Seizure Detection Using Machine Learning Algorithms

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Abstract—In this paper we study the use of machine learning algorithms in detecting epileptic seizures. We train multiple classifiers using frequency domain predictors from the intracranial electroencephalogram (iEEG) signals. The classifiers studied are "Support Vector Machines" and "K-Nearest Neighbors". Using multiple criteria for performance evaluation discussed in this paper we arrive at the best suitable classifier for seizure detection application.

Keywords: Epilepsy, detection, intracranial electroencephalogram, classifiers, interictal, preictal

1. Introduction

About 1% of the world's population suffers from epilepsy which causes spontaneous seizures. With known side effects, anticonvulsant medications are prescribed at sufficiently high doses to prevent seizures but between 20-40% of patients report no improvement. Common surgical removal of seizure focal point in young children can cause other brain dysfunctionality, and for many, the spontaneous seizures will continue to happen after the surgical procedures. Due to the possibility of a seizure occurring at any time without warning many patients suffer from chronic depression. Seizure prediction systems can be life changing for patients with epileptic seizures. By accurately identifying the periods in which seizure occurrence has a higher chance of happening we can help epileptic patients live a more normal life. If in an unfortunate case a patient with epilepsy engages in activities, such as driving or swimming, with the help of such devices they can pause or avoid a potential harm upon receiving the seizure alert and administering medications. We use machine learning techniques with the goal of predicting naturally occurring seizures in adults and children with epileptic seizures.

Our algorithm can be easily implemented in a wearable seizure warning device in conjunction with an implantable iEEG sensor. A hand-held personal advisory device can alert the patient of a possible epileptic seizure.

A prior literature review of similar works can be found in [1] through [11].

2. Background

Seizure has been defined as "a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain." by the International League Against Epilepsy (ILAE). Seizure by itself has a distinct set of signs and symptoms such as losing consciousness, which is followed by confusion, having uncontrollable muscle spasms and falling. Although in a typical seizure the borders of ictal (during a seizure), interictal (between seizures) and postictal (after a seizure) often are indistinct looking at the epileptic Intracranial Electroencephalogram signals (EEG) can be helpful for detection, classification and prediction.

From medical point of view there are common EEG patterns that helps the medical professional detect the seizure. But clinicians would also rely on researchers to come up with ways of making this detection process easier and more reliable.

Some researchers have used motion sensors [11] in seizure detection. These systems can be useful in the detection of motor seizures, such as tonicÀšclonic (which involves electric discharges instantaneously that covers the entire brain) or myoclonic seizures (which are brief shock-like jerks of a muscle or group of muscles). Accelerometers that are useful in motion detection can only be useful in the detection of ongoing seizures. But none the less this detector can potentially get hooked to a device that can then contact caretakers to alert them of ongoing seizures.

3. Methodology

Our iEEG data consists of labeled interictal and preictal signals. Intercital iEEG represents the background periods whereas preictal iEEG represents the before-seizure periods. By accurately identifying the preictal periods from the interictal ones we will be able to essentially predict the upcoming seizure onset.

To identify the preictal periods, we looked at the unique features that exist in time and frequency domain. This process as shown in the block diagram below happens in the 'transformation' and the "feature extraction" blocks right after the data collection.
In the next block we explore the use of multiple classifiers before arriving at the final block. In this step we designed linear and non-linear classifiers such as SVMs and KNNs. The last step in the process is choosing the best classifier using the AUC (Area Under The Curve) of ROC (Receiver Operating Characteristics) curve and the accuracy metrics as well as the complexity, speed and memory usage. Our methodology can be summarized as the following in Figure 1:

Fig. 1: Block Diagram of the Classification Process

3.1 Dataset

The iEEG data used in this study consists of two groups of interictal and preictal signals. Interictal iEEG represents the normal state and preictal iEEG represents the period just before and leading up to the seizure. Both signals have been sampled at 400Hz rate.

The interictal periods were restricted to be at least four hours before or after any seizure. One hour sequences of interictal ten minute data segments are also examined. The interictal data were chosen randomly from the full data record, with the restriction that interictal segments be as far from any seizure as can be practically achieved, to avoid contamination with preictal or postictal signals. In the long duration recordings it was possible to maintain a restriction of one week before or after a seizure.

3.2 Transformation and Feature Selection

The review of the current literature revealed that based on the nature of the iEEG signals it appears that the magnitude of different frequencies during the interictal and preictal can be served as a prominent feature to identify the healthy and pre-seizure states[3]. This will be coupled with other pre-processing filters to extract the desired features. Distribution of energy in different frequency bands from the figure below shows that there is a strong evidence of a change in the FFT pattern between interictal and preictal states. This has been proven across multiple test subjects. Power spectra in the lower frequency range tends to have higher energy in preictal iEEG. This is used as feature vector for the binary classifiers.

