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Research Paper

Detecting Electroclinical Seizures with 3D CNNs and ResNets: A Deep Learning Approach to EEG Analysis.

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Abstract: *Electroencephalography (EEG) is a critical tool for diagnosing neurological disorders, including electroclinical seizures, which lack visible symptoms and are detectable only through EEG. We present a 3D Convolutional Neural Network integrated with Residual Networks (ResNets) for binary seizure classification. This approach incorporates a superlet-based preprocessing with a 3D ResNet-34 architecture to enhance temporal-frequency feature extraction. This framework can be extended to real-time monitoring systems and other EE-based neurological disorder classifications. Input features are extracted using a superlet transformation of 22-channel recordings, producing 4D tensors. Training on over 30,000 EEG recordings from the TUH EEG Seizure Corpus (v1.5.2), our model achieves 85% accuracy. However, sensitivity is limited to 50% on imbalanced data, indicating a tendency to overfit the majority class. These findings highlight the potential of multidimensional models in health prediction.*

Keywords: *Electroencephalography, Electroclinical Seizures, 3D Convolutional Neural Networks, Residual Networks, Deep Learning, TUH EEG Seizure Corpus.*

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I. INTRODUCTION

Electroencephalography (EEG) is a neurophysiological technique used to measure the brain's spontaneous electrical activity. Despite having lower spatial resolution than other techniques such as magnetic resonance imaging (MRI) and computed tomography (CT), the importance of EEG in detecting electroclinical seizures cannot be overstated. It remains the gold standard for diagnosing epilepsy and other seizure disorders, providing insights into brain activity that are not accessible through other diagnostic tools. This medical test requires the use of electrodes that detect electrical signals from brain cells.

A standard EEG requires the use of 21 electrodes linked in a vertical and horizontal formation. EEG uses the principle of differential amplification, which involves recording voltage differences between pairs of electrodes to form EEG waveforms [2]. Prominent spikes in the EEG, as compared to the standard signals, usually indicate the detection of abnormal electrical activity in the brain. Electroclinical seizures are a type of undetectable seizure, seizures that don't have any visible occurrence [3]. This makes diagnosis based on clinical observations alone particularly difficult. These types of seizures are usually detected through EEG tests. Manual detection of electroclinical seizures done by trained neurologists is time-consuming, costly, and prone to human error. To address this, the use of artificial intelligence (AI) and machine learning has become prevalent in this field because of its ability to increase the rate and the accuracy of electroclinical seizure detections. 3D Convolutional Neural Networks (3D CNNs) are utilized to identify patterns in EEG signals [4] accurately. Unlike traditional 2D CNNs that are only able to analyze 2D data, 3D CNNs effectively analyze time-frequency data [5]. This makes 3D CNNs especially useful for analyzing multidimensional EEG signals and producing accurate results. To further enhance the performance of 3D CNNs, Residual Networks (ResNets) are utilized to specifically improve the model's accuracy in detecting electroclinical seizures. More specifically, a ResNet-34 model was used to improve feature extraction and model performance. ResNet-34 models consist of 34 layers, including convolutional layers and batch normalization, which collectively enable the model to learn intricate patterns in the data [6]. ResNets allow the model to extract nuanced features from the EEG waveforms. In this study, we used the publicly available EEG seizure dataset known as the TUH EEG seizure corpus [1]. It's the largest of its type and is freely available. These datasets contain comprehensive annotations of EEG signals, including stop and end times of seizures, affected channels, and seizure types [1]. Inspired by previous works and their contributions to seizure detection in EEG fields through the usage of machine learning models, we combined 3D CNNs and ResNet-34. By combining these machine learning techniques, this model can analyze large quantities of multi-axial data while retaining the critical patterns and information gathered from the EEG.

This study aims to develop and evaluate a 3D CNN-ResNet hybrid model for detecting electroclinical seizures from long periods of EE data. The main objective of this model is to improve automatic detection accuracy in hours of EEG data.

