Final project on "Advanced topics in physiological signal processing"

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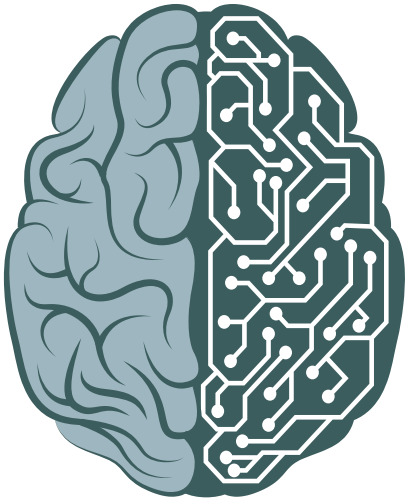
Paroxysmal slow wave events as predictive markers for epilepsy

אירועי גל איטי התקפי כמנבאים לאפילפסיה

Based on the article: Paroxysmal slow wave events predict epilepsy following a first seizure.
Zelig at el. ; 2021 ; 'Epilepsia'



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Introduction

1. Epilepsy

According to the International League Against Epilepsy (ILAE) epilepsy is characterized as a brain disorder with various qualifying conditions: " (1) At least two unprovoked (or reflex) seizures occurring >24 h apart; (2) one unprovoked (or reflex) seizure and a probability of further seizures similar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years; (3) diagnosis of an epilepsy syndrome" [1]. Epilepsy is one of the most common neurological disorders in children and adults, characterized by the occurrence of spontaneous seizures derived from different etiologies such as genetics, head trauma, tumors, cerebrovascular diseases and infectious [2]. About 50 million people worldwide are epileptic, often suffering from reduced quality of life and neuropsychiatric impairments [3]. The first line treatment for epilepsy are medications, and yet, about 30% of patients are drug-resistant and referred to other treatments such as neurosurgical operation, neuro- stimulation and dietary therapy [4]. According to a recent report of the ILAE, epileptic seizures are a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain [1]. Seizures can be classified into two main types, focal in which seizures occur in a certain, unilateral, area of the brain, generalized when seizures originate in a specific location and rapidly spreads bilaterally.

2. Diagnosis and prediction of epilepsy using an electroencephalogram (EEG)

2.1 EEG - The gold standard method for diagnosis of epilepsy is electroencephalography.

EEG measures the electrical activity of the brain by using recording electrodes that are placed on the scalp and detect the collective excitatory and inhibitory postsynaptic potentials generated by large groups of neurons at a depth of several millimeters, firing synchronously and producing a strong electric field [5]. An EEG signal's amplitude is determined by the level of synchrony of the neurons: Large amplitude signals are produced when a group of neurons fire synchronously, while asynchronous excitation results in a low-amplitude irregular EEG signal. The frequency of the signal is between 0 Hz to half of the recording's sampling rate, and is classified into five frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (>30 Hz). Physiologically, delta rhythm is dominant in frontocentral brain regions, during deep sleep; Theta rhythm is dominant in frontocentral regions during drowsiness and early stages of sleep; Alpha rhythm is most dominant in relaxed adults with eyes closed, in the occipital and posterior parietal electrodes, and is attenuated or diminished in open eyes; Beta band is prominent in awake or alert adults and is typically recorded in the frontal regions; Gamma waves characterized by high frequency electrical activity and often associated with heightened cognitive functions such as attention, memory, and problem-solving. EEG recording can be done using two types of montages, bipolar and unipolar: bipolar recording consists of 2 electrodes located close to each other, one of them positive and one negative, and the potential difference is measured. In unipolar recording the potentials are measured in location of one electrode relative to a second remote reference electrode [6].

2.2 EEG-based biomarkers for epileptogenesis

According to the FDA-NIH Joint Leadership Council (2015), a biomarker is a characteristic that is measured as an indicator of normal biologic processes, pathogenic processes, or responses to an exposure or intervention. It includes categories such as susceptibility/risk, diagnostic, monitoring, prognostic predictive, pharmacodynamics/response and safety. A prognostic and diagnostic biomarker for epilepsy is particularly necessary after first seizure or brain insult, when it is uncertainty whether patient will develop epilepsy [7] [8]. Several modalities have been suggested as biomarkers for epileptogenesis, including molecular (plasma HMGB1 and hair cortisol), imaging (brain MRI) and electrophysiology [9]. In this project I will focus on PSWE as a prediction feature for epilepsy.

3. Paroxysmal slow wave events

Paroxysmal slow wave events (PSWEs) are defined as slow transient events (<10 sec in rodents and <5 sec in humans), in which the network switches from apparently normal activity to brief periods of low-frequency activity (median power frequency (MPF) <5 Hz in rodents and <6 Hz in humans). It previously was shown that PSWEs are common and focal in epileptic patients and animals [10]. Moreover, Zelig et al (2021) showed in patients that 72 hours after first seizure PSWEs have a high predictive value for epilepsy, and that epileptic patients compared to seizure-free had a lower mean power frequency and longer duration of PSWEs [11].

4. The need in research

The ability to predict individuals at risk of developing epilepsy is of paramount importance for the effective disease management. This is particularly important in cases where differentiation between a single isolated seizure and a chronic condition is challenging after an initial seizure or brain injury when the probability of epilepsy development remains uncertain. Individuals who progress into epilepsy may suffer severe effects that can prevented with early prediction-associated intervention [4].

