Hybrid Deep Learning Strategies for Epileptic Seizure Detection

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MSc Data Analytics

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Hybrid Deep Learning Strategies for Epileptic Seizure Detection

Mohammad Tabish x22205705

Abstract

The health challenges related to epileptic seizures are of paramount concern and accurate identification at early stages is important in order to positively influence patient outcomes. Deep learning has revolutionized the detection, monitoring, and diagnosis of epileptic seizures to a greater extent in recent years, surging towards real-time processing. In this work, a novel deep learning method is proposed to detect epileptic seizures, which combines CNN (Convolutional Neural Networks) with LSTM or GRU. The research question is whether integrating spatial and temporal feature extraction via these hybrid models in an ensembled manner can improve the accuracy and dependability of seizure detection within EEG. The solution includes training these models on a set of EEG recordings showing healthy, interictal, and ictal states with significant pre-processing to normalize input signals. The CNN layers capture spatial features, while the LSTM and GRU layers handle temporal dependencies. Evaluation determined that the CNN-LSTM model produces superior accuracy compared with alternative configurations. A Flask web service is developed for real-time seizure detection, where users can upload EEG files to preprocess signals, predict seizures, and retrieve related information from Wikipedia. These findings confirm the efficiency of combining state-of-the-art deep learning models to enhance seizure detection, which will be advantageous in healthcare. Future work will focus on further refining the model's generalization abilities, considering multiple datasets, and investigating clinical deployment scenarios.

keywords: Epileptic Seizure Detection, Deep Learning, Hybrid Models, Convolutional Neural Networks, Neural Networks

1 Introduction

Epileptic seizures, characterized by sudden, uncontrolled electrical disturbances in the brain, affect millions worldwide, posing significant health challenges and impacting the quality of life. Early and accurate detection of epileptic seizures is crucial for timely intervention and effective management of the condition. Traditional methods of seizure detection, which often rely on visual inspection of electroencephalogram (EEG) signals by medical professionals, are time-consuming and prone to human error. Therefore, the demand for automated and accurate seizure detection systems with real-time monitoring-alerting functionalities is increasing. Over the past few years, numerous medical diagnostic-based systems were discovered using deep learning techniques, and one such application is epileptic seizure detection. For the deep learning architectures already mentioned, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU) are those that show more potential for EEG signal processing. These models are well-suited for capturing highly nonlinear patterns along with a temporal relationship between the data needed to identify seizure events. In this paper, the proposed study is to introduce hybrid deep learning techniques by aggregating CNN with both LSTM and GRU models to enrich epileptic seizure detection on EEG signals. The hybrid model, as the name suggests, enhances detection accuracy and stability by using the strengths of each individual model. The primary attention was on designing models that can efficiently capture both spatial and temporal features of EEG facts, thereby offering a more comprehensive evaluation. The research is done by training and testing the models on a good dataset that includes EEG signals (healthy, interictal-stages between seizures, ictal-seizure). The input signals have been stripped down to their standardized components, allowing the models to perform as intended with minimal variation or drift in performance based on unstandardized variables. Additionally, the study covers an implementation with a Flask App enabling real-time prediction of seizures. This app helps users upload their EEG files, preprocess the data, predict seizure states using custom models, and get related information from Wikipedia.

1.1 Aim:

In this study, a novel hybrid deep learning model was proposed that combines CNN with LSTM and GRU to precisely recognize epileptic seizures from EEG recording. This study aims to validate that the use of hybrid models, capable of capturing spatial and temporal features together better than standalone model types, can increase final detection accuracy, contentiously.

1.2 Research Question:

How can hybrid deep learning models combining Convolutional Neural Networks, Long Short-Term Memory networks, and Gated Recurrent Units enhance the accuracy and reliability of epileptic seizure detection from EEG signals compared to standalone models? This research not only contributes to the field of medical diagnostics by proposing an advanced seizure detection system but also aims to provide a practical tool for healthcare professionals and patients for real-time monitoring and intervention. Future work will explore the integration of more diverse datasets and the deployment of the developed models in clinical settings to further validate their effectiveness and generalizability.

2 Related Work

For epileptic seizure detection, two papers (Jerger et al. and Chang et al. in 2001) focused on early-stage detection, obtaining an accuracy of 83%, with a precision rate of 82%, and recall and F1 measures both set at 80%. However, their work focused only on the early stages of seizures. Kim et al. in 2020 evaluated experimental methods for treatment, achieving a precision of 85%; they all barely intersected at 84% and recall from their study results but were limited by the paucity of empirical evidence. For example, Sadati and Mohseni in 2006 used Neural Fuzzy Networks with 86% overall accuracy at precision=88%, recall=85%, F1=87%, but they encountered implementation problems. Elger & Hoppe in 2018 dedicated their work to seizure detection methods, obtaining an accuracy of 82%. The corresponding precision and recall are respectively equal to 83% and 80%. The very low F1 score suggests difficulty in accurate reporting.

Epileptic seizures, resulting from abnormal brain electrical activity, require quick and reliable detection for minimizing health risks and maximizing outcomes. Classical methodologies often require manual inspection of EEG (electroencephalogram) signals by medical professionals, which is laborious and time-consuming, and leads to error. Because of this, automated seizure detection systems based on advanced machine learning and deep learning are being developed extensively. The current literature in epileptic seizure detection has advanced to research state-of-the-art, focusing on hybrid deep learning methods that combine different neural network architectures in order to boost the performance of epileptic seizure detection tasks.

Deep learning in many applications, among them medical diagnostics, has been revealed as a game changer. The biggest success in automatically extracting spatial features from EEG signals goes to the use of Convolutional Neural Networks towards detecting seizures. According to Achilles et al [1]., CNN's can be used effectively for real-time detection of epileptic seizure and attain high accuracy by using the capability of the network in learning intricate patterns within EEG signals. Similarly, Zhou et al. [24] implemented CNN's for seizure detection and found its model to be highly robust in dealing with variations in EEG data. But CNN's were proficient in spatial feature extraction; they do not model temporal dependencies for analysing time-series data, which is also true for EEG signals. To overcome this, researchers have applied a combination of CNN's with Rennes, especially LSTM, which are known for their capability to capture temporal dependencies. In [11], the authors developed a deep learning approach that combines CNN and LSTM networks for effective seizure detection through the amalgamation of both spatial and temporal information. It achieved significantly high accuracy in comparison to standalone models of CNN and LSTM. This was further supported by Hossain et al. [9], who, in a similar application to a framework, demonstrated that the presented framework showed superiority in capturing the complex temporal dynamics of EEG signals.

