Automatic seizure onset detection from EEG data using different Machine Learning approaches

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***Abstract*—Epilepsy affects millions worldwide, and prompt seizure detection is crucial for effective management. This study explores using Machine Learning (ML) classifiers with various feature extraction and pre-processing techniques to detect seizure onset from EEG data. The training is done using parts of 6213 EEG recordings from epileptic patients and two feature extraction methods are analysed: Discrete Wavelet Transform (DWT) and statistical features. For classification Gradient Boosting, Random Forest, and Convolutional Neural Networks (CNN) are put to test. The evaluation metrics used are F1-Score, latency and WKI-Score [1]. The best result is obtained by the CNN together with epoch division in pre-processing. For further work, some more pre- and post-processing techniques are recommended.**

I. Introduction

EPILEPSY is a chronic neurological disorder characterized by recurrent seizures, which are short episodes of involuntary movement of the body or part of it and loss of consciousness. They typically last from seconds up to minutes and can lead to serious physical injuries as well as stigma around the disease. Approximately 50 million people are affected by epilepsy, making it one of the most common neurological diseases globally [2], hence the importance of developing accurate detection methods for effective management and treatment.

Traditionally, the seizure detection relies on visual analysis of electroencephalogram (EEG) data by trained specialists, a process that can be subjective and time-consuming. On that matter, Machine Learning (ML) techniques for pattern recognition have been successfully applied on EEG data for seizure detection and could assist or even replace trained specialist. Even though researchers have been working on it since the late 80's ([3], [4], [5]), only in the last decade have these methods been largely applied due to increased computational power, to advancement and diffusion of ML techniques and to the growing availability of data.

This study investigates the use of different ML classifiers alongside diverse feature extraction and pre-processing techniques for detecting seizure onset from EEG data. The paper is structured to first review solutions from related work. Following this, an overview of all our developed models is presented. The method employed is detailed in section IV, with results presented in section V, leading to the conclusions offered in section VI.

II. Solutions from related work

Siddiqui *et al.* [6] make a detailed review on epileptic seizure detection using ML classifiers. One conclusion is that statistical features can provide meaningful information for seizure detection, specially line length. Guo *et al.* [7] achieved 99.6% accuracy on the BONN dataset [8] using Discrete Wavelet Transform (DWT) and line length as feature and an ANN as classifier. On the impact of proper normalization and the relevance of line length, Logesparan *et al.* [9] achieved 52% accuracy using only signal normalization and line length as feature on the CHB-MIT dataset [10]. A combination of features can also improve results, taking care not to select irrelevant ones since they can increase the computational power required and the number of insensible patterns. Siddiqui *et al.* [11] applied 9 statistical features (min, max, σ, mean, skewness, energy, kurtosis and spectral entropy) with Decision Forests and obtained 100% accuracy on the UCSF dataset [12].

Another conclusion from Siddiqui *et al.* [6] is that Decision Forests should be the go-to algorithm for seizure detection due to the fact that they can handle high-dimensional datasets, require less computational time and have logic rules that may be interpreted by specialists. Tzimourta *et al.* [13] use epoch division, DWT, 5 features and a Random Forest classifier and achieve 99.74% sensitivity on the Freiburg dataset [14].

Bairagi *et al.* [15] use a 0.5-40Hz finite impulse filter (FIR) to eliminate noise and artifacts, then divide the signal in epochs and apply DWT, from which 11 features are extracted. These features are fed to an ANN and a novel sequential window algorithm is applied to improve results in post-processing. They achieve 99.44% accuracy and reduce latency to as low as 4.12s on the CHB-MIT database [10].

Another interesting approach is transforming the EEG signal into images and then feed them to a CNN for seizure detection. Mao *et al.* [16] did just that using Continuous Wavelet Transform (CWT) to obtain scaleograms as input for a CNN.

III. Overview

The EEG dataset used is provided by the KISMED division in TU Darmstadt [1]. 6213 EEG recording are provided for training and local validation. For internal train and test, the X EEG recordings were divided in 5 smaller datasets with similar proportion of seizure and non-seizure recordings as the original dataset. Even though the data contain X channels, only the signals from 3 montages (Fp1-F2, Fp2-F4, C4-P3) or 6 montages (Fp1-F2, Fp2-F4, C3-P3, F3-C3, F4-C4, C4-P4) were used for simplification.

