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EPILEPSIE**

**DEEP NEURAL NETWORK-BASED TECHNIQUES FOR THE
DETECTION AND MONITORING OF EPILEPTIC SEIZURES**

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Chapter 1

Introduction

This thesis examines the application of deep neural networks as a method for monitoring epileptic seizures captured by electroencephalographic signals. There are many benefits this can bring to patients with epilepsy, such as an improvement in quality of life and decreased treatment duration. It also benefits doctors and researchers, allowing them to save time in a clinical environment, where repetitive tasks, such as manually annotating seizures for diagnostic and treatment purposes, can be automated.

However, there are significant challenges in achieving automatic monitoring of electroencephalogram (EEG) seizures, mainly due to patient variability, background noise, eye and muscle movements, incorrect labeling by clinicians, differences in equipment, and even faulty equipment that can increase the noise level in the data. EEG recordings are lengthy, occupying substantial memory and usually skewed, with seizures underrepresented, leading to imbalanced data.

Although many studies on this topic focus on expert systems and machine learning for a subset of patients of a pre-cleaned dataset, which may not always represent typical EEG recordings and interpretation needs.

The work advances the field with novel deep learning pipelines and a framework that enables a consistent approach, and allow for a significant increase in research output. The framework automates extensive EEG data extraction, model training and results collection.

1.1 Presentation of the field of the doctoral thesis

Doctors use EEG recordings in clinical settings to monitor, detect, and diagnose epilepsy. The process of automating these tasks will reduce the repetitive workload of the staff, whilst helping them to allocate more time to interpret the results and treat the patients. Automated EEG signal monitoring also benefits patients with severe forms of the disease, who require constant medical staff supervision and attention.

Real-world applications include:

1. Epilepsy monitoring units, where neurologists evaluate patients over long periods with forms of epilepsy that are difficult to diagnose and treat. Automating the monitoring process can help improve treatment accuracy, as essential data, such as seizure onset time and frequency, can be collected more efficiently by medical staff.
2. Applications in the area of patient safety and quality of life, where wearable devices

can alert medical staff, caregivers, or relatives. The benefits are primarily for patients who have intractable, severe forms of epilepsy that lead to loss of consciousness and have an increased risk of accidental injury.

3. Preventative intervention, where automatic detection devices can trigger on-the-spot treatment such as deep brain stimulation to mitigate seizure severity.
4. Research, where big data analysis and annotation automation will help progress and improve the treatment of patients with epilepsy.

Classical machine learning has been widely used for classification and prediction tasks, especially with smaller datasets and typically requiring less training time and resources.

However, it relies on manual feature engineering. In contrast, Deep Learning (DL) algorithms extract features automatically from the raw data, and are successful with larger datasets, even noisy ones, and require minimal pre-processing. They have better generalization power; however, they require more training time and careful setup.

The key to enabling Deep Learning in the medical field is to develop a method for researching solutions at an accelerated pace. While a variety of applications and frameworks in EEG signal processing is available, they often lack automation. DL is well-suited for EEG processing, but the research process must allow for quick iterations between different datasets, model building, and performance evaluation to identify the most suitable pipeline.

1.2 Scope of the doctoral thesis

The scope of the doctoral thesis is to monitor EEG signals for detecting and predicting epileptic seizures using a general classification algorithm that is independent of patient-to-patient variability, equipment differences, and noise, thereby providing a reliable output. The method involves developing a deep learning framework for rapid iteration and evaluating the most effective deep learning pipelines to provide an objective view of the solution landscape.

1.3 Content of the doctoral thesis

The next chapters of the doctoral thesis are arranged as follows: (i) Chapter 2 describes theoretical concepts and a detailed assessment of the state of art, setting the scene for the subsequent research; (ii) Chapter 3 proposes a pipeline with hand-engineered features and a low-complexity neural network model for low-latency seizure classification validated on multiple datasets; (iii) Chapter 4 describes a novel machine learning framework to automate the research process in the development of DL models and EEG as big data. Further, framework derivatives in the field of image segmentation of magnetic resonance images are discussed; (iv) Chapter 5 continues to evaluate improved applications of the machine learning framework, by enhancing the performance of the proposed pipelines. In the end, Chapter 6 presents a summary of the conclusions and proposes research directions for future development.

Chapter 2

State of Art for Epileptic Seizure Recognition and Prediction

2.1 Introduction

The World Health Organization (WHO) describes epilepsy as a brain disease affecting around 50 million people around the world. Symptoms include involuntary movement of the body and loss of bladder control among others. The seizures are caused by anomalous electrical activity of a group of neuron cells, characterized by synchronous, uncontrolled discharges of brain cells [1].

The motivation of this work is to develop automatic seizure detection and prediction that are necessary to improve diagnostic methods, prevent sudden death during seizures, and enhance the patient's quality of life.

2.1.1 What are key methods for detecting seizures in medicine?

Typical diagnostic evaluation involves neurologic examination by a physician and look for focal features including premonitory signs such as aura. Next the neurologist would try to assess the localization of the cerebral pathology that may be responsible for triggering the ictal events.

The main tool used for detection is the electroencephalography, where a sensitive machine will record the electrical brain activity, usually measured in μV , by placing electrodes either on the patient's scalp, or by implanting them inside the brain. The machine records the measurements as electroencephalograms (EEG), where each electrode has assigned a channel, over a specific period of time determined by the clinician. The neurologist will evaluate the recording to determine whether the seizure occurred or not.

2.1.2 How would a deep learning algorithm help?

A paper by Christoph Baumgartner et al. [2] describes the need for automatic warning and detection devices for epileptic seizures.

Seizure detection devices enhance treatment by eliminating the need for prolonged hospital monitoring, especially for patients with low seizure frequency.

Another reason for detection of seizure is the minimization of sudden unexpected death in epilepsy (SUDEP), which allows a timely medical intervention.

Classification algorithms enable automatic patient data recording and mining, enhancing understanding and treatment, as well as potentially enabling automatic treatments like deep-brain stimulation. Seizure forecasting devices can help prevent accidents and injuries caused by loss of body or consciousness. Both seizure warning and detection devices promise to enhance patient monitoring and treatment, improving patient care.

2.1.3 Machine Learning Algorithm architecture

This section quickly describes the basic principles of a machine learning algorithm. The objective of the algorithm is to train itself to predict an output based on learning examples. For instance, the input of a learning algorithm includes data such as pixels, sound waves, or the output from another algorithm.

During training, the model learns by adjusting its weights based on the difference between the output and the expected output, as depicted in Figure 2.4. Once the algorithm training is complete, it can be used to predict outputs for new inputs

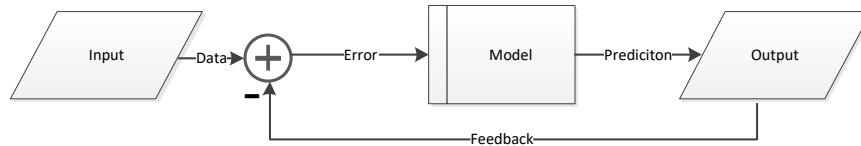


Figure 2.4 Machine Learning Algorithm in training, given a set of training data

Typically, there are three classes of learning algorithms: supervised, unsupervised and semi-supervised.

Most of the work done so far in the field of seizure prediction has been based on supervised learning.

2.1.4 Performance of a learning algorithm

For the detection and classification tasks, visual identification by human clinicians is considered the gold standard. However, for warning algorithms, there are no human counterparts, with the exception of self-warning through auras. To measure the performance, a large number of key indicators can be used, such as True Positive (TP), True Negative (TN), False Negative (FN), False Positive (FP), Sensitivity, Specificity, Accuracy, Area Under a Receiver Operating Curve (AUROC) and so on.