Figure 2 shows the frequency domain representation of the interictal and preictal signals.

Fig. 2: Frequency Domain Representation of the iEEG Signals. Interictal vs. Preictal.

3.3 Classification


As a vital part of the process in our models we use 5-fold cross validation technique to ensure accurate results[4]. As a summary in 5-fold cross-validation, the original sample is randomly partitioned into 5 equal size subsamples. Of the 5 subsamples, a single subsample is set aside as validation data for testing the model, and the remaining 4 subsamples are used as training data. The cross-validation process is then repeated 5 times, with each of the 5 subsamples used exactly once as the validation data (we repeated this process for every single classifier we trained). The 5 results from the folds can then be combined or averaged to produce a single estimation. The advantage of this very accurate method is that all observations are used for both training and validation, and each observation is used for validation exactly once. So this way we would avoid false accuracy rates.

For classification problems, one typically uses stratified 5-fold cross-validation, in which the folds are selected so that each fold contains roughly the same proportions of class labels.

3.3.1 Support Vector Machine

A support vector machine is designed as a decision hyperplane to separate our two classes. The optimal plane should be in the middle of the two classes, so that the distance from the plane to the closest point on either side is the same.
Kernel SVM is the use of a mapping function that maps our data into a higher dimensional space, then, the maximization and decision rule will depend on the dot products of the mapping function for different samples. We used polynomial of degree two and three as well as the Gaussian kernels, fine to coarse, to compute the best support vector machine.

3.3.2 K Nearest Neighbor

K-Nearest Neighbor classifier is a non-parametric approach, which classifies a given data point according to the majority of its neighbors. The KNN algorithm completes its execution in two steps, first finding the number of nearest neighbors and second classifying the data point into particular class using first step. To find the neighbor, it makes use of distance metrics like euclidean distance. It chooses nearest k samples from the training set, then takes majority vote of their class where k should be an odd number to avoid ambiguity. Just like the SVMs, we analyzed fine to coarse, cosine and cubic kernels.

3.4 Performance Measures (Accuracy and Area Under Curve)

Accuracy of classifier refers to the ability of the classifier. In particular, the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.
Equation 1 defines the accuracy in terms of TP, TN, FP and FN:

\[
\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}
\]

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Figure 3 visualizes the accuracy comparison of the eleven classifiers used in this experiment.

Fig. 3: Accuracy Comparison of SVN and KNN Classifiers

Using the same terminology as above the True Positive Rate and False Positive Rate are defined in equations 2 and 3 respectively. These two equation also define the Sensitivity and Specificity.

\[
\text{True Positive Rate (Sensitivity)} = \frac{TP}{TP + FN} \tag{2}
\]

\[
\text{False Positive Rate} = 1 - \text{Specificity} = 1 - \frac{TN}{TN + FP} \tag{3}
\]

The ROC curve is then created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity, recall or probability of detection in machine learning. The false-positive rate is also known as the fall-out or probability of false alarm and can be calculated as specificity.

Figure 4 illustrates the ROC curves of SVMs and the KNNs designed for our experiment.

Fig. 4: ROC plot of SVNs vs KNNs

For the purpose of the illustration and avoid over crowding the graph, we picked the best SVM and best KNN model to show the ROC curve.

4. Results

From the ROC curves above the area under the curve is calculated and used as the second performance measure next to the accuracy of the classifier.
This comprehensive study of the support vector machines and the k-nearest neighbors on the iEEG data shows that there is a trade off that needs to be made when selecting the best classifier. Linear SVM and the coarse KNN have similar performance where linear SVM outperforms the coarse KNN in accuracy and the coarse KNN slightly outperforms linear SVM in the AUC measures. These two are also computationally faster and more efficient.
than the other classifiers. Either one would result in a very satisfying classification.
Table 1 brings together both performance measures of accuracy and the area under the ROC curve. This is particularly helpful in picking the most suitable classifier for this application.