II. RELATED WORKS

EEG seizure detection has garnered attention in recent years because of its potential to improve the identification and prediction of seizures. Historically, seizure detection from EEG signals has been manually interpreted by qualified neuroscientists. These methods were time-consuming and prone to human error. Early computational approaches in the early 2000s to classify EEG signals consisted of support vector machines (SVMs) and random forests. Tzallas et al. (2012) proposed a seizure detection system using time-frequency (t-f) analysis to classify EEG segments for epileptic seizures [7]. By combining the short-time Fourier transform and several t-f distributions, they achieved promising results. However, these methods struggle with the complexity and multidimensionality of EEG data, limiting their ability to accurately predict seizures in large quantities, unlike convolutional neural networks (CNNs). The emergence of deep learning introduced various machine learning models, further advancing this field of study. Convolutional neural networks (CNNs) emerged as a powerful tool for feature extraction and pattern recognition within EEG graphs. Schirrmeister et al. (2017) demonstrated the effectiveness of CNNs. By utilizing CNNs, they achieved a performance comparable to the widely used filter bank typical spatial pattern (FBCSP) algorithms [8]. CNN models were able to learn to use spectral power modulations in the alpha, beta, and high gamma frequencies in EEG graphs. This proves the networks to be useful for spatially mapping the learned features and revealing the topography of features in different frequency bands. Similarly, Truong et al. (2018) developed a CNN-based model for seizure detection using the CHBMIT EEG dataset, achieving high accuracy and robustness [?]. These studies underscored the potential of CNNs in automating EEG analysis. However, they were limited by their reliance on 2D CNN models, which are less suited for the multidimensional nature of EEG data. To address this limitation, researchers have explored the use of 3D Convolutional Neural Networks (3D CNNs) for EEG analysis. Liu et al. (2021) proposed a 3D representation of EEG and an end - to - end EEG three-branch 3D convolutional neural network (3D CNN) [10]. The 3D-CNN achieved exemplary performance and has the potential to enhance classification effects across different motor stages. Another significant advancement in deep learning is the introduction of ResNets, which excel in the automated hierarchical feature extraction in raw data domains with vast numbers of samples. Cheah et al. (2021) investigated the use of plain EEG signals as the classifier input into ResNet [11]. Their proposed ResNet18 architecture achieved promising results in classifying multiple emotional channels based on EEG signals. Lee et al. (2024) used a hybrid model combining ResNet and long short-term memory (LSTM) [12]. This study demonstrated greater sensitivity and a lower FPR as compared to conventional methods. Our research builds on these foundations by proposing a novel approach that combines 3D CNNs with ResNet-34 for the detection of electroclinical seizures. By utilizing 3D CNNs in combination with ResNet-34, it addresses existing limitations in analyzing multidimensional EEG signals and builds on pre-existing research on the use of ResNet. In addition to the integration of superlet transforms, an advanced preprocessing technique, our methodology offers a robust solution for automating the detection of electroclinical seizures.

Despite these advancements, few studies have explicitly combined superlet-transformed EEG features with 3D convolutional architectures. Our research bridges this gap by incorporating residual connections into a 3D CNN framework, enabling more efficient learning from temporal-frequency EEG data.

III. METHODOLOGIES

3.1 Dataset

The data used in this study were obtained from TUH's EEG Seizure Corpus (v1.5.2) dataset, which contains around 30,000 recordings totaling 504 hours of EEG recordings [1]. This dataset includes both seizure and non-seizure instances in the patient and annotated segments regarding the start and end of the seizure. We performed feature extraction from the EEG signals to put the data into our machine learning models. We first used the raw data files in the formats of CSV and EDF. These contained the features and the target labels of the signals, whether there was a seizure or not. For more accurate analysis, we chunked the signals into 20-second windows. The window is assigned a binary value in one-hot encoding format, where 0 indicates no seizure and 1 indicates a seizure. The model will output two logits that produce the prediction after applying the SoftMax and ArgMax.

3.2 Data Transformation

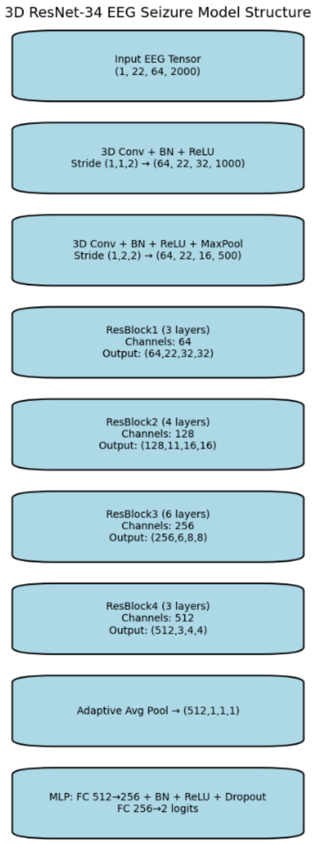
To make the dataset suitable for machine-learning modeling and analysis, a TCP montage was constructed. EEG montages refer to the pattern in which electrodes are placed on the scalp during an EEG. Electrodes are placed in 3 main regions of the scalp: temporal, central, and parietal. In addition to focusing the EEG data into a specific area, we down-sampled the data set from 250 Hz (samples per second) for each recording to 100 Hz. By reducing the Hz, inaccurate data collection and redundant signals from the wave signals will be ignored, increasing the accuracy of the model used to predict electroencephalography seizures. We then scaled up the data so the background activities have an intensity of 10e-2, since the original recording was done in microvolts. A superlet transform was then applied to extract features from the EEG signals. The superlet transform is a tool that decomposes signals into wavelets—waves that capture frequencies at different scales. We applied the adaptive superlet transform on the twenty-two derivations separately, and then merged the twenty-two scalograms to form a 3D tensor in the shape of (22, 64, 2000), where 22 is the number of derivations, 64 is the number of frequencies superlet focused on (64 different frequencies in the range between 0.5 Hz