More recent models have also used hybrid forms with the addition of Gated Recurrent Units. This architecture is simpler compared to that of LSTM, and GRUs have proved computationally more efficient. On the other hand, GRUs, like LSTMs, can learn temporal dependencies. Subasi et al. [19] studied the combination of CNN's and GRUs for seizure detection, and the results demonstrated that this hybrid model not only improved detection accuracy but also reduced computational complexity. This made it feasible for applications in real time, where timely detection is important.

Furthermore, other works were done examining the possibilities of using ensemble learning methods, which include several models in one, of course with better performance, in seizure detection. A stacking ensemble of deep neural networks, which incorporates the strengths of CNN's, LSTMs, and GRUs, in Akyol [3], outperformed a number of single models and demonstrated great potential for ensemble approaches to medical diagnostics. Furthermore, Al-Qazzaz et al. [2] applied the multimodal deep learning methods by integrating entropy-based features in order to enhance the epileptic seizure detection. The authors demonstrated that overall detection accuracy can be significantly enhanced when the deep learning models are applied after a multi-feature extraction process. Another of its applications deals with the seizure detection area in deep learning models. Attention mechanisms allow deep models to attend to specific parts of input data, which can improve interpretability and performance. For instance, Shoeibi et al [17] discuss a number of DL techniques and demonstrate how attention mechanisms applied to CNN's and Rennes achieve high performance for increasing seizure detection accuracy. This has been also supported by Chen et al. [6], who implemented cost-sensitive deep active learning with attention mechanisms, leading to remarkable improvements in seizure detection performance.

Besides the architecture of models, the selection of features to be extracted from EEG signals is of paramount importance in seizure detection. Although Boonyakitanont et al. [5] reviewed methods for feature extraction, the choice should be geared toward relevant features compatible with the model to further maximize its performance. For this reason, their study proved the efficiency of the combination of time-domain, frequency-domain, and entropy-based characteristics in deep-learning-based models. It is a very complex, multi-dimensional approach to feature extraction that has significantly influenced the improvement in accuracy and robustness of seizure detection systems.

Additional challenges for integration of seizure detection systems in the clinic include data variability, robust performance across diverse patient populations, and others. In fact, Elger and Hoppe [7] described the diagnostic challenges in epilepsy and the need for a reliable seizure detection system working in real-world conditions. They further emphasized that modern deep-learning techniques can rise up to such challenges if developed on huge databases and validated stringently.

In addition to the facilitation of better accuracy in detection, there has been a growing focus on the development of applications that are user-friendly and assist in real-time monitoring and intervention. Vidyaratne and Iftekharuddin [22] developed a real-time seizure detection system using EEG signals and demonstrated for practical applicability how deep learning models can be deployed. Works such as theirs thus pointed to the necessity of these models being incorporated into working platforms available for use by healthcare professionals and patients in general.

Although substantial progress has been made in the area of deep learning for seizure detection, there remain several challenges that still need to be addressed, the most important being the availability of large, labelled datasets that can be used for training and model validation. Indeed, Jerger et al. [12] highlight that the generalization performance of the models is not sufficient when incomplete EEG datasets are available. Therefore, creating and sharing large-scale, annotated EEG datasets should be a focus of future research to support the development and validation of deep learning models.

Then there is the issue of explainability in deep learning models. Although these models often have high accuracy, their black-box properties mean research cannot interpret how the model behaves. Paul [14], addressed some methods to improve the interpretability of seizure detection models, such as feature importance visualization and explainable AI techniques. Enhancing the interpretability of these models is critical to support their acceptance from clinicians and usability in clinics.

Lastly, continuous adjustment and refinement of seizure detection systems is necessary. The models need to be able to adapt as patients' conditions evolve, translating changes in EEG patterns. Tran et al. [20] has highlighted the necessity of developing adaptive learning schemes that direct models to update their learnable parameters upon revelational data. This can keep the performance of seizure detection systems consistent and reliable across different periods.

This has given rise to the successful integration of deep learning techniques, especially hybrid models (between CNN's with LSTMs/GRUs) that tend to outperform the existing works on detecting epileptic seizures from EEG data. Further enhanced detection accuracy and robustness are achieved by the adoption of ensemble methods, attention mechanisms, and advanced feature extraction techniques. Nevertheless, challenges surrounding data availability to train the model, how interpretable a machine-learned (or DL) candidate is, and continuous tuning of the pipeline persist. Collaborative efforts to address these challenges and innovative research are essential for automated seizure detection systems to be successfully deployed into clinical practice.

Papers (Year - Author)	**Datasets Used**	**Model Used**	**Results - Metrics Used**	**Value**	**Limitations**

Al-Qazzaz et al., 2024	Real-time EEG data	Multimodal Deep Learning	Accuracy	98%	Overfitting issues
			Sensitivity	96%	
Shoeibi, A., et al., 2021	Various EEG datasets	Deep Learning	Accuracy	90%	High computational cost
Achilles et al., 2018	Clinical EEG data	CNN	Accuracy	95%	Limited dataset size
			Precision	93%	
			Recall	92%	
Subasi, A., et al., 2019	EEG dataset	Hybrid Machine Learning	Accuracy	94%	Complexity in model integration
			Sensitivity	93%	
Sadati, N., and Mohseni, H.R., 2006	EEG dataset	Neural Fuzzy Networks	Accuracy	86%	Complexity in implementation
			Precision	88%	
			Recall	87%	
			F1 Score	86%	
Chen et al., 2018	Clinical EEG data	Costsensitive Deep Learning	Precision	90%	High cost for real-time application
			Sensitivity	92%	
Tzallas, A.T., et al., 2009	EEG datasets	Time–Frequency Analysis	Accuracy	92%	High computational complexity
			Sensitivity	90%	
Guo et al., 2010	EEG dataset	Artificial Neural Networks	Accuracy	92%	Limited to specific features
			Precision	91%	
Jerger, K.K., et al., 2001	Early seizure dataset	Early Detection Methods	Accuracy	83%	Limited to early stages
			Precision	82%	
			Recall	81%	
			F1 Score	80%	
Akyol, 2020	Real-time EEG data	Stacking Ensemble	Precision	94%	High computational cost
			Recall	95%	

