A Study on Seizure Detection Performance in an Automated Process by Extracting Entropy Features

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***Abstract*—Millions of people of all ages have been diagnosed with epilepsy all over the world. Electroencephalography (EEG), a quantitative component, is vital in identifying and analyzing epileptic seizures. Manual EEG detection takes a long time and has serious consequences. To prevent this circumstance, the world needs alternative detection technologies. For more than a decade, several strategies and procedures have been used to assist medical doctors in detecting technological improvement. Numerous automated seizure identification frameworks that use machine learning approaches have recently been presented to replace traditional methodologies. However, because multichannel EEG data is unpredictable, selecting optimal channels as well as characteristics and classifying them remain unsolved issues. During automatic signaling, the gadget also emits a noisy signal, making detection and prediction challenging. In this paper, we have tested various entropy features and selected the best features to classify seizure patients. First, we preprocessed the data using IMF of the raw signal, and then entropy features were extracted to classify the epileptic patients. The proposed channel selection method, SVM-GA, works well with our framework and successfully removes redundant channels from the data.**

***Index Terms*—Fuzzy Entropy, Distribution Entropy, Sample Entropy, EEG, SVM, Random Forest**

I. Introduction

Epilepsy is a neurophysiological disorder in the CNS due to which abnormal activities are induced, causing behavioural issues, loss of awareness, and sometimes sensations [1], [2]. Treatment with surgery or medications will probably control seizures for the majority. It takes a lifetime for some people to get treatment. The seizures eventually go away. Some instruments that aid in the diagnosis of epilepsy are known as electroencephalograms (EEGs) [2], [3]. Because EEG data has excellent temporal resolution but limited spatial resolution [4]–[6], it has been considered as one of the finest medical tests for assisting in epilepsy diagnosis. Automatic EEG seizure identification, characterization, and classification have been topics of interest and research in the medical, science, and engineering disciplines since the mid-1960s. In clinics, patients with medically intractable partial epilepsy usually require time-consuming video EEG monitoring of spontaneous seizures.

The rationale for utilizing longer signal recordings may be in part because the techniques used in most previously reported work, such as EMD, Signal Wavelet Transform, and DFA analysis protocol, a huge bulk of data points are required in order to obtain accurate classification results [7], [8]. Although the authors reported that their statistical characteristics were derived from the two fifty-six pointer segments (= 1.5 sec) of the IMF (intrinsic mode derived using the EMD algorithm), their preprocessing (filtration using a Butter-worth band-pass filter) the EEG decomposition of IMF's were carried out on full EEG data. Nonetheless, the findings have not yet been recorded precisely in this way to the best of our understanding (including existing research, and see for review). Although various models were developed that combined several classification issues, most of them were found to cover only some of the problems. Despite the fact that significant epileptic EEG feature-extraction [9] research has been published, few publications on EEG channel selection have been documented in recent decades. Furthermore, research on machine learning performance comparisons between outcomes with chosen channels and results with all channels is scarce. The utilization of epilepsy seizure in this paper [10] The detection was carried out, and the ictal and variance values were calculated. Non-ictal periods were estimated for use in channel analysis. selection. The channels with the greatest value were then selected. chosen by subtracting the variance value from the computed for the ictal and calculated for the variance value for the interictal period. Ibrahim et al. [11] also showed that the seizure prediction probability by the chosen channel and characteristic was greater than 70 percent, whereas the false-alarm probability was less than 30 percent. A classifier was used to categorize the channels. SVM combines Recursive Feature Elimination with Zero-Norm in reference [12]. Optimization was employed as a feature selection filter. The study shows that the number of channels may be lowered without affecting classification error [12]. Right-left hand control was demonstrated in the paper [13]. Data from an EEG. Using the top ten channels chosen by GNMM has reached 80 percent classification accuracy. Then, by picking 6 channels from a

