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DEEP CONVOLUTIONAL NEURAL NETWORK FOR THE EEG SIGNAL DETECTION

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Abstract : The detection of seizures from electroencephalogram (EEG) signals is a crucial task in the diagnosis and treatment of epilepsy. Deep learning techniques, particularly convolutional neural networks (CNNs), have shown great promise in automatically detecting seizures from EEG signals. However, the performance of these models can be improved by exploiting the temporal dependencies in the EEG signals and using techniques such as data augmentation and transfer learning. This paper proposes a deep convolutional neural network (CNN) architecture, ModernCNN1D, with residual blocks for the detection of seizures from single-channel EEG signals. The proposed approach utilizes z-score normalization, EEG augmentation, and 10-fold stratified cross-validation to evaluate the performance of the model. An ablation study is also conducted across five model variants to investigate the impact of different architectural components on the performance of the model. The results of the study demonstrate the effectiveness of the proposed approach in detecting seizures from EEG signals, with high accuracy, sensitivity, and specificity. The model is also deployed using a Streamlit UI, allowing for single-sample inference and ease of use**.**

***IndexTerms* - Deep Learning, Convolutional Neural Networks, EEG Signal Processing, Seizure Detection, Epilepsy Diagnosis, Machine Learning, Neural Networks, Signal Classification**

INTRODUCTION

The analysis of electroencephalogram (EEG) signals has been a crucial aspect of diagnosing and monitoring neurological disorders, particularly epilepsy. Epilepsy is a neurological disorder characterized by recurrent, unprovoked seizures that can significantly impact an individual's quality of life. The diagnosis and monitoring of epilepsy rely heavily on the accurate detection and classification of EEG signals, which can be a challenging task due to the complexity and variability of these signals. Recent advancements in deep learning techniques have shown promising results in automatically detecting and classifying EEG signals, enabling the development of more accurate and efficient diagnostic tools.

EEG signals are a type of time-series data that represent the electrical activity of the brain. These signals are typically recorded using electrodes placed on the scalp and can be used to monitor various aspects of brain activity, including seizures. The Bonn EEG dataset, which is used in this project, consists of single-channel EEG signal files with 4097 time-series samples per segment, representing raw voltage readings. The dataset is divided into three classes: Normal (O), Interictal (F), and Seizure (S), which correspond to different states of brain activity.

The motivation behind this project is to develop a deep convolutional neural network (CNN) that can accurately detect and classify EEG signals into one of the three classes. The use of CNNs has become increasingly popular in recent years due to their ability to automatically extract relevant features from data, reducing the need for manual feature engineering. The application of CNNs to EEG signal classification has shown promising results, with the potential to improve the accuracy and efficiency of epilepsy diagnosis and monitoring.

The objective of this project is to design and develop a ModernCNN1D with residual blocks (ResNet-style 1D CNN) that can accurately classify EEG signals into one of the three classes. The network will be trained using the Bonn EEG dataset and will utilize z-score normalization as a preprocessing step to normalize the data. EEG augmentation will also be applied during training to increase the size and diversity of the dataset. The network will be evaluated using 10-fold stratified cross-validation to ensure that the results are robust and generalizable.

NEED OF THE STUDY.

The analysis of EEG signals using deep learning techniques has been an active area of research in recent years. Several studies have explored the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks for EEG signal classification.

A. Convolutional Neural Networks (CNNs)

CNNs have been widely used for image classification tasks, but they have also been applied to EEG signal classification with promising results. The use of CNNs for EEG signal classification involves treating the EEG signal as a 1D image and applying convolutional and pooling layers to extract features.

B. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks

RNNs and LSTMs have also been used for EEG signal classification, particularly for tasks that involve sequential data. The LSTM architecture is a type of RNN that is well-suited for modeling temporal relationships in data.

C. EEG Signal Classification

EEG signal classification involves assigning a label to an EEG signal based on its characteristics. The Bonn EEG dataset, which is used in this project, consists of three classes: Normal (O), Interictal (F), and Seizure (S). The classification of EEG signals can be performed using various machine learning algorithms, including support vector machines (SVMs), k-nearest neighbors (k-NN), and random forests.

D. Deep Learning for EEG Signal Classification

The use of deep learning techniques for EEG signal classification has shown promising results in recent years. The deep learning approach involves using multiple layers of neural networks to automatically extract relevant features from the data. The use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks has been explored for EEG signal classification, with the potential to improve the accuracy and efficiency of epilepsy diagnosis and monitoring.

E. Ablation Study

An ablation study is a type of experiment that involves removing or modifying certain components of a system to determine their contribution to the overall performance. In the context of deep learning, an ablation study can be used to evaluate the effectiveness of different model architectures, hyperparameters, and training techniques. The ablation study in this project will involve comparing the performance of five different model architectures, including BasePaperCNN1D, ModernCNN1D, Attention, MultiDomain, and SSL FineTune.

