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Hybrid Deep Learning Approach for EEG-based Epilepsy Detection

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Epilepsy is a chronic neurological disorder characterized by continuous relentless seizures resulting from abnormal activity in the brain. Early and accurate diagnosis is very critical. The usual methods can take a lot of time for diagnosis and it can also often vary from one specialist to another. There have been many approaches implemented for detecting seizures with varying success. Electroencephalogram (EEG) analysis is a critical tool for diagnosing neurological conditions like epilepsy. A key focus in medical technology has been automating the detection of epilepsy but it has been challenging due to its complexity and large amount of data. Although the results of some studies have been encouraging, the use of these approaches has not been practical due to various issues i.e. imbalanced data signal variability to name a few. This research presents a new approach to improve performance and accuracy. A Hybrid Deep Learning model combines a number of paradigms of neural networks to leverage the best of multiple models in processing complex data like EEG signals. EEG. As EEG has both temporal and spatial data this hybrid approach is quite practical in handling different EEG components. In addition, a multimodal method is explored to enhance prediction performance. This involves enhancing EEG data with complementary data, such as clinical history and other biomarkers. Through integrating data from multiple sources, the model gains a broader context for epileptic activity detection. Which helps in bypassing the inefficiencies inherent in EEG signals. This combined approach can potentially provide stronger and clinically informative outcomes, hence enabling advancements in the early diagnosis of epilepsy.

Keywords: Electroencephalogram, Independent Component Analysis, Principal Component Analysis, Gated Recurrent Unit, Tunable-Q Wavelet Transform, Synthetic Minority Oversampling Technique, European Data Format

Introduction:

Epilepsy is one of the most common and serious neurological disorders in humans. It affects over 70 million people over the world [1]. Children and aged groups are at higher risk of epilepsy. Epilepsy is a collection of symptoms influenced by various risk factors. A significant genetic predisposition, rather than a singular condition with one specific cause or manifestation [1]. Seizures may occur quite suddenly; however, some adults have demonstrated the ability to sense if a seizure is about to happen [2]. These attacks come and go rapidly and arise from abnormal electrical activity in the brain. They can lead to long-term brain damage and can also affect other body organs due to environmental factors during a seizure [3]. Furthermore, those diagnosed with epilepsy often experience emotional distress as they live with the constant risk of an attack happening at any time.

Traditional methods of diagnosing epilepsy mostly depend on the visual analysis of EEG recordings by neurologists. Specific patterns like spikes or sharp waves are identified as signs of seizures. While this method is effective, it is time-consuming and subjective. It is heavily reliant on the specialist's expertise making it less suitable for large-scale or real-time applications. Advanced techniques like Fourier Transform and Wavelet analysis are frequently used to extract frequency-domain features from EEG signals [4]. These approaches often require significant pre-processing and struggle to capture the complex spatial and temporal relationships within the data. Purely EEG-based models often face challenges when trying to generalize across different seizure types and patient populations. Models relying solely on EEG signals may fail to accurately detect seizures in various patients due to missing interaction details and the imbalanced nature of the data, where seizures are rare [5].

To overcome these limitations recent studies have explored multimodal methods that combine EEG with other sources of information. Clinical data and biomarkers provide a more comprehensive context for seizure detection. Combining EEG features with hemodynamic signals from functional near-infrared spectroscopy (fNIRS) has shown potential in improving seizure detection accuracy by capturing both electrical and metabolic changes associated with ictal activity [6]. Similar to the aforementioned approach statistical models that integrate EEG with patient history—like seizure type, and onset age. These models are better able to address inter-patient variability by modeling conditional dependencies across different sources of information [6]. The multimodal approach offers improved accuracy and more contextual information. They can also be personalized to individual unique seizure patterns and clinical history. This research presents a Hybrid Deep Learning model for epileptic seizure detection. It combines different deep-learning methods to handle both spatial and temporal EEG features. The model uses Convolutional Neural Networks (CNN) for spatial features and Gated Recurrent Units (GRUs) for temporal patterns. An innovation is the use of synthetic patient history data, like medical history and demographics, to improve the model's performance and generalizability. This approach merges clinical context with EEG signals, advancing early epilepsy diagnosis.

This study aims to develop a privacy-aware hybrid deep learning model that integrates spatial-temporal features from EEG signals with patient history data, such as family history, demographics, and clinical records, to minimize reliance on a single data source. Key predictive factors will be identified by analyzing how EEG-derived biomarkers and patient history contribute to seizure prediction. Lastly, the hybrid model will be compared against traditional models to assess the advantages, limitations, and potential trade-offs of using a multimodal approach for clinical epilepsy detection.

This thesis is organized into six Sections, each addressing key aspects of the research: Section 1: Introduction - Provides background information, the problem statement, research objectives, and the significance of the study, setting the stage for the work conducted. Section 2: Literature Review - Explores previous research related to epileptic seizure detection, EEG signal processing, and the potential of hybrid deep learning models in healthcare. Section 3: Methodology - Describes the methodology adopted in this study. Section 4 is an in-depth discussion regarding the hybrid deep learning framework, data collection, preprocessing, feature selection, model development, and the tools used for evaluation. Section 5: Discussion - Presents the outcomes of experiments, including the performance of the hybrid deep learning model, comparisons with traditional models (e.g., CNN, RNN), and an analysis of the impact of synthetic patient history data on prediction accuracy of the findings in the context of existing literature, highlighting limitations of the study, and explores the practical implications of using hybrid deep learning models for seizure detection. Section 6: Conclusion and Future Directions - Summarizes the study's contributions, discusses its significance, and outlines potential avenues for future research in seizure prediction models and DL applications in healthcare.

