Use of Deep Learning in Harmful Brain Activity Classification

Paulina Dziwak
Computer Science - Data Science student
at AGH University of Science and Technology
Email: paulinadz@student.agh.edu.pl

Piotr Ludynia
Computer Science - Data Science student
at AGH University of Science and Technology
Email:piotrztych@student.agh.edu.pl

***Abstract*—This paper presents a deep learning approach to classify harmful brain activity using EEG data, developed as part of the Medical Informatics course at AGH. The idea comes from the HMS Harmful Brain Activity Classification competition conducted on Kaggle. Our results demonstrate significant improvements over baseline models, underscoring the effectiveness of our methodology in accurately detecting harmful brain activity.**

1. Introduction

1.1. Background

Electroencephalography (EEG) is a method used to record the electrical activity of the brain. Detecting harmful brain activities such as seizures and other brain-related issues through EEG data is crucial for medical diagnostics and treatment. This project aims to develop a model to classify harmful brain activity using given EEG data. That model will help automate EEG analysis to improve accuracy and speed in detecting brain abnormalities.

1.2. Motivation

Currently, EEG analysis is done manually by specialized neurologists, which is time-consuming and prone to errors. Relying solely on human expertise has limitations. Neurologists may miss subtle patterns, suffer from fatigue-related errors, or exhibit variability in their interpretations. Accurate classification of harmful brain activities can lead to timely interventions, improving patient outcomes. The project provides an opportunity to apply advanced machine-learning techniques to a critical real-world problem. This algorithm could revolutionize how seizures and other brain activities are detected, potentially aiding in the development of new treatments and improving patient outcomes.

1.3. Objectives:

- To process the raw EEG data for noise reduction.
- To extract differences signal between neighboring electrodes and generate time series
- To develop and optimize machine learning models for accurate classification.

2. Data Description

2.1. Overview

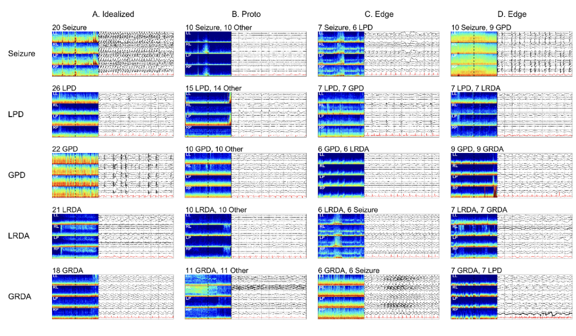
The data for this study has been provided by the Sunstella Foundation, in collaboration with Persyst, Jazz Pharmaceuticals, and the Clinical Data Animation Center (CDAC). This data comprises EEG recordings annotated by a group of expert neurologists. The annotations classify the EEG segments into six distinct patterns of interest, that serve as classification targets:

- **Seizure**: This pattern indicates the presence of seizure activity, characterized by sudden, abnormal electrical discharges in the brain. Seizure patterns can vary widely in appearance but are typically marked by high amplitude, rhythmic spikes or sharp waves, often followed by slow waves.
- **Generalized Periodic Discharges (GPD)**: EEG patterns associated with widespread brain dysfunction, typically showing periodic, repetitive discharges across both hemispheres.
- **Lateralized Periodic Discharges (LPD)**: These are periodic discharges localized to one hemisphere, often indicating acute brain injury or structural lesions.
- **Lateralized Rhythmic Delta Activity (LRDA)**: Rhythmic delta wave activity localized to one hemisphere, commonly linked to focal brain lesions such as strokes or tumors.
- **Generalized Rhythmic Delta Activity (GRDA)**: Rhythmic delta waves distributed across both hemispheres, often associated with diffuse brain disorders like toxic-metabolic encephalopathies.
- **Other**: EEG segments that do not fit neatly into the above categories.

Each EEG segment falls into one of three categories based on the level of agreement among experts:

- **Idealized Patterns**: Uniform agreement among experts on the classification.
- **Proto Patterns**: Approximately half of the experts label the segment as one of the five named patterns, while the other half classify it as "Other."
- **Edge Cases**: Experts are roughly split between two of the five named patterns.

2.2. Examples of EEG Patterns with Different Levels of Expert Agreement:



Recording regions of the EEG electrodes are abbreviated as LL = left lateral; RL = right lateral; LP = left parasagittal; RP = right parasagittal.