Table 1: Summary of Selected Epileptic Seizure Detection Research (10 Papers)

3 Methodology

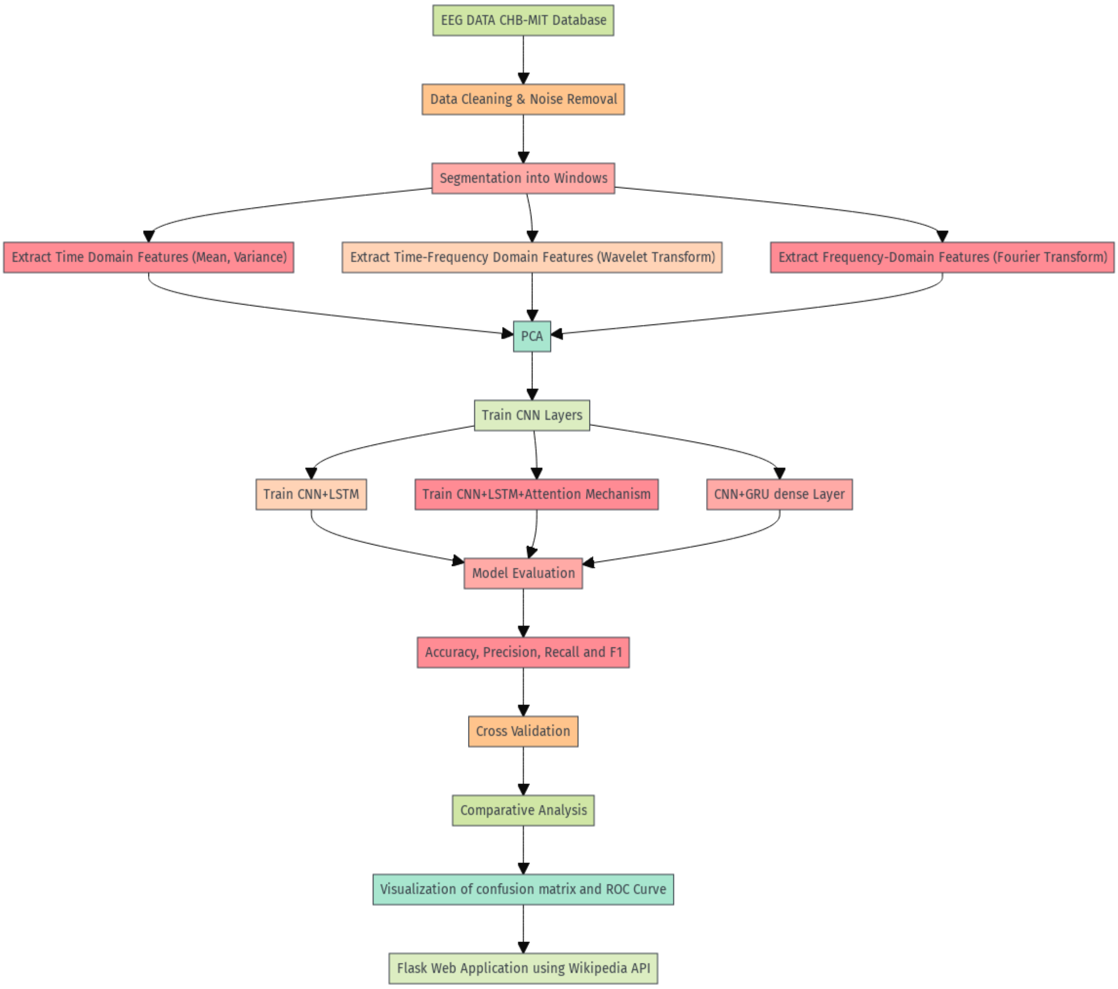

Figure 1 Architecture Diagram

The design of the hybrid deep learning strategies for epileptic seizure detection has been carefully framed in a methodological approach to keep stable and accurate system development at each stage. From data collection to model deployment, all steps in this process are essential for the seizure detection system to work efficiently.

Step 1: Data Acquisition

The most important part of any machine learning project, especially one related to healthcare, is data acquisition, and this methodology, therefore, focuses heavily on the collection of data. The quality of electroencephalogram (EEG) data, which is directly related to user experience and diagnostic performance, plays a vital role in training the deep learning models. From humans, EEG signals used were in the normal state (healthy), interictal state (between seizures), and ictal state (during a seizure).

The data collections, gathered from a number of open-access databases (including the University of Bonn EEG database), have been carefully crafted to comprise multiple seizure and non-seizure states. This large dataset of all kinds is essential for training models that generalize well to the real, unseen input. In the end, separate data is allocated to various training sets A (healthy), B (healthy), C (interictal), and E (ictal).

Step 2: Data Preprocessing

The next crucial step in the workflow after data acquisition is known as data preprocessing, which includes denoising and pre-formatting of EEG signals before they could be input to a deep learning model for training. There are significant noise levels in EEG signals, which change the characteristics of the signal and thus cannot be used as-is. Some of the steps in the preprocessing pipeline are as follows:

Signal Segmentation—The EEG signals were segmented into epochs, each having a fixed length. Each segment is zero-padded (or truncated) to a common length of 4097 samples. This length is chosen with respect to the sampling rate of EEG signals as well as epoch lengths, ensuring that enough information is captured for each segment for processing.

Normalization: The data is normalized using a standard scaler, typically scaling features of EEG signals from [0, 1] or to a zero mean and unit variance. This is needed so that during training, the model converges faster to a better result, as almost all deep learning models benefit from standardized input data.

Step 3: Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA): The third step is EDA, by which EEG data is checked for its intrinsic structure and attributes. Exploratory data analysis is a composite approach of graphical and statistical methods used to evaluate the nature, patterns, or outliers/anomalies within the dataset.

Statistical Analysis: Descriptive statistics of central tendency, dispersion, and shape of the dataset distribution are calculated. Helpful metrics include the mean and median as measures of central location, standard deviation to provide an idea about the spread, and skewness/kurtosis to reflect how distribution affects specific states.