One key challenge is to standardize performance metrics for algorithms. The equivalence between the AUROC, Sensitivity and Specify values may be realised by assuming the latter are defined at a point on the curve with best results.

2.2 Datasets

This section presents public EEG datasets containing epileptic seizure labels.

The seizure classification task is usually split into two categories: (1) seizure detection and (2) seizure prediction. For seizure detection tasks, models are designed to differentiate between ictal (for example, during a seizure) and non-ictal data, which is usually annotated together with the EEG dataset. In contrast, the classification of pre-seizure data is not typically annotated. There are numerous datasets around EEG that researchers use for further exploration and development of new methods, and some of them are: Children's Hospital Boston free dataset, created in partnership with Massachusetts Institute of Technology (CHB-MIT) [3],[4], University of Bonn [5], Kaggle [6], University of Pennsylvania (UPenn and Mayo Clinic [7] [8], and Temple University Hospital (TUH) EEG Corpus [9] .

2.3 Seizure detection

2.3.1 CHB-MIT Dataset

Alotaiby et al. [10] selected 5 patients out of 24 belonging the CHB-MIT dataset. They used as features the EEG signal amplitude, derivative, local mean, local variance, median and channel selection with channel(s)-histogram(s)-bin(s). Their corresponding window is 10 seconds long on each channel. The data is fed to a threshold process algorithm to classify patient-wise between ictal and non-ictal classes. With leave-one-out cross validation they achieved an average accuracy of 97.86%, average sensitivity of 97.14% and average specificity of 95.58%. The paper clearly explains what is each feature supposed to detect, however, it is not clear on how the channels have been selected and also why training has only been done on five patients, since the dataset consists of a broad selection of 24 patients.

2.3.2 University of Bonn Database

Türk et al. [11] implemented deep learning on the University of Bonn dataset. The data is transformed using the continuous wavelet transform into time-frequency scalograms. The training is done across different class combinations: A-E, A-D, D-E, A-D-E and A-B-C-D-E, and not patient-specific, making this a global algorithm. A 6-layer CNN is used and the validation split is 80% training and 20% testing with 10-fold cross-validation. The maximum average is high up to 100% for A-D, but more meaningful 93.6% for A-B-C-D-E. The paper demonstrates that deep learning models are feasible generalisation algorithm for EEG classification.

2.3.3 University of Freiburg Database

Donos et al. [12] developed a seizure detection algorithm based on data from the University of Freiburg. Features are computed from one second non-overlapping windows of single EEG channels in the time and frequency domains. The following

features are used for the time-domain: mean, mean absolute deviation, skewness, kurtosis, autocorrelation, and line-length. In the frequency domain, the authors employ: power in the infra-slow (0.1-0.5 Hz), beta (13-30 Hz) and gamma bands (30-128 Hz), and finally the power ratios between alpha (7-13 Hz), beta and gamma bands. Next, features are selected, for each patient, based on the Gini index. The selected classifier is Random Forest. The authors achieved an average sensitivity of 93.84% with a specificity of 0.33 FP/h and a mean latency of 5.47s.

2.4 Seizure prediction

2.4.1 CHB-MIT dataset

Usman et al. [13] split the EEG recordings in CHB-MIT dataset into 30 seconds long non-overlapping clips, after applying a bandpass filter to remove line noise and EEG baseline noise. The authors claim to have used data from all 24 patients; however, it is not clear whether the training is performed per patient or globally. Next, the clips have a Short Time Fourier Transform (STFT) applied to convert the time-domain signals into frequency domain signals. A 5-layer CNN model is proposed to extract features automatically that are then fed to a linear support vector machine (SVM). Finally, one of two classes are identified: preictal and ictal and leave-one-out validation is performed. With a 21 minutes average anticipation time, the authors have achieved an average sensitivity of 92.7% and average specificity of 90.8%. The validation method is not specified either, so it is not clear if the data shown results from training, validation or testing.

2.4.2 University of Bonn Database

Acharya et al. [14] is one of the first papers to apply deep learning algorithms to the Bonn dataset. The data is normalized using Z-score normalization. The signals are classified into three classes: ictal, pre-ictal, and non-ictal. The labelling of pre-ictal signals does not originate from the EEG dataset. Features are not explicitly extracted and a deep Convolutional Neural Network of 13 layers is used. Overfitting is addressed by using 70% of the data for training, 30% for validation, and 10% for testing. The model achieves 88.65% accuracy through 10-fold cross-validation. The paper describes the application of a bagging algorithm to improve performance.

2.4.3 University of Freiburg Database

Yang et al. [15] evaluated their model on patient-specific data from the University of Freiburg, selecting 19 out of 21 patients with at least 2 seizures. Data was filtered using a band-pass filter and features were generated based on Shannon Permutation Entropy (PE) in a 5 second sliding window clip, no overlap. Next, an SVM classifier is used to discriminate between preictal and interictal states, employing 6-fold cross validation. A post-processing pipeline uses 2-minute window, embedded into a longer 6-minute

window, called 2-step firing power to avoid FP. The firing power parameters are hand-engineered and not tested or validated otherwise. The study defines some relevant metrics but lacks common performance metrics, such as accuracy and AUROC, and the algorithm is not thoroughly evaluated.

2.4.4 AES Seizure Prediction Challenge Database

The winner of the American Epilepsy Society (AES) Seizure Prediction Challenge (Kaggle), Medial Research NK Team [16] sampled the data on 1-minute intervals and used 8 second windows with 97% overlap. They next developed a time-domain feature set involving: (1) Energy average and energy standard deviation over time (in 15 seconds bands), for each channel; (2) Fast Fourier Transform (FFT), logarithm of energy in different frequency bands for each channel; (3) FFT, logarithm of energy, and total energy (without log) in different frequency bands for the average of all the channels; (4) correlation of energy in frequency bands between channels and (5) square root or power for each feature, in order to exploit nonlinear behaviour of each feature. The model used was an iterative least-squares ensemble model, with a resultant AUROC of 0.871. They required a model with high regularisation. The authors suggest their model cannot be used for real-life detection devices.

2.5 Discussion

2.5.1 Mitigating limitations of existing datasets

The Bonn dataset appears to favour the best results. This could be linked to the approach of manually removing artefacts.

The Freiburg dataset is no longer openly accessible, therefore new models cannot use it for comparison information. A dataset that includes the Freiburg dataset can be accessed by paying a fee making it more difficult to develop new algorithms and compare to previous research.

The Kaggle datasets for both detection and prediction offer seizure recordings that include artefacts are a step closer to allow training for real-world applications.

Finally, private or self-recorded datasets do not allow researchers to easily reproduce results, therefore, works based on private datasets have not been considered in this paper.

With a few exceptions, most of the papers train their algorithm on a single dataset. The vast majority of papers show very good results for patient-specific training.

2.5.2 Overcoming Seizure Detection Challenges

Looking at the number of patients employed in the presented studies, it is found that the University of Bonn has data only from five patients, whereas CHB-MIT will

provide data from 24. This, however, does not mean that all of the works will utilise the full dataset. Among CHB-MIT papers, a smaller number of patients yields better results. Finally, looking at the clip length used for detection purposes, generally a longer clip length can mean a better result, provided the data available is sufficient.

2.5.3 Seizure Prediction

The highest performance is achieved for the prediction tasks using deep learning models, specifically CNNs, being of similar behaviour to the detection task. They are more efficient in automatically extracting features, as opposed to hand-engineered features based on human intuition. In the era of deep learning, prediction models use transfer learning from detection models.

