Epileptic Seizure Recognition

Support Vector Machine & Random Forest

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ABSTRACT

Epilepsy is a neurological disease that involves irregular actions, impulses, and lack of consciousness in some cases. Seizures, which are periods with irregular patterns of brain activity, are caused by this. To have successful instantaneous care and reduce the risk of damage, early diagnosis or identification of epileptic seizures is crucial. This has become an active research field, fueled by the growing affordability of EEG capture devices and the rapid growth of algorithms for machine learning. This report provides a thorough comparison of two classification algorithms: Support Vector Machine (SVM) and Random Forest (RF). Such approaches have been compared to different used algorithms in literature based on their accuracy, f1 score, and interpretability. The report results show that RF and SVM can both be used for this problem domain. Although SVM and RF have nearly the same accuracy, it is recommended to use the RF model for further analysis because of its higher interpretability.

KEYWORDS

Epileptic Seizure Recognition, Machine learning, Random Forest, Support Vector Machine

1. Introduction

Epilepsy is a neurological disorder that affects the Central Nervous System (CNS) causing seizures or unusual behaviours, abnormal brain activity, or loss of consciousness sometimes [1]. It can affect anyone with no preferences in race, gender, age, or ethnic background. The symptoms of seizures can vary among epileptic patients very widely. Some of them may stare blankly for a few seconds during a seizure, while others may repeatedly twitch their arms or legs [1]. Brain cells communicate with each other by sending electrical signals in an orderly pattern. In epilepsy, these electrical signals become abnormal, giving rise to an electrical storm that produces seizures. These abnormal electrical storms may be within a specific part of the brain or be generalized, depending on the type of epilepsy [2]. Seizure signs and symptoms differ among epileptic patients and they may include temporary confusion, psychic symptoms such as fear or anxiety, loss of consciousness, or uncontrollable jerking movements [1]. These symptoms vary depending on the type of seizure that the patient has. In most cases, the patient will tend to have the same type of seizure each time.

Seizures can be categorized into two main categories based on their initial start point in the brain: focal and generalized. Focal seizures are that type of seizures that result from an abnormal activity in just one area of the brain [1]. They fall into two categories depending on consciousness level during the seizure. Symptoms of focal seizures may be confused with other neurological disorders, such as migraine, narcolepsy or mental illness. On the other hand, generalized seizures appear to involve all areas of the brain. They are categorized into 6 types depending on the muscles and movements involved [1].

Epilepsy has no identifiable cause in about half the people with the condition. In the other half, the condition may be traced to various factors. Researchers have linked some types of epilepsy to specific genes, but for most people, genes are only part of the cause of epilepsy. Certain genes may make a person more sensitive to environmental conditions that trigger seizures [3]. Infectious diseases, such as meningitis, AIDS and viral encephalitis, can cause epilepsy [3]. Moreover, Head trauma as a result of a car accident or other traumatic injury can cause epilepsy [4]. Epilepsy can sometimes be associated with developmental disorders, such as autism and neurofibromatosis.

A physician can make sure of diagnosing a patient with epilepsy based on the Electroencephalogram (EEG) record and symptoms. The EEG is a test that records the electrical signals of the brain by using small electrodes attached to the scalp. Brain cells do communicate with each other using electrical impulses. They always work, even if the person is asleep. That brain activity will show up on an

EEG recording as wavy lines. It's a snapshot in time of the electrical activity in the brain [5]. The EEG looks like a series of wavy lines that look different depending on subject state whether awake or asleep during the test, but there is a normal pattern of brain activity for each state. If the normal pattern of brain waves has been interrupted, that could be a sign of epilepsy or another brain disorder [5].

2. Problem Definition

Recently. new epilepsy prediction methods have been developed for different purposes. These techniques can assist the patient to predict the seizure before it happens. Meanwhile, epilepsy prediction is particularly useful for the wellbeing of the patient. Predicting a seizure before its onset can help the patient take the necessary precautions needed or seek a medical emergency. Consequently, this report focuses specifically on epilepsy prediction that requires the detection of the seizure features from an EEG. This report focused on using 2 main models for classification: Support Vector Machine (SVM) and Random Forest (RF). Both models were used for predicting a set of test samples and their accuracies were used for comparison to choose the best model.

3. Relevant Prior Work

Most of the papers working with the same dataset we used for EEG signals performed a type of fourier transformation on the data as a part of their preprocessing. In [6], they used Fast Fourier Transform (FFT) which converts our problem from a time domain to a frequency function. They also used the decision tree as the classifier and 5-fold cross validation. However, they dealt with the problem as a 2-class problem instead of a 5-class as they only used class A & E (1 & 5) making their classifier into either seizure or non-seizure. Their average sensitivity was 98.87% and specificity was 98.50% as shown in table 1.

