Epileptic Seizure Detection on a Large-Scale EEG

Dataset: A Comparative Study of a Custom CNN

and EEGNet

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*Abstract*—Epilepsy is a prevalent neurological disorder characterized by recurrent seizures. Electroencephalography (EEG) is commonly used for diagnosing epilepsy , but manual interpretation of EEG recordings is time-consuming. This study utilizes a large publicly available EEG dataset from 121 subjects (50 epileptic, 71 healthy) to train and evaluate deep learning models for automated epilepsy detection. A custom convolutional neural network (CNN), referred to as YY\_model, was developed and then pruned using a semantic dictionary-based channel selection approach (YY\_model\_pruned). As a benchmark, we also implemented the EEGNet architecture , a compact CNN designed for EEG signals. All models were evaluated using accuracy, precision, recall, and F1-score. EEGNet achieved the highest accuracy (88.23%), outperforming YY\_model (86.44%) and YY\_model\_pruned (77.99%). These results demonstrate the effectiveness of EEGNet for seizure detection and highlight the trade-offs involved in channel pruning.

Keywords—EEG; Epilepsy; Convolutional Neural Network; EEGNet; Channel Pruning; Deep Learning

# INTRODUCTION

Epilepsy affects approximately 50 million people worldwide and is one of the most common neurological disorders . It is characterized by recurrent seizures resulting from abnormal brain activity. Electroencephalography (EEG) is a primary clinical tool for diagnosing and monitoring epilepsy, as epileptic seizures produce distinctive EEG patterns. However, manual analysis of EEG recordings by neurologists is labor-intensive and subject to human error [1]. This has driven research into automated seizure detection using machine learning and deep learning techniques.

Early machine learning approaches for EEG-based epilepsy detection often relied on handcrafted feature extraction and classical classifiers . In recent years, deep neural networks have shown great promise in automatically learning features from raw EEG signals. Convolutional neural networks (CNNs) in particular have been effective for EEG classification tasks. A notable example is EEGNet, proposed by Lawhern et al. (2018), which is a compact CNN architecture specifically designed for EEG-based brain– computer interfaces [2]. EEGNet uses depthwise and separable convolutions to efficiently capture temporal and spatial features from multi-channel EEG data.

Despite these advances, many studies have been limited by relatively small EEG datasets . In this work, we leverage a large-scale EEG dataset of epileptic and healthy subjects to evaluate and compare different CNN models for seizure detection. We introduce a custom CNN model (denoted as YY\_model) tailored to this epilepsy detection task, and we further refine it by pruning less informative EEG channels using a semantic dictionary approach (resulting in YY\_model\_pruned). We compare the performance of our models to the benchmark EEGNet architecture. This comparative study provides insights into the benefits and drawbacks of a specialized EEG-specific architecture versus a customdesigned model, as well as the impact of channel selection on model performance. The following sections describe our methodology, experimental results, and key findings in detail.

# METHODS

## Data

We utilized a publicly available Turkish epilepsy EEG dataset , originally introduced by Taşcı et al. (2023). This dataset contains 10,356 EEG signal segments recorded from 121 subjects (50 with epilepsy and 71 healthy controls) [1]. Each EEG recording includes 35 channels corresponding to standard scalp electrode locations . The signals in the dataset are labeled as either epileptic (seizure activity) or normal, making it suitable for supervised learning. The large size of this dataset addresses the limitation of earlier studies that used smaller EEG collections.

*B. Data Pre-Processing*

In the data preprocessing stage, we transformed the existing 1D data available in .mat format into a 2-dimensional format by stacking each sample vertically. Specifically, the shape of the data for one patient, originally structured as 145 (number of samples), 36 (EEG channels), 1 (signals per channel), and 7500 (signal length), was reshaped by concatenating each of these 145 samples vertically into a new shape of 145 by (36 × 7500). Consequently, the entire epilepsy dataset of 145 samples for the same patient was converted into two-dimensional matrices, each with dimensions 36 × 7500.

## C. Models

We developed a custom deep CNN, referred to as YY\_model, to serve as our baseline model. The **YY\_model** architecture consists of multiple convolutional and pooling layers designed to extract discriminative features from the multi-channel EEG input. After initial training, we applied a channel pruning strategy to this model using a semantic dictionary-based approach. This pruning method identifies the most informative channels on last layer of CNN model and removes the less contributory channels from the input, yielding a simplified model termed **YY\_model\_pruned**. The pruned model trains and tests faster and potentially has fewer parameters, which can reduce computational complexity and the risk of overfitting. In addition to our models, we implemented the standard **EEGNet** architecture as described by Lawhern et al. (2018) [2]. EEGNet is a compact CNN that employs depthwise separable convolutions to efficiently capture temporal dynamics and spatial correlations in EEG data, and it has been proven effective for various EEG classification tasks

*D. Training and Evaluation*

All models were trained on the same dataset and evaluated under identical conditions for a fair comparison. For each model, we computed standard performance metrics: accuracy, precision, recall (sensitivity), and F1-score. Accuracy reflects the overall proportion of correctly classified EEG segments, precision indicates the proportion of detected seizures that are actual seizures, recall measures the proportion of actual seizures correctly detected, and F1-score is the harmonic mean of precision and recall. These metrics provide a comprehensive evaluation of the models' detection capabilities.

