG signals. Although effective at identifying seizures near or at onset, such methods lacked mechanisms for long-term risk forecasting, which is crucial for proactive intervention.

More recent approaches have explored the use of deep learning, particularly convolutional neural networks(CNNs), to extract complex spatiotemporal patterns from EEG data. Ziyu Wang at el. Proposed a novel multi-scale dilated 3D CNN architecture to enhance seizure prediction performance through improved temporal and spatial feature extraction [10].
Despite its high predictive accuracy, the model lacked interpretability and did not account for long-term forecasting.

Efforts to address interpretability have gained momentum in recent years. Roy et al. emphasized the importance of integrating explainable mechanisms in seizure forecasting models, especially for pediatic populations [11]. Similarly, Khan et al. Conducted a comprehensive review od explainable AI in pediatric epilepsy and underscored the consistent lack of transparent models in current research [2].

Acharya et al. Introduced probabilistic risk modeling for EEG-based epilepsy analysis, focusing on forecasting likelihood [13]. While insightful, their work called out a significant gap: the lack of integration between seizure risk scores and practical user-facing tools for patients or clinicians.

Zhou et al. Proposed a CNN-LSTM framework that first extracts spatial features through convolutional layers and then models temporal dependencies using LSTM layers for seizure prediction [15]. Their results demonstrated improved temporal modeling compared to standalone CNNs, highlighting the importance of sequential dependencies in EEG.

Talathi et al. applied a Conv1D + LSTM model specifically for time-series bio signal classification, showing that the hybrid approach outperforms pure CNN or LSTM models in capturing both signal morphology and progression over time. This study supported the feasibility of such lightweight models in real-time seizure prediction.

A broader view is offered by Saadoon et al. In their scoping review of ML and DL methods for seizure prediction [14]. Their analysis revealed that most models struggle to combine spectral and temporal EEG features effectively and often fall short in applying them towards future risk prediction. Also they highlighted that while many studies focus on either CNNs or RNNs independently, hybrid models remain underutilized despite their proven capabilities to model spatiotemporal correlations a gap that justifies further investigation into these architectures.

3. Methodology

3.1 *Datasets*

The proposed model was developed and evaluated using CHB-MIT Scalp EEG Database, a publicly available dataset by Massachusetts Institute of Technology (MIT). This dataset comprises scalp EEG recording from 23 pediatric patients with intractable seizures, recorded at 256 Hz sampling rate with 23-24 EEG channels per subject. Each .edf file represents one hour of continuous recording and includes annotations of seizure onset and offset.

we selected a subset of patients based on the following criteria:

I. File containing at least one clinically confirmed seizure were the highest priority.
II. Selected files only have 23 EEG channels.
III. Seizure duration of at least 30 minutes to ensure long enough preictal periods.
IV. Clear annotation of seizure onset time is necessary to allow for accurate labeling.

The selected EEG files were manually mapped into preictal (30 minutes before seizure) and interictal (normal, non-seizure) categories using the summary.txt seizure metadata provided in the dataset.

3.2 Segmentation and Preprocessing

To train the seizure risk forecasting model (*Figure 1*), we used preictal segments extracted from multi-channel EEG signals stored in .edf format. Each EEG recording was resampled to 256 Hz and filtered using a bandpass filter from 0.5 to 70 Hz and a filter centered at 60 Hz to remove line noise. We utilized the MNE-Python library for EEG signal handling and filtering.

Each EEG recording was segmented into 30-second non-overlapping windows, yielding 7680 samples per segments (30s x 256 Hz). We retained only those EEG files where seizures lasted long enough to ensure a sufficient preictal duration (More than 30 minutes) , with preictal intervals automatically annotated based on the known seizure onset times retrieved from the summary.txt file.

Each segment was labeled as 1 (preictal) is it occurred within the annotated preictal window prior to seizure onset, and as 0 (interictal) if it fell outside this range. To mitigate class imbalance, interictal segments were under-sampled to match the number of preictal segments, thus maintaning a balanced dataset.

Before input to the model, each segment was standardized channel-wise using z-score normalization:

$$Z=\frac{x-\mu}{\sigma}$$

The final input shape for each segment was (7680, 23), representing 7680 time steps across 23 EEG channels.