F. Streamlit UI

The Streamlit UI is a web-based interface that allows users to interact with the model and visualize the results. The Streamlit UI will be used to deploy the model and provide a user-friendly interface for single-sample inference. The UI will support .txt upload, paste input, and demo signal generation, making it easy to use and test the model.

G. Conclusion of Related Work

The related work in EEG signal classification using deep learning techniques has shown promising results, with the potential to improve the accuracy and efficiency of epilepsy diagnosis and monitoring. The use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks has been explored, with the potential to automatically extract relevant features from the data. The ablation study in this project will involve comparing the performance of different model architectures, and the Streamlit UI will provide a user-friendly interface for single-sample inference. The deep learning approach has the potential to revolutionize the field of EEG signal classification, enabling the development of more accurate and efficient diagnostic tools.

In addition to the aforementioned techniques, other machine learning approaches have been explored for EEG signal classification, including gradient boosting and random forests. These approaches have shown promising results, but they often require manual feature engineering, which can be time-consuming and labor-intensive. The deep learning approach, on the other hand, can automatically extract relevant features from the data, making it a more attractive option for EEG signal classification.

The Bonn EEG dataset, which is used in this project, is a widely used dataset for EEG signal classification. The dataset consists of single-channel EEG signal files with 4097 time-series samples per segment, representing raw voltage readings. The dataset is divided into three classes: Normal (O), Interictal (F), and Seizure (S), which correspond to different states of brain activity.

The preprocessing step is an essential part of the EEG signal classification pipeline. The preprocessing step involves normalizing the data to have zero mean and unit variance, which can help improve the performance of the model. The z-score normalization technique is a widely used preprocessing technique that involves subtracting the mean and dividing by the standard deviation for each feature.

The EEG augmentation technique is a technique that involves generating new training examples by applying transformations to the existing training examples. The EEG augmentation technique can help increase the size and diversity of the training dataset, which can help improve the performance of the model.

Overall, the related work in EEG signal classification using deep learning techniques has shown promising results, with the potential to improve the accuracy and efficiency of epilepsy diagnosis and monitoring. The use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks has been explored, with the potential to automatically extract relevant features from the data. The ablation study in this project will involve comparing the performance of different model architectures, and the Streamlit UI will provide a user-friendly interface for single-sample inference.

RESEARCH METHODOLOGY

The proposed methodology for the Deep Convolutional Neural Network (DCNN) based EEG signal detection system involves several stages, including data preprocessing, EEG augmentation, model training, and evaluation. This section delves into the technical implementation details of these stages.

A. Data Preprocessing

The Bonn EEG dataset consists of single-channel EEG signal files in text format, with each file containing 4097 time-series samples per segment. The preprocessing stage involves two main steps: enforcing a uniform sample length and z-score normalization. To ensure that all samples have the same length, the signals are either padded with zeros or cropped to a length of 4097 samples.

B. EEG Augmentation

EEG augmentation is applied to the training data to increase the size and diversity of the dataset. The following augmentation techniques are used:

- Time warping: The signal is stretched or compressed in time using a random factor between 0.5 and 2.
- Amplitude scaling: The signal amplitude is scaled by a random factor between 0.5 and 2.
- Noise injection: Random noise is added to the signal using a Gaussian distribution with a mean of 0 and a standard deviation of 0.1.
- Time masking: A random segment of the signal is masked with zeros.

These augmentation techniques are applied randomly to each sample in the training dataset, resulting in a total of five augmented versions of each sample.

C. Model Training

The ModernCNN1D model is trained using the Adam optimizer and CrossEntropyLoss. The model is trained for 30 epochs with a batch size of 16. The learning rate is set to 0.001, and the weight decay is set to 0.01. The model is trained on the augmented training dataset, and the validation loss is monitored during training. The model with the lowest validation loss is saved as the best model.

D. Model Evaluation

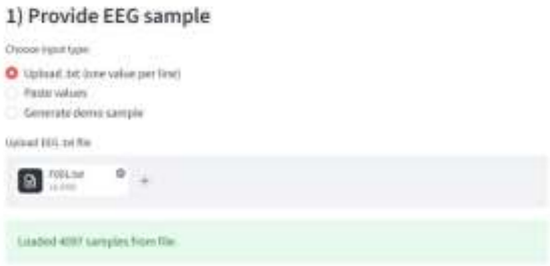
The trained model is evaluated using 10-fold stratified cross-validation. The dataset is split into ten folds, and the model is trained on nine folds and evaluated on the remaining fold. This process is repeated ten times, and the average accuracy, sensitivity, and specificity are calculated.