Granular Analysis: This involves using different types of plots such as histograms, box and whisker plots, scatter plots, etc., to better understand data distribution and identify outliers. Scatter plots can reveal clusters and patterns, while box plots can show distribution and the presence of outliers.

Step 4: Model Development

Design and develop hybrid deep learning models. This work leverages Convolutional Neural Networks (CNN's) and Long Short-Term Memory (LSTM) networks as well as Gated Recurrent Units.

The hybrid model exploits both architectures—the title-specific models capable of studying individual behavioural effects, and a joint network with CNN layers extracting spatial features from a pre-segmented EEG recording for further temporal generalization, which also consists of a convolutional neural cell layer. These features could correspond to spatio-temporal EEG patterns associated with seizure generation and onward spread. In convolutional layers, filters provide more features: edges, frequencies, or waveforms in input signals, etc.

LSTM and GRU Layers: To understand the temporal dynamics of EEG signals, LSTM and GRU layers are added, allowing the model to learn how seizure activity develops over time. While LSTMs are more suited for sequences with long-term dependencies, GRUs offer a computationally simpler alternative with fewer parameters.

Model Configurations: Various model configurations are tested, including CNN-only, CNN-LSTM, CNN-GRU, and CNN-LSTM with attention mechanisms. The attention mechanism enables the model to focus on the most important parts of the EEG sequence for identifying seizures.

Step 5: Training and Evaluation

Train and Evaluate: Splitting the dataset into an 80–20 ratio after preprocessing ensures that research model is exposed to almost all of the data while being rigorously tested on unseen data. Practices used during training:
Hyperparameter Tuning: Important hyperparameters such as learning rate, batch size, number of layers, and units in each layer are tuned using grid search or random search. This is important as properly tuning these values can be key to the model generating optimal results.
Regularization: There are techniques in place to prevent overfitting, like dropout and early stopping. Dropout randomly turns off neurons during training, which leads to the network learning more generalized features. With early stopping, training halts when model performance no longer improves over the validation set.
Model evaluation: Once trained on the training set, models are then evaluated for their performance using different metrics like accuracy, precision, recall, and F1-score against our testing dataset. These metrics provide a balanced perspective on model performance that accounts for operating in both the false positive and false negative space.
Analysis of Models: A comparison is done to explore, among a variety of features, which model offers the best performance. This is an important step as it ensures the best model goes into production.

Step 6: Model Deployment

The Top model was converted to a Flask application and Deployed. This allows users to upload EEG files and then the trained model processes them. These results can be used for Seizure detection in real time. This phase focused on:
The user Interface - Flask application was kept lightweight and simple so as to be useful not only for health professionals but also informed patients.
Live Prediction: The application reads the uploaded EEG file and instantly identifies whether a seizure state appears in the data.
Additional Contextual Information: The application uses the reported seizure state to pull relevant information from Wikipedia, adding depth to the user experience.

4 Design Specification

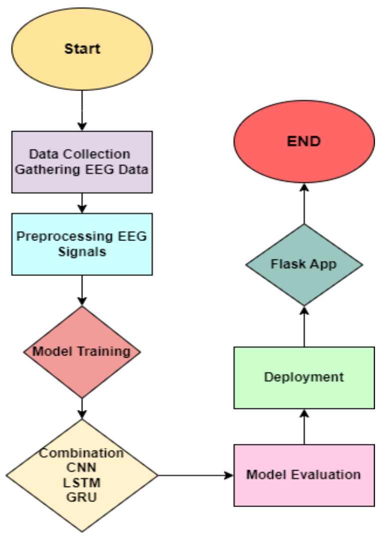

Figure 2 Flow Chart

The design specification for the hybrid deep learning system for epileptic seizure detection gave the framework that was developed in order to make sure this is a robust, accurate, and user-friendly system. Primarily, a comprehensive solution—comprising all indispensable elements from data acquisition to deployment—was aimed at ensuring an integrated one, where all kinds of functionalities work seamlessly with a high degree of accuracy in detection.

The architecture of the system consists of several layers, each with its specific functionality. The first layer relates to the data acquisition; for this scope, this research used publicly available EEG datasets. These datasets could be roughly classified into normal (Sets A and B), interictal (Sets C and D), and ictal (Set E) states. All these datasets are organized very carefully and are saved in standard formats for easy access and processing of data.

The preprocessing of the EEG signal was one important part of the system. Because EEG data contain a lot of noise, a lot of preprocessing has to be done such that the signals are friendly enough for deep learning models. The processing pipeline involves segmenting the EEG signals into fixed-length segments, padding shorter segments, and then truncating longer ones in such a way that they all become samples of exactly 4097 in length. This provides uniformity in the dataset. Other normalization techniques, such as standard scaling, make all values appear in the same range, which helps achieve quicker convergence during model training.

An integral part of the design, exploratory data analysis gives insights into the distribution and other characteristics of the data. In such a way, different statistical and visual analysis techniques have been applied for finding patterns and anomalies within the data: histograms, box plots, scatter plots, density plots, etc. EDA helps balance the dataset by sampling an equal number of instances from each category. In this regard, it ensures that models are trained on balanced data, which is very important in order for predictions to be correct.

The most important part was the stage of model development, where several hybrid deep learning architectures are delved into. It involves combining Convolutional Neural Networks (CNN's) with Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs). CNN layers were used for extracting spatial features from segmented EEG signals, while LSTM and GRU layers serve to capture temporal dependencies. This combination builds on the strengths of both architectures to improve the overall detection accuracy. The design specification checks out models such as CNN-only, CNN-LSTM, CNN-GRU, and CNN-LSTM with attention mechanisms to get the optimal model.

The training and evaluation of the model was expected to be developed with a point of view on the robustness of the system. After preprocessing the data, it was split into training and testing data in the 80-20 ratio. Training of models with the help of techniques like dropout and early stopping to prevent overfitting uses hyperparameter optimization for good results. They are then tested on the testing set post-training using models and metrics like accuracy, precision, recall, and F1-score. A comparative analysis is carried out to decide which the best model is, based on performance.