2.3. Data format

The dataset consists of 50 second long sequences of EEG signals for different electrodes collected with sampling frequency of 200 Hz.

The classes are stored as count of annotator votes for a given brain activity class. Tthe total number of annotators varies between measurements.

3. Implementation

3.1. Tools and Libraries

The project was done using Python with following libraries:

- **NumPy**: A fundamental package for scientific computing with Python, providing support for large multidimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.
- **SciPy**: An open-source Python library used for scientific and technical computing. It builds on NumPy and provides many higher-level functions for optimization, integration, interpolation, eigenvalue problems, and other scientific computations.
- **Pandas**: Data manipulation and analysis library for Python, offering data structures like DataFrames to handle structured data intuitively, along with tools for data cleaning, preparation, and analysis.
- **Scikit-learn**: A machine learning library for Python that provides simple and efficient tools for data mining and data analysis. It includes various algorithms for classification, regression, clustering, and dimensionality reduction.
- **PyTorch**: An open-source deep learning framework that provides a flexible and efficient platform for building and training neural networks. It supports dynamic computation graphs, making it ideal for research and development in deep learning. PyTorch enables the use of CUDA - a parallel computing model that let's us use the resources of GPU for faster model training.

3.2. Data Preprocessing

The training data was stored in .parquet files, containing individual read values of separate electrodes placed on a patient's head during EEG examination. To train a deep learning model, this data had to undergo a proper preprocessing.

- **Differential signal**: Typically, specialists do not analyze the separate signals, but rather focus on the differences between neighboring electrodes. This technique also gets rid of low frequencies of high amplitude in the signal, which makes for a better and more uniform input for the model.
- **Filtering**: With a use of Butterworth low-pass filter, the data was filtered to get rid of low rumbling frequencies and higher noise. The signal was sampled at a rate of 200 Hz, and the filtering was performed to eliminate noise frequencies above 20 Hz and below 0.5 Hz.
- **Target transformation**: As the targets consist of count values, they have to undergo an uniformization. Instead of predicting the number of experts, the model predicts probabilities of classifying a given brain activity. This can be achieved simply by division of the target by the number of experts to get probability values that sum up to 1.

3.3. Model Architecture

The architecture of the model is a simple convolution network consisting of 4 convolution layers and a multilayer perceptron with dropout layers. One specific thing about this model is the use of group convolution in the first layer of the mode to extract information about different channels separately and then combining information about them in later layers. No final activation function was specified, as different ones were used in different training stages.

3.4. Optimizer

The training was performed in two stages - pretraining for 100 epochs and main training for 200 epochs. This approach was chosen empirically as it allowed us to achieve better scores. For both of these stages, an Adam optimizer was used. It is an adaptive learning rate optimization algorithm that combines the strengths of two other stochastic gradient descent (SGD) extensions: Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). This adaptive learning rate approach allows for dynamic adjustments to the learning rate for each parameter, making it an efficient and well-suited choice for large datasets and complex models. The learning rate used for the optimizer was initialized as 1e-4 and weight decay to 1e-5.

3.5. Loss Function

In the stage of pretraining, a mean squared error was used as a loss function. The outputs of the network were transformed to a probability distribution vector using softmax function.

In the main training, a Kullback-Leibler divergence was employed as the loss function, as recommended by the scientists who developed the top-performing solutions for the HMS competition. Kullback-Leibler divergence is defined as the expectation of the logarithmic difference between the probabilities P and Q, where the expectation is taken using the probabilities P. It is a Loss function typically used to measure the difference between probability distributions.

3.6. Regularization

In the experiment stage, the model displayed a heavy overfitting. To reduce it, a simple upsampling method was introduced. Instead of using the whole 50 seconds of measurement, a random 10 seconds were selected from each input entry in every epoch. Additionally, the values before activation were noised by adding values from a normal distribution with a mean equal to 0 and standard deviation equal to 0.3.

4. Results

During the pretraining and training, the loss value of MSE was lowered to to approximately 0.065 (figure 1) and KLDiv to 0.83 (figure 2). The resulting predictions were not perfect, but they approximated the expert assigned labels pretty well (figures 3, 4).