Obtained 5-fold CV test results by decision tree classifier for detection of epileptic seizure

Fold	Training			Test			Classification accuracy (%)	Specificity (%)	Sensitivity (%)
	Patient	Normal	Total	Patient	Normal	Total			
1	1280	1280	2560	320	320	640	99.80	99.68	100
2	1280	1280	2560	320	320	640	99.80	99.68	100
3	1280	1280	2560	320	320	640	98.00	97.81	98.11
4	1280	1280	2560	320	320	640	98.90	98.45	99.36
5	1280	1280	2560	320	320	640	96.90	96.87	96.87
Average results							98.68	98.50	98.87

Table 1: [6] results

In [7],they performed discrete wavelet transformation which is the same as FFT but it takes into consideration the location of the wave. They also transformed their problem as [6] into a 2-class problem with class A & E.They used SVM as their classifier.Moreover, they did dimension reduction using Principal components analysis (PCA), independent components analysis (ICA) and linear discriminant analysis (LDA) to see which is the best. Their results showed that PCA was the worst for feature selection with sensitivity and specificity of 99.0% and 98.50% respectively as shown in table 2.

Feature extraction method	Accuracy	Specificity	Sensitivity
PCA (%)	98.75	98.5	99.00
ICA (%)	99.5	99	100
LDA (%)	100	100	100

Table 2: [7] results

[8] also used the same dataset we utilized, However, they were the only ones that used it as a 5-class problem and did not perform a transformation as a pre-processing. They performed normalization instead. They used the Deep Neural Network (DNN) as their classifier then compared its accuracy with other traditional classifiers for this problem domain: multilayer perceptron (MLP) and k-nearest neighbor (KNN). The results showed that the DNN is the best classifier in terms of accuracy. Hence, the paper claimed that the DNN model exhibits the best signs of performance and can be concluded as the ideal classifier for this problem, despite the fact that DNN has the lowest F1 score among the three as shown in table 3.

	DNN (%)	KNN (%)	MLP (%)
Accuracy	80	76	78
Precision	64	70	77
Recall	80	76	79
F-Measure	71	72	78

Table 3: [8] results

4. Proposed Method

As DNN yielded low F1-score and has low interpretability, two models were tested: Random Forest (RF) and Support Vector Machine (SVM) to improve the F1-score and interpretability of the model. The final objective is to find the ideal classifier for this problem domain in terms of interpretability and F1-score.

The used dataset in both models is available online in [9]. The dataset was originally collected using a 128-channel amplifier system and the EEG signal recorded for 3.3 h and sampled at 173.61 Hz while the settings of the bandpass filter were set at 0.53–40 Hz (12 dB/oct.). The data were digitized at 173.61 samples per second using 12 bit resolution. After analyzing for artifacts, e.g., because of activity in the muscular area or optic movement, 28 channels were excluded and only 23.6 seconds were used.

The original dataset contains 5 different folders each representing a specific class. Each folder has 100 files (File/subject). Each file is a recording of brain activity for 23.6 seconds. The corresponding time-series is sampled into 4097 data points. They divided and shuffled every 4097 data points into 23 chunks, each chunk contains 178 data points per 1 second, and each data point is the value of the EEG recording at a different point in time. In total, we have 23 x 500 = 11500 pieces of information(row), each information contains 178 data points for 1 second(column). The last column represents the label y {1,2,3,4,5}. These 5 labels represent 5 classes: class 1 represents an epileptic activity inside the brain, while classes 2-5 represent normal brain activity but with different actions.

SVM is one of the common techniques used in the classification of the issue of seizure prediction. It is a supervised learning method that tries to find the best hyperplane to distinguish between the two classes and optimize the distance between the two classes.

RF creates decision trees on randomly selected data samples, gets prediction from each tree and selects the best solution by means of voting. It can be used in both classification and regression problems. It also provides a pretty good indicator of the feature importance which gives it higher interpretability than most classifiers..

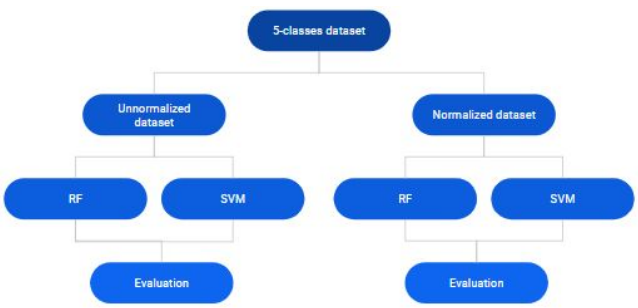

Figure 1: The proposed algorithm

The proposed algorithm followed the pipeline shown in figure 1 and it was repeated for a 2-classes dataset after changing its classes into 2 main classes instead of 5. These 2 classes represented the 2 main classes to be distinguished based on EEG features which are seizure occurrence or not. The original 4 normal classes of EEG data were gathered in one class in this modified 2-classes dataset. .