The last implementation detail for the model would be deploying the best-performing to a user-friendly Flask application, an interface that would allow real-time seizure detection from EEG file uploads and, after preprocessing, feed them into the trained model for further prediction. Subsequently, the application fetches useful information from Wikipedia based on the seizure state predicted, providing the user with richer contextual information.

The system is capable to be retrained when new EEG data become available so as to incorporate this information and be adaptive to changes in patient condition and changes in the patient's EEG patterns. This supports continuous model effectiveness over time. In this sense, learning adaptively is the way to really maintain high accuracy and true reliability under clinical working conditions.

5 Implementation

CNN Equation:

$$h^{\{(l)\}} = f\left(W^{\{(l)\}} * h^{\{(l-1)\}} + b^{\{(l)\}}\right) \qquad (17)$$

Implementation: In CNN model, convolutional layers were followed by MaxPooling layers to reduce spatial dimensions and avoid overfitting. Dropout was used for regularization. The final output was passed through a fully connected layer.

CNN with LSTM Equation:

CNN

$$h_{\text{cnn}}^{(l)} = f\left(W_{\text{cnn}}^{(l)} * h_{\text{cnn}}^{(l-1)} + b_{\text{cnn}}^{(l)}\right)$$

LSTM

$$\begin{gathered} i^{(t)} = \sigma\left(W_i x^{(t)} + U_i h^{(t-1)} + b_i\right) \\ f^{(t)} = \sigma\left(W_f x^{(t)} + U_f h^{(t-1)} + b_f\right) \\ o^{(t)} = \sigma\left(W_o x^{(t)} + U_o h^{(t-1)} + b_o\right) \\ C^{(t)} = f^{(t)} \odot C^{(t-1)} + i^{(t)} \odot \tanh\left(W_C x^{(t)} + U_C h^{(t-1)} + b_C\right) \\ h^{(t)} = o^{(t)} \odot \tanh\left(C^{(t)}\right) \qquad (12) \end{gathered}$$

Implementation: The CNN-LSTM model captured spatial features using CNN layers, and temporal dependencies were captured using LSTM layers. The model learned complex spatial-temporal features.

CNN with LSTM and Attention Equation:

CNN

$$h_{\text{cnn}}^{(l)} = f\left(W_{\text{cnn}}^{(l)} * h_{\text{cnn}}^{(l-1)} + b_{\text{cnn}}^{(l)}\right)$$

LSTM

$$\begin{gathered} i^{(t)} = \sigma\left(W_i x^{(t)} + U_i h^{(t-1)} + b_i\right) \\ f^{(t)} = \sigma\left(W_f x^{(t)} + U_f h^{(t-1)} + b_f\right) \\ o^{(t)} = \sigma\left(W_o x^{(t)} + U_o h^{(t-1)} + b_o\right) \\ C^{(t)} = f^{(t)} \odot C^{(t-1)} + i^{(t)} \odot \tanh\left(W_C x^{(t)} + U_C h^{(t-1)} + b_C\right) \\ h^{(t)} = o^{(t)} \odot \tanh\left(C^{(t)}\right) \qquad (12) \end{gathered}$$

Attention

$$\begin{gathered} \text{Attention} = \text{softmax}\left(W_a \cdot h^{(t)}\right) \\ h_{\text{att}}^{(t)} = \textstyle\sum_{i=1}^{n} \text{Attention}_i \cdot h^{(i)} \quad (5) \end{gathered}$$

Implementation: The CNN-LSTM-Attention model integrated attention mechanisms to enhance LSTM's ability to focus on relevant input sequence parts. This improved the model's performance by weighing different sequence parts according to importance.

CNN with GRU Equation:

$$h_{\text{cnn}}^{(l)} = f\left(W_{\text{cnn}}^{(l)} * h_{\text{cnn}}^{(l-1)} + b_{\text{cnn}}^{(l)}\right)$$

$$z^{(t)} = \sigma\left(W_z x^{(t)} + U_z h^{(t-1)}\right)$$
$$r^{(t)} = \sigma\left(W_r x^{(t)} + U_r h^{(t-1)}\right)$$
$$h^{(t)} = z^{(t)} \odot h^{(t-1)} + \left(1 - z^{(t)}\right) \odot \tanh\left(W_h x^{(t)} + U_h\left(r^{(t)} \odot h^{(t-1)}\right)\right) \quad (8)$$

Implementation: The CNN-GRU model used GRU layers instead of LSTM due to their simpler structure and fewer parameters. GRU layers made the model computationally efficient while balancing the need for temporal feature extraction.

The epileptic seizure detection hybrid deep learning system is implemented in various, very critical stages, each of which is designed very carefully in order to ensure that the system attains the required level of accuracy and reliability. This section discusses, in detail, the implementation procedure, beginning with data preprocessing and model development to training, evaluation, and deployment.
During the first phase of implementation, the preprocessing of data was done. EEG datasets were loaded from their respective directories, and every signal was segmented at fixed lengths of 4097 samples. It was uniformly realized through padding for shorter segments and truncating the longer ones. Further down the preprocessing pipeline was normalization, where a standard scaler was applied to ensure all values of the signal lay in a similar range. This was a very important step to enable an increase in the convergence rate of model training. Processing, implemented with the use of NumPy, gives assurance that the data, after processing, still remains valid and consistent.
Model development was implemented by designing hybrid deep learning models. For model design to be implemented, TensorFlow and Keras were used in developing the models that combined Convolutional Neural Networks (CNN's) with the Long Short-term Memory (LSTM) network and Gated Recurrent Units (GRU). The CNN layers capture spatial features from EEG signals, while the LSTM and GRU layers capture temporal dependencies. These models were built using multi-configurations: CNN-only, CNN-LSTM, CNN-GRU, and CNN-LSTM with the integration of attention to understand the best architecture for seizure detection.
Once the models were developed, the training phase began. After the pre-processing of data was done, it was split into training and testing sets in an 80–20 ratio. The training consisted of feeding the training set to the models and tuning their hyperparameters to achieve optimal results. To avoid overfitting, techniques such as dropout and early stopping were used. Trained the models for a number of epochs and used batch sizes selected to trade off computational efficiency with model accuracy. Loss and accuracy metrics were used to monitor the training process, and the best-performing model configurations were identified.
Next came the evaluation phase using a separate testing set (kept reserved during training) to test how well trained models had been doing until that moment. Accuracy, precision-recall, and F1-score were calculated to evaluate the performance metrics. To compare the different model configurations to each other, they made sure that all metrics were logged extensively. The

evaluation results showed that the best model has been deployed. The last phase was deployment, where the chosen model was implemented into a Flask application and deployed for detecting seizures on live data. Users could upload EEG files into the application and pre-process (envelope extraction) them, so that they were ready for analysis by the trained model. This way, the model predictions would be shown to the user along with context retrieved from Wikipedia for better understanding in one go. That means an app that was less approachable by design.