During the course of three months, three models (A, B and C) were submitted for verification of metrics on a separate validation set. Each model submitted was an improvement of the previous one and a result of different techniques for seizure detection. At the end of that period, the best model (D), according to metrics on the local dataset, was sent as the final submission and evaluated on a different test set. The overview of the models can be seen in figure 1. The implementation of all models can be found in the `sophiamoyen/ubatuba` Git repository [17].

- **Model A**: Mainly based on the method described by Tzimourta *et al.* [13] and also Guo *et al.* [7]. It takes the raw signal from montages and applies DWT level 4 decomposition with Debauchies order 4 wavelet 'db4'. As in Guo *et al.*, the feature 'line length' is extracted from each of the 5 decomposed signals (CD1, CD2, CD3, CD4, CA4), totalling 15 features per signal. As in as in Tzimourta *et al.*, these features are finally fed to a Random Forest classifier.

- **Model B**: Mainly based on the method described by Siddiqui *et al.* [11]. It takes the raw signal from 3 montages and calculates the following 9 features for each signal: minimum, maximum, standard deviation σ, mean, skewness, energy, kurtosis and spectral entropy. The resulting 27 features are then analysed using Mutual Information Gain and the 5 most relevant ones are fed to a Gradient Boosting classifier. The feature selection guarantees that the most relevant features for each individual channel are chosen. The method was implemented also with 6 montages, but provided similar results with greater runtime on the local test sets.

- **Model C**: Model C is an improvement of Model A by applying pre-processing techniques and non-overlapping sliding windows for epoch division. An epoch division was made for each signal, similarly as described in Bairagi *et al.* [15] and in Tzimourta *et al.* [13]. Each epoch was fed to a Random Forest classifier. In post-processing, the signal was put back together to determine the presence and onset of the seizure.

- **Model D**: It applies the same pre-processing and epoch division as in Model C, but with undersampling. The signal from each epoch is then fed to a CNN. This CNN model for seizure detection is inspired by Zouh *et al.*'s [18] approach, but focuses exclusively on time domain signals. It utilizes convolutional layers, followed by batch normalization, ReLU activation and Max pooling layers. The model concludes with fully connected layers, finalizing the classification between seizure and non-seizure events. After prediction, the signal is put back together to determine the presence and onset of the seizure.

IV. Method

A. Pre-processing

The same pre-processing techniques were applied to Models C and D, while no pre-processing was applied to models A and B. According to Saab *et al.* [19], most of the brain activity relevant for seizure detection occurs between 0.5-29Hz. Bairagi *et al.* used a bandpass filter from 0.5-40Hz following that premise. Such bandbass filters were tried, but provided worse results, suggesting the higher frequency signals also play a role in our method for seizure detection. Artifact filtering using Independent Component Analysis (ICA) was also tried, as well as the Automatic and Tunable Artifact Removal Algorithm (ATAR) with Wavelet Decomposition from Bajaj *et al.* [20]. Both provided worse results despite a few attempts of tuning. We believe a more thorough hyperparameter search could have brougth better results. Finally, it was decided to keep the initial guess of a bandpass filter from range 0.5 to 70 Hz. A notch filter was also used to remove 50 Hz power line noise and its harmonic. The signal was also normalized using a standard scaler from Scikit-Learn [21]. The figure 2 in Appendix B represents this process.

B. Epoch Division

Within the paradigm of epileptic seizure detection using EEG data, the technique of epoch division with fixed-length windows presents a well-established method for segmenting the continuous EEG signal into discrete units for analysis. Let $X(t)$ represent the continuous EEG signal as a function of time, t. Fixed-length windowing entails discretizing $X(t)$ into N non-overlapping segments x_i of equal duration T, denoted as:

$$\begin{aligned} x_i(t) &= X(t-(i-1)\cdot T), \\ &\quad with\ t \in [i \cdot T,\ (i+1)\cdot T] \\ &\quad and\ i = 1, 2, ..., N \end{aligned}$$

This method was successfully applied to Model C and then on to Model D. For this dataset, we used the size of the windows of $N = 2000$ samples and as the sampling frequency of data collection is majorly 256 Hz, the T of the windows is approximately 8 seconds. Epochs that are between the seizure's onset and offset, are labeled as "1", and "0" otherwise. The figure 3 in Appendix B represents this process.