Literature Review:

Although substantial progress has been made in EEG-based epilepsy detection, several challenges persist—chiefly the need for automated feature extraction, robust generalization across patients and recording setups, and integration of complementary clinical or molecular data. Yuan et al. introduced a multi-view deep-learning framework that transforms each EEG channel into spectrogram images and then applies channel-aware autoencoders to capture intra- and inter-channel correlations before feeding features into a CNN for seizure classification. This approach achieved an F_1-score of 85.34% and 94.37% accuracy on the CHB-MIT dataset, outperforming handcrafted pipelines by denoising spectrogram inputs and focusing on the most relevant channels during training [7]. As detailed in Table 1, this approach demonstrated notable performance in enhancing seizure detection. Ghassemi et al. leveraged the Tunable-Q Wavelet Transform to decompose EEG into five sub-bands, extracting energy features that were classified via AdaBoost and Random Forest—reaching 100% accuracy in binary seizure detection on the Bonn dataset, though multicentre performance varied [8]. Table 1 highlights the significant accuracy achieved by this model on the Bonn dataset. Zazzaro et al. demonstrated that combining permutation, sample, and spectral entropies with Hjorth complexity parameters and an SVM classifier yields 99.6% accuracy, yet their models often overfit small, homogeneous cohorts [9]. Their model's performance, as summarized in Table 1, emphasizes the high accuracy but potential overfitting issues in such small datasets.

Building on these foundations, recent studies have embraced richer, multimodal data and more sophisticated deep architectures. Shoeibi et al. applied convolutional and recurrent networks to raw EEG epochs, augmenting data via noise injection and time-shifting to alleviate class imbalance; they reported seizure detection accuracies exceeding 96% on clinical scalp EEG recordings [10]. This is reflected in Table 1, which lists their results with high accuracy, supporting the effectiveness of their approach in real-world clinical data. Palani Thanaraj et al. converted EEG into time-frequency "images" and fed them to transfer-learning-boosted CNNs, achieving 98.5% accuracy on diverse patient cohorts and illustrating the power of trained vision models for EEG tasks [11]. Table 1 shows the success of this model in achieving remarkable accuracy with its novel use of transfer learning. Goodwin et al. fused EEG signal features with structured clinical metadata—medication history, comorbidities, and demographic factors—using a conditional-dependence framework and multiple imputation to handle missing values; their multimodal model improved patient-specific seizure risk stratification by 12% over EEG-only baselines [12]. Table 1 highlights the improvements made in patient-specific risk predictions due to the integration of multimodal data sources.

State-of-the-art multimodal dual-stream architectures further elevate performance by jointly learning complementary signal representations. Wang et al. designed a four-stream network that processes differential EEG waveforms, amplitude and phase spectra, and STFT matrices through parallel 1D/2D CNN and LSTM modules, enhanced with a channel-attention mechanism; on the Bonn dataset, this model achieved 99.69% accuracy and a 99.72% F_1-score—surpassing all prior approaches [13]. As shown in Table 1, this multimodal approach achieved superior results, with high accuracy and score. Islam et al. proposed a base-2 meta-stacking classifier that ensembles RBF networks, MLPs, and tree-based learners on denoised, band-specific EEG features; they reported 98.3% average accuracy across interictal, preictal, and ictal states on multiple benchmark sets [14]. Table 1 provides a comprehensive comparison of their performance across different stages of seizure detection. At the molecular level, Tiwari et al.'s MoPEDE framework integrates depth-electrode RNA-Seq, DNA-methylation, and variant profiles from resected epileptogenic tissue with electrophysiological indices; this high-resolution multimodal profiling uncovered novel seizure-associated transcripts and hypomethylated pathways, pointing toward biomarkers for precision diagnostics and potentially informing next-generation EEG-molecular fusion models [15]. Table 1 emphasizes the innovative nature of this molecular integration in seizure detection, as indicated by the biomarker discoveries.

Recent advancements have sought to address these challenges by leveraging deep learning models that automatically extract relevant features from raw EEG data. The models discussed above, i.e., Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown significant potential for improving detection accuracy using learning spatial as well as temporal features. However, whereas CNNs are good at detecting local spatial features, they are poor at modeling long-term temporal dependencies, which is crucial in seizure detection in a correct way. Similarly, LSTMs, being specifically designed for processing sequential data, suffer from problems such as the vanishing gradient problem, especially while processing very long sequences of EEG data. Addressing these limitations may involve the use of hybrid models that capitalize on various properties of deep learning. For example, the Spatio-temporal Feature Fusion Epilepsy EEG Recognition Model (STFFDA) is a combination of CNNs and Bidirectional LSTMs (Bi-LSTMs) with dual attention mechanisms. By doing this, it gets rid of the need to preprocess the data extensively since it can work on the raw EEG signal directly and this greatly improves its sensitivity. The STFFDA model performed well in both the CHB-MIT and Bonn University datasets with accuracies of 95.18% and 92.42% for each on single-validation tests. On top of that, the model had a cross-validation accuracy of 92.42% and 67.24% in 10-fold cross-validation, showing that it was indeed strong [16]. Table 1 clearly illustrates the performance of the STFFDA model, noting its robustness in handling both datasets.