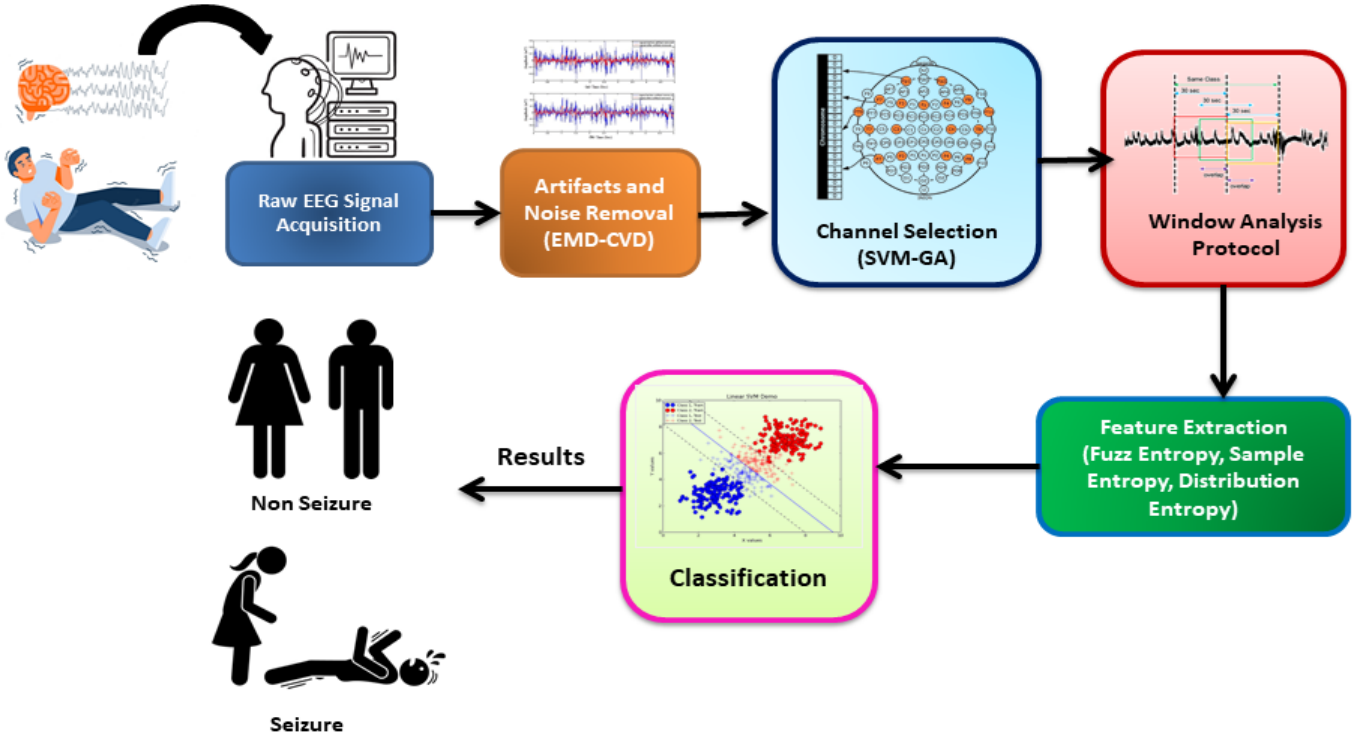


Fig. 1: Overview of the work

possible 32, 82 percent of hand control was acquired with precision.

In fact, a few experiments that addressed the diagnosis of epileptic seizures often set ”S” as a single class and one or a mixture (e.g. ZOF, ONZ, or rather rarely FZNO) of the sets F, Z, O and N. At the ictal level, several studies centered on distinguishing the EEG from those in the interictal phase. However, along with element S, the models were built using only one member of the interictal class (either N or F). While these three-class models theoretically meet traditional therapeutic criteria, their applicability will need to be tested more while taking into account ongoing monitoring, say for online tracking and prompting epileptic behavior, as all of them have been established based on long records of 4,097 sampling points. So the objectives of this work are:

1) Proposing a method for channel selection to improve the seizure detection process and reduce the time complexity.
2) Analyzing the trends and training a predictive classification model to distinguish seizure sleep patterns using available data sets.
3) Studying the feature extraction process of EEG Signals using metrics such as Fuzzy Entropy and Sample Entropy on short-term EEGs.

II. Methodology

A. Data Pre-processing

The first step we have taken after downloading the data set is preprocessing the data to remove noise and artifacts that have been generated during the collection of the data from subjects. Due to the unusual symptoms of this particular disease, lots of muscle movements are common, and that is why the muscle artifacts most likely will be imposed in the data set. A method called Canonical Empirical Mode Decomposition has been applied to remove those muscle artifacts, as well as a bandpass filter, has been used to get noise-free data. Intrinsic mode functions have been generated for each channel and to separate the data, the Canonical Variate Analysis method has been applied.

B. Channel Selection Algorithm

Identifying essential channels for this sort of experiment is critical since the purpose of this study is to identify the optimal answer in the shortest amount of time. Reducing the number of channels simplifies the procedure and reduces the temporal complexity. We suggested an SVM-GA model pick the appropriate channels for this experiment. SVM is a promising machine learning classifier, and GA mimics and follows Charles Darwin’s idea of natural selection. There are three phases to this procedure. Cross-over, mutation, and selection: this approach may be used for feature selection.

In this study, the total SVM-GA channel selection procedure is as follows.