Goals

This study aimed to confirm prior research suggesting certain PSWE features could forecast epilepsy. This article focuses on characterizing a novel form of pathological cortical slowing termed paroxysmal slow wave events (PSWEs). The primary objective of this study was to identify a new biomarker for epilepsy that could predict the likelihood of epilepsy following an initial seizure. To achieve this, researchers examined four distinct characteristics of PSWEs (1. Occurrence per minute; 2. Mean MPF; 3. Event duration in precent of the total time; 4. Average num of channels that pick up PSWEs) and compared their differences between an epilepsy group and a control group. Employing a logistic regression model, they demonstrated that the occurrence of PSWEs per minute significantly increased the risk of future seizures among patients experiencing their first seizure, with an odds ratio (OR) of 3.56. To replicate the results of the article, I will utilize logistic regression model as a classification model between epilepsy and non-epilepsy groups, using ten features of PSWEs.

Methods

1. Research data

In this research, 'The TUH EEG Epilepsy Corpus' (TUEP) was utilized, comprising 156 subjects diagnosed with epilepsy and 184 subjects without epilepsy, verified by a certified neurologist. Each patient had EEG data recorded using the conventional 10-20 method with 19 electrodes, with a minimum recording duration of 20 minutes. The sampling rate for data is uniform across all patients, set at 250 Hz [12].

2. Preprocessing

The preprocessing was performed based on Makoto's preprocessing pipeline [13] and previous studies [10],[11],[14], and written in MATLAB by a research member in my lab. The preprocessing includes:

2.1 DC removal : performed by reducing the signal average for each electrode.

2.2 BPF 1-45 Hz : Consistent with a previous studies [10],[11],[14] , the PSWEs were characterized after using a band-pass filter (BPF) applied to frequencies ranging from 1 to 45 Hz. Consequently, event detection was performed within the same frequency range to maintain consistency.

2.3 Re-reference the data to average: approximation of scalp potentials that is independent of reference location in a location of the head.

3. Detection of paroxysmal slow wave events (PSWE)

PSWE are defined as slow transient events characterized by high activity in the delta and low theta range. In humans, PSWE were defined as segments in which the median power frequency (MPF) <6 Hz for > 5 seconds. The analysis was conducted individually for each electrode, and PSWE events were identified as occurrences detected in at least two different electrodes. To calculate the MPF I buffered the signal into 1 sec windows using MATLAB (respectively to the sampling rate). For each window I calculated the power spectrum of the signal, sort the power spectrum values in ascending order, and found the cumulative sum of the sorted power spectrum values and then determine the frequency at which the cumulative sum crosses half of the total power (i.e., 50% power). Fig 1 shows an example of MPF per sec for ECoG signal of rat, when PSWE is colored in red. Fig 2 verifies the algorithm's results for patient number 2118 with PSWE detection on electrodes 2, 11, and 12 within the time interval from 653 to 658 seconds. As shown in this figure, the algorithm's detection is accurate because all three electrodes exhibit an MPF lower than 6 Hz during this period, unlike the remaining electrodes.

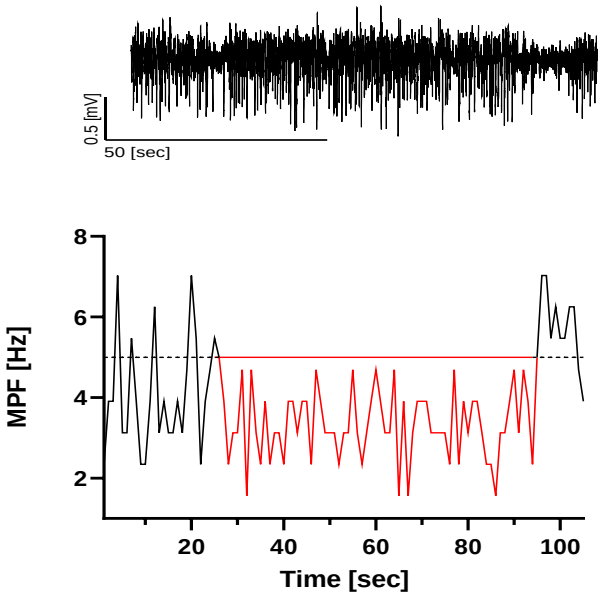

Figure 1: ECoG signal and MPF per sec respectively**.** PSWE can be seen in the middle of the graph (in red) – when the MPF is less than 5 [Hz] for at least 10 [sec] (rats definition of PSWE).