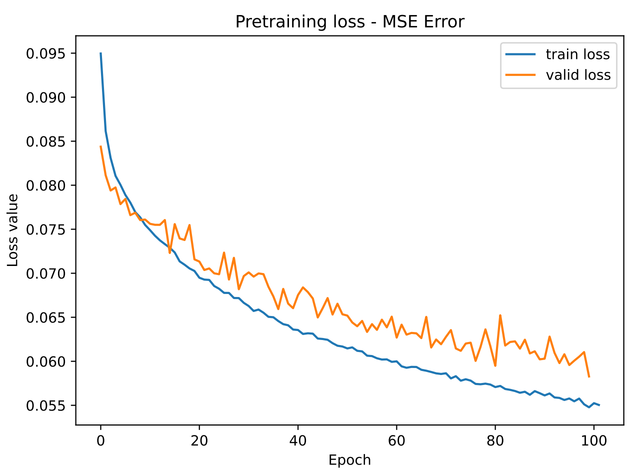


Figure 1. Pretraining loss function values

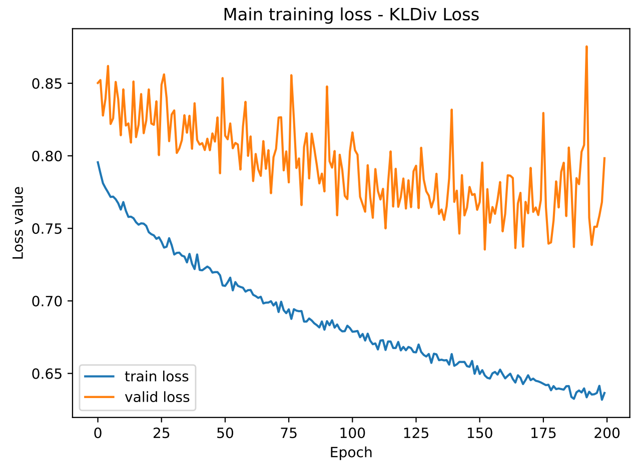


Figure 2. Training loss function values

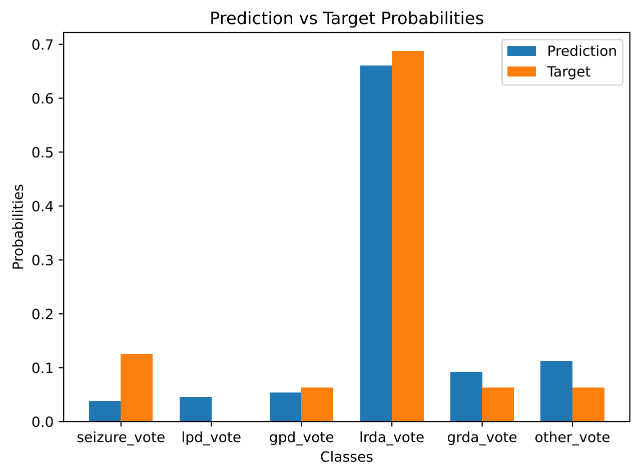


Figure 3. Example model prediction 1

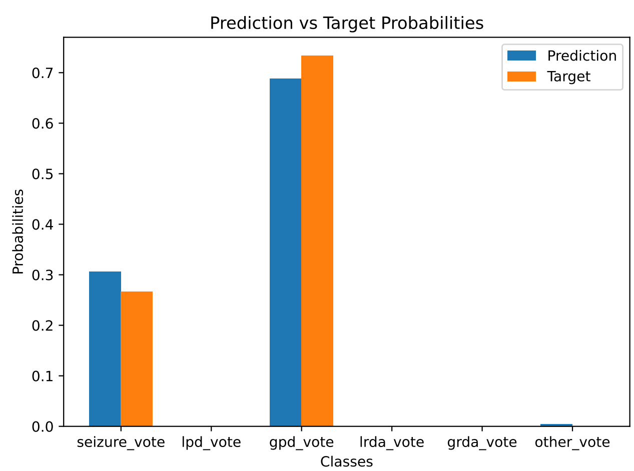


Figure 4. Example model prediction 2

5. Conclusion

The neural network created as a result of this project models expert decisions in classifying harmful brain activities. The creation of this model required the understanding of the complex problem domain of EEG brain measurements and harmful brain activity.

References

[1] https://www.kaggle.com/competitions/hms-harmful-brain-activity-classification/overview