2.5.4 Conclusions and Future Direction

Next generation seizure classification algorithms are very likely to benefit from deep learning implementation. Training across multiple datasets can reveal very robust mapping of EEG seizure signals. The aim is to develop a dataset and patient independent, scalable model that can be used to classify EEG signals for pre-ictal, ictal, inter-ictal and normal classes. Channels selection will prove very important for this role and will also allow the development of a scalable architecture for different in-field applications such as, hospital EEG monitors, implantable warning devices and deep brain stimulators.

Chapter 3

Low Latency Automated Epileptic Seizure Detection: Individualized vs. Global Approaches

3.1 Introduction

This chapter proposes a fast-response algorithm that utilizes hand-engineered features. To minimize computational complexity, the focus is solely on time-domain features, which are then input into a fully connected neural network designed to classify EEG recordings as ictal early, ictal not early, or interictal. Content in this chapter is based on the previously published paper [17].

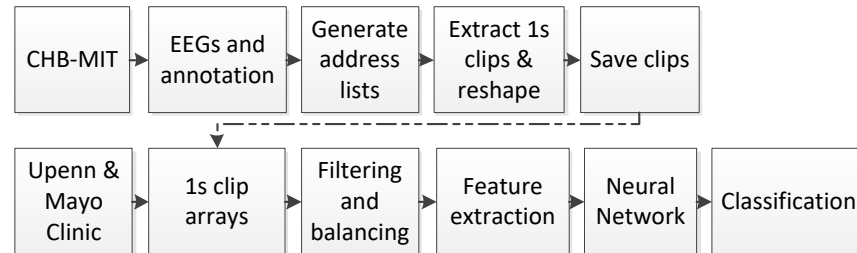


Figure 3.1 Pipeline: The top layer converts CHB-MIT format into Upenn and Mayo Clinic format of 1-second clips. The bottom layer includes the main feature extraction and classification section.

3.2 Proposed Approach

3.2.1 Overview

First, the CHB-MIT data is converted into the Upenn-Mayo Clinic format, consisting of one-second clips. Next, data from both datasets is filtered and balanced. After that, features are extracted using hand-engineered techniques. The final classification is performed using a neural network pipeline, as shown in Figure 3.1. The evaluation is performed on both patient-specific and global data.

3.2.2 Data pre-processing

For CHB-MIT recordings, the pre-processing pipeline adjusts the number of channels by either removing extra channels or padding missing ones, as illustrated in the top layer of Figure 3.1. The data is first organized into 1-D continuous arrays for each clip and then filtered using a 1-47 Hz bandpass filter [18]. Since a neural network with a mean squared error performance target is employed, the data is balanced to ensure equal representation of ictal and interictal clips by randomly discarding the extra interictal segments.

3.2.3 Feature Extraction

The following features are extracted from each EEG channel:

Mean Signal Energy per Clip: This is calculated from the total number of discrete samples across all channels in clip x . This feature is effective at detecting significant ictal events that span multiple channels with high amplitude.

Minimum Channel Energy per Clip: is useful for identifying recordings with low signal energy per channel, which are more likely to be interictal in nature.

Minimum Epoch Energy per Clip: aids in identifying interictal clips that have very low signal energy. The epoch size is defined as one-tenth of the signal's sampling rate.

Total Line Length per Clip: This feature measures the line lengths of all channels across one clip and is calculated as below. Higher values indicate a greater probability of seizure activity.

Maximum Moving Window Cross-Correlation: This feature indicates the best zero-lag cross-correlation for one epoch containing samples across two adjacent channels.

Maximum Cross-Correlation across a Moving Window: This feature provides the maximum raw cross-correlation, calculated in the same manner as the maximum moving window cross-correlation.

Number of Zero-Crossings per Normalized Clip: Each clip is normalized so that the maximum value is 0.5 and the minimum value is -0.5.

Number of Peaks per Recording: This feature calculates the total number of peaks with a prominence of 0.3, which is chosen empirically based on the recordings. It is aimed at detecting high-frequency, high-amplitude seizures.

Clip Eigenvalues: The function of the correlation matrix is to predict synchronization across all channels. However, to use this effectively as a feature, it must be transformed into an eigenvector whose size corresponds to the number of channels.

Clip Derivative Eigenvalues: This feature detects synchronized changes across channels and is not dependent on raw amplitude, focusing instead on the rate of change. It effectively minimizes amplitude differences between channels.

3.2.4 Neural Network Structure

Table 3.1 Neural Network (NN) Hidden Layer Structures

Neural Network	Number of neurons per hidden layer (HL)			
	HL1	HL2	HL3	HL4
NN11	1	-	-	-
NN12	25	-	-	-
NN13	50	-	-	-
NN21	10	5	-	-
NN22	20	10	-	-
NN23	50	20	-	-
NN31	10	5	2	-
NN32	20	10	4	-
NN33	40	20	8	-
NN41	16	12	3	2
NN42	32	24	6	3
NN43	64	48	12	6

The prediction model utilizes a neural network with the following characteristics:

- Input Layer: variable, depending on the number of channels for each clip.
- Hidden Layers: up to four layers, as illustrated in Table 3.1.
- Output Layer: two neurons to predict the probability of a seizure and the probability of an early seizure.

3.3 Experimental Results

3.3.1 Datasets

The algorithm was developed using the UPenn and Mayo Clinic Seizure Detection Challenge dataset and further improved on the CHB-MIT dataset. CHB-MIT consists of 24 patients with a sampling rate of 256 Hz whereas Upenn comes with a sampling rate between 400 Hz to 5000 Hz. All publicly available data from both datasets is used.

3.3.2 Metrics

To evaluate performance, the proposal adheres to best practices for the selected datasets and employs AUROC to assess seizure detection capability.

3.3.3 Parameter Tuning

The parameter tuning was conducted exclusively on the Upenn-Mayo Clinic dataset. Performance of each network configuration listed in **Table 3.1** has been evaluated using the AUROC seizure parameter as the assessment criterion. It is observed that a higher number of neurons and layers leads to better results, at least up to a certain

point of inflection. In this study, it has been decided to proceed with the top performing network N23.

3.3.4 Comparison Results

The results from the Upenn-Mayo Clinic dataset demonstrate comparable individual and global performance. A k-fold validation method with $k=10$ has been employed. For the global assessment, the work has focused exclusively on the dog data that had an equal number of channels. In contrast, the CHB-MIT dataset exhibited greater variation, resulting in slightly lower individual performance than the Upenn-Mayo Clinic dataset, which can be attributed to the larger and more diverse nature of the dataset. Additionally, the global performance was also lower when compared to individual performance.

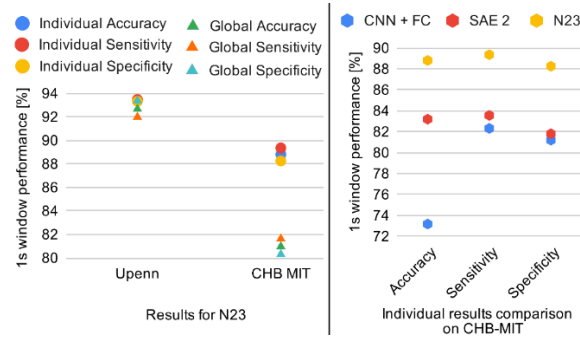


Figure 3.7 Left: N23 mean performance across Upenn-Mayo Clinic and CHB-MIT datasets. Right: Comparison between N23 and the semi-supervised deep learning architectures CNN+FC and SAE2 presented by Tautan et al.[19] .

