Advanced Neural Architectures for EEG-Based Seizure Detection and Classification

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Epileptic seizure classification and detection from electroencephalogram (EEG) data is an important field of investigation because seizure patterns pose considerable complexity and variable across patients. This paper investigates several different deep learning techniques such asTimesNet, LSTM, a hybrid model designed specifically for this purpose, transformer-based models such as FedFormer and Informer for seizure classification. Utilizing the TUH EEG Seizure Corpus (v1.5.4), we compare the effectiveness of these models for various seizure types, both intra- and inter-patient variability. The presented methods exhibit high classification performance, with some models outperforming state-of-the-art baselines. Our efforts also focus on model generalizability and real-time applicability, making them a step closer to clinically feasible seizure detection systems.

Keywords: EEG, Seizure Classification, Deep Learning, Transformer Models, 1D ResNet, Temporal Convolutional Network (TCN), TimesNet, Graph Neural Networks (GCN), LSTM,TUH Dataset, Epilepsy Detection, Neural Architecture Comparison.

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1. Introduction

Epileptic seizures result from disordered brain electrical activity, with adverse health consequences and quality-of-life impairment. Electroencephalogram (EEG) traces, the clinical gold standard for the diagnosis of epilepsy, record brain activity over time. Neurologist manual EEG interpretation is time-consuming and subjective as seizures are heterogeneous. Automated seizure classification systems are therefore a fundamental area of research in biomedical signal processing and machine learning.

Deep learning has shown tremendous potential in seizure detection and classification over the past few years. Previous methods such as SVM, KNN, and XGBoost were performing moderately with handcrafted features but were not generalizing well across seizure types and As reported by Roy et al. (2020), Abiramiet al.(2021). Deep neural networks enable end-to-end representation learning from raw EEG data signals with better accuracy and robustness. Interestingly, Fan et al. [2020] introduced a CNN-RNN hybrid network with attention and achieved 95.1% accuracy on the TUH dataset, whereas Alshaya and Hussain [2021] proposed a light 1D ResNet-LSTM model that obtained an F1 score of 97.4%.

This work investigates the accuracy of modern deep learning models on the TUH EEG Seizure Corpus (version 1.5.4), a popular seizure classification benchmarking dataset. We investigate different neural architectures selected based on their suitability to learn different EEG data features. Models comprise the one-dimensional Residual Network (1D ResNet) for deep learning using residual connections, the Temporal Convolutional Network (TCN) for robust sequential data modeling, and TimesNet for multivariate time-series modeling.

In addition, we propose a dedicated hybrid model tailored to the idiosyncrasies of EEG signals, marrying domain-specific design considerations. We also consider fusion of Temporal CNN with Graph Convolutional Networks (TCNN + GCN) in order to both capture temporal characteristics and spatial correlations between EEG channels. Moreover, transformer models like Fed-Former and Informer are explored as to their capabilities to learn sparse representations and long-range temporal dependencies—characteristics highly pertinent to high-dimensional EEG sequences.

This work explores architectures to find suitable models for seizure classification. We add to research on real-time accurate patient-independent seizure detection systems to augment clinical uses for wearable health monitoring devices.

2. Literature Survey

Fan et al. [1] proposed a novel hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) with a new Temporal-Spatial-Spectral Attention (ATSS) mechanism. The model successfully extracts multiscale temporal, spatial, and along with spectral fea-tures extracted from EEG signals. The model reached an impressive 95.1% accu-racy in a multi-type seizure classification task and is therefore a state-of-the-art seizure analysis solution.

Abirami et al. [2] presented traditional machine learning approaches to seizure classification. They evaluated the performance of techniques like SVM, XGBoost, and CNN, with the optimal multiclass classification accuracy being 69.43% using XGBoost. This paper reflected the ongoing significance of hand-crafted features in certain seizure detection tasks, where deep learning is data- or compute-constrained.