C. Feature Extraction

For Model B, 9 statistical features were calculated for each signal, following Siddiqui *et al.* [11]. They are described in table I. For each epoch from each of the montages, these features were calculated. Only the 5 most relevant features applied to each individual montage were used, that way a feature that works well on a specific montage won't necessarily be calculated for another montage. Or a montage that is overall not relevant for seizure detection may not be included in the model. The method used for feature selection was Mutual Information (MI), which measures the dependency between the specific feature and the binary label indicating seizure or non-seizure for each epoch. The MI rate is equal to zero if and only if the two variables are independent, and higher values mean higher dependency. The function for Mutual Information used from Scikit-Learn [21] relies on nonparametric methods based on entropy estimation from k-nearest neighbors distances as described in Kraskov *et al.* [22]

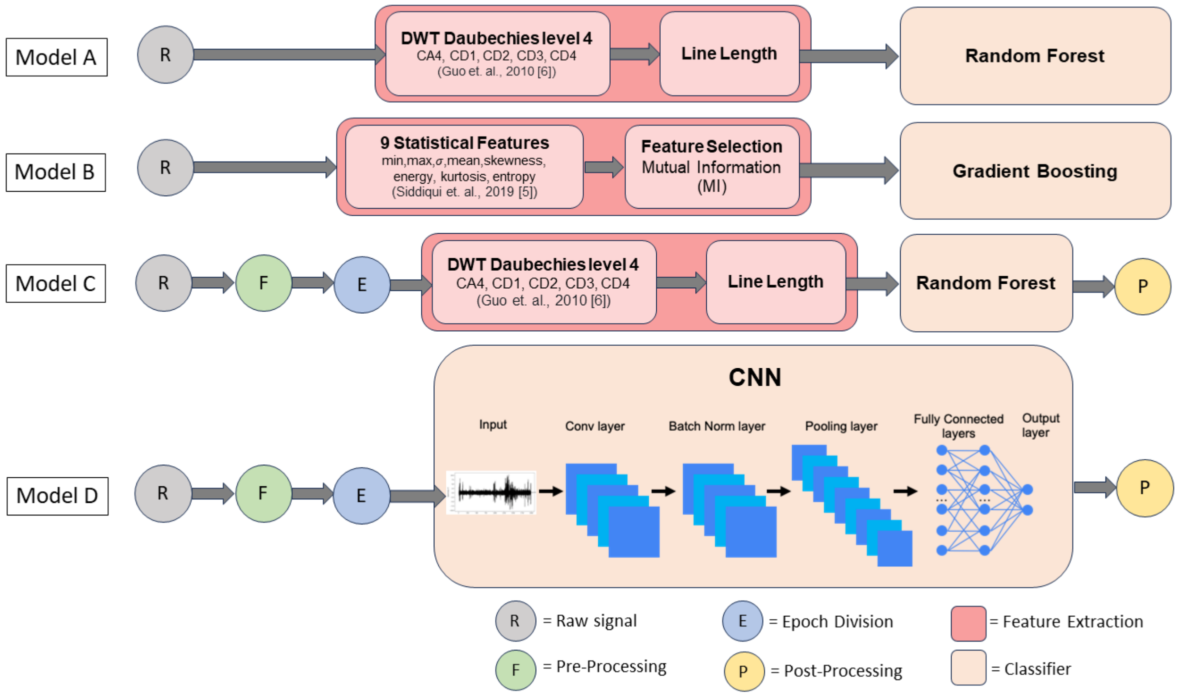

Fig. 1. Overview of methods used for Models A, B, C and D. For Models A and B no pre-processing techniques were used. Model D had the best performance and used no feature extraction method.

and Ross *et al.* [23]. Over different training sessions, 'line length', skewness and kurtosis consistently proved themselves to be the most relevant with the highest MI rate, varying from dataset to dataset.