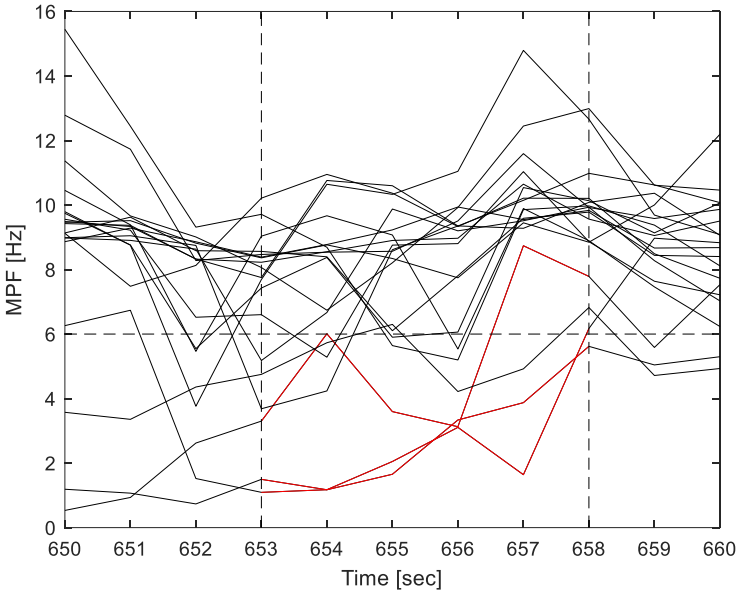

Figure 2: MPF per sec respectively**.** PSWE can be seen in the middle of the graph (in red) – when the MPF is less than 6 [Hz] for at least 5 [sec] (humans definition of PSWE).

4. Features calculation

Based on the article, PSWE features that calculated per patients are: [11]

1. Occurrence per minute – the time of PSWEs as percentage of the total time of the signal.
2. Mean MPF – PSWEs defined when the MPF is lower than 6 Hz for at least 5 sec. This feature looks for the mean of the MPF of specific event (ranges between 1 to 6 Hz).
3. Mean of event duration – This feature calculates the average duration of PSWEs for a specific patient, providing insight into the typical length of these events within the patient's recordings.
4. Average number of channels that pick up PSWEs - calculate the mean number of channels that pick up the events. It offers an indication of the spatial distribution or involvement of channels in capturing PSWEs within the patient's recordings.

Also, additional features chosen and calculated using MATLAB:

1. Energy of the signal: The energy of a signal is a measure of its total power or strength over a given period of time, $E = \frac{1}{N}\sum_{n=1}^{N} \mathrm{x_n^2}$
2. Zero crossing: Zero crossing refers to the points in a signal where the amplitude changes its sign, crossing the zero axis. Zero crossing rate is an estimation of instantaneous frequency, meaning measure of how often these transitions occur within a signal over a specified period of time, $ZC = \sum_{n=2}^{N}(x_n \cdot x_{n-1} \leq 0)$

Relative power in brain waves: Relative power refers to the proportion of power within a specific frequency band relative to the total power across all frequency bands in a signal. It provides valuable insights into the relative contribution of different frequency components within the signal.

3. Relative power in delta: 0.5-3 Hz, $FT = \sum_{\text{all freq}} f_j \ ; \ \delta = \frac{1}{FT} \cdot \sum_{j=0.5}^{3} f_j$
4. Relative power in theta: 3-8 Hz, $FT = \sum_{\text{all freq}} f_j \ ; \ \theta = \frac{1}{FT} \cdot \sum_{j=3}^{8} f_j$
5. Relative power in alpha: 8-12 Hz, $FT = \sum_{\text{all freq}} f_j \ ; \ \alpha = \frac{1}{FT} \cdot \sum_{j=8}^{12} f_j$
6. Relative power in beta: 12-20 Hz, $FT = \sum_{\text{all freq}} f_j \ ; \ \beta = \frac{1}{FT} \cdot \sum_{j=12}^{20} f_j$

The code segments the data into epochs of 2 sec (according to the sampling rate) with a 1 sec overlap. The size was chosen based on previous studies [16] so that it would allow local stationary assumptions and satisfactory temporal and frequency resolution. For every PSWE epochs, 10 features are computed separately for each electrode, followed by calculating the mean across electrodes and patients. In the MATLAB code, the calculation saves the results of the features per segment and per electrode, in addition to per patient, for future studies as part of my thesis.

4.1 Normalization:

As can be seen, the occurrence of PSWEs is normalized with the total time of the recording to prevent the time of the recording from influencing the results (as every patient has a different recording duration). Additionally, the relative powers are normalized with the total energy across all frequencies. This helps to account for individual differences in overall signal power or amplitude. By normalizing, I am essentially standardizing the power values to be comparable across different signals or recording sessions. This normalization step is particularly important in comparative analyses where the focus is on the relative contribution of different frequency bands rather than the absolute power values.

I chose not to normalize the other features for several reasons. Firstly, if the features already have similar scales or if the model tolerates variations in feature magnitudes, normalization may not be needed (e.g., all patients have 19 channels, so the PSWE channels are out of 19). Moreover, normalization could potentially distort natural feature relationships, especially if they naturally fall within a specific range. Additionally, in some cases, normalization might add unnecessary complexity without significantly improving model performance or preserving information. Lastly, by avoiding normalization, the interpretability of the model's coefficients remains clearer, reflecting the direct impact of each feature on the outcome without scaling adjustments.

5. Features selection

For reducing the dimensionality of datasets, dimension reduction algorithms are used to simplify complex models and prevent overfitting. These techniques reduce the number of features while retaining essential information, improving computational efficiency and generalization performance. In this project I decided to use feature selection algorithms instead of feature extraction to maintain the interpretability of the model, prioritizing the retention of original features while effectively reducing dimensionality. This choice avoids the inherent loss of direct data interpretation associated with feature extraction methods. Feature selection involves choosing a subset of the original features based on their relevance to the target variable. This approach is beneficial when interpretability is paramount, as it preserves the original features, making it easier to understand the model's decision-making process. By discarding irrelevant or redundant features, feature selection reduces the complexity of the model, potentially improving its generalization performance and training efficiency.