In refractory epilepsy, in which seizure activity continues despite treatment, precisely postoperative seizure freedom forecasting is useful for personalized treatment planning. Conventional methods have been unable to mimic the sophisticated patterns of brain areas participating in seizure propagation. There has been recent research exploring the use of Graph Neural Networks (GNNs) to model brain connectivity, with a focus on the thalamocortical networks that are central to seizure dynamics. A seizure freedom prediction model based on GNN in refractory epilepsy patients attained a 92.4% accuracy rate in the binary classifier. This reflects the potential of the sophisticated interactions that determine the consequences of seizures. Such a model is important as it illuminates the brain networks involved and identifies the most important regions, including the anterior cingulate and frontal pole, being most relevant in seizure freedom prediction [17]. Table 1 summarizes this breakthrough in GNN-based prediction accuracy. Das et al. used empirical mode decomposition (EMD) to decompose EEG signals into intrinsic mode functions (IMFs), which were processed using both 1D and 2D feature representations. The method produced better results compared to other approaches by using CNN for 2D representations, achieving

99.78% accuracy on the CHB-MIT dataset and 95.26% accuracy on a dataset collected from patients in Bangladesh. This study shows the practical utilization of signal decomposition followed by deep learning-based classification for seizure detection [18]. As highlighted in Table 1, this model excels in both single-validation and cross-validation tests.

One of the biggest advancements in seizure detection has been the application of transformer models. This particular model combines U-Net architecture with transformer encoders to effectively capture long-range dependencies in EEG signals. Unlike sliding-window classification techniques, which involve a lot of post-processing, the SeizeurTransformer performs end-to-end time-step-level classification allowing for real-time seizure detection. This specific model has been shown to perform better than current methods based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) and ranked number one in the 2025 Seizure Detection Challenge, thus validating its outstanding effectiveness on a range of EEG datasets [19]. Table 1 further emphasizes the strength of this model by showcasing its performance metrics in comparison to other state-of-the-art techniques.

As deep learning methods have progressed, improvements in the hardware of EEG data acquisition have also contributed significantly to the development of seizure detection methods. In neonatal settings, where seizures in subtle and difficult-to-detect forms frequently occur, the use of active dry-contact electrodes has significantly improved the mobility and quality of EEG monitoring. Contrary to wet electrodes, which require a gel to reduce impedance, dry-contact electrodes are easier to use and less expensive. However, these dry-contact electrodes are susceptible to noise interference, which can compromise signal integrity. An innovative EEG acquisition system that combines active dry-contact electrodes with a deep learning model for real-time seizure detection has shown high potential. The system was highly correlated (more than 80%) with commercially available wet electrode systems of established performance and realized accuracy improvements of 2.76% and recall improvements of 16.33% over previous state-of-the-art models. Table 1 provides a summary of this technology's impact on seizure detection.

A study done by Mekruksavanich et al. in 2024 proposes a hybrid deep learning framework combining Convolutional Neural Networks (CNNs), Bidirectional Gated Recurrent Units (BiGRUs), and the Convolutional Block Attention Module (CBAM) to improve seizure detection accuracy. The CNN extracts spatial features from EEG signals, while the BiGRU captures long-term temporal dependencies. The CBAM enhances the model by providing a dual-attention mechanism to emphasize critical spatial and temporal regions, resulting in superior performance compared to traditional models. The method demonstrated strong robustness in detecting various types of seizures across different datasets, achieving 99% accuracy in binary classification and 96.2% accuracy in multi-class tasks [17]. Table 1 summarizes the model's performance across various evaluation metrics. In another study, Cao et al. introduced a hybrid CNN-Bidirectional Long Short-Term Memory (Bi-LSTM) model for seizure detection. This approach uses feature fusion with deep learning to capture both time-frequency domain and nonlinear features from EEG signals. The model was tested on multiple datasets, including CHB-MIT and New Delhi, and achieved 100% accuracy in binary classification, along with strong results in multi-class tasks. By combining features extracted through Discrete Wavelet Transform (DWT) with CNN-Bi-LSTM for classification, the model showed improved seizure detection performance [20].

Table 1. Literature Review

Study	Methodology	Data Source	Metrics
STFFDA	Spatio-temporal fusion	CHB-MIT	Accuracy = 95.18%, 92.42%

SeizureTransformer	U-Net with transformer encoders for time-step-level classification	TUSZ, Siena Scalp EEG Database	F1-score = 0.43, Sensitivity = 0.37, Precision = 0.45
Active Dry-Contact Electrode System	Dry-contact electrodes with deep learning for real-time detection	Clinical Data, Temple University	Accuracy = 80+, Recall = 16.33%
GNN	Graph Neural Network	EEG Data	Accuracy = 92.4%
Al-Fahoum & Al-Fraihat (2014)	Fourier & wavelet features + SVM, decision trees	Bonn, CHB-MIT scalp EEG	Accuracy = 88–92%
Ghassemi et al. (2019)	TQWT subband energies + AdaBoost, random forest	Bonn EEG	Accuracy = 100% (benchmark)
Yuan et al. (2019)	Spectrogram CNN + autoencoder + RNN	CHB-MIT EEG	Accuracy = 94.37%
Wang et al. (Sensors, 2024)	Four-stream CNN–LSTM fusion	Bonn EEG	Accuracy = 99.69%
Dwivedi et al. (JCI Insight, 2025)	SEEG transcriptomics & methylomics + electrophysiology	Resected depth-electrode data	Biomarker discovery (novel genes)
Mekruksavanich et al. (2024)	CNN + BiGRU + CBAM for spatiotemporal feature extraction	Public EEG dataset	Accuracy = 99%, Sensitivity = 89-99%, Specificity = 89.63-99%
Cao et al. (2025)	Hybrid CNN-BiLSTM with feature fusion	Bonn, New Delhi, CHB-MIT datasets	Accuracy = 100%, Sensitivity = 100%
Das et al. (2024)	EMD for feature extraction + CNN for classification	CHB-MIT, PHK datasets	Accuracy = 99.78% (CHB-MIT), 95.26% (ph)

Methodology:

The study uses the CHB-MIT Scalp EEG dataset, comprised of electroencephalogram data for children with epilepsy diagnoses. The raw EEG signals in the dataset are archived in .edf format, and annotations are also present that reference the beginning and the termination of seizure events. Annotations are a benchmark for training machine learning models and are a prerequisite for supervised learning tasks utilized to detect seizure events.