# RESULTS

The performance of the three models on the EEG dataset is summarized in Table 3.1. EEGNet achieved the highest overall accuracy at 88.23%, substantially outperforming the custom CNN (86.44%) and the pruned CNN (77.99%). Similarly, EEGNet obtained the highest precision (90.25%), recall (88.11%), and F1-score (88.06%) among the models, indicating a superior ability to detect epileptic seizures with fewer false alarms. In comparison, the YY\_model reached a precision of 86.56% and recall of 85.71%, while the YY\_model\_pruned obtained a precision of 79.36% and recall of 77.88%. The pruned model's performance is lower across all metrics, which is the trade-off for its reduced complexity.

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| *Table 3.1: Model Performances* | | | | |
| **Model** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| YY | 86.56% | 85.71% | 86.06% | 86.44% |
| YY\_pruned | 79.36% | 77.88% | 77.68% | 77.99% |
| EEGNet[2] | 90.25% | 88.11% | 88.06% | 88.23% |

Notably, the reduction in accuracy from YY\_model to YY\_model\_pruned (approximately 4.7 percentage points) suggests that removing channels led to some loss of important information. Nonetheless, the pruned model still achieved nearly 78% accuracy, which may be acceptable for certain applications where computational efficiency or hardware constraints demand a smaller model. All three models performed significantly above chance level, confirming that they successfully learned to distinguish epileptic EEG patterns from normal activity. In fact, the EEGNet model's accuracy slightly exceeds the 87.78% reported on this dataset using a feature-engineering and kNN approach [1]. This highlights the effectiveness of deep learning models in leveraging the rich information present in multi-channel EEG data. In figures 1, 2 and 3, graphs of the loss and accuracy values of the respective models are shown.

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| *Figure 1: Loss- and Accuracy over Epochs for YY\_model, left one is Loss over epochs and right one is Accuracy over Epochs.* |

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| *Figure 2: Loss- and Accuracy over Epochs for YY\_pruned\_model, left one is Loss over epochs and right one is Accuracy over Epochs.* |

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| *Figure 3: Loss- and Accuracy over Epochs for EEGNet\_model, left one is Loss over epochs and right one is Accuracy over Epochs.* |

# DISCUSSION

The results demonstrate that the EEGNet architecture is highly effective for automated epilepsy detection from EEG data. EEGNet's superior performance can be attributed to its specialized design: by using depthwise and separable convolutions, EEGNet captures both frequency-specific patterns and spatial correlations in the EEG signals . This allows it to learn complex features that generalize well across subjects. In contrast, the custom YY\_model, while achieving decent performance, may not be as optimized for extracting EEG features, which likely explains its lower accuracy and F1-score compared to EEGNet. The fact that our YY\_model reached over 82% accuracy still indicates that a well-designed CNN can learn useful representations from raw EEG, even if it does not incorporate all the architectural innovations of EEGNet.

The pruned model (YY\_model\_pruned) yielded somewhat lower performance than the full model. By removing channels deemed less informative, the model becomes simpler and faster, but some loss of discriminative information is inevitable. The drop in recall for YY\_model\_pruned suggests that a few seizure instances that were detectable using all channels became missed when using the reduced channel set. Nevertheless, the pruned model's precision and recall (around 79% and 78%) indicate that it still reliably identifies a majority of seizures while potentially generating fewer false positives than the unpruned model. In scenarios where computational resources are limited or only a subset of EEG channels is available (such as wearable EEG devices), a pruned model might offer a practical trade-off.

Another noteworthy observation is the high precision of EEGNet (90.25%), which is beneficial in clinical practice as it means fewer false alarms for seizures. False positives in epilepsy monitoring can cause undue stress for patients and caregivers, so a model that is more precise, even at the expense of a slight reduction in sensitivity, can be desirable. In our results, however, EEGNet maintained both high precision and high recall, showing it did not significantly sacrifice sensitivity for specificity. The custom CNN and its pruned version had lower precision, implying they may trigger more false alarms. Further tuning of these models or incorporation of EEGNet-like architectural features could potentially improve their precision.

Overall, our comparative study highlights that leveraging a well-established architecture like EEGNet can provide excellent performance on a large EEG dataset, slightly surpassing the performance of traditional feature-based methods on the same data [1]. Meanwhile, custom models allow flexibility; they can be tailored or simplified to specific needs (e.g., fewer channels), but they require careful design to match the efficacy of proven architectures. Future work could explore hybrid approaches, such as using the EEGNet architecture as a starting point and applying channel selection or pruning techniques to further reduce complexity without significant loss of accuracy. Additionally, evaluating these models on other EEG datasets or in real-time seizure detection scenarios would be valuable to confirm their generalizability and practical utility.

##### References

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