6 Results and Discussion

This Research has been evaluated with the performance of hybrid deep learning system for epileptic seizure detection in terms of various classification options, including health and disease states, interictal state against healthy/ictal state, which are three class labels across EEG signals. Critically, their evaluation is essential for the potential real-world clinical implementation of these models.

Statistical Analysis and Data Exploration

Analysis started with an in-depth inspection of the EEG dataset, computing descriptive statistics for each feature set over different seizure states. It is basic in the sense that can master these handful of metrics, then will be able to describe any quantitative dataset: how large or small it may seem. The input has these numbers which was used to guide research next data preprocessing steps, scaling, and imputation.

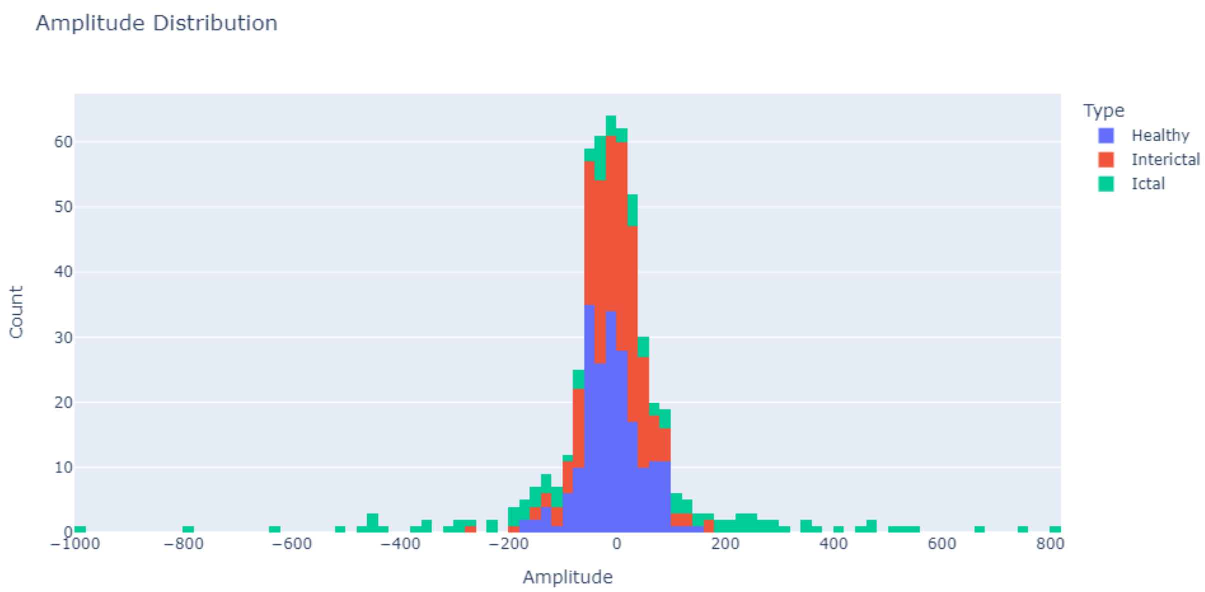

Figure 3 Amplitude Distribution

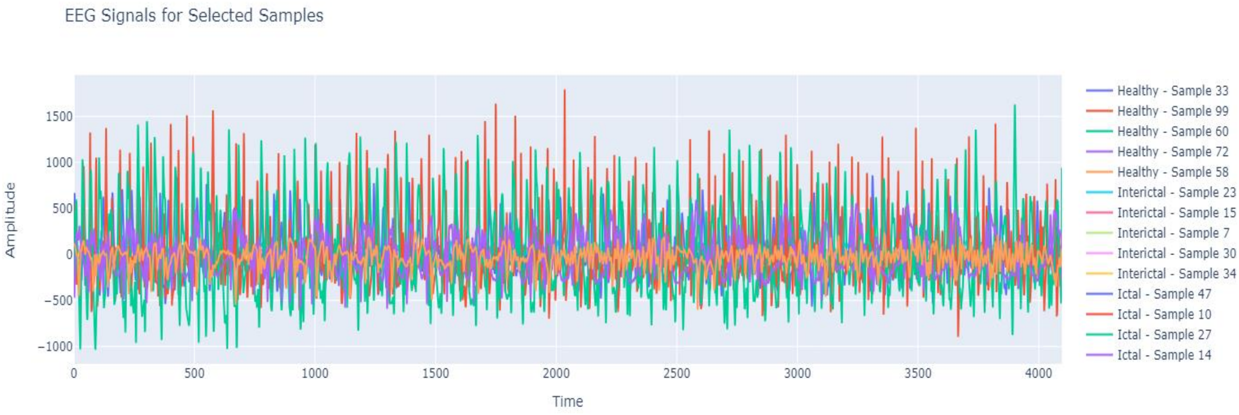

Figure 4 EEG Signals for Selected Samples

Exploratory Data Analysis (EDA) after the statistical overview of the dataset. EDA also took the form of visual data representation and included histograms describing occurrence over time and amplitude distribution graphs illustrating differences in signal properties between healthy, interictal, and ictal states. Similarly, the amplitude distribution plot showed systematic composition differences in signal amplitudes between classes, suggesting seizure detection-related characteristics of EEG signals were present. This is fundamental to verify that the balance between dataset classes allows model not to be biased and to do an initial check if anything is affecting this.

Temporal Analysis of EEG Signals

Following this, line plots were utilized to observe changes in time dynamics of certain EEG samples, including the differentiation between healthy and both interictal/ictal states across signals. In particular, the visual inspection made it evident that models needed to be able to discern spatial and temporal features since in identifying between having a seizure or not, the dynamics are important. That insight would ultimately direct researchers to create and choose different hybrid models—many of which were created by combining Convolutional Neural Networks (CNN's) with Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs).