TABLE I
STATISTICAL FEATURES CALCULATED FOR MODEL B.

Features	Equation
Minimum value	$min(x_i(t))$
Maximum value	$max(x_i(t))$
Mean μ	$\frac{1}{N}\sum_{n=1}^{N} x_i^n(t)$
Entropy	$\sum_{i=0}^{N-1} log(x_i(t)^2)$
Line Length	$\frac{1}{N}\sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$
Standard Deviation σ	$\frac{1}{N}\sum_{n=1}^{N}(x_i^n(t) - \mu)^2$
Kurtosis	$\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^4}{[\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2]^2}$
Skewness	$\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^3}{[\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2]^{3/2}}$
Energy	$\sum_{i=0}^{N-1} \lvert x_i(t) \rvert^2$

For the models A and C, the feature 'line length' was extracted from the DWT Daubechies level 4 output signals. According to Tzimourta *et al.* the 'db4' proved to be the most appropriate order of the Debauchies family for analysing EEG data, so that was the wavelet chosen. The DWT decomposes the raw EEG signal into multiple frequency bands, called detail levels (CD1, CD2, CD3, CD4) and an approximation level (CA4). The frequency-range for each level depends on the frequency of the original signal. The recordings from the KISMED dataset are sampled in the frequencies that range from 250 Hz to 400 Hz. Most of them are sampled in 256 Hz, for which the decomposition levels coefficients and their frequency range can be seen on table II. Finally, from the resulting coefficients, the 'line length' feature essentially calculates the Euclidean distance between consecutive data points, creating a series of "line segments" representing the amplitude changes. According to Saab *et al.* [19], most brain activity occurs between 3-29 Hz, which would mean the that the most important composition levels for seizure detection are CA4, CD4 and CD3. When running the Mutual Information method on the local dataset, the features with the highest rates were indeed CA4 and CD4, with a distinction to these applied to the second montage (Fp2-F4). However, when using only these levels for feature extraction, the classifier got a worse performance. Thus, all decomposition levels were kept.

TABLE II
DECOMPOSITION LEVELS COEFFICIENTS AND THEIR FREQUENCY RANGE FOR MODELS A AND C.

Level	Decomposition Coefficient	Frequency range (Hz)
1	CD1	64-128
2	CD2	32-64
3	CD3	16-32
4	CD4	8-16
4	CA4	0-8

D. Classifier

Models A and C used a Random Forest as the classifier. The hyperparameters chosen based on tuning using grid search were 300 trees per forest, 10 as maximum depth of each tree, minimum 1 sample per leaf and number of maximum features to consider at each split is the square root of the number of given features. Model B uses the Gradient Boosting classifier and the hyperparameters chosen via tuning are 100 boosting stages, maximum depth of 3 for each individual regressor and learning rate equals to 1.

The classifier for Model D is a CNN model, inspired by the methodology of Zouh *et al.* [18]. While Zouh *et al.* [18] utilized both time and frequency domain signals as inputs for their CNN model, this paper narrows its focus exclusively to time domain signals. The CNN architecture was designed to extract and learn complex patterns from the EEG signals, which are inherently time-series data with significant temporal dependencies. The model comprises several convolutional layers, each followed by batch normalization and ReLU activation functions to introduce non-linearity and stabilize the training process. Max pooling layers are incorporated after convolutional layers to reduce the dimensionality of the feature maps, thereby highlighting the most significant features for seizure detection.

The first layer of the CNN model is a convolutional layer designed to capture the initial patterns in the EEG data. Subsequent layers delve deeper into the extracted features, refining them for more accurate classification. Batch normalization is applied to accelerate training and improve the performance of the model by normalizing the input layer by adjusting and scaling the activations. The ReLU activation function is chosen for its efficiency and effectiveness in adding non-linearity, allowing the model to learn complex patterns. Max pooling is utilized to reduce the computational complexity and overfitting by downsampling the feature maps.