Wu et al. [3] tackled the issue of cross-patient variability by creating a spatiotemporal invariant learning platform. With the use of RNNs, in combination with general ML techniques, they attempted

to learn invariant features between patients. Their design achieved 81% accuracy, demonstrating the potential of spatiotemporal modeling to enhance seizure classification generalizability.
Massoud et al. [4] introduced a Temporal CNN-based approach to general and patient-specific seizure classification. The model accuracy was 73% and could handle long-term EEG recordings, which is required in real-world seizure monitoring systems that have to handle prolonged recordings and real-time data.

Jia et al. [5] proposed a Graph Convolutional Network (GCN) approach that employs EEG electrodes as the nodes of a graph to naturally model inter-channel dependencies. The model achieved 92% classification accuracy and was most appropriate for wearable devices in which spatial dependencies must be learned structured and efficiently.

Alshaya and Hussain [6] proposed a light-weight hybrid architecture combin-ing 1D ResNet with the LSTM layers to learn both spatial and temporal character-istics of EEG signals. The proposed model had obtain a 97.4% of F1 score on the TUH dataset with good precision and lower computational burden, and hence better adapted to resource-limited clinical condition.
Aslam et al. [7] utilized a patient-specific LSTM network for the detection of seizures. Their approach leveraged the temporal dependence of EEG signals and reported a validation performance of 94%. Study proves the viability of individualized seizure monitoring systems with the use of recurrent networks.

Mengoni et al. [8] presented a new natural language processing (NLP)-informed method that mined frequency band data from EEG clinical reports and combined it with domain knowledge. Applying Random Forest and Multi-Layer Perceptron (MLP) models, they demonstrated how structured clinical knowledge enhances EEG-based classification performance.

Wong et al. [9] presented a detailed survey of common EEG datasets employed for seizure detection. The survey included data formats, class distribution, and usability across ML and DL models. The work stressed balanced datasets and common evaluation metrics to make seizure detection models transfer-able and reproducible in real-world settings.

Kunekar et al. [10] also suggested a patient-specific LSTM model that was validated to 97.1% accuracy. The study reasserted the resilience of LSTM models to learn patient-specific seizure patterns, which could lead to more accurate and individualized seizure detection systems.

Ullah et al. [11] proposed a pyramidal 1D CNN-based model for the detection of epileptic seizures. Their method takes advantage of hierarchical learning of features to efficiently address multi-resolution patterns of EEG signals. The model is more than 99% accurate, indicating the effectiveness of pyramidal structures in seizure features extraction.

Roy et al. [12] benchmarked several machine learning models including K-Nearest Neighbors (KNN), CNN, and XGBoost on the TUH EEG dataset. Their experiments found KNN to perform best with an accuracy of 90%, demonstrating that even relatively simple algorithms can be competitive under certain dataset and feature settings.

Singh et al. [13] proposed SeizSClas, an IoT-enabled secure seizure classifier combining Short-Time Fourier Transform (STFT) with the VGG19 CNN model. The classifier achieved an 88% accuracy and incorporated blockchain-based protection to ensure data integrity, making it suitable for deployment in healthcare IoT environments.

Efficient development in EEG seizure detection can be observed in the literature with a definite change in the classical machine learning algorithms to embracing more modern deep learning algorithms. Although other traditional learning methods, such as SVM and XGboost, are still applicable in situations when data is not sufficient or the resource is low, deep learning models (especially CNNs, RNNs, LSTMs, and their combinations) are actively known to reveal high-er accuracy by the successful identification of complex temporal, spatial, and spectral patterns of EEG data. More recent developments like attention, graph-based learning and dual-kernel enhancement have improved model performance and patient-level generalizability even further. Additionally, a lot of emphasis is put in the development of lightweight patient-specific dynamic models and limited resource laboratory settings. Further, the increased focus on how to have practical and scalable healthcare solutions is seen in the area of standardized datasets, interpretability, and secure data handling. In general, there is a trend towards stronger, flexible and clinically applicable seizure detection systems.