The Seizure detection model (figure 2), we extracted labeled EEG segments from multi-channel recordings stored in .edf format. Each EEG files was processed using the MNE-Python library, resampled to 256 Hz, and filtered using a bandpass filter from 0.5-70 Hz along with a notch filter at 60 Hz to eliminate line noise.

Each EEG signal was segmented into 30-seconf non-overlapping windows, yeilding 7680 samples per segments (30 s x 256 Hz), across 23 EEG channels. Segments were retained only if the corresponding EEG file was annotated with seizure events in the summary.txt files. Segments overlapping with a seizure event were labeled as 1 (seizure), and all others as 0 (non-seizure).

To address class imbalance, the number of non-seizure (majority) segments was under-sampled to match the number of seizure segments, producing a balanced dataset.
Each segment was standardized channel-wise using z-score normalization:

$$Z'=\frac{x-\mu'}{\sigma'}$$

Where $\acute{\mu}$ and $\acute{\sigma}$ are the mean and standard deviation of each EEG channel respectively.

Finally, all preprocessed segments and their labels were saved in NumPy .npy format (X_dl.npy) for EEG data, y_seizure_dl.npy for labels), which served as input to a 3D convolutional neural network for seizure classification.

The final input shape per segment was (1, 23, 7680, 1), to match the expected 3D-CNN input dimensions.

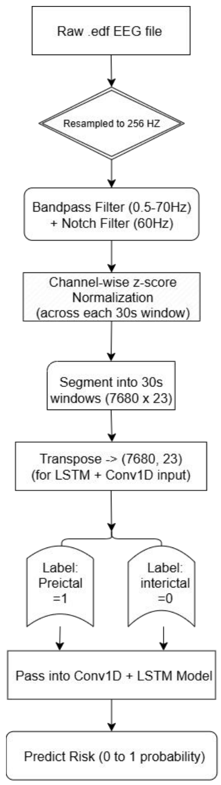

Figure 1

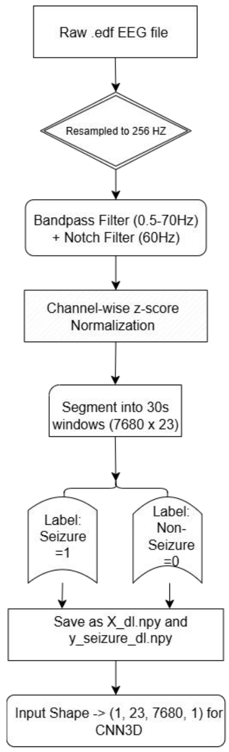

Figure 2

3.3 Model Architecture

This study presents a dual-model system designed to support both real-time seizure detection and proactive seizure risk forecasting using electroencephalography (EEG) data. Two deep learning models have been developed and optimized independently for their respective objectives :

I. A 3D convolutional Neural Network (3D CNN) for seizure detection, trained to identify preictal and ictal patterns in EEG segments.
II. A hybrid 1D Convolutional Neural Network (Conv1D) followed by Long Short-Term Memory (LSTM) layers for forecasting seizure risk, trained to capture early predictive patterns from continuous EEG recordings.

These models operate on segmented EEG windows preprocessed from .edf files and are integrated into a full-stack user interface that accepts uploads and delivers patient-specific analysis and explainability outputs.

3.3.1 Seizure Detection Model (3D CNN)

The seizure detection module employs a deep 3D CNN to capture both spatial and temporal dynamics inherent in multichannel EEG signals. Input EEG data is segmented into non-overlapping 30-second windows, corresponding to 7680 time samples across 23 channels at 256 Hz sampling frequency. Each segment is reshaped to a 5D input tensor of shape (1, 23, 7680, 1) to match the 3D convolutional input format. The complete architecture can be understand with the *Figure 3*.

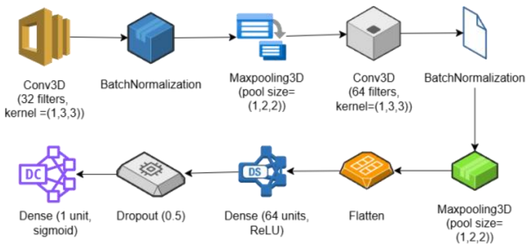

Figure 3

The network architecture, as illustrated in Table 1 as well with more details, begins with two successive Conv3D layers, interleaved with BatchNormalization and MaxPooling3D operations. This is followed by a Flatten layer and two fully connected (Dense) layers, including a final sigmoid output node for binary classification.