1) *Step 1:* The permutation entropy was calculated for each channel used in this experiment. PE is a resilient time series approach that provides a quantifiable assessment of the complexity of a dynamic system by capturing the

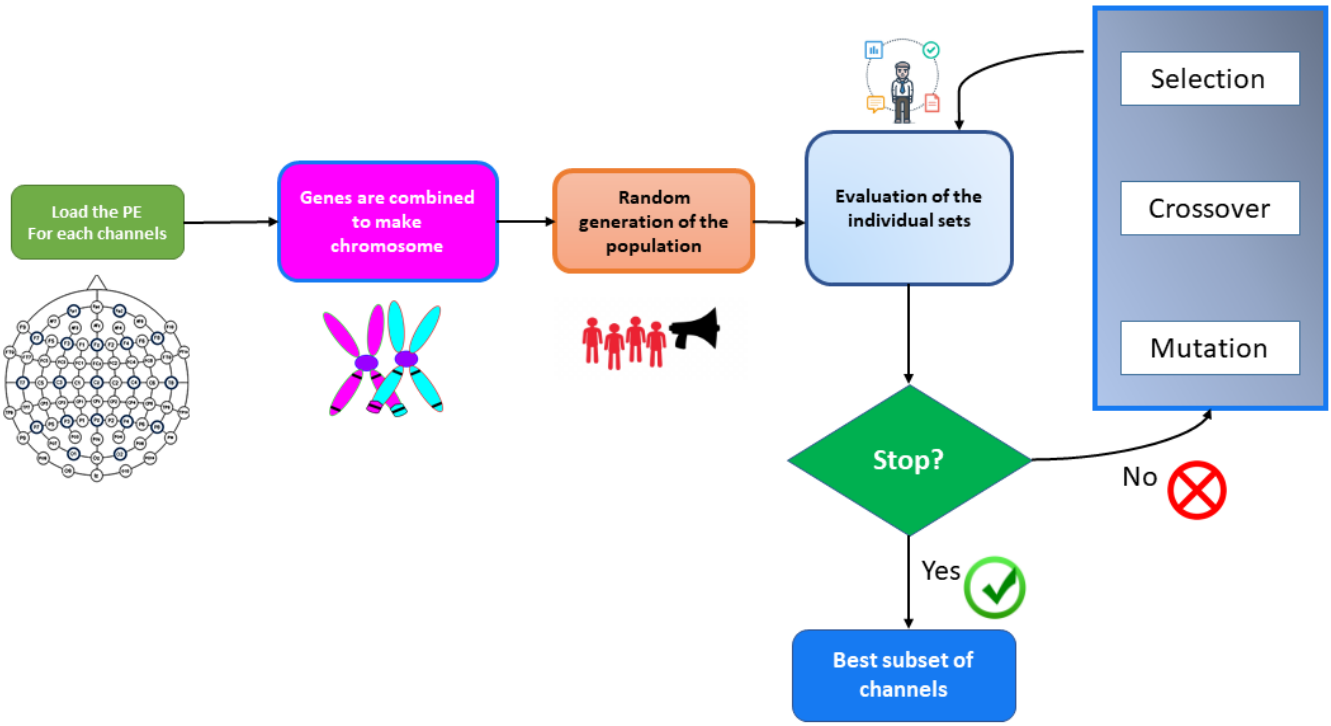


Fig. 2: Channel selection process by SVM-GA method

TABLE I: Comparison of accuracy with a different type of features with different numbers of channels

Serial No	Entropy Features	Classifier	Number of Channels									
			1	2	3	4	5	6	7	8	9	10
1	Fuzzy Entropy	SVM (Linear Kernel)	0.766	0.723	0.756	0.723	0.756	0.742	0.623	0.621	0.615	0.611
	Sample Entropy		0.792	0.759	0.723	0.795	0.721	0.761	0.712	0.712	0.623	0.621
	Distribution Entropy		0.713	0.736	0.729	0.723	0.713	0.695	0.693	0.65	0.635	0.62
2	Fuzzy Entropy	SVM (RBF Kernel)	0.51	0.556	0.562	0.523	0.521	0.512	0.511	0.552	0.545	0.512
	Sample Entropy		0.500	0.512	0.552	0.541	0.653	0.541	0.523	0.552	0.518	0.513
	Distribution Entropy		0.513	0.636	0.642	0.643	0.613	0.619	0.578	0.563	0.542	0.513
3	Fuzzy Entropy	Random Forest	0.552	0.586	0.572	0.561	0.521	0.511	0.510	0.596	0.542	0.522
	Sample Entropy		0.524	0.553	0.576	0.635	0.523	0.521	0.600	0.574	0.572	0.513
	Distribution Entropy		0.523	0.636	0.642	0.643	0.60	0.618	0.617	0.615	0.602	0.601

order linkages between time series data and providing a probability distribution of the ordinal patterns [14].

