Using Machine Learning to Predict Epileptic Seizures from EEG Data

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Abstract

With the recent Artificial Intelligence (AI) progress, especially Machine Learning (ML), researchers aim to apply techniques for improving and automating certain clinical practice facets. This paper proposes and investigates the efficiency of several machine learning approaches to predict epileptic seizure onsets accurately to prepare patients for recurrent convulsion episodes, enhancing their quality of life. The study was performed in collaboration with industry and analyses the non-invasive scalp Electroencephalography (EEG) signals. The feature space is extracted using statistical, and wavelet transforms. The results from K-Nearest Neighbour (KNN), Support Vector Machines (SVM), and an Ensemble Classifier are compared. The proposed techniques are evaluated using one of the most extensive seizure EEG datasets, the CHB-MIT dataset, which includes 192 seizure readings from 22 patients suffering from intractable seizures. It is among the first seizure prediction studies and shows that the three methods perform similar, although the Ensemble Classifier achieves a higher specificity, sensitivity and accuracy.

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1 Introduction

Epilepsy is a neurological disorder which includes episodes of abnormal electrical brain activity [1, 2]. Individuals with epilepsy suffer from recurrent episodes, known as seizures, which usually are extremely hard to predict and occur without warning. During a seizure, the body's nervous system is disrupted, and as a result, sufferers experience a period of muscle spasms that are referred to as convulsions. Patients may have difficulty speaking, swallowing, and breathing during a seizure. Also, a result of a seizure may include loss of consciousness, the risk of obtaining injury and the possibility of death [3,4,5]. The different seizure types include intractable seizures, a drug-resistant form of seizure.

Although effective medication can prevent seizures, it works only on approximately 70% of the patients [5]. Not all seizures are epileptic, as they can be triggered by other underlying conditions such as stroke and drug toxicity. Often, people living with epilepsy have to cope with persistent anxiety of impending seizures, which negatively impacts their daily lives, including driving a car or other social and financial disadvantages [6]. Epilepsy research has always been of importance throughout the years. One reason is that individuals with epilepsy are three times more likely to die prematurely than those without the disease [5,6]. The brain activity state of epilepsy patients can be broken down into categories which include: pre-ictal (moments before a seizure), ictal (during a seizure), post-ictal (moments after a seizure), and inter-ictal (in between seizures).

Epileptic seizure prediction is a classification problem involving discriminating between pre-ictal and inter-ictal states. One way to study the brain's electrical activity is via Electroencephalography (EEG), the most effective tool to examine the brain's behaviour during a seizure. The epilepsy medication involves thoroughly analysing non-stationary, and non-normally distributed EEG data. Through EEG signals, separation from normal and abnormal brain electrical activity can predict a seizure accurately. Still, given its non-linearity, it is challenging to interpret from a human's perspective and usually requires an expert neurologist to interpret the readings. Despite the difficulties of analysing EEG signals for seizure prediction, studies confirm that epileptic patients all share a similar route toward seizure [7,8,9]. Another pressing issue with this approach is the lack of seizure data, which usually takes researchers months to obtain sufficient data.

Following successes in predictive tasks from all fields, ML attracts healthcare providers and researchers' interest in improving clinical diagnosis and outcome prediction tasks [10]. Studies involving ML algorithms' applications to predict epileptic seizures from EEG data have already been applied, and techniques from Deep Learning (DL), a form of advanced ML [11-14]. Previous studies have achieved high-performance metrics. However, most of these studies focused on patient-specific classifiers. Also, some studies include analysing intracranial EEG, another form of recording brain activity. However, intracranial EEG is an invasive monitoring technique that involves placing the EEG electrodes on the surface or inside the brain instead of scalp EEG, which consists in placing the electrodes on the scalp [27]. Figure 1 is an Illustration of normal and seizure EEG signals.

Figure 1: Illustration of normal EEG signals (top) and seizure EEG signals (bottom)

Given the impracticality of intracranial EEG and patient-specific classifiers, this study will focus on *training* patient-independent machine learning classifiers from scalp EEG data. This study will concern the comparative analysis of three supervised machine learning algorithms: Support Vector Machine (SVM), Ensemble Classifier and K-Nearest Neighbour (KNN) for epileptic seizure prediction. Furthermore, no deep learning techniques were applied. Instead, a traditional ML approach was undertaken, which does not involve automatic feature extraction.