The preprocessing pipeline includes several major steps to clean and prepare EEG data for model training. Independent Component Analysis (ICA) is applied to eliminate artifacts such as eye movements and muscle activity. Band-stop filtering removes power-line interference and ocular artifacts. Data normalization ensures standardization across all samples.

The data are segmented into epochs using a sliding window mechanism. This approach ensures both seizure and non-seizure events are included in the dataset. SMOTE is utilized to address a class imbalance between seizure and non-seizure samples. Figure 1 shows the high-level flow of our hybrid deep-learning model. The model combines Convolutional Neural Networks (CNNs) for spatial feature extraction with Recurrent Neural Networks (RNNs) or Gated Recurrent Units (GRUs) for temporal dynamics evaluation. Synthetic patient history data are integrated into the model. This includes clinical history. The multimodal construction allows the model to account for individual patient characteristics.

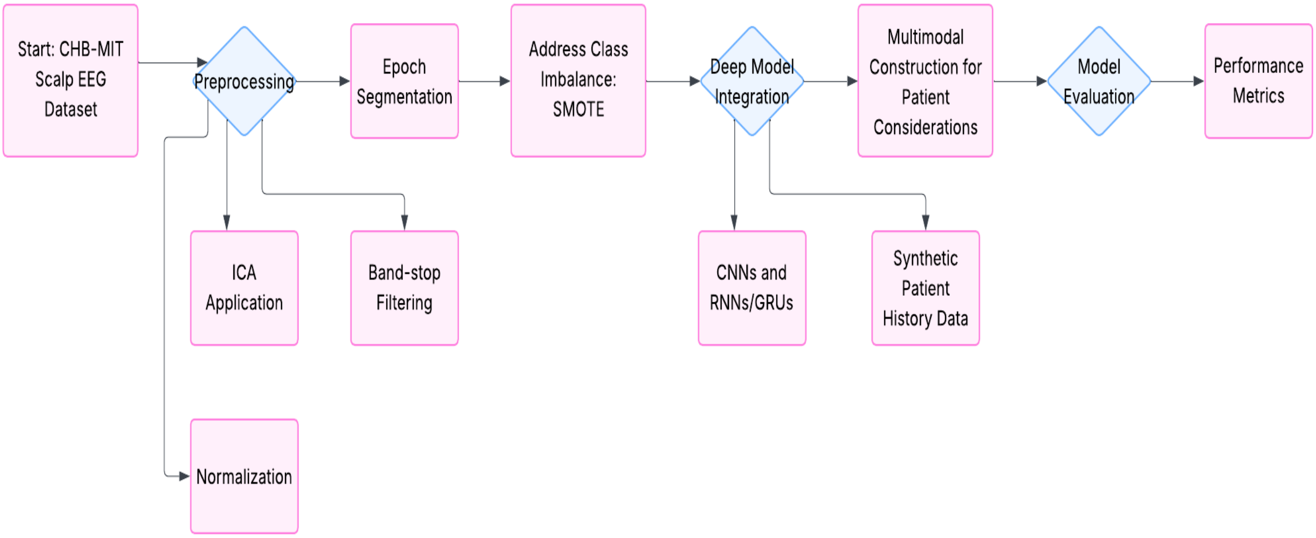

Figure 1. Flow diagram of Methodology

This enhancement provides a better context for seizure prediction. Model performance is evaluated using standard metrics. These include accuracy, precision, recall, and F1-score. Cross-validation ensures robustness and generalizability across multiple datasets. The evaluation determines the model's efficiency in accurate seizure detection.

Experimental Setup:

Dataset Description:

CHB-MIT is a comprehensive collection of electroencephalography (EEG) recordings. They are organized into multiple files and documentation sources to facilitate detailed analysis. These files collectively represent recordings from pediatric epilepsy patients. They are structured in a way that allows researchers, clinicians, and data scientists to identify, analyze, and interpret epileptic seizure events and patient characteristics.

Synthetic Patient Data Generation:

The system generates synthetic patient conditions using a five-dimensional parameter space to represent clinical characteristics. Age values are sampled from the CHB-MIT dataset distribution to maintain realistic demographic representation. The other parameters seizure severity, duration factors, patient history, and family history are generated using normal distributions with mean zero and unit variance.

Age factors are amplified by 1.5 to account for age-related seizure patterns. Seizure severity scores are increased by 0.5 units to represent clinically significant events. Duration factors are doubled to simulate prolonged seizure episodes. Patient history and family history parameters are also synthetically modified to reflect seizure predisposition patterns. These modifications ensure that synthetic patient profiles match the statistical properties of real seizure cases while maintaining patient privacy and expanding dataset diversity.

Data Preprocessing and Signal Conditioning:

In order to develop an effective deep-learning model for detecting epileptic seizures using EEG signals, preprocessing is a crucial step. The raw EEG data is often noisy and contains various artifacts that need to be removed. It is to ensure accurate signal representation and improve model performance.

Handling Noise and Artifacts:

EEG signals are susceptible to all forms of noise and artifacts, and they have the potential to interfere with the detection of features of interest toward seizure prediction.