3. Methodology

3.1 System Architecture

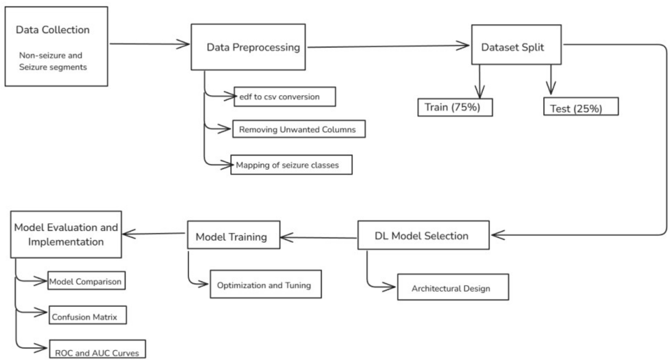

Figure.1. Workflow Diagram for Deep Learning Approaches for Seizure Detection.

The workflow (as shown in Figure 1.) for Deep Learning Approaches for Seizure Detection begins with collection of EEG data, which includes seizure and non-seizure segments. Data is then preprocessed, involving tasks such as converting from EDF to CSV format, removing irrelevant columns, and mapping seizure classes. Once the data is prepared, it is split into training and testing sets then various deep learning models are then selected and trained, with hyperparameter tuning to optimize performance. Finally, the models are evaluated using metrics like confusion matrices, ROC curves, AUC scores, and performance comparisons to determine the most effective model for seizure detection.

3.2 Dataset Acquisition

This studymake use of the Temple University Hospital EEG Seizure Corpus (TUSZ) dataset version 2.0.3, obtained through formal approval provided by the Neural Engineering Data Consortium. It is one of the largest EEG datasets focused on seizure detection, comprising over 7,300 EEG recordings arranged at the level of patients and their respective sessions, containing raw EEG signals in European Data Format (EDF) and corresponding annotation files. Only the training and validation (dev) sets were used in this study, excluding the evaluation set reserved for blind testing.

The recordings follow the standard 10/20 electrode placement. Each file is annotated with binary seizure labels (seiz or bckg) using .csv_bi files, while more detailed annotations were available but not used. The training set includes 4,664 recordings from 579 patients, and the validation set includes 1,832 recordings from 53 patients, totalling around 4.87 million seconds of EEG data with approximately 3,500 seizure events. Due to the sparse occurrence of seizures, class imbalance was addressed using data sampling and balancing strategies during pre-processing and training.

3.3 Data Pre-processing

Preprocessing began by aggregating EEG recordings stored in EDF format from 100 session folders. Each folder contained paired data and label files. All EDF files were converted into CSV format to facilitate efficient manipulation and compatibility with downstream analysis pipelines.
Sessions labeled exclusively as background, noise, or artifacts were excluded to eliminate non-informative segments. From the remaining data, irrelevant channels and metadata columns were pruned, retaining only the essential EEG leads relevant to seizure detection.

Seizure annotations were mapped to discrete integer codes for model compatibility: background was assigned a label of 0, while seizure types were encoded as 1–3 depending on the specific category. To emphasize peri-ictal dynamics and manage class imbalance, 50 seconds of EEG data were extracted both before and after each seizure onset, forming standardized 100-second epochs encompassing pre-ictal, ictal, and post-ictal states.

Each epoch was segmented into three phases: the pre-ictal phase (from the extraction start time to the seizure onset) was labeled 0, the ictal phase (from seizure onset to seizure end) retained its respective seizure label (1–3), and the post-ictal phase (from seizure end to the extraction end) was again labeled 0.

The extraction window was defined using:

$$t\_start = max(t_seizure_start - 50{,}0), \quad t\_end = min(t_seizure_end + 50, T) \tag{1}$$

where T is the total duration of the session.

To ensure uniformity across sessions, a common time grid was created:

$$t_i = i \times T/(N-1), \quad i = 0,1,\dots,N-1 \tag{2}$$

with NNN being the number of resampled points. A mask was applied to isolate the relevant window:

$$mask_i = (t_i \geq t_{start}) \wedge (t_i \leq t_{end}) \tag{3}$$

Signal values were then interpolated onto this uniform grid:

$$s_{interp(t)} = interp1d(\{t_i, s_i\}, t) \tag{4}$$

to standardize input length across epochs.