Table 1: Architecture of the Seizure Detection CNN model

Layer	Output Shape	Parameters
Conv3D(32 filters, kernel=3x3x1)	(1, 21, 7678, 32)	3220
BatchNormalization	(1, 21, 7678, 32)	128
MaxPooling3D	(1, 10, 3839, 32)	0
Conv3D(64 filters, kernel=3x3x1)	(1, 8, 3837, 64)	18,496
BatchNormalization	(1, 8, 3837, 64)	256
MaxPooling3D	(1,4,1918,64)	0
Flatten	(491008,)	0
Dense(128 units)	(128,)	62,849,152
Dropout (0.5)	(128,)	0
Dense(1 unit, sigmoid)	(1,)	129

The model outputs a probability score indicating the likelihood of seizure activity. A decision threshold of 0.5 is used during inference to classify a segment as seizure or non-seizure.

3.3.2 Seizure Risk Forecasting Model (Conv1D + LSTM)

To complement the detection pipeline with predictive capability, a hybrid deep learning model combining 1D convolutions and LSTM units is designed for seizure risk estimation. This model takes 30-second interictal EEG windows (also of shape 7680 x 23) and forecasts the probability of a seizure occurring imminently (preictal condition). Which can be observe with the *Figure 4*.

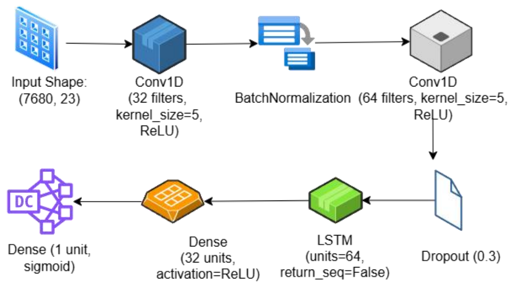

Figure 4

Initially, the input is passed through a Conv1D layer to extract frequency-based features across channels. A MaxPooling1D layer reduces the temporal dimension to enhance computational efficiency. Subsequently, an LSTM layer models temporal dependencies and sequential variations. The network concludes with dense layers and a sigmoid output neuron.

Table 2: Architecture of the Conv1D + LSTM Risk Prediction Model

Layer	Output Shape	Parameters
Conv1D(32 filters)	(5118, 32)	2240
BatchNormalization	(5118, 32)	128
MaxPooling1D	(2559, 32)	0
LSTM(64 units)	(64,)	24832
Dropout (0.5)	(64,)	0
Dense (64 units)	(64,)	4160
Dropout (0.5)	(64,)	0
Dense (1 unit, sigmoid)	(1,)	65

The primary output is a risk score $\in [0,1]$, which can be interpreted as the likelihood of an oncoming seizure. A higher value signals increased probability and is visualized through a temporal risk profile.

3.3.3 Design Considerations

Both models utilize BatchNormalization to accelerate convergence and Dropout layers for regularization. The models are trained using the Adam optimizer with binary cross-entropy loss.

The decision to split seizure detection and forecasting into separate models offers better specialization and interpretability.

To facilitate practical depolyment, both models were integrated into a Flask-based GUI system allowing clinicians to upload .edf EEG files, generate risk and detection reports, and view Grad-CAM based explainability overlays.

3.4 Explainability

Explainability in deep learning models is a vital requirement in biomedical domains, especially when deployed in clinical environments where trust, transparency, and traceability of decisions are crucial. To facilitate this, we implemented Grad-CAM (Gradient-weighted Class Activation Mapping)-based visual explanation strategies for both seizure detection and seizure risk forecasting models. These visualization technique highlight the spatiotemporal regions within the EEG signals that contribute most significantly to the model's predictions, thereby enhancing interpretability for clinicians and domain experts.