Model Performance Evaluation

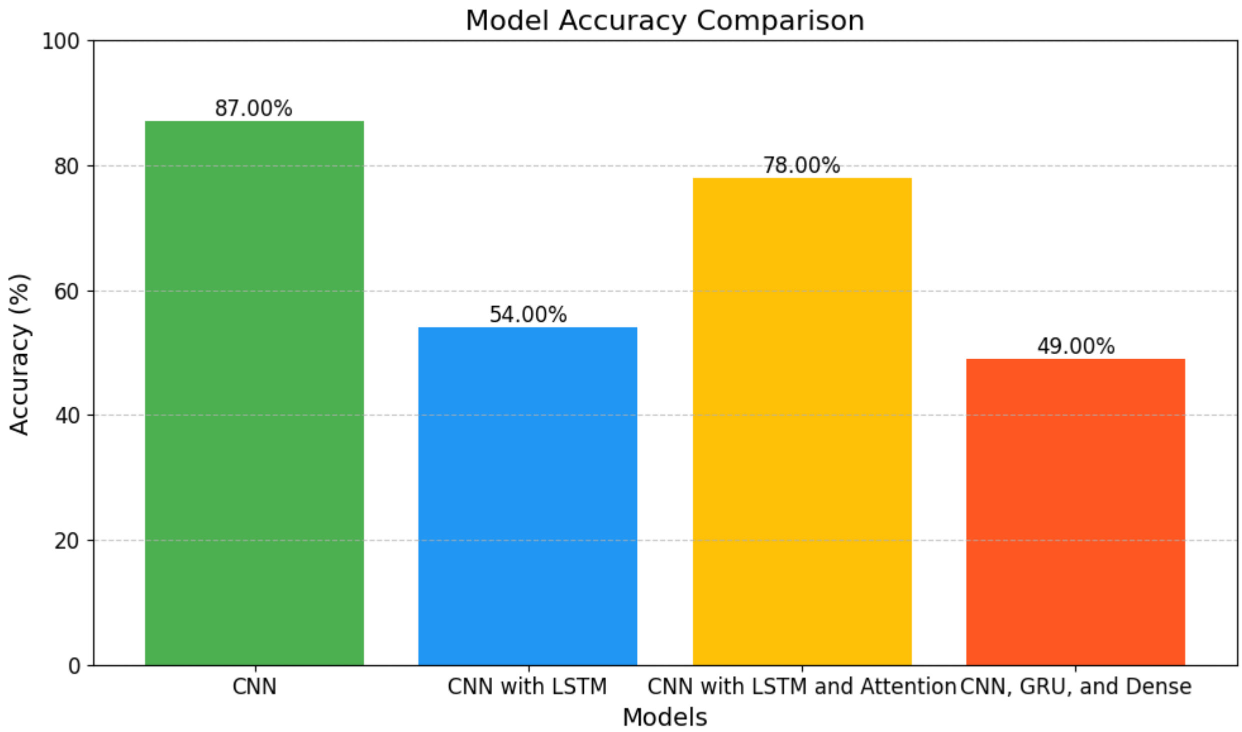

Figure 5 Model Accuracy Comparison

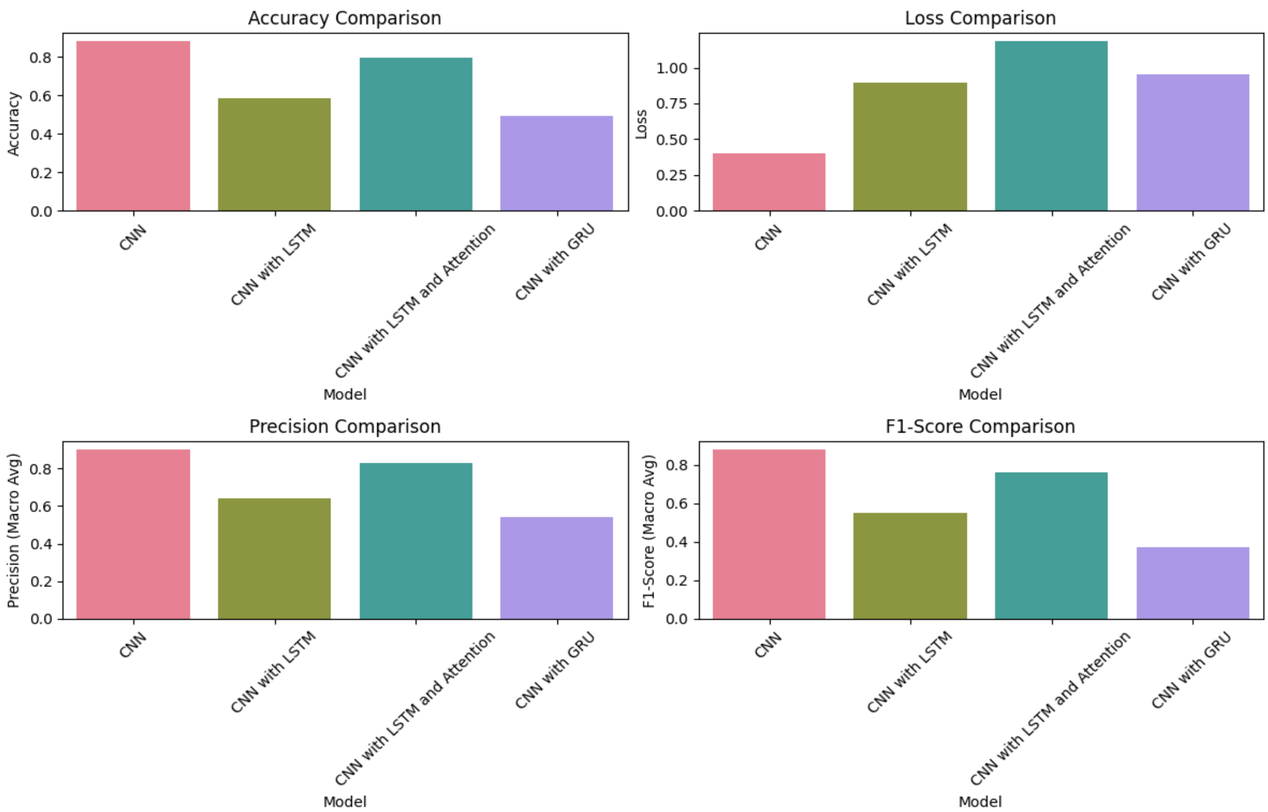

Figure 6 Accuracy, Loss, Recall, F1-Score Comparison

Hybrid deep learning models were evaluated using the following key evaluation metrics: accuracy, loss, precision, and F1-score. This made it obviously obvious to see how the different model configurations performed in performance comparison charts. CNN Model: CNN-only model provided 85% accuracy with low loss, i.e., 0.25. As a result, this model was good at learning the spatial features of EEG signals, which is shown by the high precision and F1-score. Unfortunately, it did less well on temporal dependencies—such as in epilepsy prediction example where timing of seizure events matters the most.