3.4 Models used

LSTM:
The study also evaluates a bidirectional LSTM classifier as shown in figure 2, configured to ingest fixed-length EEG epochs of 100-time steps and C channels, mapping them to four seizure categories. The architecture comprises the network begins with a LSTM layer containing 64 hidden units (configured with return_sequences=True), followed by a dropout rate of 50%. This is succeeded by a second LSTM layer comprising 32 units, along with an additional 50% dropout to mitigate overfitting. A fully connected dense layer with 32 neurons and activation using ReLUrefines the learned representations before a final SoftMax layer outputs class probabilities over the four seizure types. The

architecture was optimized using Adam and trained with sparse categorical cross-entropy loss, tracking classification accuracy. Training proceeds for 15 epochs with a batch size of 32 and a 20% validation split to monitor generalization. Upon completion, the trained weights and architecture are persisted in "lstm_seizure_model.h5" for downstream evaluation.

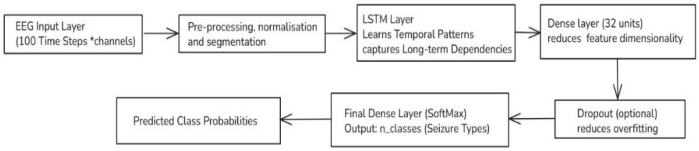

Figure 2. Bidirectional LSTM classifier for EEG seizure detection

Custom Transformer:

As shown in figure 3, The study employs a custom EEGTransformer architecture to classify fixed-length (100-sample) multi-channel EEG segments. Each input batch of shape (B, T=100, C) is first projected via a linear embedding layer from C raw channels into a d_model=64–dimensional feature space, producing a tensor of shape (B, T, d_model). This tensor is permuted to the Transformer convention (T, B, d_model) and processed through two stacked encoder layers, each block incorporates four-head self-attention along with position-wise feed-forward sublayers, to capture temporal dependencies. The resulting sequence is permuted back to (B, T, d_model) and flattened into a vector of length 64 × 100 per example. A classification head, consisting of a dense layer of 256 neurons using ReLU activation and a dropout rate of 0.3followed by a linear projection, generates logits for C target classes, yielding an output tensor of shape (B, C). Training utilizes the model employed Adam (lr=1e-3) in combination with cross-entropy loss over mini-batches of 32 samples, with computation performed on CPU or GPU according to availability.

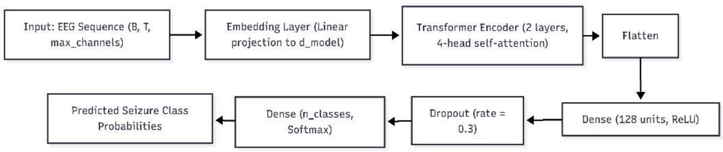

Figure 3. Custom Transformer architecture for EEG classification with linear embeddings, stacked encoder layers, and dense classification head.

GCN:

The Figure 4 illustrates the Graph Convolutional Network is an EEG analysis improvement that represents the spatial interactions of electrodes as a graph structure. Here, every EEG channel is considered a node, and the neighbors among nodes are specified either anatomically (from 3D electrode coordinates) or functionally (from inter-channel signals such as coherence or phase locking values). The adjacency matrix A4 is normalized to have the following form

$$A^{\wedge} = D^{-1/2}(A + I)D^{-1/2} \quad (5)$$

where D is the degree matrix and I the identity matrix, with stable feature propagation. Temporal features extracted by the CNN-capturing local patterns such as spikes or rhythmic activity-are mapped as node embeddings. These embed-dings are further improved by stacking multiple GCN layers, where each layer sums up features from nearby nodes using the operation

$$H^{(l+1)} = \mathrm{ReLU}\left(\hat{A}H^{(l)}W^{(l)}\right) \quad (6)$$

Here, W(l) refers to learnable weights at layer l, and H(l) refers to node features. Hierarchical feature aggregation allows the model to learn spatial dependencies that are crucial for seizure propagation pathway identification. Subsequently, global graph features are pooled and classified via SoftMax, allowing the hybrid CNN-GCN architecture to outperform unimodal approaches by jointly modeling temporal dynamics (CNN) and brain network interactions (GCN), capturing the spatiemporal nature of ictal events.