The proposed solution will build patient-independent classifiers by utilising various machine learning algorithms. All the available recordings that involve seizure data on the CHB-MIT Scalp EEG database will be used for the task [1,2]. The data stored in the *.edf* format, which includes one hour EEG recordings, is labelled with the appropriate seizure states at the right times by using provided annotation files stored in the *.edf.seizure* format. Frequency and time-domain features will be extracted from the data using an appropriate feature extraction technique. Once features are extracted, the values obtained can be used for classification. The results will be visualised accordingly, and the metrics will be compared with existing research in the field. The software used for this study is MATLAB and its libraries.

This paper is categorised into five sections. The first section is an introduction, which involves the motivation, the problem statement, and the aims and objectives of the study. The second section concerns the methods used for signal preprocessing, feature extraction and classification. The results are presented and discussed in the third section. The fourth section describes the evaluation and a comparison with other related work in the field. The fifth section includes the conclusion regarding the results obtained, limitations of the systems and future work.

2 Materials & Methods

This section involves describing further the data and techniques used in the paper. Furthermore, the filtering and feature extraction implementation techniques are explained. The section ends with a description of the performance metrics used in the study and details concerning the ML algorithms and the training parameters.

The tools and software used include MATLAB R2020a and two toolboxes, the Signal Processing and the Statistics and Machine Learning toolboxes [20]. Another software package used is the WFDB Toolbox, a downloadable software package for MATLAB/Octave, which includes a collection of functions for reading, writing, and processing physiologic signals in the formats used PhysioBank databases [11].

2.1 Dataset

The dataset used in this study is the publicly available CHB-MIT Scalp EEG Dataset obtained from physionet.org [9,18-20]. This repository, collected at the Children's Hospital Boston, consists of EEG recordings from pediatric subjects with intractable seizures. Recordings were collected from 22 patients (5 males, ages 3–22; and 17 females, ages 1.5–19). Each patient has a folder which contains several *edf* files, which are 1 hour long EEG recordings.

All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (in some cases, 24 or 26). The International 1020 EEG electrode positions and nomenclature system was used for these recordings. The database contains 664 .edf files, with only 129 files including seizure recordings. Given this paper's goal is to classify inter-ictal and pre-ictal seizure phases, only the recordings with seizures are used.

2.1.1 Data Preprocessing

The first step of data processing was to obtain all *.edf* seizure files gathered from Physionet. MATLAB and the WFDB toolbox extract the epoched EEG signals' features and their class information, whether inter-ictal (minimum 10 minutes before seizures) or pre-ictal (one minute before seizures). The length of one epoch/segment is defined as 2 seconds. Figure 2 is the schematic representation of the seizure prediction process used.

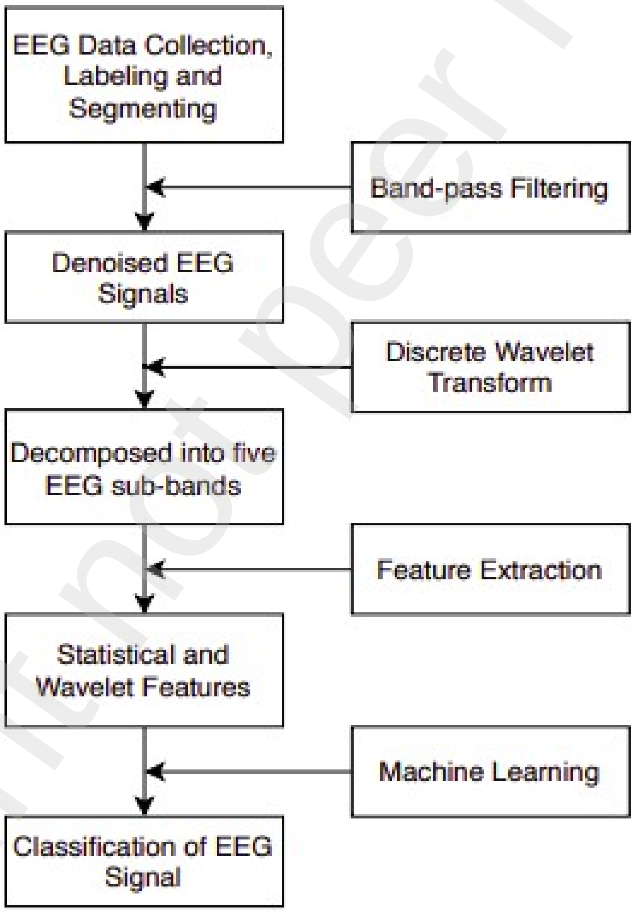

Figure 2: Describing the seizure prediction process using a simple flowchart, from preprocessing to classification.