To connect the high-level feature representation to the final classification, the model employs several fully connected layers, culminating in a softmax layer that classifies the EEG segments into seizure or non-seizure categories. This design choice ensures a balance between model complexity and computational efficiency, enabling the CNN to run on large datasets without compromising on performance. The model's parameters were carefully selected through empirical testing and validation on a portion of the dataset reserved for this purpose. This approach allowed the determination of an optimal set of hyperparameters that maximize the model's performance and generalization ability across unseen data.

E. Post-processing

The same post-processing technique was applied to models C and D. In this stage the predictions for each epoch are put together to a final conclusion about the signal. The technique uses the labeled epoch divided signal to calculate the onset being the first segment in which a seizure is detected by the classifier. This was applied with the Algorithm 1. For example, for the list of predicted values for each epoch Predictions = $[0\ 1\ 1\ 1\ 0\ 0]$, the second epoch was detected as containing seizure $P_2 = 1$, so the onset timestep is attributed to the start of that epoch $onset = t_2$. For Predictions = $[0\ 0\ 0\ 0\ 0]$, no seizure is detected for that signal.

Algorithm 1 Epoch prediction post-processing

seizure_present $\leftarrow$ False
for $P_{epoch} \in$ Predictions **do**
  if P_{epoch} == 1 **then**
    seizure_present $\leftarrow True$
    onset $\leftarrow t_{epoch}$
    break
  end if
end for

V. Results

The official results, run in an external validation dataset by the KISMED team is presented in table IV. As for the metrics, it was used the WKI-Score the F1-Score, the Latency and the runtime, see Appendix A for more information on the metrics. The results are similar to the ones run in the local 5 test sets. The improvement of metrics from Model A to Model C shows the importance of an adequate pre-processing technique, even tough it increased the runtime in 1900%. The final Model D using CNN obtained the best results in all metrics and also had the second fastest runtime.

TABLE III
Evaluation metrics on external validation set.

Model	WKI-Score	F1-Score	Latency	Runtime
A	0.1822	0.3309	52.6909	00:03:18
B	0.2887	0.5866	36.8352	00:11:09
C	0.3303	0.5866	33.2407	00:59:04
D	0.3894	0.6111	29.7048	00:03:21

VI. Conclusion

This study explored different machine learning methods, including Gradient Boosting, Random Forest, and Convolutional Neural Networks (CNNs), for detecting seizure onset from EEG data. We analyzed two feature extraction techniques Discrete Wavelet Transform (DWT) and statistical features across 6213 EEG recordings from epileptic patients. The CNN, combined with epoch division in preprocessing, achieved the best results based on F1-Score, latency, and WKI-Score metrics.

Looking ahead, further work should focus on refining the model in several key areas. Firstly, implementing well-tuned artifact filtering mechanisms such as ICA and ATAR could enhance the quality of the training data, potentially improving model performance. Secondly, exploring different channel selection methods and montage configurations could allow to leverage specific brain regions that hold key information for seizure detection. Furthermore, investigating alternative normalization techniques, such as Logesparan *et al.* [9], could potentially lead to further performance improvements. Finally, a better post-processing technique such as the sequential sliding windows algorithm described in Bairagi *et al.* [15] could eliminate outlier epochs and reduce the number of false positives.

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Appendix A
Performance Metrics

The WKI performance metric created by the KISMED lab in TU Darmstadt uses another definition for TP, FP, FN, TN and calculates the F1 score so that minimum accuracy in onset detection is guaranteed. The prediction will be evaluated as

- Onset present:
  TP if $\|onset_{pred} - onset_{ref}\| < 30s$
  FN else
- Onset not present:
  TN if no seizure predicted
  FP else

The latency metric is described in equation 1.

$$MAE_{onset} = \frac{1}{N}\sum^{N} min(|Onset_{pred} - Onset_{gt}|, 60s) \quad (1)$$