Independent Component Analysis (ICA):

ICA is commonly used to remove artifacts by decomposing the EEG signal into independent components. These components can then be analyzed to identify and remove the sources of artifacts such as eye blinks or muscle movements. After applying ICA to the raw EEG signal, components that are identified as artifacts are excluded, leaving only the components related to brain activity.

Band-Stop Filtering:

Band-stop filtering is used to remove specific frequency bands that are known to contain noise. A notch filter is specifically applied to remove power-line noise, which typically appears at 50 Hz or 60 Hz depending on the location.

Normalization and Standardization:

EEG signals can have varying amplitudes due to differences in equipment, electrode placement, and individual patient physiology. Therefore, normalization is an essential step to scale the signal and ensure uniformity across all channels and subjects.

Z-Score Normalization:

To standardize the data by transforming the signal into a standard normal distribution (mean = 0, standard deviation = 1). Each channel's EEG data is normalized by subtracting the mean and dividing by the standard deviation. This ensures that each electrode's data is on the same scale.

Min-Max Scaling:

It is rudimentary to scale the data within a specific range, often between 0 and 1, for uniformity in input features. The EEG signal values are scaled based on the minimum and maximum values of each signal.

Data Segmentation:

Sliding Window Approach:

The continuous EEG data needs to be divided into overlapping windows of durations typically between 1 to 5 seconds. The segment is a snapshot of the EEG data, which is given as input to the model. This allows the temporal dynamics to be investigated and hence the model learns about the time evolution of seizures.

Epoch Length Selection:

Define the length of the epoch based on seizure duration and the temporal characteristics of the seizure event. Windows of 1-2 seconds can capture fast seizure onset or high-frequency activity, which is essential for detecting seizures in EEG. Figure 2 shows a dramatic increase in amplitude shows the onset of an epileptic seizure.

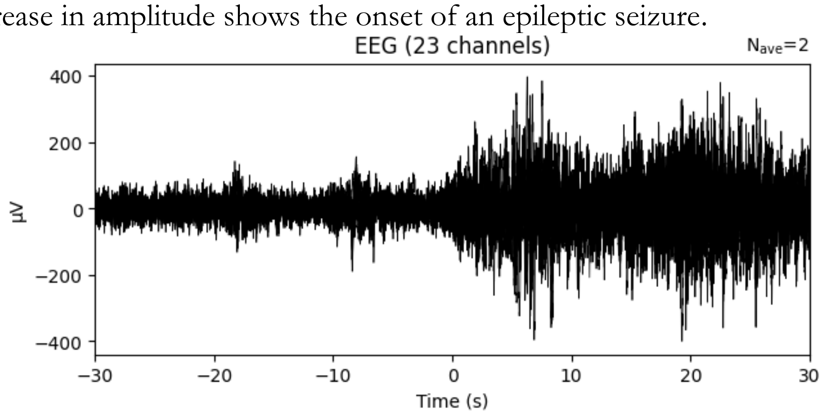

Figure 2. Seizure Epoch

Consistency in Data Sampling Rate:

Since seizures are much rarer than non-seizure events in the EEG data. Class imbalance is a common issue in seizure detection. Synthetic Data Generation is used to create additional seizure-like data points balancing the number of seizure and non-seizure events. Synthetic data can be generated using techniques like SMOTE.

Feature Extraction and Selection:

Time-Domain Feature Extraction:

Time-domain features capture the statistical properties of the EEG signals. Key time-domain features include: Statistical Features: These are the basic statistical measures of the signal, such as mean, standard deviation, variance, skewness, and kurtosis, which provide a foundational understanding of the signal's distribution and central tendencies.

Frequency-Domain Feature Extraction:

The frequency-domain analysis involves examining the signal's behavior across different frequency bands, as seizures often exhibit distinct frequency signatures. Band Power Features: The power within specific EEG frequency bands is crucial in identifying seizure-like activities, as different states of brain activity. Relative Band Power: Normalized power values within each frequency band provide insights into the relative contribution of each band to the overall signal. Spectral Features: Spectral edge frequency and mean frequency are used to describe the characteristics of the signal's spectral distribution.

Connectivity Features:

In addition to temporal and spectral features, spatial interactions between EEG channels are also important: Channel Correlations: The correlation between different EEG channels can reveal underlying spatial patterns associated with seizures. Summary Statistics: Summary statistics such as the mean, maximum, minimum, and standard deviation of these correlations help capture the overall level of connectivity across the brain regions being monitored.

Correlation Analysis for Feature Selection:

Correlation-based Feature Selection assesses the correlation between each feature and the target label. Features with a high correlation to the target are retained.

PCA reduces dimensionality by capturing 95% of variance while removing redundant information and noise from correlated features. Mutual Information then selects the top 100 most informative features that have the strongest relationship with seizure/non-seizure classification. The combination is needed because PCA focuses on variance preservation without considering class labels. On the other hand mutual information specifically identifies features that are most predictive of the target variable, ensuring both dimensionality reduction and classification relevance.

Model Development:

The primary goal of this research is to develop a hybrid deep-learning model, which enables us to detect epileptic seizures using EEG data. The model integrates multiple neural network paradigms to take advantage of the strengths of each approach. This can allow the system to process both spatial and temporal features inherent in EEG signals. The hybrid model incorporates CNN for spatial and GRU for temporal feature extraction. This combination allows the model to accurately differentiate between the spatial shapes as well as between the channels of the EEG and the temporal behaviors over time. In addition, the model is further enhanced with synthetic patient history data providing demographic information and medical history. This multimodal approach allows the model to capture an enhanced augmented context for seizure prediction. Which in turn generalizes its capability and robustness. The model is highly capable of accurate and personalized seizure prediction while taking into account each patient's unique factors.