The objective of this project is to replicate the findings outlined in the article. For this purpose, logistic regression is employed as the classification algorithm. Consequently, I have the flexibility to determine the criterion for feature selection optimization (J) using this classification model. Thus, I opt to utilize the Area Under the ROC Curve (AUC-ROC) metric of the logistic regression model as the criterion for feature selection.

ROC is a graphical representation of binary classification model performance. The ROC curve provides a visual summary of the classifier's performance across different classification thresholds. Each point on the curve corresponds to a particular threshold for classifying instances as positive or negative. TPR represents the amount of epileptic identified as such and FPR represents the amount of non-epileptic identified as epileptic. The area under the ROC curve (AUC-ROC) is often used as a summary statistic to measure the overall performance of a classifier. AUC-ROC ranges from 0 to 1, with a higher value indicating better discrimination power.

Additionally, as I do not have prior knowledge of the ideal number of features to use, I aim to assess the performance of the classification model across various feature subsets. To accomplish this, I plan to execute the algorithm for different numbers of features, ranging from 1 to 10. By employing this method, I can systematically evaluate the logistic regression model's performance with each subset of features and select the number of features (m) that yields the optimal classification performance, determined by the AUC metric. This approach enables me to identify the most effective feature combination for achieving accurate classification results. As a result, I've opted for the forward selection algorithm, which involves a total of $\frac{1}{2}m(2d - m + 1)$ searches (in this case d=10). This selection method starts with an empty set of features and iteratively adds one feature at a time. At each step, the algorithm evaluates the performance of the model with the added feature and selects the one that improves performance the most according to a predefined criterion (J). This process continues until a stopping criterion is met, in this case reaching a specified number of features (m).

In conclusion, I will employ forward selection as the feature selection method, utilizing the AUC of logistic regression classification (J) as the performance criterion when the calculations will be on the training data.

6. Classification model

Using the logistic regression model, the researchers demonstrated that the occurrence of PSWEs per minute significantly increased the risk of future seizures among patients experiencing their first seizure, with an odds ratio (OR) of 3.56 (p=0.009). Furthermore, they attempted to refine the model by exclusively using early EEG tests conducted within 72 hours post-seizure, resulting in an increased odds ratio of 5.73 (p=0.02) [11]. To replicate the results of the article, I will utilize logistic regression model as a classification model between epilepsy and non-epilepsy groups.

Logistic regression is a statistical method used for modeling the relationship between a categorical dependent variable (in this case epilepsy and non-epilepsy) and one or more independent variables (the features). It predicts the probability of occurrence of an event by fitting data to a logistic curve.

When the observed values of the observation j are:

$$Y_j(\ 1\ for\ epilepsy\ and\ 0\ for\ non-epilepsy)$$

$$X_j = \left(x_{1j}, \dots x_{Mj}\right) - when\ M\ is\ the\ number\ of\ features$$

$$if\ \pi(X_j) = P(Y_j = 1\ |X_j) : \log\left(\frac{\pi(X_j)}{1-\pi(X_j)}\right) = \beta_0 + \beta_1 x_{1j} + \cdots + \beta_M x_{Mj}$$

We wish to find the values of $\beta_{0,\dots}\beta_M$ which give the "best fit" to the data. The measure of the goodness of fit is the squared error loss (the sum of the squared deviations of the fit from the data points (yj)), and the best fit is obtained when that function is maximized: [17]

$$\log P(\beta|Y,X) = \sum_{j=1}^{N} Y_j \cdot \log \pi(X_j) + (1-Y_j) \cdot \log\left(1-\pi(X_j)\right)$$

$$\hat{\beta} = \arg\max \log P(\beta|Y,X)$$

After conducting the logistic regression model, the classification threshold is chosen using Youden's J statistic. Youden's J statistic is a single number that summarizes the performance of a diagnostic test: J =sensitivity + specificity - 1. This statistic helps determine the optimal balance between sensitivity and specificity, maximizing the model's overall performance. It ranges from 0 to 1, with higher values indicating better test performance.

7. Performance criteria

In the article, the researchers showed that PSWE occurrence has an odd ratio of 3.56 and AUC equal to 0.72. In this study, I will evaluate the algorithm's performance using the Area Under the Curve (AUC), Odds Ratio, specificity, and sensitivity.

As mentioned before, the area under the ROC curve (AUC-ROC) is often used as a summary statistic to measure the overall performance of a classifier. AUC-ROC ranges from 0 to 1, with a higher value indicating better discrimination power. Sensitivity refers to the proportion of true positive cases correctly identified by the model, indicating its ability to detect the condition when it is present. Specificity, on the other hand, measures the proportion of true negative cases correctly identified by the model, indicating its ability to correctly identify the absence of the condition when it is indeed absent. Mathematically:

$$sensitivity = \frac{TP}{TP + FN}\ , specificity = \frac{TN}{TN + FP}$$

In logistic regression, the odds ratio (OR) quantifies the likelihood of an event happening based on predictor variables. It compares the odds of the event occurring in different groups defined by these predictors. Each predictor has its own odds ratio, revealing the strength and direction of its relationship with the outcome. This measure is particularly useful in binary logistic regression, offering interpretable insights into how predictors influence the outcome's probability. After training the model, there is coefficients associated with each feature. These coefficients represent the log-odds of the outcome variable associated with a one-unit change in the predictor variable.