The dataset was tested twice for each model: with normalization and without normalization. The accuracy and f1 score of all of these models were then compared to get the best model among them. The normalization method used by sklearn scales the data so that the mean is zero and variance is 1. Normalization is a method that makes the training process less sensitive to the scale of the features. It results in getting better coefficients after training. For better validation for model performance, the dataset was splitted into training, validation and testing data and their accuracies were reported. The normalization step was first fitted to the training data, then applied on both validation and testing data to be transformed.

5. Evaluation/Experiments/Result

5.1. List of questions the experiments are designed to answer

This project main objective was to examine EEG signals data to answer the following questions:

1. Can we use EEG signals to classify epilepsy patients to seizure and non seizure patients?
2. Can SVM or RF be recognized as the ideal classifier for this problem domain? If so, Which one of them is better?
3. Is our problem better examined as a 2-class problem like [6] & [7] or 5 class problem like [8]?
4. Can standard normalization improve the classification & perform better than transformation?or not?

5.2. Details of the experiments, observations, findings.

For the SVM model, it was tested 3 times with different kernels: linear, polynomial, and radial. The radial kernel gave the highest accuracy among the 3 kernels with a notable difference and that is why it was fixed to be used in all the remaining SVM models. The splitting percentage of data for training : validation was reported 2 times: 80:20 and 70:30 and their corresponding accuracies and f1 scores were reported. The accuracies of these models are reported in tables 4 and 5. Moreover, their f1 scores are reported in tables 6 and 7.

	SVM (normalized data) 5 classes			SVM (unnormalized data) 5 classes
	kernel = radial	kernel = linear	kernel = poly	kernel = radial 0.3
training	57	37	37	57
validation	53	27	27	53
test	53	29	26	53
training	58	34	38	58
test	20	20	20	55

Table (4): SVM models accuracies for 5-classes dataset

	SVM (normalized data) 2 classes		SVM (unnormalized data) 2 classes
	kernel = radial 0.3	kernel = radial 0.2	kernel = radial 0.3
training	98	98	98
validation	97	97	97
test	97	97	97
training	98	98	98
test	80	80	97

Table (5): SVM models accuracies for 2-classes dataset

	SVM (normalized data) 5 classes			SVM (unnormalized data) 5 classes
	kernel = radial	kernel = linear	kernel = poly	kernel = radial 0.3
training	55	38	29	55
validation	51	27	18	51
test	51	29	18	51
training	56	36	31	56
test	7	7	7	54

Table (6): SVM models f1 scores for 5-classes dataset

	SVM (normalized data) 2 classes		SVM (unnormalized data) 2 classes
	kernel = radial 0.3	kernel = radial 0.2	kernel = radial 0.3
training	98	98	98
validation	97	97	97
test	97	97	97
training	98	98	98
test	71	71	97

Table (7): SVM models f1 scores for 2-classes dataset

Based on the results shown in tables 4-7, the SVM model using normalized and unnormalized data with a 2-classes dataset gave the highest accuracy and f1 score among these SVM models. It is highlighted in green in tables 5 and 7. Moreover, these models were reevaluated using stratified k-fold method to report the highest accuracy it can achieve and the results were as reported below in table 8

	SVM (unnormalized data) 2 classes	SVM (normalized data) 2 classes
Stratified KFold =5	kernel = radial	kernel = radial
1	97.65	97.69
2	96.86	96.91
3	97	97.04
4	96.86	96.96
5	97	97
overall	97.078	97.12

Table (8): stratified k-fold SVM model testing accuracies for 2-classes unnormalized and normalized dataset

Both SVM models of normalized and unnormalized 2-classes dataset gave nearly the same accuracies using stratified k-fold. Although they are close, it is recommended to use the normalization method for better sensitivity from the model in further investigations.

For the RF model, it was firstly tested randomly at two different numbers of trees 40 and 50. Using a Grid search algorithm with a range between 5 and 100 with a step of 5, it gave 95 as the best then changing the ranges from 100 to 150 with also a step of 5, it gave 145 as the best number of trees. Despite this, when comparing the results between the 95 trees and the 145, both gave the same results. That is why 95 was chosen as the ideal number of trees, to decrease the computational power. The splitting percentage of data for training : validation was constant as 80:20. The corresponding accuracies and f1 scores were reported. The accuracies of the different trees are reported in tables 9 and 10. Moreover, their f1 scores are reported in tables 11 and 12.