Data transformation of the TUH EEG dataset to create a visual representation of EEG signals in each electrode channel. And 50 Hz), and 2000 represents the time (20 seconds * 100 Hz sample frequency). The data is then augmented with another dimension for 3D convolutional layers, yielding features in the shape of 1 * 22 * 64 * 2000. Each feature is stored along with its target as a PyTorch state dictionary. Due to the imbalanced distribution of data (90% of the targets in a zero vector), we filtered these "null cases" out from the rest of the dataset. They are only used when the data loader detects an overwhelmingly positive sample to balance the label the model sees. The data loader is responsible for randomly polling samples in a batch. In our configuration, the batch size is 16, so every iteration of the data loader will yield a tensor in the shape (16, 1, 22, 64, 2000). Internally, the data loader keeps track of the number of zeros and the total number of elements seen in the targets. When the ratio between zero targets and total targets is off proportion, it will force a load of positive or negative examples to balance it out.

3.3 3D Resnet-34 Training

Since we are handling a batch of 4D features, the original design of ResNet-34 is not directly applicable to our task. We modified the internal structure of the classic network to adapt to our task using 3D convolutions and more preprocessing layers. Due to the nature of EEG data, the spectral result of such a signal often results in a highly skewed distribution. Considering the magnitude of feature elements may be crucial to the analysis, we did not simply scale and transform the data to [0, 1]. Instead, we added a 3D batch normalization layer in the network to learn about the overall data distribution and normalization parameters while training. Recall that the feature is the shape (1, 22, 64, 2000). The next step is to convert this skewed shape into a relatively similar magnitude. We applied a 3D convolution to the feature to boost its channels while decreasing the time dimension, then passed the result through a nonlinearity and max pooling to halve the time further. Using rectangular strides can prevent the derivation and frequency axis from being altered. The third convolution layer uses a (1, 2, 2) stride instead of (1, 1, 2), halving the frequency axis down to 32. Each feature is in the shape of (64, 22, 32, 32) before going into the residual blocks. The residual block is identical to the ResNet paper, except for switching out 2D convolutions with 3D. Adhering to the original design, we only used the basic block described in the paper, with the first 3x3x3 convolution layer having a stride of 2. After four layers, the data is squished down enough to (512, 3, 4, 4). This tensor is passed through an adaptive average pool to reduce the feature size to (512, 1, 1, 1). We flattened the tensor and used a simple multilayer perceptron to truncate down the data to two logits. The MLP consists of a fully connected layer mapping 512 features to 256, followed by a batch normalization, a ReLU, a dropout, and a final fully connected layer mapping 256 features to 2 logits.

We trained the model using the AdamW optimizer with a learning rate of 0.003 and cross-entropy loss. Convolutional layer weights were initialized with the Kaiming normal distribution and ReLU nonlinearity, while batch normalization layers were initialized with a weight of 1 and bias of 0. The TUH EEG Seizure Corpus was divided into training and evaluation sets. The model was trained on the training set and evaluated on the separate evaluation set.