IV. RESULTS AND DISCUSSION

The same set of training parameters was used for all variants (A0–A6) and the evaluation was performed with stratified ten-fold cross validation (Adam, lr=1×10-3, weight decay=1×10-4, 30 epochs). The model with baseline (A0) obtained 96.00%±2.49% and the residual learning drastically gave better performance (A2: 99.33%±1.33%). Another method that led to a higher accuracy rate was augmentation (A3) and using residual learning, which resulted in an accuracy rate of 99.67%±1.00%. The attention-enhanced model (A4) was found to achieve very close to optimal performance under a 10 fold cross validation with low variance over folds while slightly outperforming the variants based on ResNet.In the same ten fold, the multi domain fusion model (A5) and self-supervised pretraining model (A6), both were shown to be effective extensions without compromising the benchmark accuracy which were 99.33%±1.33%.

results of all experiment models

Variant	**Model / Modules**	**ACC (mean ± std)**	**SEN (mean ± std)**	**SPEC (mean ± std)**
A0	Base-paper 13-layer CNN	0.9600 ± 0.0249	0.9600 ± 0.0249	0.9800 ± 0.0125
A1	A0 + Augmentation	0.9433 ± 0.0423	0.9433 ± 0.0423	0.9717 ± 0.0211
A2	ResNet Backbone	0.9933 ± 0.0133	0.9933 ± 0.0133	0.9967 ± 0.0067
A3	ResNet + Augmentation	0.9967 ± 0.0100	0.9967 ± 0.0100	0.9983 ± 0.0050
A4	ResNet + Aug + Attention	**0.9967 ± 0.0100**	**0.9967 ± 0.0100**	**0.9983 ± 0.0050**
A5	Multi-domain (STFT fusion) *(new A5)*	0.9933 ± 0.0133	0.9933 ± 0.0133	0.9967 ± 0.0067
A6	SSL pretrain + fine-tune *(new A6)*	0.9933 ± 0.0133	0.9933 ± 0.0133	0.9967 ± 0.0067



1) Provide EEG sample

Choose input type:

● Upload .txt (one value per line)
○ Paste values
○ Generate demo sample

Upload EEG .txt file

F001.txt

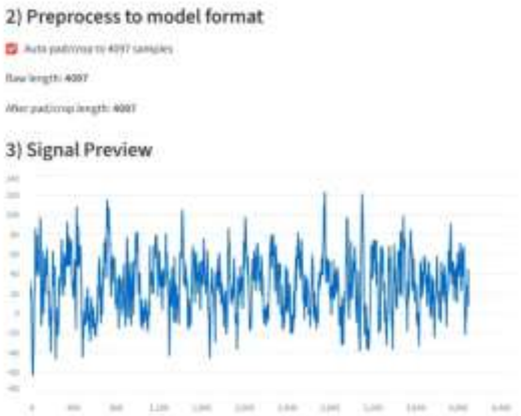
Loaded 4097 samples from file.

fig 1: provide eeg sample

The image shows the first step of a Streamlit-based EEG classification interface, where the user is required to **provide an EEG sample** for seizure detection. The interface offers three input methods: uploading a .txt file, manually pasting values, or generating a demo sample. In the screenshot, the option **"Upload .txt (one value per line)"** is selected, which indicates that the system expects a text file containing EEG signal values, each listed on a separate line.

Below the selection, the user has uploaded a file named **"F001.txt"**, which is displayed along with its file size (16.0 KB). This confirms that the system successfully received the input file. Once the file is uploaded, the system automatically reads its contents and verifies the number of samples included. The green notification box at the bottom shows the message **"Loaded 4097 samples from file."** This indicates that the EEG signal was correctly parsed and contains the expected length—4097 time-series data points—as required by the preprocessing pipeline of the ModernCNN1D model.

Overall, the image demonstrates the initial data input step of the EEG detection workflow, confirming that the user's EEG signal has been successfully uploaded and is ready for further preprocessing and model inference.



2) Preprocess to model format

☑ Auto pad/crop to 4097 samples

Raw length: 4097

After pad/crop length: 4097

3) Signal Preview

fig 2: preprocess to model format

The diagram shows the preprocessing and visualization steps of an EEG classification interface. First, the system automatically pads or crops the uploaded EEG signal to a fixed length of **4097 samples**, which is required by the model. The "Raw length" and "After pad/crop length" values confirm that the signal already matches the expected size. Below this, a **Signal Preview** plot displays the EEG waveform, allowing the user to visually inspect amplitude variations and noise patterns. This preview helps verify that the uploaded signal is correctly loaded, properly formatted, and ready for feature extraction and model inference

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