	RF (normalized data) 5 classes			RF (unnormalized data) 5 classes
	40	50	95	95
training	100	100	100	100
validation	65	66	68	68
test	66	66	69	69
training	100	100	100	100
test	66	68	70	70

Table (9): RF models accuracies for 5-classes dataset

	RF (normalized data) 2 classes		RF (unnormalized data) 2 classes
	50	95	95
training	100	100	100
validation	97	98	98
test	97	97	97
training	100	100	100
test	97	97	97

Table (10): RF models accuracies for 2-classes dataset

	RF (normalized data) 5 classes			RF (unnormalized data) 5 classes
	40	50	95	95
training	100	100	100	100
validation	65	66	68	68
test	65	66	69	69
training	100	100	100	100
test	66	68	70	70

Table (11): RF models F1 Scores for 5-classes dataset

	RF (normalized data) 2 classes		RF (unnormalized data) 2 classes
	50	95	95
training	100	100	100
validation	97	98	98
test	97	97	97
training	100	100	100
test	97	97	97

Table (12): RF models F1 Scores for 2-classes dataset

Based on the results shown in tables 9-12, the RF model was not affected by the normalization. Moreover, the chosen parameters that performed the highest accuracy and highest F1 score are highlighted in green. The chosen parameters were reevaluated using stratified 5-fold cross validation and their results were shown in table 13 below.

	RF (normalized data) 2 classes	RF (unnormalized data) 2 classes
	95	95
Stratified KFold =5		
1	98	98
2	97	97
3	98	98
4	97	97
5	97	97

Table (13): Stratified 5-fold RF models testing F1 Scores for 2-classes unnormalized and normalized dataset

Both RF models of normalized and unnormalized 2-classes dataset gave nearly the same accuracies using stratified k-fold.

While investigating the interpretability of the results in the RF using the feature importance, the results showed that when we are dealing with a 5-class problem, feature 11 has the highest weight with 0.09995. The importances of the first 20 features are shown in figure 2 attached below.

```
Variable:                 11 Importance: 0.009995437439961343
Variable:                 13 Importance: 0.00970534083142594
Variable:                103 Importance: 0.009245042001091861
Variable:                160 Importance: 0.009173467108123294
Variable:                159 Importance: 0.008695458424355344
Variable:                 12 Importance: 0.008572288278845938
Variable:                157 Importance: 0.007710302188090627
Variable:                 18 Importance: 0.0076305043797853245
Variable:                 38 Importance: 0.007490151484302998
Variable:                 15 Importance: 0.007265824266410699
Variable:                 16 Importance: 0.007200457332309053
Variable:                101 Importance: 0.007059919216656207
Variable:                161 Importance: 0.00705290652446748
Variable:                156 Importance: 0.00699912624514228
Variable:                123 Importance: 0.006870271330074008
Variable:                152 Importance: 0.006821316723932926
Variable:                145 Importance: 0.006811097132897002
Variable:                 35 Importance: 0.006809941053597274
Variable:                139 Importance: 0.006722262378930338
Variable:                137 Importance: 0.006691411231572104
```

Figure 2: The feature importance of the first 20 features, proving the interpretability of RF

Comparing both proposed models (RF & SVM), the results showed that RF is not affected by the normalization unlike the SVM. Moreover, when dealing with our problem as a 5-class problem, the RF model performed better than the SVM with an F1 score of 70 % in RF and 54% in SVM for the testing data.

6. Conclusion

Both SVM & RF performed better than DNN in the F1 score proving that DNN is not the ideal model for this problem domain as claimed in [8]. Moreover, when dealing with the problem as a 2 class problem like [6] & [7], our models reached nearly the same accuracy and F1 score as them. In conclusion, Support Vector Machine & Random Forest can be considered as the ideal models for this problem domain regardless of the number of classes used, especially that the Random forest provides higher interpretability than the others.

7. Suggestion and Improvement

To further investigate this problem, both the SVM & RF should be used with the transformation as a preprocessing in order to examine whether it would improve the to be even better than the reported results in [6] & [7]. Moreover, it should be tested using the original dataset with the 500 samples and 4097 features and using different combinations of the classes.

8. Workload Distribution

The preprocessing was done by both Mayar and Muhammad together. Muhammad was responsible for the SVM Model and its optimization while Mayar was responsible for the Random forest model and its optimization. Both models were then evaluated using the accuracies and F1-scores. We both worked on models analysis to choose the best model.

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