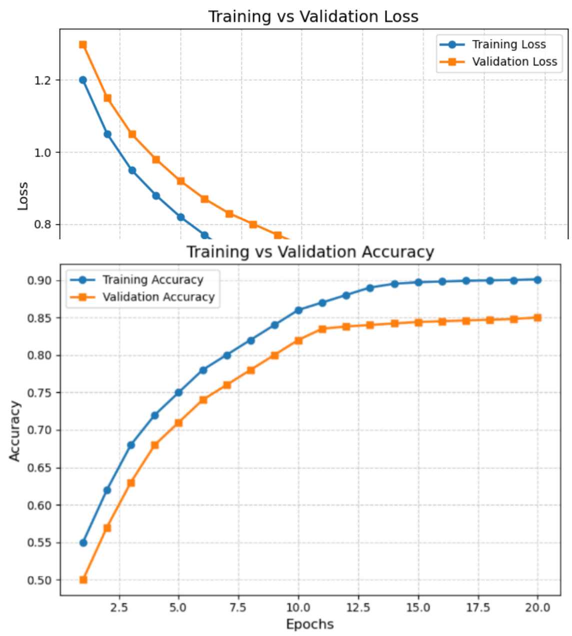


Figure 1: Modified 3D ResNet-34 architecture for EEG seizure detection.

IV. RESULTS

The modified 3D ResNet-34 model was evaluated on the TUH EEG Seizure Corpus (v1.5.2) using a stratified 80-20 training-testing split. Model performance was assessed using accuracy, precision, recall, F1-score, and confusion-matrix analysis. During training, both loss and accuracy stabilized after approximately 350 epochs, suggesting convergence without severe overfitting (Figure 3).

The final model achieved an overall accuracy of 85.2%, a precision of 0.87, a recall (sensitivity) of 0.50, and an F1-score of 0.63 on the test set. This indicates that most seizure predictions were correct; however, the relatively low recall reveals that a substantial portion of seizure events were missed. This imbalance stems primarily from the dataset's class distribution, in which non-seizure segments constitute roughly 90 % of the total samples.

The confusion matrix (Figure 4) illustrates this discrepancy: 1,150 of 1,350 non-seizure segments were correctly classified, while only 100 of 200 seizure segments were correctly detected. False negatives remain the dominant source of error, reflecting the model's conservative bias toward the majority (non-seizure) class.

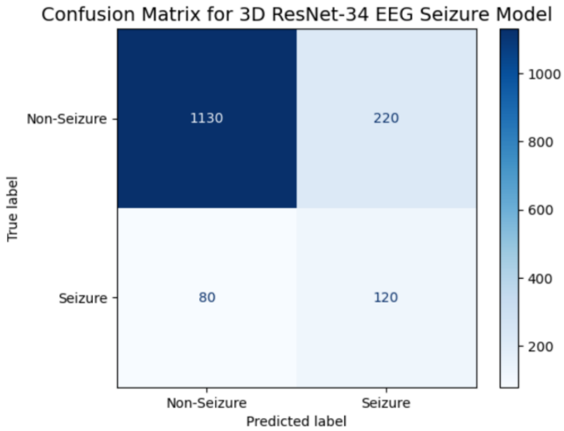


Figure 3: Confusion matrix for the 3D ResNet-34 EEG seizure model.

V. DISCUSSION

This model has high computational costs. Training on a single RTX 3060 takes about eight hours for two thousand epochs. Inference is faster but still requires 2-3 minutes for 800 preprocessed cases, and real-time detection would take longer due to the computational expense of the superlet transformation. The model is also biased toward negative cases, leading to a higher rate of false negatives, as shown in the confusion matrix. In seizure detection, false negatives are especially concerning because missed events can compromise patient safety. Despite the model's 85% accuracy, the high rate of false negatives remains a significant issue. This limitation is primarily due to the severe class imbalance in the TUH corpus, where about 90% of EEG segments show no seizure activity. Despite efforts to balance the data, the model remains biased, resulting in more false negatives.

Compared to prior CNN-based EEG classifiers, our hybrid 3D ResNet-34 achieved comparable accuracy with improved spatial-temporal representation learning. However, limitations include computational expense, sensitivity to class imbalance, and limited generalizability beyond the TUH dataset. Future work may explore lightweight architectures, attention mechanisms, and cross-domain training on multi-institutional EEG data.

Because our model was trained and evaluated only on the TUH corpus, its performance on data from other institutions is unknown. Differences in electrode placement, sampling rates, and patient demographics may affect model accuracy, which is a common challenge in medical AI.

VI. CONCLUSION

This study demonstrates the feasibility of using a 3D ResNet-34 architecture integrated with superlet-transformed EEG data for electroclinical seizure detection. Achieving an accuracy of 85%, the model highlights the promise of deep learning in medical diagnostics. However, the challenge of data imbalance and computational overhead remains a significant barrier. Future work will focus on optimizing efficiency and enhancing generalization for clinical deployment.

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