Table 3.2 . Kaggle Competition results on AUROC average

Network	AUROC average
[12] – Random Forest	0.9749
[11] – Neural Networks	0.9566
N23 – K-fold validation	0.9494
N23 – K-fold validation – global	0.9511
N23 – 80/10/10 validation	0.9967
N23 – 80/10/10 validation - global	0.9872

When comparing the performance using one-second windows to the approach proposed by Tautan et al. [19], improvements can be seen in Figure 3.7 (right section) and **Table 3.2**. The individual performance across datasets is comparable, and it shows an enhancement over the deep learning algorithm.

In the final experiment, **Table 3.2** compares N23’s performance with entries from the Kaggle Competition [7]. The results demonstrate the maximum theoretical performance achieved with 300 iterations and 10,000 epochs, divided into 80% training, 10% validation, and 10% testing. The performance achieved exceeded the threshold established by [20], indicating that the pipeline can attain performance comparable to other algorithms.

3.4 Conclusions

This chapter has introduced a fast-response algorithm for the automated detection of epileptic seizures, optimized for 1-second EEG windows. Although detecting seizures from very short clips is challenging for humans, this proposal demonstrates that it can be achieved effectively. This rapid detection capability is particularly beneficial for real-time devices, such as implantable deep brain stimulators.

Using a hand-engineered feature set and a simple 3-layer neural network (N23), the pipeline consistently achieved strong performance across two different datasets, utilizing k-Fold cross-validation ($k=10$) and an 80/10/10 split for validation. This was applicable both for individual subjects and across the datasets as a whole. However, the algorithm does have limitations related to global training; one can only use clips with the same number of channels. This restriction allows us to use the entire CHB-MIT dataset but limits us to only a portion of the Upenn-Mayo Clinic dataset. Despite this, it is expected for the results to generalize well to larger datasets.

For future work, it is proposed to explore deep learning architectures that can be trained on multiple datasets with varying EEG types, channel configurations, and sampling rates. A deep learning approach may benefit significantly from this diversity in data and could lead to improved performance in developing a more generalized detection algorithm.

Chapter 4

Smart-EEG – An End-to-End Deep Learning Framework for EEG Signal Analysis and Prediction

4.1 Introduction

Most of the time researchers have relied on a combination of manual feature engineering and classical machine learning methods for EEG analysis and model development [21]. For instance, researchers design features, extract relevant segments, and then apply different algorithms such as Support Vector Machines, naïve Bayes algorithms [22] and so on to distinguish brain activities, which makes it time-consuming and fails to scale large datasets.

This chapter introduces *smartEEG*, an end-to-end framework developed to resolve this discrepancy. It is designed to work efficiently with limited hardware resources, and run unattended configurations regardless of the number of model architectures used.

4.2 Motivation

The motivation of building smartEEG is to first accelerate the EEG DL research by automating essential tasks like data collection, preprocessing, labelling, and model configuration using Graphical Processing Unit (GPU)-accelerated training. The framework is designed to enable large-scale experimentation, using two datasets the CHB-MIT [4] and TUSZ [9] that contain thousands of hours of recordings across hundreds of patients with focus on detection, and detection plus prediction tasks.

4.3 Literature overview

4.3.1 Existing EEG Frameworks

Several EEG frameworks have been developed, each having its own capabilities.

Some of the frameworks, like pySPACE [22], MNE-Python [23], BciPy [24], EEGLAB [25] and many others, focus on signal preprocessing and visualization, classical machine learning and others incorporate deep learning into their context. However, none of the existing frameworks provide a fully integrated, end-to-end solution capable of automatically evaluating new pipelines based on predefined settings.

4.4 Architecture of the smartEEG framework

4.4.1 Framework Design Goals

SmartEEG is a Python-based end-to-end deep learning framework that minimizes hardware resource usage while maximizing performance and iteration speed. This pipeline enables efficient training and validation on large-scale datasets, including thousands of patients and hundreds of thousands of EEG clips, without exhausting system resources.

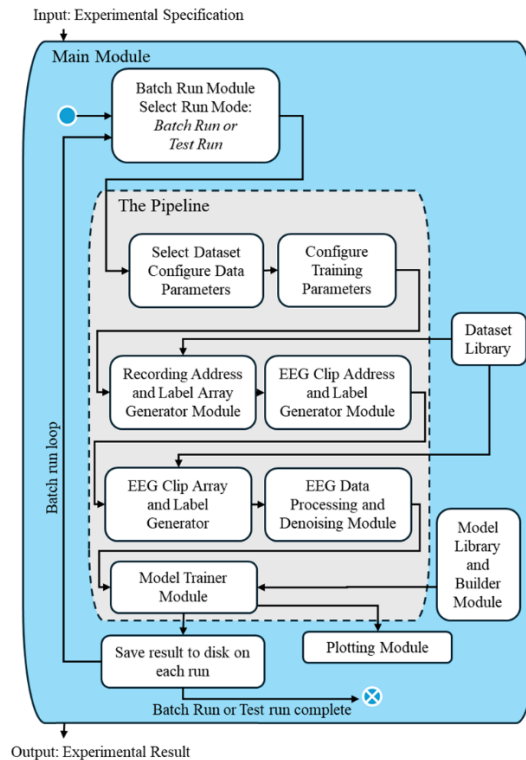


Figure 4.1 Overview of the Main Module of the smartEEG framework [26].

4.4.2 The Main Module

The smartEEG pipeline is run from the main module, and consists of all the modules necessary to run the framework. First, there is the batch run module that enables the pipeline to run either using multiple configurations in a loop or running on the default configuration. One of the two datasets is selected. Next, the data and training parameters are defined and selected, which are part of the main module. The recording address and

label array generator module is called in the main module to generate this data, which also relies on the data library. Therefore, there are two distinct EEG clip address and label generator modules, created for each dataset, that is used to collect all the required information.

The EEG clip array and label generator module generate the input data array (Data X) and label array (Data Y). The EEG data processing and denoising module can be used to turn on different denoising methods presented in the following sections. After the EEG clip array and labels are generated, they are then fed into the model trainer module, where the training is performed based on the configuration set.

4.4.3 Configuration Parameters

The configuration parameters provide a series of parameter keys for each category, data parameters and training parameters, like clip length, model and others.

4.4.4 Recording Address and Label Array Generator Module

This module takes as inputs the data and training configurations and the dataset selected. It is used to generate a standard format recording address array containing patient code, file paths, sampling frequency, number of channels, the start and end of a seizure. It then generates as output the recording address array of standard format.

4.4.5 EEG Clip and Label Address Generator

The main objective of the EEG clip and label addresses module is to generate a balanced and randomized array of EEG clip addresses of identical lengths, and their corresponding labels. The module performs a number of functions to achieve this like creation of a set of EEG clip references (or addresses) with 4 default labels, balancing and randomisation to finally build an EEG clip array address and its labels.

4.4.6 EEG Clip Array Generator Module

The Clip Array Generator Module, is proposed to provide the following functionality: (i) EEG clip addresses pooling based on their location in each patient file, (ii) the EDF file reading, (iii) time-domain resampling to a common sampling rate, (iv) signal data normalization, (v) channel padding, (vi) disk backed storage for very large clip arrays and (vii) label vectorization to one-hot encoding so the Data X and Data Y can be created.

4.4.7 EEG Data Processing and Denoising Module

Since the EEG can be noisy, some channels may be faulty during the recording. To mitigate this, the EEG Data Processing and Denoising Module is introduced, which consists of various methods, including channel ranking using LassoCV, RFE, and

SelectKBest. Additionally, methods such as the Hilbert transform, derivatives, and band-pass filters are employed.