Appendix B
Additional Figures

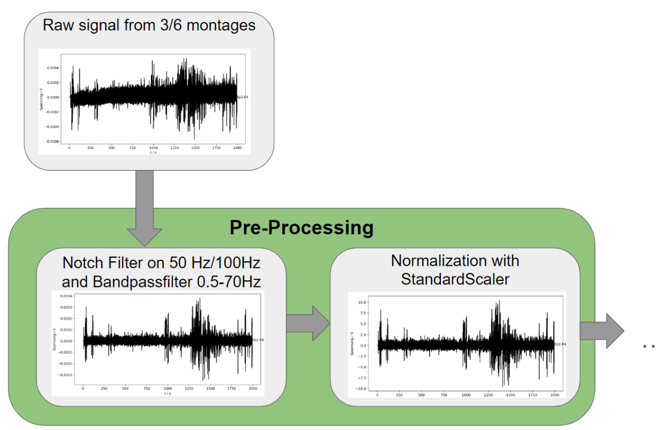

Fig. 2. The Pre-Processing for models C and D filtered out the power line noise and its harmonic as well as irrelveant frequency bands for seizure detection.

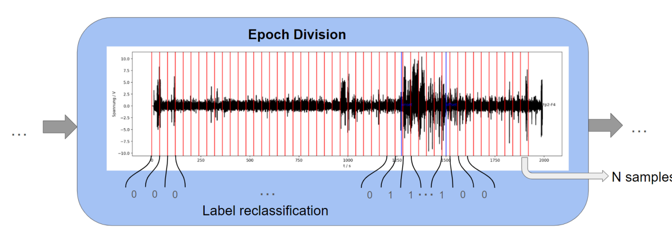

Fig. 3. The signal divided in N non-overlapping windows. If the last piece of the signal is not long enough, it is discarded.

APPENDIX C
FURTHER RESULTS

The Model D with the CNN classifier was tested on other 3 datasets: CHB-MIT [10], a private one from the Frankfurt neurology department and an the another test dataset from KISMED. The results are shown in table.

TABLE IV
EVALUATION METRICS OF MODEL D ON OTHER DATASETS.

Dataset	WKI-Score	F1-Score	Latency	Runtime
CHB-MIT	0.0429	0.4044	55.598	00:01:16
Frankfurt	0.1154	0.8049	54.7467	-
KISMED Eval.	0.3345	0.5776	32.0531	-

APPENDIX D
OTHER EXPERIMENTS

One extra model was tried, but was not submitted for evaluation. Its feature extraction and classifier is based on Mao *et al.* [16]. It applies the same pre-processing techniques and epoch division as in Model C and D. The divided signals are then oversampled with Synthetic Minority Oversampling Technique (SMOTE) [24]. To each epoch a Continuous Wavelet Transform (CWT) is applied. These are then fed to a CNN in form of a 2D scaleogram. In post-processing a sequential window algorithm of size 5, as described in Bairagi *et al.* [15], is used to reduce the number of epochs with false positive. The training of the model proved itself very time-consuming and the resulting model was very large (over 100 MB), so it was abandoned for further tries.

The sequential window algorithm of size 5 developed for the Post-processing of this model is described in algorithm 2.

Algorithm 2 Sequential Sliding Window Algorithm of size 5

```
r ← len(Predictions)
if r ≥ 5 then
    c ← 0
    for i in range r-4 do
        if P_i = 0&P_{i+4} = 0 then
            for j in range (i,i+4) do
                if P_j == 1 then
                    c ← c + 1
                end if
            end for
            if c ≤ 1 then
                for k in range (i,i+3) do
                    P_k ← 0
                end for
            end if
            c ← 0
        end if
    end for
end if
```

Algorithm 2 converts epochs falsely detected as containing seizure to a non-seizure epoch. The algorithm overlaps epochs one by one and if there is a window of 5 epochs in which only one is classified as seizure, it converts that prediction to non seizure. For example, for Predictions = $[0, 0, 1, 0, 0]$ or Predictions = [0,0,0,1,0], and so on, the updated list after running this outlier removal technique is Predictions = $[0, 0, 0, 0, 0]$. After this outlier removal the new Predictions list is then given as input for algorithm 1, that was used in Models C and D.

Algorithm 2 could possibly have been successfully applied to models C and D to reduce the number of false positives, but due to approaching deadlines, it was not tested.