Results

1. Data properties

The dataset contains 184 patients with epilepsy and 156 patients without epilepsy. Two non-epilepsy patients were characterized as persistently slow, meaning that 99% of their EEG recording consisted of PSWE so I excluded them from this project.

In epilepsy patients- 117 are females and 67 males. The range of the age of the patients is 43.53 ± 14.80.

In non-epilepsy patients- 95 are females and 59 males. The range of the age of the patients is 43.42 ± 14.83.

2. Training model

To train the model, I divided the data into three subsets: training set, validation set, and testing set. The training set is used to train the model, while the validation set is utilized to tune the parameters of the feature selection algorithm and assess its generalization. The testing set, kept separate from the training set, is employed to evaluate the model's performance. Typically, a standard split is 80-20, where 80% of the data is allocated for training and the remaining 20% is reserved for testing purposes. The validation set comprises 20% of the training data. The separation was conducted randomly while ensuring a balanced distribution between the classes:

Train data contains 118 epilepsy patients (Sex: 80 female and 38 males, Age: 42.52 ± 14.32) and 99 non-epilepsy patients (Sex: 60 female and 39 males, Age: 43.69 ± 14.84).

Validation data contains 29 epilepsy patients (Sex: 17 female and 12 males, Age: 44.79 ± 18.12) and 25 non-epilepsy patients (Sex: 13 female and 12 males, Age: 41.92 ± 13.73).

Test data contains 37 epilepsy patients (Sex: 20 female and 17 males, Age: 45.78 ± 13.53) and 30 non-epilepsy patients (Sex: 22 female and 8 males, Age: 43.77 ± 15.37).

2.1 Feature selection

As detailed in the methodology section, I conducted forward selection to identify the most optimal logistic regression model. I conducted five repetitions of the experiment, and now I will present the results obtained from the best-performing model. Figure 3 illustrates the area under the curve (AUC) of the ROC, which was selected as the optimal criterion, plotted against the number of features included in the model. This criterion has checked on the validation data. From the graph, it is the highest AUC (indicating maximal performance) is achieved when the model incorporates four features, denoted as m=4.

The features that selected are: ' mean_MPF', ' mean_delta', 'mean_beta',' Mean_duration'.

The best AUC is equal to 0.7261 and ROC graph illustrated in Figure 4.

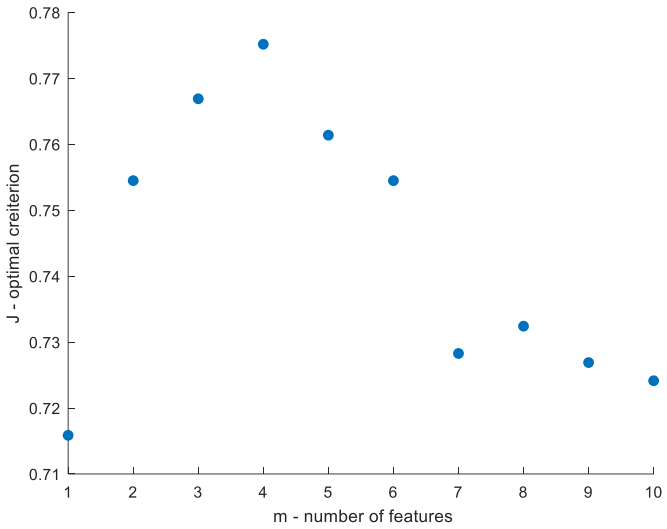

Figure 3: The AUC as function of the number of chosen features.

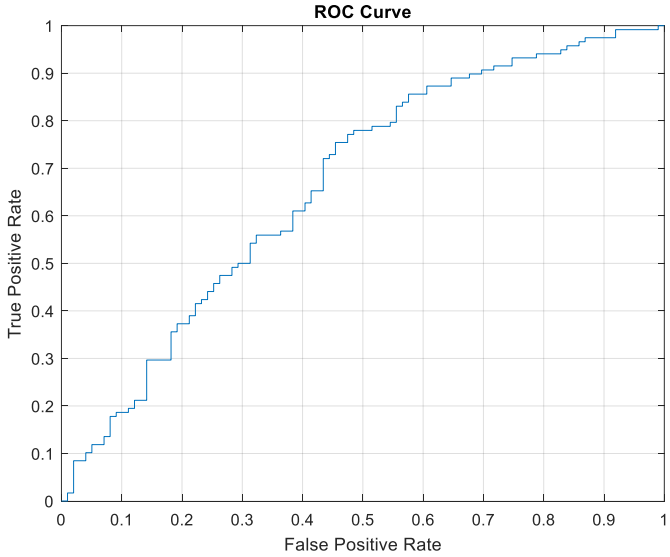

Figure 4: The ROC of the chosen model.

3. The classification model performance

The performance of the algorithm in this part was tested on the testing data. According to Youden's J statistic, the optimal threshold in the ROC is 0.5984 (Figure 5). Using this threshold, the sensitivity is 0.8378, the specificity is 0.6667 and the AUC is 0.7621. Specifically, out of the epilepsy group (37 patients), 31 have been identified as epileptics by the model, and out of the non-epileptic group (31 patients), 21 have been identified as non-epileptics by the model.