4.4.8 Model Library and Builder Module

This module is where models can be built and selected. Therefore, the focus in this study is on a variety of deep neural networks, starting from fully connected networks (NN), and continuing to one-dimensional and two-dimensional CNNs (C1D, C2D) as well as RNN-Elman (RNE), RNN-GRU (RNG), and RNN-LSTM (RNL) have been built in the pipeline and tested. In the code of the model, the 2nd last digit represents the number of hidden layers.

4.4.9 Model Examples in the Library

All the model architectures are designed with different number of layers and parameters. For instance, a C1D1H-2 model refers to a one-dimensional CNN with a kernel size of 64 and 50 features. Of course, there are also combinations of the same network but with different configurations, such as the kernel size, the number of hidden layers, or even the number of classifier layers used.

4.4.10 Model Training

The model training is done considering different steps, like training and validation splits, setting the training hyperparameters, creating mini-batches, upload the selected model and mini-batches to the GPU RAM, perform backpropagation, capture the performance metrics and store the model parameter and performance.

4.4.11 Batch Run Module

The batch run is enabled when experiments with different configurations of the data and training parameters listed in the configurator need to be performed. This is done to save time during research by enabling the user for example to perform multiple experiments overnight.

4.4.12 Plotting Module

To enable visualisation of data, a plotting module was developed that can perform the plotting of the following: (i) performance data such as accuracy and loss curves, and confusion matrices, (ii) statistical data such as box plots for k-fold validation and plots of the EEG signals.

4.5 Experimental application results

This section presents the model performance achieved using the smartEEG pipeline at various configurations, as presented in the published work [26]. Therefore, Figure 4.34 Left displays the network search conducted with a 1-second clip length and

no augmentation of the CHB-MIT data used for training. The two classes, ictal and interictal, are used and the fitting was performed globally, using 80% of the entire dataset for training and 20% for a random split for validation and the training was done on 50 epochs for each model.

Figure 4.34 shows the comparison of the model sensitivity to different EEG clip lengths using the early stopping regularization technique, which was implemented with a patience of 5 epochs on the CHB-MIT dataset employing the C1D1H-2 network. The training and validation are the same except for the early stopping implementation.

Table 4.6 Comparison to previous work

CHB, 1 s, global, 10-fold valid.	Average		
	Sensitivity	Specificity	Accuracy
Ciurea et al. [17]	0.8164	0.8031	0.809
C1D1H-2	0.925	0.938	0.931

Since this chapter focuses on the entire smartEEG pipeline setup, the model's performance is compared with that of previous work and is shown in Table 4.6. The training is performed on a 1-second-long CHB-MIT clip for seizure detection, and a ten-fold validation technique is applied. No early stopping or augmentation is enabled.

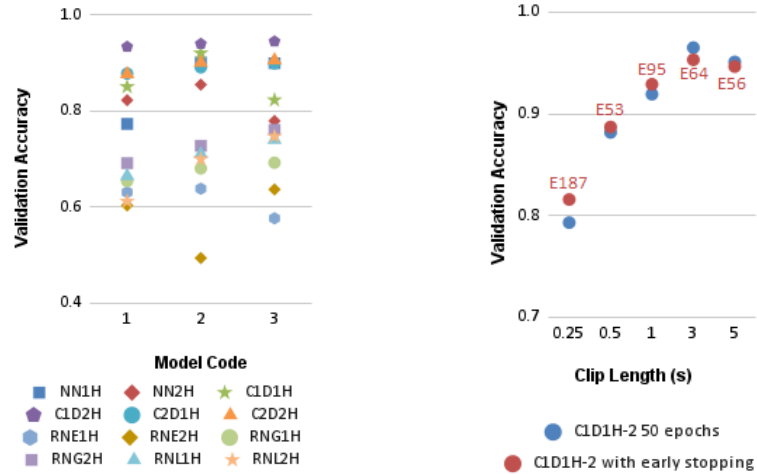


Figure 4.34 Left: Overview of the model search across 36 networks defined in Model Architecture table on the CHB-MIT dataset. The legend placed below the horizontal axis indicates the last characters of the model code; Right: Effect of the clip length and early stopping regularization for global training on CHB-MIT dataset. The number Exxx (e.g E187) indicates the best epoch where the validation is done on 80/20 % of the data

4.6 Conclusions

To evaluate seizure detection and prediction, the smartEEG pipeline is designed to support different configurations. Firstly, it facilitates data extraction, making it easier

for researchers to integrate additional datasets as needed. After training, the pipeline generates model weights and results, enhancing both efficiency and reusability. The experimental results section presents a variety of model architectures, with the CNNs being the best suited for detection tasks when the feature extractor is limited to two layers and training is performed on the global dataset.

Comparing the results to previous work reveals that deep learning networks can surpass the performance of classic machine learning.

4.7 smartMRI: smartEEG framework derivative applied on MRI Images

Building upon the smartEEG pipeline, initially developed for EEG detection and prediction, its methodology was extended to Magnetic Resonance Imaging (MRI) images. This adapted framework is referred to as smartMRI, introduced in the previous paper [27].

4.7.1 Introduction

MRI is a medical imaging technique for diagnosis planning. It provides high-quality, detailed images of internal structures, which can aid in the detection and localization of abnormalities.

4.7.2 Overview of the smartMRI framework

To mitigate these challenges and accelerate computation, the smartMRI framework is introduced, similar to the smartEEG pipeline, to automate multiple deep learning models. The structure of the MRI framework consists of similar modules to smartEEG, as previously presented, but the way the data is read and processed differs for medical images.

4.7.3 Dataset

The MRI dataset was obtained from SK10 [28], which was publicly available, and consists of 60 training and 40 validation MRI images from patients. The labels were provided by clinicians that manually segmented the multi-class mask for each knee joint slice in the MRI image.

4.7.4 Training set-up and evaluation metrics

The data was trained on one anatomical plane. The optimizer used in this study is the same as used in smartEEG pipeline, namely, Adam. Compared to the smartEEG in this study different metrics are assessed, like average symmetric surface distance (ASSD), and the root mean squared distance (RMSD), and dice similarity coefficient (DSC).

4.7.5 Convolutional Neural Networks Results

The best model performance for ASSD and RMSD is compared between the top

ones, along with an additional state-of-the-art paper. The results are presented in Table 4.8 where the lower the standard deviation is, the better the prediction was detected.

Table 4.8 Comparison of the surface distance metrics

Methods 60 training/ 40 validation	Average			
	Femoral ASSD	Tibial ASSD	Femoral RMSD	Tibial RMSD
Lee et al [29]	0.58 (0.45)	0.47 (0.32)	1.73 (0.85)	1.53 (1.05)
P3D U-Net128	0.35 (0.20)	0.46 (0.37)	0.87 (0.82)	1.32 (1.21)
P3D GU-Net128	0.34 (0.18)	0.47 (0.31)	0.85 (0.64)	1.33 (1.18)
P3D GU-Net868	0.30 (0.16)	0.37 (0.30)	0.72 (0.58)	0.90 (1.01)

4.7.6 Discussion

The smartMRI framework, developed based on the smartEEG framework has shown effectiveness in other applications by generating results using multiple deep learning models, making the baseline pipeline effective for a broader range of applications and easier to find the best model performance across a variety of models.

Chapter 5

EEG-Based Seizure Detection and Prediction: Hybrid CNN, Denoising, and Comparative Deep Learning Approaches

5.1 Introduction

The EEG signals are predisposed to noise and vary across patients.