Signal data up to 1 minute before seizure/s is considered as pre-ictal. In reality, pre-ictal could be as long as 30 minutes before the seizure starts. However, to make it fast and space-efficient, only 1 minute before the seizure begins. The 1-minute-long pre-ictal signal is divided into segments of 2 seconds. Therefore 30 pre-ictal segments are created from a *.edf* file containing one seizure reading, and 60 are formed for two seizure readings. It is essential to have a balanced dataset. Therefore, for 30 extracted pre-ictal segments, 30 inter-ictal segments are extracted as well. Inter-ictal segments are extracted from the beginning of the signal if there are at least 10 minutes between pre-ictal segments and the signal's start. Otherwise, inter-ictal segments are extracted from the end of the signal in case of overlap. When reading inter-ictal segments of the signal, extra precaution is taken to prevent overlapping of pre-ictal and inter-ictal segments.

2.1.2 Signal Processing Filter

Pre-ictal and inter-ictal segments are filtered by a second-order bandpass Butterworth filter with 0.5 and 40 Hz cutoff frequencies. Butterworth filter is ideal because it offers good transition band characteristics at low coefficient orders, which can be implemented efficiently. The specified range of frequencies is chosen because no relevant seizure activity exists outside this range. No seizure activity occurs with a frequency value of less than 0.5 Hz, and the little there is can not be adequately studied by EEG methods. Signals below 0.5 Hz usually represent noise, such as motion, eye blinks, muscle activity or heartbeat.

2.1.3 Selection of EEG Channels

As shown in Figure 3, the EEG electrode channels that are used are FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, and FT10-T8. Since seizures usually occur in different brain areas [21], it is crucial to use data from electrodes scattered around different scalp areas.

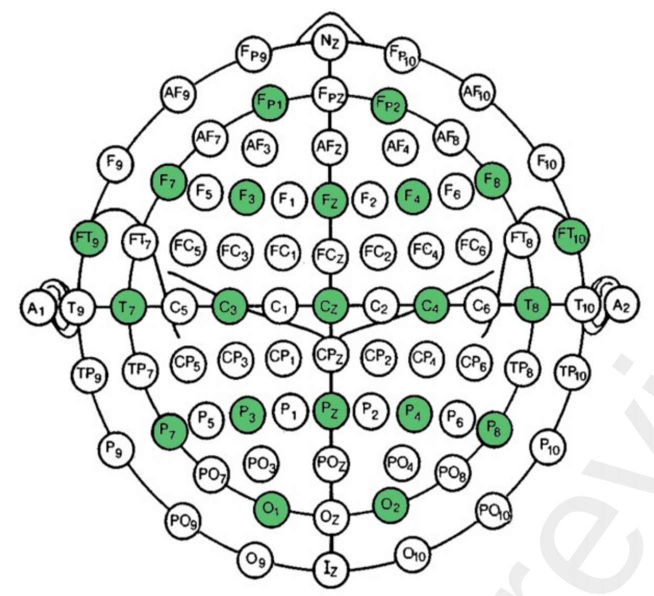

Figure 3: The standardised EEG electrode array of the IFCN [21]. The ones highlighted in green are the ones used in this paper.

2.2 Feature Extraction

After signal preprocessing and filtering, feature extraction was applied to transform the signals into information to train the ML models. In this work, the frequency domain features were extracted using wavelet decomposition. Figure 4 is a schematic representation of a Wavelet decomposition over three levels. The 5th level wavelet decomposition is calculated. The 5th level wavelet decomposition was chosen due to previous studies [19,22,23], proving it effective for seizure prediction. The 5th level approximate and 3rd, 4th and 5th detail coefficients are extracted. Mean, skewness, standard deviation, and root mean square (RMS) values of each coefficient are calculated. A total of 16 wavelet features and four frequency-time features are extracted for each channel. Since there are 23 channels, there is a total of 23x20 = 460 features for each epoch.