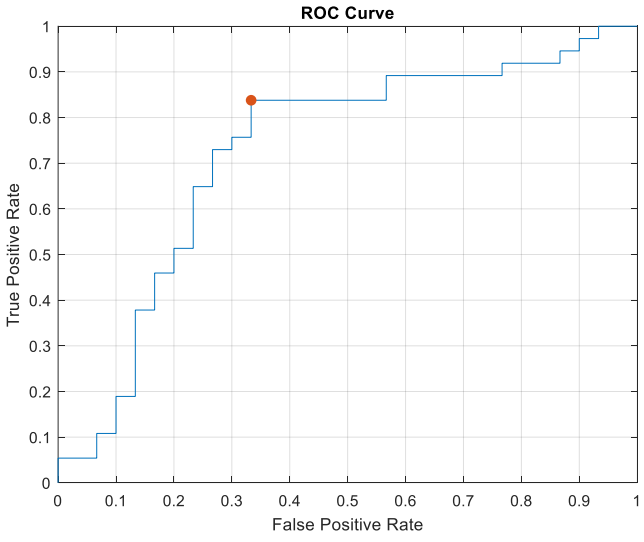

Figure 5: The ROC of the chosen model on the test data. In red- the threshold that chosen using Youden J statistic.

After training the model, there is coefficients associated with each feature. The maximal OR is for the mean relative power in delta and equal to $e^{30.9934}$ meaning that this coefficient reflects better classification.

4. Replicate the article model

In this part, I train a model based on the four features present in the research to assess the differences in performance between the models using various criteria. The logistic regression model is trained on 80% of the data and tested on the remaining 20%. After training the model, the classification threshold is determined based on Youden's J statistic, as I've done in my model. The optimal threshold in the ROC curve is found to be 0.618 (Figure 6). Using this threshold, the sensitivity is calculated to be 0.7838, and the specificity is 0.5806. The AUC of the model is 0.6495. Specifically, out of the epilepsy group (37 patients), the model correctly identifies 29 as epileptic, and out of the non-epileptic group (31 patients), the model correctly identifies 18 as non-epileptic. The maximal OR in this model is for the mean relative power in alpha and equal to $e^{8.79}$ meaning that this coefficient reflects better classification.

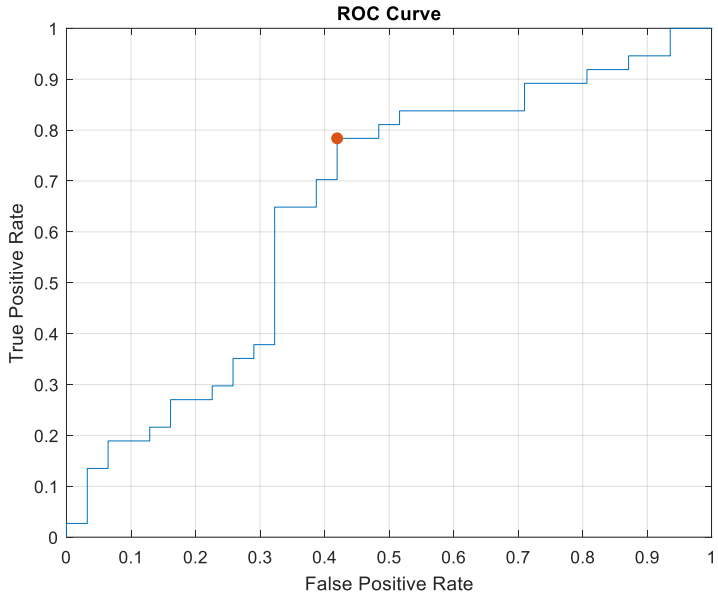

Figure 6: The ROC of the chosen model on the test data. In red- the threshold that chosen using Youden J statistic.

Discussion

The aim of this study was to replicate previous research findings suggesting that certain features of PSWEs could serve as predictive indicators for epilepsy. In the prior study, researchers developed a logistic regression model based on four key features: occurrence per minute, mean MPF, mean duration, and the average number of channels that pick up PSWEs. To replicate these findings, I conducted a logistic regression analysis using a cohort of 338 patients, comprising 184 with epilepsy and 154 without epilepsy. In contrast to the previous study, I expanded the feature set to include six additional features. Furthermore, I incorporated a forward feature selection (FFS) algorithm to identify the most informative features for the model, aiming to mitigate overfitting and enhance generalization.

The FFS algorithm determined that four out of the total ten features contributed to the optimal model performance: mean of MPF, mean relative power in delta, mean relative power in beta, and mean duration of event. This model was evaluated using validation data, demonstrating its ability to effectively distinguish between epilepsy and non-epilepsy cases. To validate these results, I also trained a logistic regression model using only the original four features utilized in the previous research. The results, as presented in the findings, indicated that this simplified model exhibited inferior AUC, sensitivity, and specificity compared to the model incorporating the FFS algorithm. This underscores the effectiveness of the FFS approach in improving classification performance and generalizability of the model. Also, the results show that mine model has a higher maximum odds ratio (30.9934) than second model that replicate the article (8.79), indicating stronger predictive power for epilepsy-related features in this model. This suggests that the features selected or included are more influential in predicting epilepsy compared to those in article model. The greater odds ratio highlights the significant impact of specific variables on epilepsy prediction within that model. This implies that the additional features or feature selection methods may have identified more effective predictors, potentially improving the model's ability to differentiate between epilepsy and non-epilepsy cases.