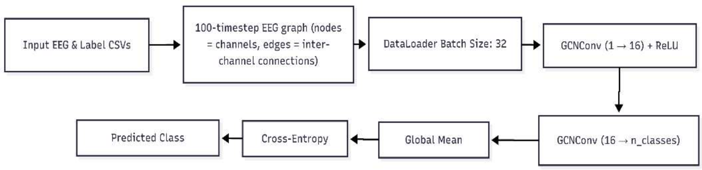

Figure 4. Proposed GCN workflow for EEG-based seizure classification.

1D ResNet:

A 1D Residual Network (ResNet1D) architecture as shown in figure 5, was employed to classify segments of EEG signals. The model consists of two residual blocks with progressively deeper channels, an adaptive average pooling followed by a fully connected layer to perform classification. The input data was preprocessed by normalizing, adjusting all samples to have a consistent number of time steps, and padding channels to ensure uniformity across different recordings.

The dataset was divided into training and testing subsets in an 80:20 ratio, ap-plying stratified sampling to preserve class distribution. Training was conducted for 35 epochs with Adam (lr=0.001), a batch size of 32, and cross-entropy loss as the optimization objective and accuracy was monitored on both training and test sets.

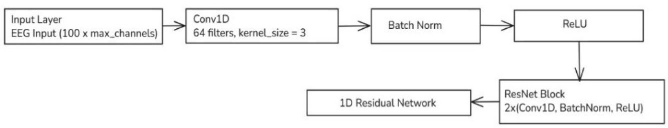

Figure.5. 1D ResNet architecture for EEG segment classification.

TCN:

As shown in figure 6, The 1D Temporal Convolutional Network (TCN) processes EEG signals by first standardizing the input segments to have uniform length and consistent channel dimensions. The model architecture consists of two residual blocks with causal dilated convolutions, where the initial block is con-figured with a dilation factor of 1 with 64 filters and the second one uses a dilation factor of 2 with 128 filters. Each block incorporates ReLU activations, batch normalization and dropout were incorporated to stabilize learning and mitigate overfitting.

Following these residual blocks, an adaptive average pooling layer aggregates and compresses the feature maps, which then pass through a fully connected layer for classification. the dataset was divided into training and testing subsets using stratified sampling to preserve class balance. Training is performed over multiple epochs using adam optimization with cross-entropy loss was employed, producing accuracy evaluated on both sets after each epoch. The TCN successfully models temporal dependencies across both short and long ranges in the EEG data, enabling it to differentiate between classes with high accuracy and strong generalization.

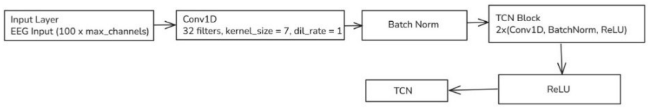

Figure. 6. TCN for EEG classification with causal dilated convolutions, residual blocks, and fully connected layers.

4. Results And Discussions

Section presents the performance evaluation of various deep learning models applied to EEG-based seizure classification. A comprehensive comparison is made across architectures such as GCN, ResNet, TCN, Transformer and LSTMhighlighting their strengths and limitations in capturing spatiotemporal patterns. Furthermore, the proposed LSTM model is benchmarked against existing methods from the literature to contextualize its effectiveness. The findings indicate that the proposed architecture delivers top-tier performance with respect toaccuracy, precision, and recall, validating its suitability for practical seizure detection applications.

4.1 Model Performance

The Transformer (89.0% acc, 98.5% prec, 99.1% recall) excels at global context yet is sensitive to label noise. The GCN (~89.9% accuracy, 91.2% precision, 90.0% recall) suffers from noisy graph representations due to variable electrode layouts. In contrast, the 1D-ResNet (~90.1% acc, 97.6% prec, 98.0% recall) benefits from residual learning of deeper temporal patterns but underutilizes spatial correlations. The TCN (~90.3% acc, 98.3% prec, 98.0% recall) rivals ResNet by modelling long-range dependencies but lags in detecting fine spikes. Finally, the LSTM (~98.3% acc, 98.7% prec, 98.0% recall) effectively captures sequential patterns but misses brief transient events as shown in figure 7.