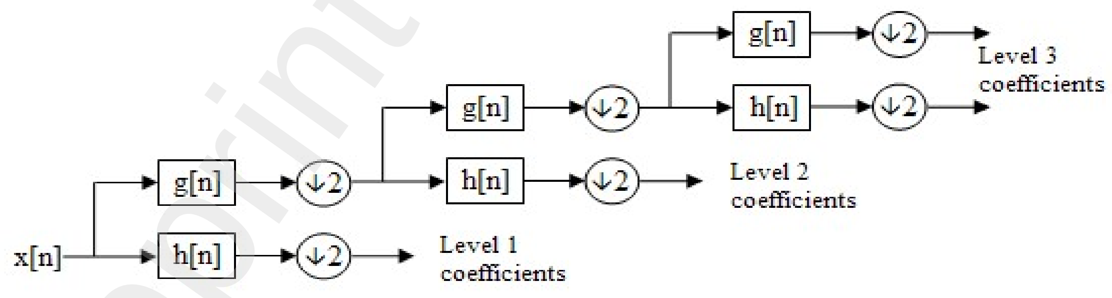

Figure 4: Wavelet decomposition over three levels. g[n] refers to the low-pass approximation coefficients, while h[n] refers to the high-pass detail coefficients

The EEG signals have a sampling frequency of 256 Hz. Thus, the maximum frequency is 128 Hz. First level detail coefficients have a frequency band of 64-128 Hz, and approximation coefficients have a frequency band of 0-64 Hz. Second level detail coefficients have a frequency band of 32-64 Hz, and approximation coefficients have a frequency band of 0-32 Hz. Third level detail coefficients have a frequency band of 16-32 Hz, and approximation coefficients have a frequency band of 0-16 Hz. Fourth level detail coefficients have a frequency band of 8-16 Hz, and approximation coefficients have a frequency band of 0-8 Hz. Fifth level detail coefficients have a frequency band of 48 Hz, and approximation coefficients have a frequency band of 0-4 Hz. Since we use third, fourth and fifth detail and fifth-level approximation coefficients, we use 16-32 Hz, 8-16 Hz, 4-8 Hz and 0-4 Hz.

The sampling frequency was 256 Hz, which means that 256 data points per second were recorded. The epoch window was set to 2*256; in other words, the epochs were divided into two-second segments. After reading and segmenting all recordings, 11100 2-seconds-long epochs are generated, i.e., 5550 inter-ictal and 5550 pre-ictal epochs. Before data division, it is good practice to normalise the features at hand, performed by the normalise function. After re-scaling, features' values fall between 0 and 1. The purpose of normalisation lies in that specific machine learning models require normalised data as input to converge to a good result [24].

2.3 Statistical Features

Four time-frequency features are extracted from the data points inside a segment for each epoch. The four features are mean, standard deviation, skewness and the root mean square.

2.3.1 Mean

The mean describes a set of data by identifying the central position within. It is a central tendency measure defined in (2.1), as proved by [25].

$$A = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{x_1 + x_2 + \ldots + x_n}{n} \tag{2.1}$$

2.3.2 Standard Deviation

It is a statistical feature that explains the data distribution concerning the mean and is defined in (2.2), as proved by [25].

$$\boldsymbol{\sigma} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}-\mathbf{1}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}(x_{\mathrm{i}} - \bar{\boldsymbol{x}})^{\mathbf{2}}} \tag{2.2}$$

2.3.3 Skewness

Skewness is a measure of asymmetry. If a variable's probability distribution around its mean is not symmetrical, it is considered skewed. The equation for skewness is defined in (2.3), as proved by [25].

$$SK = \frac{(x_{\mathrm{i}} - \mu)^3}{\sigma^3} \tag{2.3}$$

2.3.4 Root Mean Square (RMS)

The root means square (RMS) is defined as the square root of the mean square and is defined in (2.4), as proved by [26].

$$RMS = \sqrt{\frac{\sum_{i=1}^{N}({x_1}^2 + {x_2}^2 + \ldots + {x_{\mathrm{n}}}^2)}{N}} \tag{2.4}$$

2.4 Classification

2.4.1 Support Vector Machine

The Support Vector Machine for Binary Classification was used. As the data is highly non-stationary and not linearly separable, the radial basis function (RBF) kernel was used.

2.4.2 K-Nearest Neighbour

The value of K was set to five, and the distance function was set to euclidean. An immense K value would have been computationally expensive, and thus, it was avoided.

2.4.3 Ensemble Classifier (Random Forest)

The Bag method was used, which is suitable for binary classification tasks [27]. The Bag method, also known as Bootstrap aggregation, uses bagging with random predictor selections at each split (random forest) [27].