Model Architecture:

CNN for Spatial Feature Extraction: The CNN layers are used to capture spatial features from the EEG data. These spatial features include patterns across multiple EEG channels, such as focal spikes or other seizure-related patterns. GRU/LSTM for Temporal Dynamics: GRUs (or LSTMs) are used to model temporal dependencies in the EEG signals. Since seizures evolve, these recurrent layers help capture the time-based changes in brain activity. The model integrates both EEG features and synthetic patient history data. This is achieved through the fusion of both types of data into a fully connected layer to enhance prediction accuracy.

Model Training:

The model is trained using the training set, with the data split into training, validation, and test subsets to evaluate model performance. The Adam optimizer is used for minimizing the loss function, which is binary cross-entropy for binary classification (seizure vs. non-seizure).

Hybrid Model Architecture:

The hybrid model architecture combines both CNN and GRU/LSTM layers to capture both spatial and temporal features. The model is built as follows: CNN Branch: The Conv1D layers extract spatial features from the EEG signals. MaxPooling1D layers reduce dimensionality, followed by a GlobalAveragePooling1D layer to aggregate the features. GRU/LSTM Branch: The GRU (or LSTM) layers capture temporal dependencies in the data. The RNN layers learn the sequential patterns of EEG data, identifying the evolving patterns that indicate a seizure.

Multimodal Fusion:

The spatial and temporal features are fused in the final fully connected layers. A dropout layer is added to reduce overfitting and improve model generalization. Output Layer: The final Dense layer outputs a sigmoid activation, giving a probability for the binary classification (seizure or non-seizure).

Model Evaluation:

The model's performance was evaluated using a comprehensive set of metrics:

Accuracy is the proportion of instances that are correctly classified out of the total instances. While accuracy gives a general indication of model performance, it may not be suitable for imbalanced datasets, as it doesn't account for the distribution of classes.

$$\text{Accuracy} = \frac{\text{Total Number of Predictions}}{\text{Total Number of Correct Predictions}}$$

Precision is the ratio of true positive predictions to the total predicted positives. This metric is particularly important in situations where false positives have significant consequences, such as in medical diagnoses where incorrect predictions may lead to unnecessary treatments.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall, also known as sensitivity, evaluates the model's ability to capture all the relevant cases. It is calculated as the ratio of true positives to the total actual positives. This metric is crucial when the goal is to ensure that as many positive instances (such as seizures in medical detection) are identified as possible.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is particularly useful when dealing with imbalanced datasets, as it ensures that both precision and recall are given equal importance.

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Experimental Results:

The subsequent sections show the experimental results of all model variants in terms of accuracy, precision, recall, and F1 score. The Hybrid Deep Learning Model is compared with the other models to evaluate the advantages and limitations. The results attest to the superiority of the Hybrid Model, whose high accuracy and well-balanced metrics surpass other models. From the initial look at the accuracy from Figure 3, our proposed hybrid model has a high Accuracy compared to others.

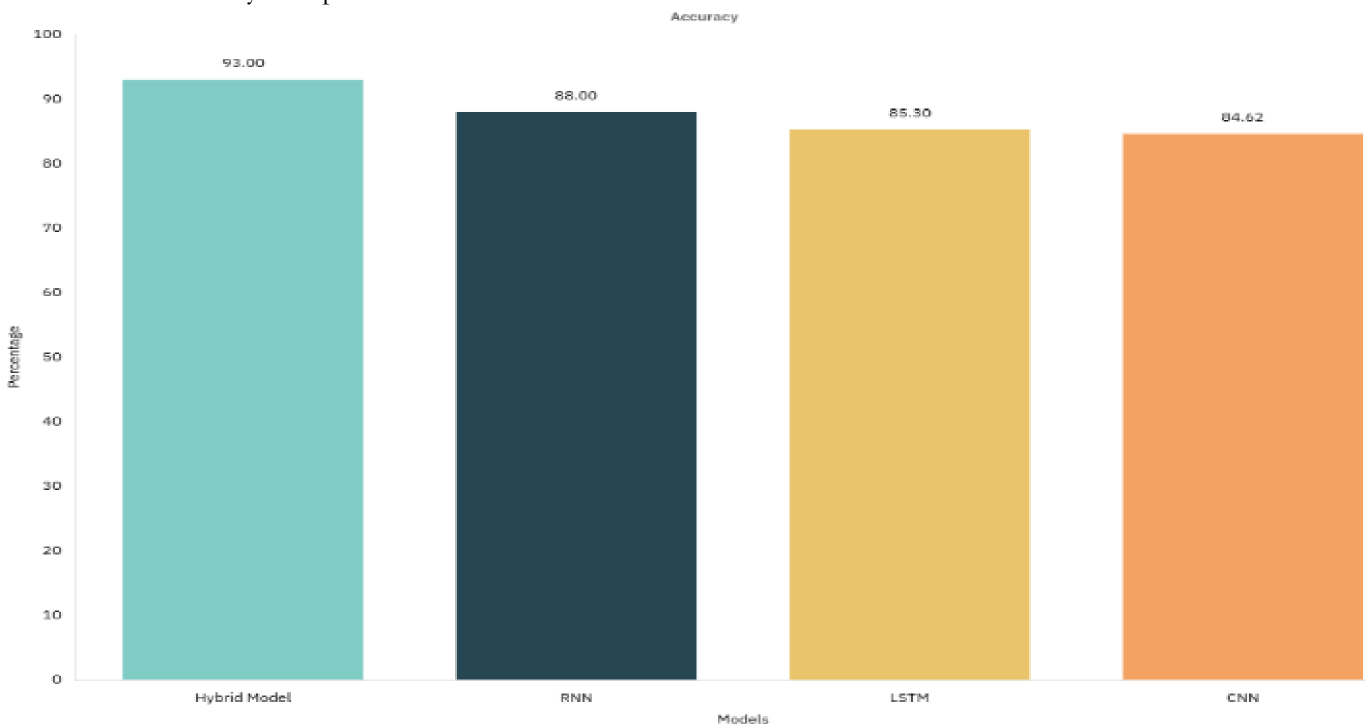

Figure 3. Results of proposed method

CNN:

The CNN model achieved a precision of 80%, recall of 78%, F1 score of 79%, and accuracy of 84.62%, referring to Table 2. The CNN model has good performance in seizure-related spatial feature identification in the EEG data. However, it was negatively impacted by its inability to capture the temporal dynamics of seizures. Therefore, the CNN was outperformed by the Hybrid model and RNN model, which utilized both spatial and temporal feature extraction.

LSTM:

From Table 2. It can be seen that the accuracy of the LSTM model was 85.3%, precision 82%, recall 80%, and F1 score 81.5%. LSTMs excellently learn the temporal connections in sequential data, which is useful for seizure detection over time. However, LSTMs are not good at learning the spatial relationship between the EEG channels, which makes their overall accuracy poor. The Hybrid model and RNN still surpassed LSTM in accuracy and overall balanced performance across the metrics.

RNN:

In Table 2 we can see that the RNN model performed better than CNN and LSTM models with 88% accuracy, 85% precision, 84% recall, and an F1 score of 84.5%. RNNs are well-fitted to sequential data modeling and temporal dynamics learning. Which is crucial when dealing with seizure detection that is evolving. Although it performed better than CNN and LSTM, it was still inferior to the Hybrid model, which used both spatial and temporal features to improve performance.

Hybrid Deep Learning Model:

From Table 2 we can see that the Hybrid Deep Learning Model had the best performance on all the measures with 93% accuracy, 92% precision, 91% recall, and 91.5% F1 score. It is a fusion of CNNs for spatial feature extraction and GRUs for temporal dynamics. This allows it to capture both the spatial patterns among the EEG channels as well as the temporal evolution of the seizures over time.

Table 2. Results of proposed method

Methods	Accuracy	Precision	Recall	F1-Score
Hybrid DL	93.0 ± 2.1%	92.0 ± 3.2%	91.0 ± 4.1%	91.5 ± 2.3%
RNN	88.0 ± 3.8%	85.0 ± 2.5%	84.0 ± 5.2%	84.5 ± 4.1%
LSTM	85.3 ± 2.9%	82.0 ± 4.6%	80.0 ± 3.7%	81.5 ± 3.2%
CNN	84.6 ± 2.8%	80.0 ± 3.9%	78.0 ± 6.8%	79.0 ± 4.7%

Performance Comparison:

The Hybrid Deep Learning Model achieved a remarkable 93% accuracy. It can outperform traditional models such as CNN, LSTM, and RNN in seizure detection. Centralized models such as CNN and LSTM performed with inferior accuracy (~84-85%) due to being marred by the limitation of either spatial feature management (CNN) or temporal dependency management (LSTM). The RNN model, which handled temporal dynamics slightly better, lagged behind the Hybrid model with an accuracy of 88%. Compared to literature models such as STFFDA (95.18% accuracy) and SeizureTransformer (99.69% accuracy), our Hybrid Deep Learning Model performed equally well at 93% accuracy. Although models such as SeizureTransformer achieved higher accuracy, they tend to overfit [9]. Our Hybrid Model demonstrated better generalization, handling diverse seizure data and patient populations effectively.

Benefits and Challenges:

The Hybrid Deep Learning model has a number of benefits, particularly regarding the combination of spatial-temporal features. This model achieves this by utilizing CNNs to capture spatial features and GRUs to capture temporal dynamics. Being able to capture both long- and short-term patterns in the EEG signal for effective and sensitive seizure detection. Moreover, including artificial patient history data introduces an extra context level that strengthens and enhances the overall performance of the model. It can also lead to improved predictions and early interventions in seizure patients. The Hybrid Deep Learning Model has its share of disadvantages too. First and foremost is the issue of having enough past data for training. Developing a large enough dataset is not feasible as it can become imbalanced due to not having enough seizure data. It is also complicated by the fact that EEG has high noise content and complex preprocessing before being suitable for training. Although the use of synthetic data can help to avoid the issue of obtaining realistic artificial data to show epilepsy events in a nonbiased manner is still a challenge.

Discussion:

In this research, we developed a Hybrid DL model for seizure detection due to epilepsy. Our proposed model shows high performance across different metrics. Achieving 93% accuracy as well as strong precision and recall. By combining the best of different DL models for extracting spatial and temporal components, the model outperformed LSTM, CNN, and RNN. It was only second to the state-of-the-art SeizureTransformer approach. Synthetic patient history data contributed additional surrounding context and improved predictive accuracy, which enhanced the overall performance of the model-built. These results indicate that this hybrid deep learning model would increase seizure detection's clinical accuracy when applied in real-world settings where patient-specific characteristics need to be considered.