To address these challenges, this chapter proposes three approaches, developed using the smartEEG framework [26]: a hybrid network, a denoising technique using channel selection, and various processing techniques.

5.2 EEG Classification using Hybrid Convolutional Neural Network with Attention Mechanism

5.2.1 Introduction

Most current approaches aim to improve EEG algorithms through various methods using deep learning. For instance, Gia et al. [30], a research study from 2023 [31], Ru et al. [32] have used multi-head attention mechanism with deep learning. Additionally, Shoka et al. [33] combined encryption of spectrograms with deep learning for EEG and Cisotto et al [34] also focused on different attention mechanisms but using the TUSZ dataset. However, none of them focused on shorter clip lengths like 1-second.

5.2.2 Proposed approach

In this study, model performance is verified using the smartEEG framework, and data originating from two datasets, CHB-MIT and TUSZ for both seizure detection and prediction.

The baseline model is the C1D1H-2 model validated in Chapter 3. This is improved by adding a Simple Attention 1-D (S-Attn1D) module set an importance to

channels in the model. This attention block consists of a couple of 1-D CNN and at the end the attention weights are multiplied element-wise with the input. Later, a novel Hybrid Convolutional Network is proposed in order to capture temporal dependencies alongside spatial dependencies, as shown below in Figure 5.1 c.

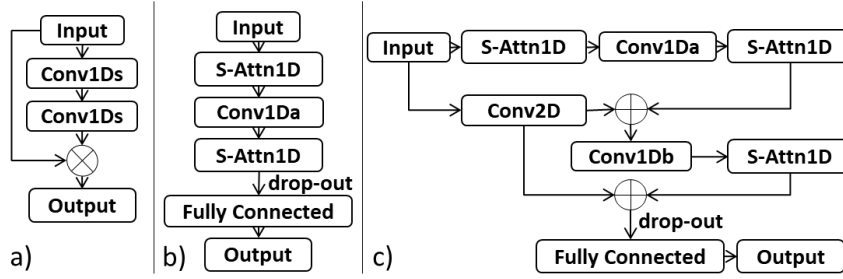


Figure 5.1 a) Simple Attention 1D block. b) C1D1H-2 network architecture with attention Module (C1D1H-2+Attn.). c) Hybrid convolutional network architecture for Lite and Large Models [35].

The model architecture is designed with a 1-second clip length and integrates parallel convolutional neural networks, specifically 1-D and 2-D CNNs, to enhance the model's ability to focus on the most important segments of the signal. The output is shaped according to the number of classification categories.

This hybrid architecture serves as the foundation for two models: a HybridConv Lite and a HybridConv Large. The difference between these two is how the kernel size and number of features are set. A larger model consists of more features and a larger kernel size.

5.2.3 Experimental results

For this experiment, both CHB-MIT and TUSZ datasets are used, however for the latter only 20 patients are considered for verification purposes.

For this study 1-second, 2-second, 3-second and 5-second clip lengths were employed for both detection and detection and prediction tasks using different normalization techniques, like -1,1, 0,1 and division by 10000.

The variation of the clip intervals not only adjusted the temporal granularity of the input but also directly affected the total number of clips available for training.

Table 5.1 Comparison of different networks

Model	Patient		Global	
	Detect	Detect & predict	Detect	Detect & predict
C1D1H-2	0.922	0.704	0.891	0.668
C1D1H-2+Attn	0.939	0.825	0.930	0.743
Hybrid Conv Lite	0.953	0.876	0.946	0.777
Hybrid Conv Large	0.678	0.679	0.968	0.852

Additionally, a sliding window technique was applied to the 1-second EEG clips, utilizing a 50% overlap to improve the TUSZ model's performance, which showed an

increase in performance.

Table 5.1 shows the advancements compared to the baseline in both patient-specific and global performance metrics, all of which were validated using an 80/20 split method. In particular, HybridConv Lite demonstrates improved results at the individual patient level but underperforms in a broader, global context. In contrast, HybridConv Large tends to perform better on a global scale but falls short in terms of individual patient outcome.

The performance of the two hybrid models was compared with other state-of-the-art attention-based networks, as illustrated in Table 5.2. A k-fold validation, with k set at 10, was employed to verify all results. The results are compared with existing literature. Notably, employing a sliding window function yields better results, which aligns with expectations.

Table 5.2 Comparison with other studies

	Model	Clip length (s)	Detect	Detect & predict
CHB	[30]	23.6	0.740	0.510
	[33]	10	0.889	-
	[31]	5	0.964	-
	[32]	30	0.928	-
	C1D1H-2 [26]	1	0.931	0.720
	Hybrid Conv Large, k-fold validation, k = 10	1	0.963	0.851
		3	0.977	0.875
		5	0.979	0.854
TUSZ	CNN+Attn. [34]	2	0.969	-
	HybridConv Large, k-fold validation, k=10, OL. 50%	2	0.981	0.943

5.2.4 Conclusions

The hybrid models developed incorporate both temporal and spatial features, which results in enhanced performance of the models due to their streamlined architecture. Utilizing techniques such as overlapping and sliding windows for data augmentation raises some concerns. One of the major issues is that identical EEG segments may lead to data leakage, so they may appear in both training and validation datasets, which can lead to an unrealistic evaluation of the model and may affect its applicability for real-world or unseen data. To address this, exploring other alternative strategies over the overlapping technique may be beneficial to boost the model performance, like channel denoising or pre-processing techniques of the EEG signal.

5.3 EEG De-Noising with Channel Selection Methods

5.3.1 Introduction

Channel selection can help mitigate issues associated with irrelevant or noisy channels, which can be unnecessary and negatively impact classification accuracy.

Several techniques have been employed to mitigate this. For instance, Jigswal et al. [36] reduced the number of EEG channels before inputting them into a classifier, which allowed them to achieve an accuracy of 0.99. Another study conducted by Tran et al. [37] focused on a single channel to accelerate the classification process; however, this approach does not accurately reflect real-world data.

5.3.2 Methods

Channel selection is used to enhance EEG classification by reducing the number of EEG channels (input features: mean, standard deviation, minimum, maximum, energy, minimum energy, number of peaks and maximum moving window) while improving model performance. In this work, three feature selection techniques are used: LassoCV, RFE, and SelectKBest. LassoCV is a regression method using cross-validation that can be used for feature selection and regularization by shrinking the coefficients to zero. This method can reduce the number of selected features based on the model's coefficients. RFE, on the other hand, is an iterative approach that recursively removes the least important features based on the estimator's coefficients or importance scores until the expected number of features is reached. SelectKBest ranks the features based on their importance in predicting the target variable using a statistical test, and the top K features are selected.

These methods are applied before training on the smartEEG framework and the aim is to denoise the data by identifying the most relevant EEG channels for seizure detection and prediction, thereby enhancing the model performance while reducing computational costs and speeding up the model training and validation.

The model used for this study is highlighted in the prior work presented in Chapter 3. The algorithm's flexibility allows the selection of a predefined number of top channels (e.g., 8, 15, or 18) so the performance can be compared between the Lite and Large models.

5.3.3 Experimental results

For this study, only the CHB-MIT was used, examining both 1-second and 5-second EEG clips.

The evaluation of the EEG seizure detection performance was assessed on all three feature selection methods presented: LassoCV, RFE, and SelectKBest.