2.5 Performance Metrics and Testing

The K-fold cross-validation technique was applied to split the train and test data and test the models' performance. Ten is the number of folds chosen, which involves dividing the data into ten folds. Nine out of ten folds are used for training the machine learning models, whilst the remaining fold is for testing the models. The entire process is repeated ten times, and a different fold is used for testing each time. Finally, the results are averaged to obtain the final accuracy, sensitivity and specificity values for all the classifiers.

2.5.1 Confusion Matrix

A confusion matrix, also known as an error matrix, is a performance metric that includes a table visualisation with columns and rows. The columns represent the instances in a predicted class, while the rows represent the instances in an actual class. In a binary classification context, a 2x2 matrix is generated, and from the table, other metrics can be derived to measure the overall performance of a classification system.

2.5.2 Accuracy

The accuracy metric refers to the number of correctly classified samples divided by the total number of samples. Accuracy is defined in (2.5), as proved by [28].

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2.5}$$

2.5.3 sensitivity

The sensitivity metric refers to the percentage of test data seizures the model correctly classified. The metric is defined in (2.6), as proved by [28].

$$sensitivity = \frac{TP}{TP + FN} \tag{2.6}$$

2.5.4 Specificity

The specificity metric refers to the percentage of non-seizure test data correctly classified as non-seizure data by the model. Specificity is defined in (2.7), as proved by [28].

$$specificity = \frac{TN}{TN + FP} \tag{2.7}$$

2.5.5 False Positives Rate

The false positives rate is the count of false-positive classifications divided by the total of positive classifications. It is defined in (2.8), as proved by [28].

$$FPR = \frac{FP}{FP + TN} = 1 - specificity \tag{2.8}$$

2.5.6 False Negatives Rate (FNR)

The false negatives rate is the count of false-negative classifications divided by the total of negative classifications. It is defined in (2.9), as proved by [28].

$$FNR = \frac{FN}{FN + TP} = 1 - sensitivity \tag{2.9}$$

2.5.7 The receiver operating characteristic (ROC) and the area under the curve (AUC)

The receiver operating characteristic (ROC) curve is a graph used to assess a classifier's performance. The graph includes plotting the true positive rate (TPR), as defined in (2.10), against the false positive rate (FPR), as described in (2.11), and proved by [29], to assess the classification model's performance at discriminating between classes.

$$TPR = \frac{TP}{TP + FN} = sensitivity \tag{2.10}$$

$$FPR = \frac{FP}{FP + TN} = 1 - specificity \tag{2.11}$$

The area under the curve (AUC) describes the separability measure a machine learning model can perform. The larger the AUC value, the better the machine learning model is at accurate classifications. Typically, an outstanding classification model has an AUC near 1, while a poor performing model has an AUC closer to 0.

3 Results

Figures 5, 6 and 7 show confusion matrices for all the classifiers used in this paper. Table 3.1 includes a summary of the relevant metrics chosen for this study. The results are the averages of all results obtained from applying 10-fold cross-validation, so no results are shown for each testing fold. The table also includes each classifier's false positives and negatives rates, calculated from the confusion matrices. The number of pre-ictal and interictal samples is 11100, i.e., 5550 for each of the two unique seizure phases. One sample includes the extracted features of either one pre-ictal or inter-ictal epoch, including a two-second EEG recording.

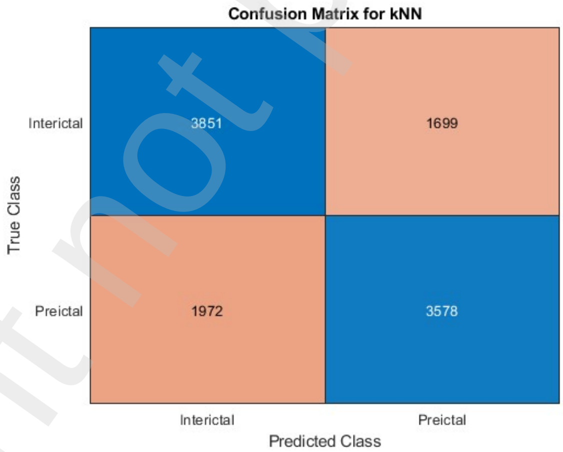

Figure 5: The confusion matrix for KNN.