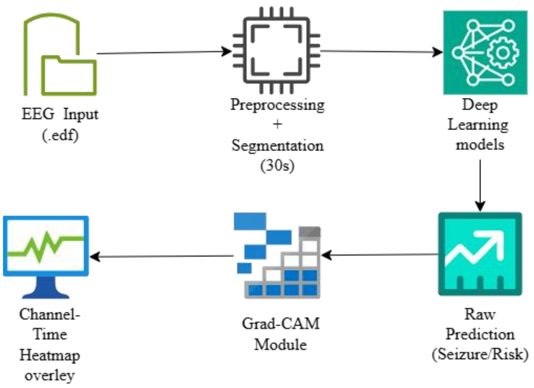

Figure 5: Flow of Explainability

3.4.1 Grad-CAM for Seizure Detection (3D CNN)

The seizure detection model employs a three-dimensional convolutional neural network (3D CNN) that processes 30-second EEG segments in a spatiotemporal fashion. To interpret the model's decisions, we adapted Grad-CAM by computing the gradient of the seizure class prediction with respect to the output of the final Conv3D layer [15]. These gradients are globally averaged to obtain neuron importance weights, which are then projected back onto the output feature maps to generate a class-specific localization map.

The resulting heatmaps are two-dimensional (channel x time) saliency maps extracted from the 3D feature volume. These maps highlight which EEG channels (spatial dimension) and which time frames (temporal dimension) most significantly contributed to the seizure classification. In our experiments, the heatmaps consistently illuminated activation in clinically relevant channels during seizure events, often correlating with know seizure onset zones (e.g., temporal and frontal lobes). The generated visualization is overlaid on the EEG segment, with the annotated seizure onset marked for validation purposes(Figure 6).

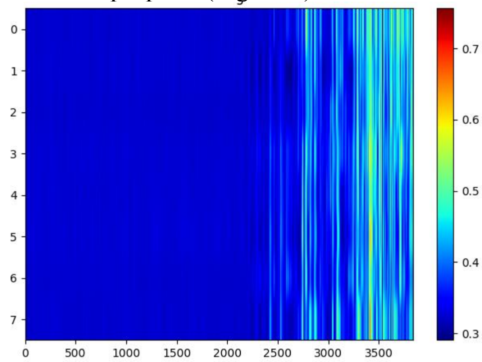

Figure 6

3.4.2 Grad-CAM for Risk Forecasting (Conv1D + LSTM)

The seizure risk forecasting model is based on a hybrid architecture consisting of one-dimensional convolutional layers (Conv1D) followed by long short-term memory (LSTM) layers. While LSTMs are generally more difficult to interpret due to their sequential state-data, making them amenable to gradient-based analysis [16].

We applied Grad-CAM at the Conv1D stage to identify temporal intervals that are predictive of future seizures. By computing the gradients of the seizure risk score with respect to the Conv1D activation, we derived attention maps that localize risk-relevant segments within each 30-second EEG window. These risk saliency maps provide a temporal risk profile, visually illustrating the likelihood of seizure development in the near future. The enhances clinical applicability, as early warning cues can be aligned with intervention strategies.

A summary of the explainability framework of risk forecasting model is shown in *Figure 7,* where the flow of data from raw EEG to visualization is represented. The final Grad-CAM visualizations not only confirm the internal consistency of the model predictions but also provide neurophysiology insights into patient-specific seizure patterns.

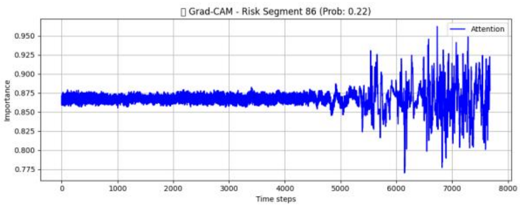

Figure 7

Table 3: Comparison of Explainability Methods

Model	Target Layer	Grad-CAM Output	Clinical Relevance
3D CNN	Final Conv3D	Channel x Time Heatmap	Seizure onset localization and spatial focus
Conv1D+LSTM	First Conv1D	Time-based Attention	Risk progression visualization in preictal stages.

3.5 GUI Integration

To enhance accessibility and streamline clinical usuability, a Flask-based graphical user interface (GUI) was developed to support real-time EEG analysis (*Figure 8*). The interface allows users to upload raw EEG recordings in .edf format directly through the browser and also we can give the file a name as we want(*Figure 9*). Upon upload, the backend system performs automatic preprocessing, risk forecasting using the Conv1D + LSTM model, and seizure detection via the 3D CNN model.