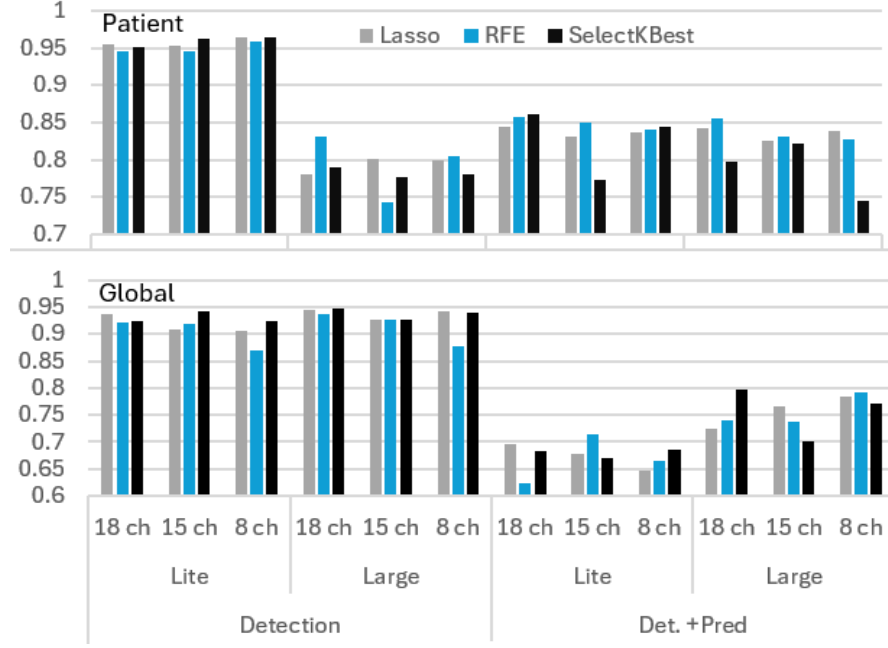


Figure 5.9 Model performance comparison across patient-specific and global datasets using 1-second clips, assessed on a channel subset of 18, 15, and 8. LassoCV, RFE and SelectKBest are used.

Figure 5.9 focuses on two key aspects: detection and detection plus prediction of seizures at a 1-second clip length. It can be seen that LassoCV and SelectKBest consistently demonstrate slightly higher performance across the three channel configurations for patient-specific data when using the Lite model, exceeding the RFE accuracy.

The input features used in all three methods share the most common features, which are mean energy and line length.

Table 5.3 Rate of Improvement with the previous work

Model	Clip length (s)	Patient		Global	
		Detect	Detect & predict	Detect	Detect & predict
Lite	1	0.965	0.848	0.941	0.731
		0.43%	1.68%	4.8%	8.36%
	5	0.811	0.778	0.960	0.830
		-0.09%	3.79%	10.88%	2.13%
Large	1	0.703	0.807	0.959	0.844
		3.65%	18.80%	-0.37%	-0.85%
	5	0.582	0.465	0.973	0.864
		4.48%	12.67%	-0.64%	1.17%

Table 5.3 outlines the best-case validation performance across feature selection methods and selected channel counts for denoising, comparing both the Lite and Large models with the baseline from previous work, as highlighted in Section 5.2.2, for both

patient-specific and global data. Specifically, with global data, the Lite model demonstrates improvements, particularly at 1-second clip length, for both detection and detection plus prediction. For example, a higher improvement is observed in the global data for the detection task, where a rate of improvement of 10.88% is achieved at a 5-second clip length using the Lite model. However, a more significant rate of improvement is observed at a 1-second clip length, where the Large model improves performance by 18.80%.

5.3.4 Conclusions

Three feature selection methods were presented, LassoCV, SelectKBest and RFE that help suppress the noise by channel ranking and selection based on hand-engineered features. The pipeline showed generally improvements for the Light model in the global classification task and for the Large model in patient-specific task, confirming that the denoising action was effective.

5.4 A Comparative Study of EEG Signal Processing Techniques for Seizure Detection and Prediction using Deep Learning

5.4.1 Introduction

To address the noise and improve the model performance, various envelop-based techniques are proposed in this study. For example, Hilbert Transform-based envelope [38] is utilised for its power to represent amplitude modulations and reduce signal phase noise. The next paragraph is a short literature review of processing techniques used with CHB-MIT and TUSZ.

Cao et al. [39] used a feature fusion methodology to decompose raw EEG signals and applied a bandpass filter, achieving an accuracy of 98.43%. Shen et al. [40] also applied bandpass filtering for a pipeline where feature extraction and classification as performed by GoogleNet CNN for real time onset seizure detection. The obtained an accuracy of 97.74%.

Deng et al. [41] applied overlapping at different windows. In their workflow they also used bandpass filter and classification was performed with help of a Deepwalk-Transformer. They achieved 99.54%. Another work that uses bandpass filtering between 0 and 128 Hz is the one belonging to Rukhsar et al. [42]. The authors employed a Lightweight Convolution Transformer (LCT) and obtained an accuracy of 96.31% for a 0.5 second clip and 95.97% for a 1-second clip length.

Chung et al. [43] used a bandpass filter ranging between 1 and 30 Hz, covering alpha (1-4 Hz) and beta (13-30 Hz) frequency bands as preprocessing techniques. A compact CNN classifier provided an accuracy of 98.47%.

Xiang et al. [44] used 18 channels EEG channels where the frequency components at 0 Hz and those ranged from 57 to 63 Hz were removed. The authors employed

overlapping and a graph spatial-temporal attention network achieving an accuracy of 94.76% for a 1-second and 98.20% for a 5-second window.

5.4.2 Methods

The following processing techniques have been evaluated on smartEEG framework: (i) Hilbert envelope, intended to compute the magnitude of the analytic signal; (ii) the Root Mean Squared envelope (RMS), employed to balance between temporal precision and smoothing; (iii) Log power envelope, computed to highlight features by applying logarithmic transformation to the squared values; (iv) temporal derivative, calculated to emphasize dynamic features as slope change and first, second and third derivatives are employed; (v) bandpass filtering used to eliminate both low and high frequencies and (vi) bandpass filtering with temporal derivative, where the bandpass filtering output is added with the first order derivative to create the new signal.

5.4.3 Experimental results

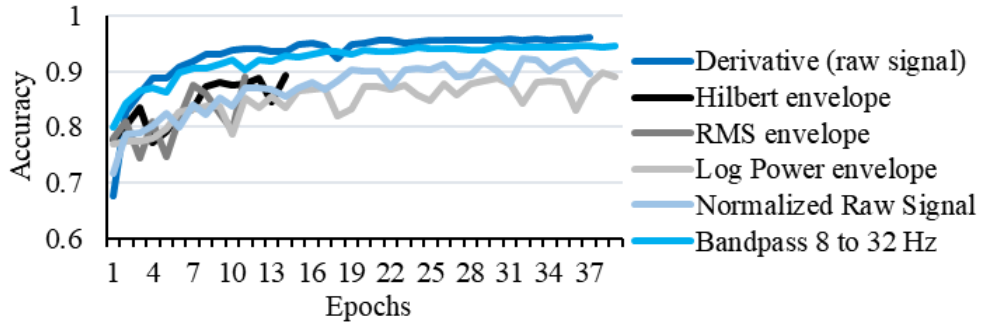


Figure 5.2 Comparison of classification validation accuracy across different EEG processing techniques: Hilbert envelope, RMS envelope, log-power envelope, normalized raw EEG signal, and first-order temporal derivative. All methods are evaluated using the global configuration, with 1-second clips in the seizure detection task.