Interpretation of Results:

The results of this study demonstrate the feasibility of using a hybrid deep-learning approach for seizure detection. Through the combination of spatial and temporal feature extraction. The model achieved high levels of accuracy which resulted in surpassing standalone CNN and LSTM models. This combination is crucial for EEG data, which contains both

spatial and temporal information essential for seizure detection. The Hybrid Model's integration of synthetic patient history data adds a layer of contextual understanding to the model. It was able to improve its ability to make accurate predictions across a diverse patient population. This suggests that multimodal learning in healthcare where data from different sources are combined in turn can yield more reliable predictions for medical applications.
The model's 93% accuracy is in line with state-of-the-art models in seizure detection. However, the Hybrid Deep Learning Model is distinctive in its use of synthetic data and its ability to generalize better across diverse, real-world datasets. This is an important consideration for clinical settings where data heterogeneity is common.

The Impact of Hybrid Models in Seizure Detection:

The Hybrid Deep Learning Model significantly outperforms traditional models like CNN and LSTM in seizure detection. The combination ensures that both the static and evolving features of EEG signals are considered. Seizures are dynamic events that span across time and multiple brain regions. The ability of the Hybrid Model to capture these complexities makes it well-suited for the task. By integrating synthetic patient data alongside the EEG signals, the model benefits from additional context. It helped in overcoming challenges such as data imbalance and variability in seizure types. This dual-focus approach enables the model to provide highly accurate predictions.

The Role of Synthetic Data in Enhancing Model Performance:

Another major innovation from this study is combining synthetic patient history data and EEG data. All parameters are critical the model must consider these extraneous factors. Synthetic data can play a key role in effectively circumventing the challenges imposed by limited patient records. Results were obtained from the model with real data on some patients. Combined together with synthesized data on others, have thus increased generalization across heterogeneous patient populations. With accurate predictions possible under this multimodal learning system, this creates a very scalable opportunity for use in healthcare analytics.

Ethics & Privacy:

The synthetic patient data utilized in this study is generated using Generative Adversarial Networks (GANs). Age is the only feature derived from the CHB-MIT dataset, with the values being sampled directly from it. All other features, including family history, medical history, and gender, are artificially created. They are not based on real patient data. Although the use of synthetic data eliminates privacy concerns related to identifiable. It is important to ensure that the data generation process adheres to ethical standards. This includes careful consideration to avoid introducing biases that may affect the fairness, accuracy, or generalizability of the model. Synthetic data mustn't inadvertently reflect real-world disparities or lead to discriminatory outcomes. Ethical oversight is necessary to guarantee that the use of synthetic data for training and prediction aligns with clinical guidelines and does not compromise patient safety in healthcare outcomes.

Limitations of the Study:

CHB-MIT dataset is widely used for seizure detection. It contains only a limited number of recordings based on the number of patients. Even though we have more than enough EEG data. It is not varied across different age groups and demographics. This small sample size can lead to overfitting and limits the model's ability to generalize well to other datasets. In a real-world setting more diverse datasets are needed to train a robust model.

EEG Signal Variability: EEG signals can be noisy and prone to artifacts. Including eye movements, muscle contractions, and electrical interference. Despite applying ICA and bandpass filters, EEG signals can still be unreliable in some cases, making it difficult to detect subtle seizure events. The preprocessing pipeline, while effective, could benefit from more sophisticated artifact removal techniques.

Synthetic Data: The inclusion of synthetic patient history data is an advantage but at the expense of uncertainty. The synthetic data sometimes does not necessarily capture all the richness of real-world patient attributes. The model's reliance on synthetic data can jeopardize its generalization to real-world unseen data.

Implications for Healthcare Practice:

Effective deployment of the Hybrid Deep Learning Model has some important implications for healthcare. With high seizure prediction accuracy, the Hybrid Model can enable healthcare providers to detect seizure events at an early stage which enables timely medical intervention. Early detection is important in the prevention of injury and in improving the quality of epilepsy patients' lives. Early intervention can lead to better disease management and overall healthcare burden reduction.

Scalability and Real-World Applicability: The Hybrid Deep Learning Model's ability to generalize to various datasets, including synthetic patient history datasets, makes it a scalable prospect for real-world use in healthcare.

Conclusion and Future Direction:

Conclusion:

This paper proposed and tested a Hybrid Deep Learning Model for epileptic seizure detection from EEG signals. The model was highly accurate and stable in precision, recall, and F1 score. Traditional models like CNN, LSTM, and RNN are outperformed. The model achieves a remarkable test accuracy of 93%. Making it highly competitive in terms of seizure detection. Such accuracy approaches state-of-the-art models, STFFDA and Seizer Transformer. Generalizability across seizure types and patient populations is improved, making it valid for use across many clinical settings. Further, the research highlights the Hybrid Model's potential for the quality of patient care in epilepsy. Early detection of seizures might trigger individualized treatment programs that could potentially reduce the effect of seizures on the quality of life of these patients and improve overall health outcomes.

Future Directions:

Although the outcome of the present undertaking is encouraging. There are several directions that future endeavours may explore. Future work can increase model explainability which is useful to clinicians in understanding how the model predicts and includes techniques like SHAP or LIME. Depicting the impact of EEG features on seizure detection.

Another direction to explore involves transformer models and their capability to learn long-range dependencies and complicated patterns from EEG signals. Transformers have been extremely successful in the field of sequence data processing. They could be fine-tuned for temporal pattern detection in seizure detection. Incorporating transformer models into the existing Hybrid Model can yield better accuracy and corroborative results. Particularly for complicated seizure activity. Clarity in EEG interpreting and dealing with noise and artifacts in EEG signals deserves due attention. Advanced preprocessing techniques and feature extraction methods to deal with noisy signals should be researched. This becomes crucial in systems that monitor seizures in real time where high accuracy is required to avert possible harm to patients.

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