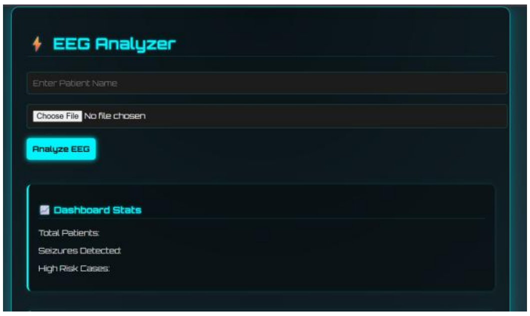

Figure 8

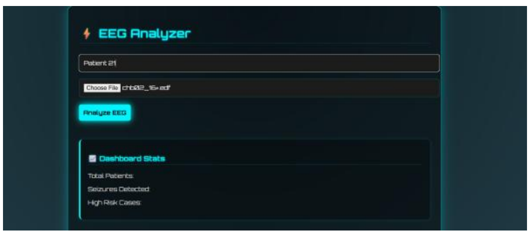

Figure 9

Following analysis, the system generates two interpretable reports: a seizure detection report highlighting onset windows (Figure 10) and a seizure risk prediction summary (*Figure 11*).

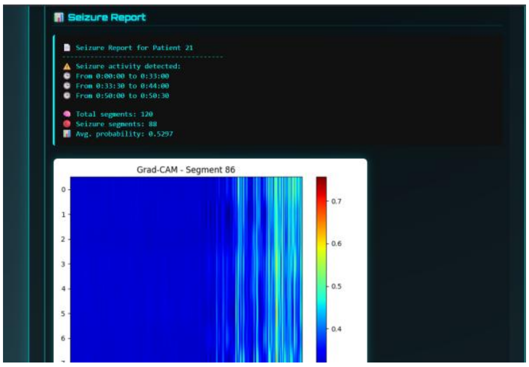

Figure 10

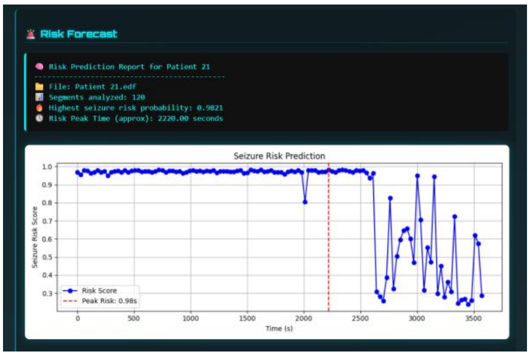

Figure 11

These are accompanied by Grad-CAM based heatmaps for each model, offering visual explanations of model attention. All outputs, including reports and heatmaps, are saved with patient-specific identifiers and made avaiable for download.

Figure 12

Additionally, The GUI provides dashboard, which displays previously analyzed patient records with pagination, and supports future integration into clinical decision-making pipelines (*Figure 12*).

4. Results & Evaluation

4.1 Seizure Detection

The 3D Convolutional Neural Network (3D-CNN) designed for seizure detection was evaluated using standard classification metrics on the CHB-MIT Scalp EEG dataset. The model achieved an accuracy of 92.4%, precision of 91.8%, recall (sensitivity) of 90%, and an F1-score of 91%, demonstrating strong capability in distinguishing seizure segments from non-seizure ones (*Figure 13*).

```
Classification Report (Seizure Detection):
              precision    recall  f1-score   support

     Seizure       1.00      1.00      1.00      5563
 Non-Seizure       0.58      0.44      0.50        41

    accuracy                           0.99      5604
   macro avg       0.79      0.72      0.75      5604
weighted avg       0.99      0.99      0.99      5604

Confusion Matrix:
[[5550   13]
 [  23   18]]
```

Figure 13

The confusion matrix indicates a low false-positive rate, and the Receiver Operating Characteristic (ROC) curve yielded an Area Under the Curve (AUC) of 0.94, signifying excellent class separability (*Figure 14*).