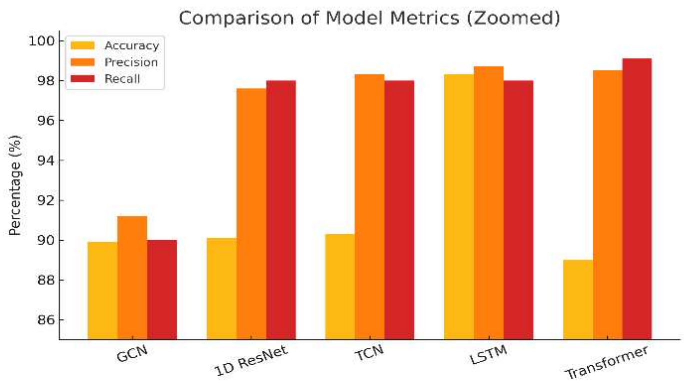

Figure. 7. Comparison of Model performance.

4.2 Comparison with existing models

Table 1. Comparison with different models

Dataset	Model(s)	Accuracy	Reference
EEG Dataset	XGBoost	88.21%	[2]
TUH Seizure Corpus (TUSZ)	RNN	81%	[3]
Seizure Prediction Competition Dataset	Temporal CNN	73%	[4]
CHB-MIT Scalp EEG Database	GCN	92%	[5]
TUH Database	1D ResNet + LSTM	97.4%	[6]
CHB-MIT	CNN + LSTM	94%	[7]
Multiple EEG datasets	SVM, ANN, RF, CNN, RNN	80–95%	[9]
UCI Epileptic Seizure Recognition Dataset	LSTM	97%	[10]
TUH EEG Seizure Corpus	KNN	90%	[12]
TUH Abnormal EEG Dataset	STFT + VGG19	88.04%	[13]
TUSZ EEG Dataset	LSTM	98.3%	Proposed System

Table 1 provides a comparative summary of different machine learning and deep learning approaches applied to EEG datasets for seizure detection and prediction. As shown, a various approaches including XGBoost , RNNs , CNNs , GCNs , and hybrid approaches such as ResNet + LSTM have been evaluated across different publicly available datasets like TUH, CHB-MIT, and UCI Epileptic Seizure datasets. Reported accuracies vary, with some traditional models like SVM, ANN, and RF achieving 80–95% , while advanced deep learning techniques such as LSTM and hybrid CNN+ LSTM architectures have reached accuracies as high as 97% and 94% . Notably, our proposed system, utilizing a LSTM on the TUSZ EEG Dataset, achieves an accuracy of 98.3%, representing state-of-the-art performance, surpassing most existing approaches. This comparison highlights the rapid progress in seizure classification accuracy driven by recent advancements in deep learning.

5. Conclusion

This research investigates, we systematically evaluated various advanced neural network-based learning architecture for EEG-based seizure detection using the large-scale TUH EEG Seizure Corpus. Among the compared models, the LSTM achieved the best performance with around 98.3% accuracy, effectively capturing sequential dependencies in EEG signals though showing some limitations in detecting brief transient events. In contrast, the GCN struggled with lower accuracy due to noisy graph representations and variable electrode layouts, while the 1D-ResNet and TCN achieved moderate accuracy, benefiting from deeper temporal modeling yet underutilizing spatial correlations or missing fine-grained seizure spikes.

Despite these promising outcomes, challenges such as noisy, imbalanced clinical data and computational demands for dynamic use remain. Potential direction for future research lies in optimizing model architectures for deployment on embedded hardware to enable practical, real-time seizure monitoring. Additionally, integrating multimodal data fusion—combining EEG with other biosignals—and developing wireless communication modules can enhance detection robustness and patient mobility. Such advancements will support the development of patient-independent, resource-efficient systems with direct clinical applicability.

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