It's important to highlight that I ran the models multiple times, and the results presented are the best outcomes. Additional results can be found in the appendices. The significant disparity observed among the models and the selected features suggests that the model's performance is susceptible to fluctuations in the data or experimental conditions. This variability may arise from various factors, such as random variations in the dataset, or the presence of outliers or noise. In such instances, it's imperative to investigate the sources of variability and evaluate the model's robustness. Further analysis, such as increasing the dataset size or exploring alternative modeling approaches, may be necessary to gain a deeper understanding of the model's behavior and enhance its reliability.

Summary

The study aimed to replicate prior research indicating certain features of PSWEs could predict epilepsy. A logistic regression analysis was conducted using data from 338 patients, expanding the feature set to include six additional features, and employing a forward feature selection (FFS) algorithm to enhance model generalization. The FFS identified four key features contributing to optimal model performance. Evaluation on validation data demonstrated the model's effectiveness in distinguishing epilepsy from non-epilepsy cases, outperforming a simplified model with only four features used in previous research. The model incorporating FFS showed superior accuracy, sensitivity, and specificity, with a higher maximum odds ratio, suggesting stronger predictive power for epilepsy-related features. However, the study noted the susceptibility of model performance to data fluctuations or experimental conditions, highlighting the need for further investigation into sources of variability and potential enhancements to model reliability, such as increasing dataset size or exploring alternative modeling approaches.

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Appendices

In folder programs:

0. Find global PSWE This folder contains the code that performs PSWE detection. The code was written by my lab mates.

1. Extract features This folder includes the code that executes features. The code was written for my thesis and includes additional calculations that are not necessary within this project.

2. Training the model and FFS This folder includes the code that performs the training of the models and the selection of the features. In order to run it, the main address that appears in main_path must be changed to the address of the folder where the Excel file appears with all the features that have already been calculated in the early stages.

Table 1: Iteration for my algorithm including FSS and test results

Iteration	chosen features	AUC	senstivity	specificity
1	• mean_delta • mean_Zerocrossing • mean_beta • mean_Energy • PSWE_per_min	0.6432	0.465	0.8333
2	• Mean_duration • mean_alpha • mean_MPF • mean_beta	0.7099	0.7027	0.7
3	• mean_delta • mean_MPF • PSWE_per_min • mean_Energy	0.7649	0.7027	0.7667
4	• mean_MPF • mean_Energy • mean_num_of_chan	0.7306	0.8378	0.6129