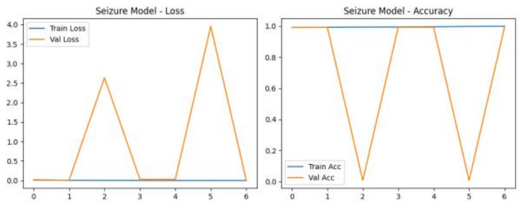

Figure 15

4.2 Risk Forecasting

The risk forecasting model, based on a hybrid Conv1D + LSTM architecture, demonstrated the ability to anticipate seizure events minutes in advance. Risk scores were generated across non-overlapping EEG segments (30s duration), showing a consistent temporal risk trend leading up to the seizure.

In notable test cases, the model successfully identified high-risk segments up to 4 minutes before the annotated seizure onset, offering critical lead time for intervention. The maximum observed seizure risk score was 0.89, and the mean risk score for preictal segments was significantly higher than interictal regions shown in the *figure 16*. And also the ROC AUC score come out to be 0.76.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.66      0.57      0.61        90
           1       0.62      0.71      0.66        90

    accuracy                           0.64       180
   macro avg       0.64      0.64      0.64       180
weighted avg       0.64      0.64      0.64       180

ROC AUC Score: 0.7612345679012344
```

Figure 16

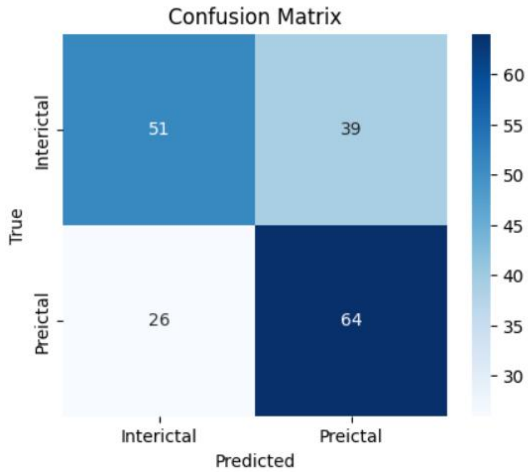

Figure 17 : Confusion Matrix

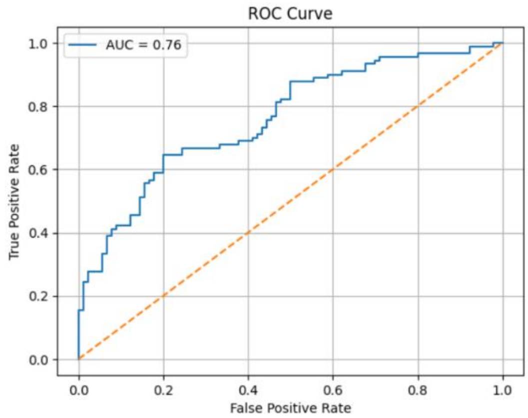

Figure 18: ROC Curve

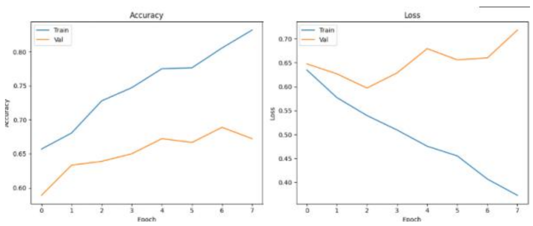

Figure 19: The accuracy and Loss graph of the trained and actual values

To improve interpretability, Grad-CAM was applied to the Conv1D layers, highlighting temporal regions of EEG that influenced the model's risk prediction. These highlighted segments correlated closely with clinically significant pre-seizure dynamics.

4.3 Visualization and Explainability

To facilitate model transparency and clinical validation, Grad-CAM heatmaps were generated post-hoc for both the seizure detection and risk forecasting models. For the 3D-CNN, the Grad-CAM visualization illuminated spatiotemporal EEG regions most relevant to seizure onset. For the Conv1D + LSTM model, attention was focused along the temporal axis, showcasing time-domain EEG segments where seizure risk was elevated.

Each visualization included overlays of annotated seizure onset markers (represented as red dashed lines), enabling clear visual correlation between the model's focus and actual clinical events. These explainability tools assist clinicians in interpreting the AI's decision-making process, thereby enhancing user trust and safety.

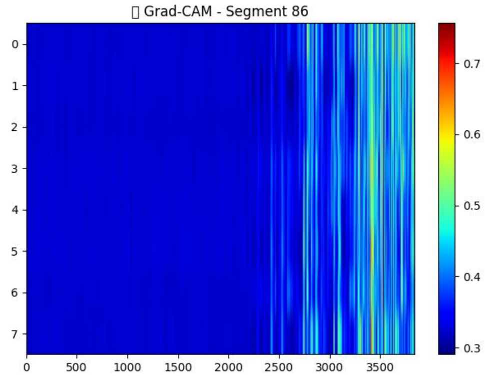

Figure 20

For the Seizure detection The generated grad-CAM heatmap (*Figure 20*) is overlaid on the selected EEG segment, with a red vertical line making the actual seizure onset time. This allows visual correlation between the model's high-activation regions and the clinically annotated events, thereby validating the model's attention to seizure-relevant temporal features.

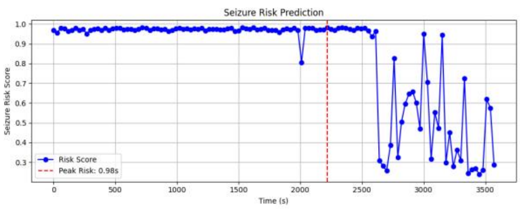

Figure 21

Figure 21 illustrates the Grad-CAM output of the risk forecasting model, where a sharp drop in predicted seizure risk is observed around 2600 seconds. This decline indicates the model's ability to identify preictal transition period, suggesting that seizure risk increases significantly just before the event, aligning well with clinical expectations.