Table 1: Accuracy and AUC in SVM and KNN classifiers.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>AUC</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear SVM</td>
<td>0.77</td>
<td>71.6%</td>
</tr>
<tr>
<td>Quadratic SVM</td>
<td>0.53</td>
<td>51.3%</td>
</tr>
<tr>
<td>Cubic SVM</td>
<td>0.39</td>
<td>41.4%</td>
</tr>
<tr>
<td>Fine Gaussian SVM</td>
<td>0.74</td>
<td>71.5%</td>
</tr>
<tr>
<td>Medium Gaussian SVM</td>
<td>0.77</td>
<td>71.5%</td>
</tr>
<tr>
<td>Coarse Gaussian SVM</td>
<td>0.77</td>
<td>71.4%</td>
</tr>
<tr>
<td>Fine KNN</td>
<td>0.62</td>
<td>62.5%</td>
</tr>
<tr>
<td>Medium KNN</td>
<td>0.75</td>
<td>68.9%</td>
</tr>
<tr>
<td>Coarse KNN</td>
<td>0.80</td>
<td>71.4%</td>
</tr>
<tr>
<td>Cosine KNN</td>
<td>0.73</td>
<td>69.3%</td>
</tr>
<tr>
<td>Cubic KNN</td>
<td>0.75</td>
<td>69.3%</td>
</tr>
</tbody>
</table>

Other factors to also keep in mind when choosing a good classifier are summarized in Table 2. This table shows that the properties of different model types of SVNs and KNNs. Linear SVM always wins the interpret-ability contest in binary classification cases. Evaluating all factors, the linear SVM shows good results with fast speed and medium memory usage and easy interpret-ability. The coarse KNN could also be considered as the best classifier if the interpretation of the results are not of a concern. On the other hand the cubic KNN should never be considered for this application.

Table 2: Accuracy and AUC in SVM and KNN classifiers.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Speed</th>
<th>Memory usage</th>
<th>Interpret-ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Easy</td>
</tr>
<tr>
<td>Quadratic SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Cubic SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Fine Gaussian SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Medium Gaussian SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Coarse Gaussian SVM</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Fine KNN</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Medium KNN</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Coarse KNN</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Cosine KNN</td>
<td>Fast</td>
<td>Medium</td>
<td>Hard</td>
</tr>
<tr>
<td>Cubic KNN</td>
<td>Slow</td>
<td>Medium</td>
<td>Hard</td>
</tr>
</tbody>
</table>

This table shows that the properties of different model types of SVNs and KNNs. Linear SVM always wins the interpret-ability contest in binary classification cases. All factors counted the linear SVM shows good results with fast speed and medium memory usage and easy interpret-ability. The coarse KNN could also be considered as the best classifier if the interpretation of the results are not of a concern. On the other hand the cubic KNN should never be considered for this application.

5. Implementation and Future Work

Once the best model is identified the model can be implemented on a chip. The chip would be receiving iEEG data in real time that is collected from the implanted electrodes in a patient with epilepsy. The mentioned chip process the data and figure out what state the patient is in. If a preictal period is detected then the chip would wirelessly communicate with a hand-held device and generate an alert to the patient. If this device is somehow connected to a caregiver’s or medical professional’s device they would be notified as well. This device could potentially contact the emergency responders.

Figure 5 shows how this algorithm can be implemented in a chip and be used as a form of a hand held device alerting patient of an incoming seizure.

6. Conclusion

We presented and analyzed multiple machine learning algorithms that use iEEG signals to detect the onset of epileptic seizures. Also using a sophisticated multi-factor selection process we arrived at the two suitable model to use for clinical application in regards to SVMs and KNNs. This detector simplifies the implementation of the seizure prediction system into a wearable device.
This system can be potentially coupled with a closed loop control system to suppress the seizure intensity and mitigate the consequences of the drug-resistant seizures. The block diagram of implementation of a future alerting device has been proposed in our paper as well.

7. Multiple Case Study

To complete our investigation, we went beyond the patient specific classifiers and looked across multiple subjects. We looked at the ROC metric of the best SVM and the best KNN model then compared the results in the table below.

This table summarizes the two human and two animal iEEG study for epileptic seizure detection.

Table 3: AUC comparison of SVM and KNN classifiers across multiple subjects.

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>SVM</th>
<th>KNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>0.79</td>
<td>0.81</td>
</tr>
<tr>
<td>Subject 2</td>
<td>0.87</td>
<td>0.89</td>
</tr>
<tr>
<td>Subject 3</td>
<td>0.84</td>
<td>0.87</td>
</tr>
<tr>
<td>Subject 4</td>
<td>0.66</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Our results are consistence with what we have seen in a single patient specific modeling. The KNN still proves to have a slight edge over the SVM in terms of AUC of ROC curve. The accuracy follows the same pattern. However the sub-type of the SVM or KNN might vary from patient to patient.

The visualization of the SVM and KNN study across multiple subjects is shown in the Figure 6.

![Fig. 6: Multi-Subject Study Results](image)

Acknowledgment

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References