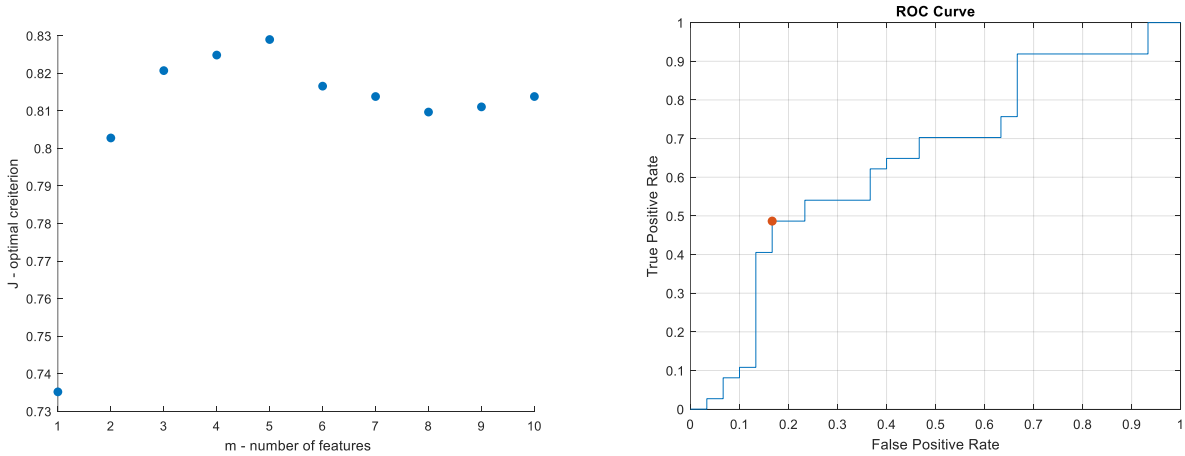

Figure 7: Iteration 1

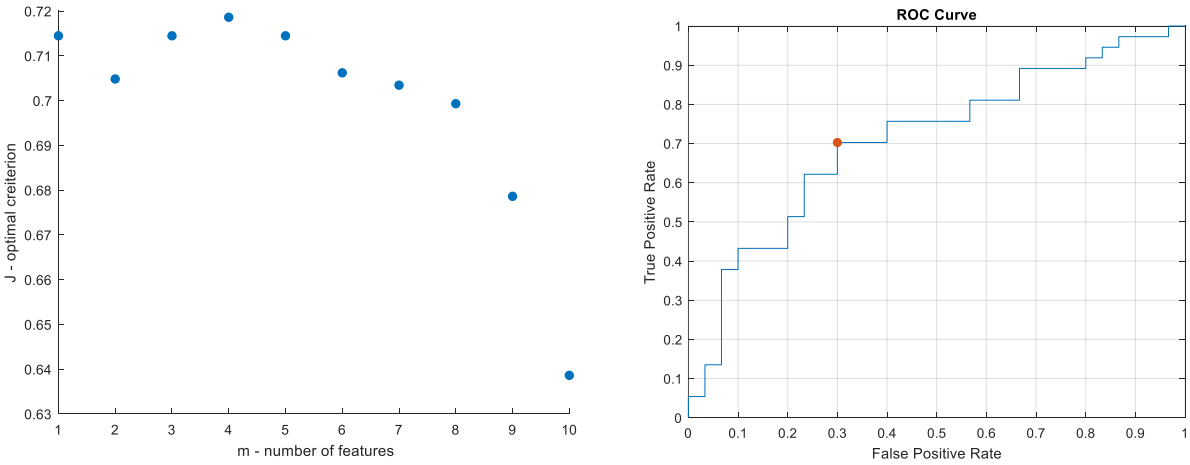

Figure 8: Iteration 2

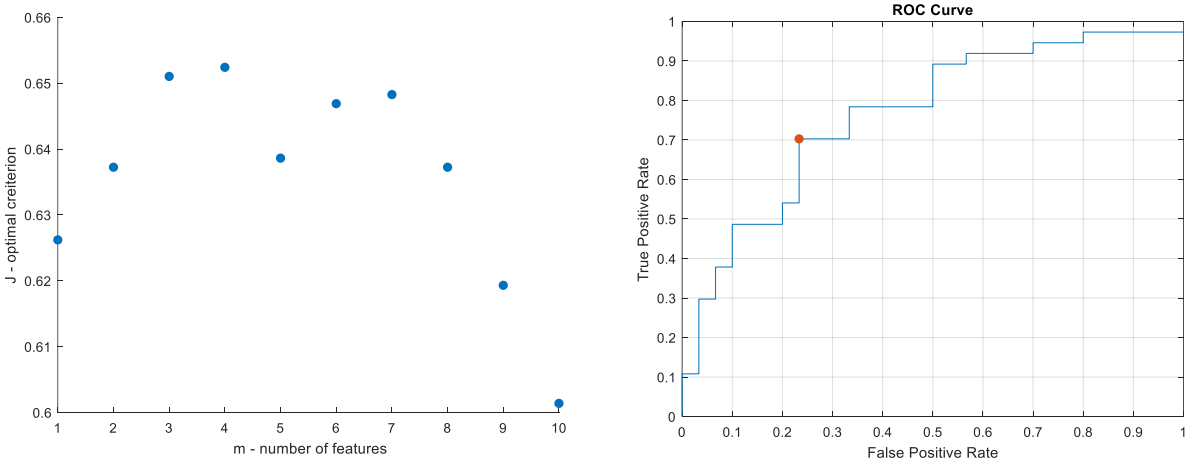

Figure 9: Iteration 3

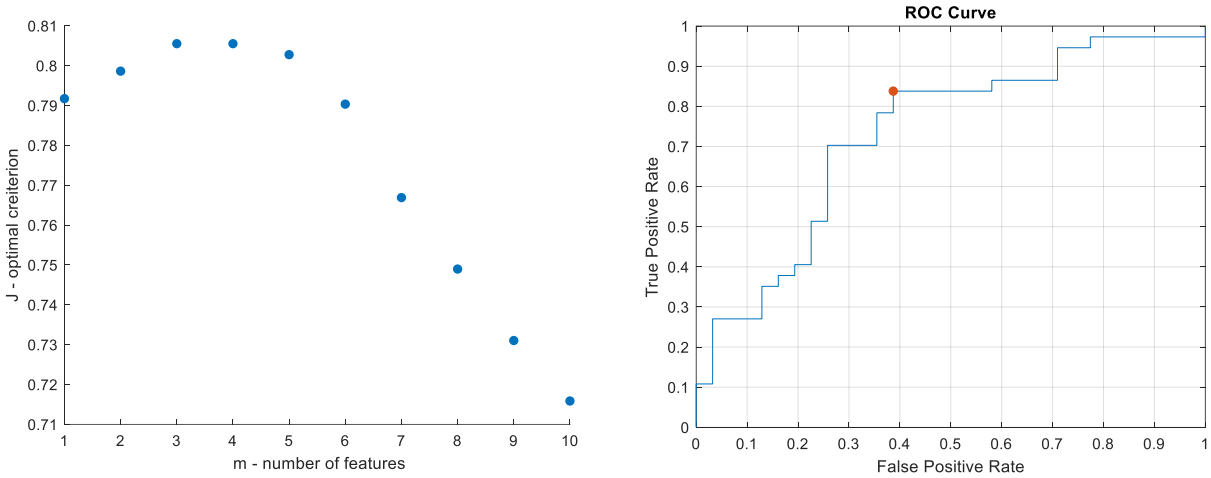

Figure 10: Iteration 4

Table 2: Iteration for research algorithm

Iteration	AUC	sensitivity	specificity
1	0.5946	0.6486	0.5806
2	0.6286	0.5946	0.7097
3	0.5702	0.7297	0.4516
4	0.5911	0.7568	0.5806