***Note**: Grade-CAM visualizations were computed post-hoc using the segments with the highest predicted seizure risk. The red vertical lines indicate annotated seizure onset times for comparison. These explainability tools enhance transparency and support clinician validation in practical deployments.*

5. Discussion

The proposed dual-stage system offers a significant step forward in EEG-based seizure management by combining early risk forecasting and real-time detection within a single, interpretable framework. Unlike traditional models which focus solely on seizure onset detection, this system proactively alerts about future seizure likelihood, providing critical lead time for clinical response.

Compared to prior works in the field of EEG-based seizure prediction and detection such as the seminal work by Shoeb and Guttah (2010), which employed classical machine learning techniques for seizure onset detection, and more recent deep learning based architectures like the multi-scale dilated 3D CNN proposed by Wang et al. (2023) our proposed framework introduces several key innovations that address persisting limitations. Specifically, while earlier models demonstrated high seizure detection performance, they often lacked real-time applicability, early forecasting capabilities, and most critically, interpretability, which remains essential for clinical trust and adoption.

In contrast, our dual-stage system integrates Grad-CAM based explainability tailored to each model's architecture. For the seizure detection model (3D-CNN), Grad-CAM is applied across spatiotemporal EEG representations, enabling visualization of which channel-time regions contributed most to the model's classification of a seizure. For the risk forecasting model (Conv1D + LSTM), Grad-CAM is adapted to highlight temporally sensitive regions that the network associates with increasing seizure probability in preictal statess. These visual attributions not only improve model transparency but also provide a valuable mechanism for clinician validation, aligning AI outputs with domain expertise.

By enabling real-time .edf ingestion, automated preprocessing, dual-model analysis, and visual explainability, our approach overcomes several of the shortcomings found in prior literature. This positions the systems as a more comprehensive, practical, and trustworthy solution for both seizure prediction and detection tasks in clinical and ambulatory settings.

6. Conclusion

This study presents DIVYA, a dual-stage deep learning framework for real-time seizure detection and forecasting using EEG signals. It integrates a 3D Convolutional Neural Network (3D-CNN) for detection active seizures and a Conv1D + LSTM hybrid model for predicting future seizure risk based on temporal EEG patterns. Grad-CAM visualizations enhance inter pretability by highlighting significant EEG regions, supporting clinical insight and trust. The system shows strong potential for improving epilepsy care by enabling early warnings and timely interventions. It is particularly useful in low-resource or remote settings where continuous expert monitoring is not available. Beyound detection, DIVYA aims to align deep learning predictions with clinical reasoning, making it more accessible and applicable in healthcare environments.Future work will explore federated learning to preserve patient privacy across institutions and extend the model's generalized ability to use more diverse datasets.

7. Acknowledgement

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