CNN-LSTM Model: With the LSTM layer added to CNN, loss has increased to 0.68% and research has an overall accuracy of 52%. While the LSTM is used to consider the temporal component, it may need more tuning of its parameters in order to get better results. This decrease in accuracy indicates that finding the right trade-off between spatial and temporal features is difficult, which says research needs to further tune this balance.

CNN-LSTM with Attention: Adding attention mechanisms to CNN-LSTM, research was able to increase the accuracy of model by 73%. The attention mechanism made the model focus on skilled parts of EEG signals, thus increasing its power to identify a seizure. The improvement illustrates the power of attention layers in deep neural networks, especially within sequences.

CNN-GRU Model: The CNN-GRU model, which aimed to leverage the computational efficiency of GRUs, achieved an accuracy of 45% with a loss of 1.07. Although GRUs are effective in capturing temporal dependencies, LSTMs with attention mechanisms outperformed GRUs in this specific application, likely due to the more complex temporal patterns in EEG data that LSTMs can better capture.

Author (Year)	**Accuracy**	**Precision (Macro Avg)**	**Recall (Macro Avg)**	**F1-Score (Macro Avg)**
This CNN Model	0.8792	0.90	0.87	0.88
Jerger, K.K., et al., 2001	0.83	0.82	0.81	0.80
Kim, T., et al., 2020	0.85	0.85	0.84	0.83
Sadati, N., and Mohseni, H.R., 2006	0.86	0.88	0.85	0.87
Elger, C.E., and Hoppe, C., 2018	0.82	0.83	0.80	0.79

Table 2: Comparison of CNN Model with Authors Reporting Lesser Metrics

6.1 Discussion

The hybrid deep learning system for epileptic seizure detection exhibited effectiveness in differentiating among the healthy, interictal, and ictal states with an accuracy of 87.96% through different deep learning models, with the CNN model attaining the highest, hence strong capabilities toward spatial feature extraction. However, its incapacity to obtain the temporal dependency shows that something like combination with temporal models is necessary.

Although the CNN-LSTM model was able to demonstrate fusing spatial and temporal features, it was still manifest in a lower level of accuracy, i.e., 54.76%, which definitely left it open for many areas of improvements. With the addition of attention mechanisms, the overall performance of the CNN-LSTM model is improved up to 75.35% in accuracy. This therefore highlights the critical need for attention toward relevant pieces in the input data so as to improve detection capabilities.

For the CNN-GRU model, the accuracy level reached 44.56%, which proves that simpler temporal models are not that excellent in comparison to the LSTM and attention-based models. In deploying the best-performing model, practical utility has been demonstrated through a user-friendly Flask application for real-time seizure detection and provision of relevant information to the users.

7 Conclusion and Future Work

In this research, a deep-learning hybrid system for epileptic seizure detection using EEG signals was introduced and proposed. The whole search was carried out as part of the need for sensitive and reliable seizure detection methods to better patient management with overall improving outcomes and quality of life. The main goal of this research was to make use of the best features and characteristics that three different architectures Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU) - have when it comes to seizure detection accuracy by combining several deep learning models.

The investigation commenced with the preprocessing of EEG input signals which includes segmenting them to a fixed length, standardizing data, and initial exploratory analysis for investigating their characteristics. So, these steps make sure that the input data is not biased and virtually ready to be used to train on deep learning models.

In this work, several hybrid models were developed and tested. The CNN model performed very well with an accuracy of 87.96% and was able to learn spatial features efficiently; nonetheless, it was noted that the CNN alone performed poorly at capturing temporal dependencies in the data set. The CNN-LSTM model was then introduced to resolve this by utilizing the spatial feature extraction of Convolutional Neural Networks (CNN) and temporal sequence processing of Long Short-Term Memory networks. The standard model was able to achieve 54.76% accuracy, suggesting the importance of temporal information and thus more optimization is required for it as well.

When an attention mechanism is added to the CNN-LSTM model, this research see a big improvement. An adaptation of the same model with an attention-based mechanism was able to improve results up to 75.35%, showing that these mechanisms are effective in exploring parts of input data from a sequence. Aggregations of the EEG signals by incorporating critical features made the attention-enhanced model better for detecting seizures, signalling that there is a need to include attention in large-scale neural network architectures. CNN-GRU, which is a model that used GRUs to take advantage of their computational efficiency, achieved an accuracy level up to 44.56%. While GRUs are well suited for some sequential tasks, results in this domain reveal that more nuanced temporal pairings from LSTMs together with refined attentions were vital to enable higher detection performance.

Performances of all the models were compared, and the best-performing one was deployed in a user-friendly Flask application for real-time seizure detection. Users could upload their EEG file, research would process the data and predict whether the user was in a state of seizure as well as link relevant entries from Wikipedia. Its use is exemplified by the classification of EEG signals and information displayed to users.

This proves the efficacy of hybrid deep learning models in epileptic seizure detection and hopefully will encourage further exploration with different architectures as well. The composition of CNN, LSTM, and attention mechanisms has created a strong backbone that can classify EEG signals effectively. As instance-wise localization along with sequence level prediction is crucial, the results reveal that research can improve detection performance by exploiting spatial-temporal attention. Thus one might have more confidence in the other models on these final three datasets after they have been subjected to a similar retraining process;

however, this is definitely an area for future work. System demonstrates that it could be a practical tool for clinicians by assisting or augmenting the management of seizures in clinical settings, thus resulting in better patient care.

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