Table 5.4 Comparison of the accuracy with other studies on CHB-MIT patient-specific EEG seizure classification

Detection Task	# patients	Clip len. (s)	Overlap window	Accuracy
Cao et al. [39]	Not specified			0.984
Shen et al. [40]	16	1.35	Yes (1s)	0.977
Deng et al. [41]	23	0.5 or 1	Yes, step unknown	0.995
Rukhsar et al. [42]	23	0.5 and 1	Yes (25%)	0.963 (0.5s), 0.959 (1s)
Chung et al. [43]	13	4	Yes (4s)	0.984
Prediction Task				
Xiang et al. [44]	19	1 and 5	Sliding	0.947 (1s), 0.982 (5s)
The proposal (Detect & Predict)	24 (all)	1	No	0.971 (Det.), 0.890 (Det. & Pred.)

Figure 5.2 illustrates the comparative performance of different processing techniques. Clearly, it can be observed that Hilbert, RMS, and LogPower envelopes not only degrade the final performance but also make the learning curves, thus making the model less stable. In contrast, the 1st order derivative, bandpass filtering, and bandpass filtering clearly show better improvement. The comparison to other works is shown in Table 5.4, and it is observed that the high accuracy obtained by others is due to the overlapping technique, which makes the metrics not representative for real-world data.

5.5 Future Directions

This chapter presents three applications of the smartEEG framework. The first is a hybrid convolutional neural network architecture that consists of two parallel convolutional neural network (1-D and 2-D). It is observed that combining temporal and spatial features improves the performance of the pipeline.

Second, it is discussed the EEG de-noising using channel selection based on ranking. Three methods have been evaluated for feature selection and channel ranking: LassoCV, RFE and SelectKBest.

The denoising effect was demonstrated through the improvement of the Lite network in the global task and the large network in the patient-wise task. An overall improvement has also been demonstrated.

Finally, it was discussed the EEG processing technique to suppress noise through envelope and filtering techniques. Applying a derivative and filtering to the signal was the best method of denoising of EEG data. This showed not only an improved performance in the validation accuracy but also the training/ validation curves were more stable

Chapter 6

Conclusions

First, the development of a light neural network classifier capable of seizure detection with a small set of hand-engineered features, was evaluated. Second, a smart Deep Learning framework (smartEEG) capable of quickly iterating through a variety of deep learning models was developed. This is essential for accelerating computational time, even overnight, and helps researchers swiftly analyse the performance matrices between various models in more detail. Third, to further improve model performance, a hybrid network that leverages both temporal and spatial dependencies in the data was demonstrated. Finally, various techniques were used to reduce the signal noise in the data to maximise model performance.

6.1 Obtained results

This section begins with a summary of the obtained results from Chapter 2 onwards.

Therefore, Chapter 2 presents the state of the art in seizure detection and prediction using various datasets, such as CHB-MIT, University of Bonn, and University of Freiburg. The outcome of is a comparative study of state of the art and sets the baseline for further research outline in the next chapters, where employment of deep learning techniques is the main research direction.

Chapter 3 explores different neural networks. It introduces a fast-response algorithm with hand-engineered features for the automated detection of epileptic seizures, optimized for very short clips. The pipeline was evaluated on CHB-MIT and UPenn datasets, both patient-wise and globally. Two-layer network with 50 and 20 neurons, respectively, yielded the best performance. However, for more complex data, it is suggested to explore deep learning further.

Chapter 4 presents a step-by-step development of the smartEEG framework to automate research work involving the development of deep learning pipelines to evaluate seizure detection and prediction. It demonstrates how the pipeline is designed to support various configurations, from data extraction and processing to data and model integration, training, validation, and generating plots, enabling researchers to run and analyse model performance easily and iterate quickly. Additionally, a set of deep learning pipelines have been developed that showed improved performance compared to previous proposal in

Chapter 3.

Chapter 5 discusses pipelines with improved performance developed on smartEEG. This was achieved by using (i) a novel hybrid CNN, (ii) a new denoising channel ranking and selection and (iii) EEG signal processing using derivative and filtering to further suppress noise. Each method shows an incremental improvement performance compared to Chapter 4.

6.2 Original contributions

Original contributions are detailed below, where P1 – P6 refers to scientific articles on the list of original publications, in the next section:

In P1, a novel simple neural network fed with hand-engineered features is evaluated on very short EEG clip segments of 1 s, for both patient-specific and global data, with performance exceeding that of comparable approaches. The limitation of this approach is that iteration speed is reduced, as new data pipelines be manually created each time. Additionally, clips with only the same number of channels could be used; therefore, only part of the UPenn and Mayo dataset was evaluated.

P2 and P3 describe in detail novel Deep Learning frameworks for EEG signal classification and MRI image segmentation, to automate and accelerate the research process. The EEG Deep Learning framework smartEEG has enabled the evaluation of a large number of complex deep learning networks against data from 1447 patients originating from two distinct datasets, objectively identifying the most suitable model, which significantly exceeds the performance of the previous proposal.

Novel hybrid deep learning models that leverage both temporal and spatial data features were evaluated in P3. The importance of data balancing and data quality was outlined when analysing individual patients and the data available for learning. The approach has further improved the performance results over the previous works.

P5 proposes further improvements to the way data preprocessing is performed by the implementation of a channel importance ranking feature. It is worth noting that channel ranking is valid in cases where data is already available for each patient and can help a model focus on relevant data. Notable improvements are seen in the case of short EEG data clips.

Finally, P6 demonstrates signal processing techniques, where the most successful are the derivative and bandpass filtering, to further denoise and improve data quality. A detailed analysis of these techniques in conjunction with the highest performing deep learning models developed is presented, where characteristics such as network stability are discussed.

6.3 List of original publications

This section lists all papers either published or under review related to this thesis:

P 1. **A. Ciurea**, C. P. Manoila, A. M. Tautan, and B. Ionescu, “Low latency

- automated epileptic seizure detection: Individualized vs. Global approaches,” *2020 8th E-Health and Bioengineering Conference, EHB 2020*, pp. 8–11, 2020, doi: 10.1109/EHB50910.2020.9280267.
- P 2. **A. Ciurea**, C.-P. Manoilă, and B. Ionescu, “SmartEEG: An End-to-End Framework for the Analysis and Classification of EEG signals,” in *2021 International Conference on e-Health and Bioengineering (EHB) 2021*, pp. 1–4.
- P 3. C.P. Manoilă, **A. Ciurea**, and F. Albu, “SmartMRI Framework for Segmentation of MR Images Using Multiple Deep Learning Methods,” in *2022 10th E-Health and Bioengineering Conference, EHB 2022*, 2022. doi: 10.1109/EHB55594.2022.9991496.
- P 4. **A. Ciurea**, C.-P. Manoilă, and B. Ionescu, “EEG Classification Using Hybrid Convolutional Neural Network with Attention Mechanism,” in *International Conference on e-Health and Bioengineering*, 2023, pp. 783–791.
- P 5. **A. Ciurea**, C.-P. Manoilă, and B. Ionescu, “EEG Denoising with Channel Ranking and Selection,” in *2024 E-Health and Bioengineering Conference (EHB)*, 2024, pp. 1–4.
- P 6. **A. Ciurea**, C.-P. Manoilă, and B. Ionescu, “A comparative Study of eeg signal processing techniques for seizure detection and prediction using deep learning,” *Series C Electrical Engineering and Computer Science*, 2025”, 2025 (under review)

6.4 Perspectives for further developments

Future research could consider the continued development of Deep Learning frameworks to expand the scope of EEG signal classification to more varied types of seizures, thereby improving the capability of automatic diagnosis. Generative artificial intelligence can help develop new pipeline that can be tested on the smartEEG framework at speed. smartEEG can be further expanded to explore different type of EEG events and could be applied to area such as brain computer interface. Finally, a hardware implementation in form of a wearable device for low latency pipeline could further help patients with epilepsy.

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