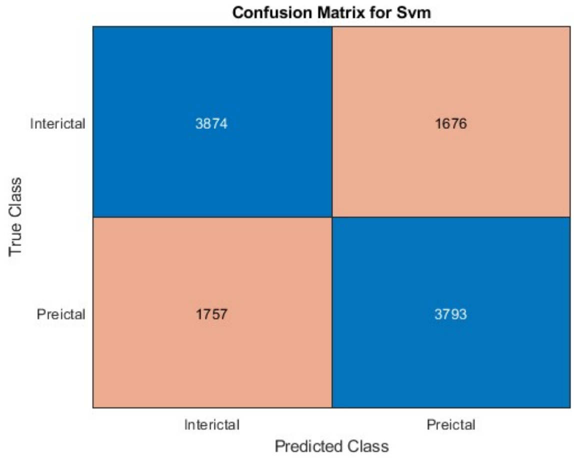

Figure 6: The confusion matrix for SVM.

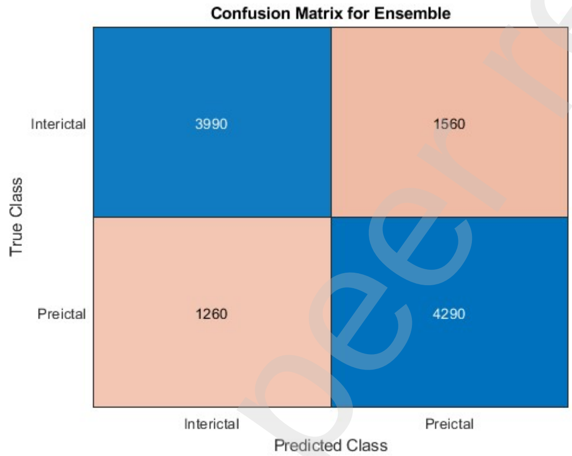

Figure 7: The confusion matrix for the Ensemble classifier.

Table 3.1: Table consisting of accuracy, specificity, sensitivity, false positives, false negatives, and AUC metrics for all the classifiers used. The number of samples is 11100, i.e., 5550 each for pre-ictal and inter-ictal seizure phases.

Classifier	No. of Samples	Accuracy (%)	Specificity (%)	Sensitivity (%)	False Positives (%)	False Negatives (%)	AUC (%)
KNN	11100	66.93	69.39	64.47	35.54	30.61	72.59
SVM	11100	69.07	69.80	68.34	31.66	30.20	75.36
Ensemble	11100	74.59	71.89	77.30	22.70	28.11	82.57

Table 3.1 shows that KNN, SVM, and the ensemble classifier (Random Forest) achieved respectively 66,93%, 69,07% and 74,59% accuracy. The ensemble classifier scored the highest sensitivity (77,30%) and specificity (71,89%), which were promising. KNN and SVM obtain an FPR and FNR of over 30%, undesirable in a medical diagnosis context. A high FPR would indicate that patients would frequently

receive unnecessary treatment, and a high false-positive rate would lead to frequent false diagnostics, which could have severe repercussions.

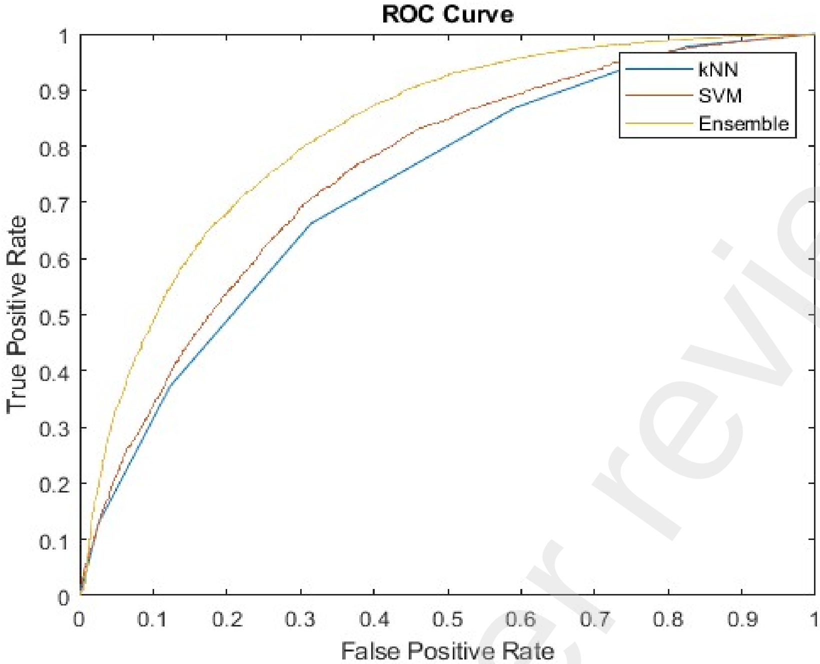

Figure 8: The AUC (Area Under The Curve) ROC (Receiver Operating Characteristics) curve

4 Discussion

Figure 8 shows that all the AUC values are over 70%, which indicates an acceptable discrimination performance, with the ensemble classifier having an AUC of 82,57%, which is promising. However, in medical diagnosis, it is sought after that classification models have a very significant AUC, if possible, over 90%. The classifiers are promising as prototypes, but it would be crucial that the classifiers be improved further. Despite this, the ensemble classifier shows promising results and could be used by medical experts for seizure prediction purposes.

This paper further contributes to the ongoing research in epileptic seizure prediction and detection in a patient independent setting. In more detail, this study compares and evaluates three machine learning algorithms that showed promising results for classifying EEG signals across patients with high variance. As explained in section 2.4, most of the successful classifiers were applied to detect patient-specific EEG signals. In most studies, the successful patient-independent classifiers involved using a high-performance computing cluster (HPCC), or a dataset with slight EEG variance across patients. In this study, a patient-independent, binary classifier was successfully implemented to distinguish between pre-ictal and inter-ictal seizure states to a certain degree, without using many samples.

This study obtained lower performance metrics than some patient-independent classifiers described in section 2.4. It is to note that some of the machine learning classifiers implemented in the studies mentioned involve using datasets that had fewer patients or had little variability across EEG signal behaviour. Some studies included a more selective channel selection, which involved manually selecting the more significant channels and excluding the channels impacting the classification performance negatively. Some studies also utilised computing clusters to analyse copious amounts of data and use extended epoch durations. The classifiers in this study did not perform as well as most mentioned classifiers, which was expected. Many studies mentioned include carefully tailored feature engineering for each patient to achieve high-performance metrics for a particular dataset. This approach is flawed because it limits the benefits of the classifiers if another dataset is used. This limits the usefulness of their methods if a different dataset is used. Although the performance metrics achieved are not satisfyingly high enough, the classifiers can still be used for clinical diagnostic purposes.

The impact of a significant false negative and false positive rate is considerable. In a real-life scenario, where a seizure prediction device is deployed to detect seizure onsets to administer patients' appropriate therapies, it is difficult to describe which would have the most negative impact. A false positive would lead to unnecessary treatment, and a false negative would mean that no therapy would be given during an up and coming seizure. It is also hard to define how high the performance metrics need to be considered beneficial or embedded in a device. However, misclassifications are acceptable because some risks are worth taking if the seizures are extreme. A looming constraint is collecting enough data to properly train the models and implementing the classifiers in a higher-performing programming language, such as the statically typed language C++.

5 Conclusions

This paper's objectives were to analyse several machine learning models for their effectiveness in accurately predicting epileptic seizures by discriminating between pre-ictal and inter-ictal EEG data to a certain degree. While evaluating the methods using one of the largest seizure EEG datasret, The ensemble classifier (Random Forest) results are promising, with an accuracy value of 74,59%, sensitivity of 77,30%, and specificity of 71,89%, which are good results for a patient-independent classifier. Two other methods, KNN and SVM, performed similarly in accuracy, sensitivity and specificity, and SVM was slightly better in accuracy and sensitivity than KNN. However, the ensemble classifier outperformed KNN and SVM in every considered metric. With some further work, the classifiers can be improved to be as effective as some of the more promising patient-independent classifiers trained on a few samples across a large patient spectrum. In reality, pre-ictal could be as long as 30 minutes before the seizure starts. However, to make it fast and space-efficient, only 1 minute before the seizure begins.

Other datasets, such as the Temple University EEG Corpus [30], can also be analysed through the same methods.

More machine learning algorithms could be applied to find the method with the best performance. EEG channel selection could be used to discard any channels with redundant signals. The effectiveness of combining multiple different ML models can also be assessed. Furthermore, the methods can be examined for predicting other diseases such as stroke.

This project's aims have been met with a successful epileptic seizure prediction method compared to other implemented methods. The progress achieved provides a solid basis for further research and development of machine learning models that can discriminate between seizure states across various subjects.

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