2) *Step 2:*After calculating PE SVM-GA takes a set of subject's data and represents one subject as one gene. To make a chromosome various combination of genes is possible. By the combination of various subject's data a string has been generated where one gene is selected out of a population.
3) *Step 3:*An fitness function by SVM has been incorporated to evaluate each chromosome in the given population. This step will help to understand how well the model predicted the pre- ictal time stamp. So for each subject a fitness score has been calculated.
4) *Step 4:*Now in the reproduction phase the operator has selected some values based on the probability distribution value. We have selected 0.95 for the probability initially. For example if $f_n(x)$ is the fitness function, then the probability of Ch_x chromosome for reproduction will be

$$probCh_x = \frac{f_n(x)}{\sum_{i=1}^{Num_{pop}} f_n(Ch_i)} \quad (1)$$

Where the Num_{pop} is the number of total chromosome.
5) *Step 5:*Next the chromosoms are mixed up to make the crossover. The genes are selected in a random order from the pre selected chromosome which is called as parent chromosome.
6) *Step 6:*Then the random mutation has been applied and in this step a small amount of probability error has been allowed for each gene.
7) *Step 7:*We need to repeat the process from step 2 untill and unless the population converge in some point. In this process the genetic algorithm actually provided a set of possible solutions to our channel selection problem.

C. Feature Engineering

In terms of features used to describe the EEG, non-linear parameters attract growing interest nowadays because non-linearity is assumed to be intrinsic in physiological processes. Different entropy parameters , i.e. approximate entropy (AppEnt), sample entropy (Sam.Ent.), combination entropy, entropy dependent functional dynamics, and fuzzy entropy (FuzzyEn), were chosen since they were capable of supplying complexity figures, a nonlinear dynamic biomarker for controlled physiology that relies on restricted tests. We have to target high accuracy for extremely short-term database collection. We have recently discovered a new method centered on distribution. This distributed entropy, which functions as a current component of the overall entropy measuring device, has demonstrated remarkably remarkable efficiency in various sectors when compared to older techniques.

D. Algorithm (Feature Definition)

Entropy increases the ability to distinguish between the ordinary and the unexpected. Signals from the EEG. Entropy is the measure of a system's unpredictability. Entropy may be used to quantify the unpredictability and complexity of a signal. Various Entropy has been discovered as features for classifying the EEG signal. We will discuss one by one:

E. Sample Entropy

Sometimes we need to know the randomness of a data which is represented in series and Approximate Entropy and Sample Entropy [15] helps to that. It estimates the value without having any prior knowledge of the source. It can be said that Sample Entropy is a kind of approximation entropy that is used to analyse the complexities of biological time-series signals in order to diagnose sick states.

1) Fuzzy Entropy: The fuzzy entropy [16] is used to calculate the subjective value of information in the context of uncertainty in the seal impression problem. Fuzzy Entropy is a sophisticated Sample Entropy algorithm focused on the fuzzy principle. By extension it does not depend on the total probability of identical vectors according to the criteria of hard thresholding as implemented in Sample Entropy. Instead, Fuzzy Entropy calculates the chance, based on the fuzzy membership function, of two vectors being identical.

2) Distribution Entropy: Initially, Distribution Entropy [17] was proposed for the mitigation of parametric dependency and robustness of Approximate Entropy Sample Entropy especially when extended to limited data sets. Through quantifying the propagation properties of the inter-vector intervals, it takes complete advantage of the state space equivalent of the under-analysed time sequence.

F. Classification

We have used various popular algorithm to test the features and we select the the best performing classifiers and noted their results in this paper.

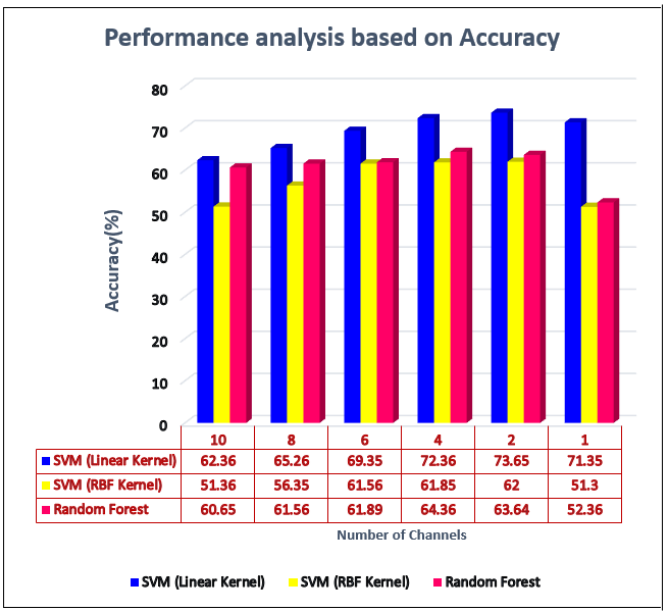


Fig. 3: Accuracy-based performance study of SVM and RF classifiers

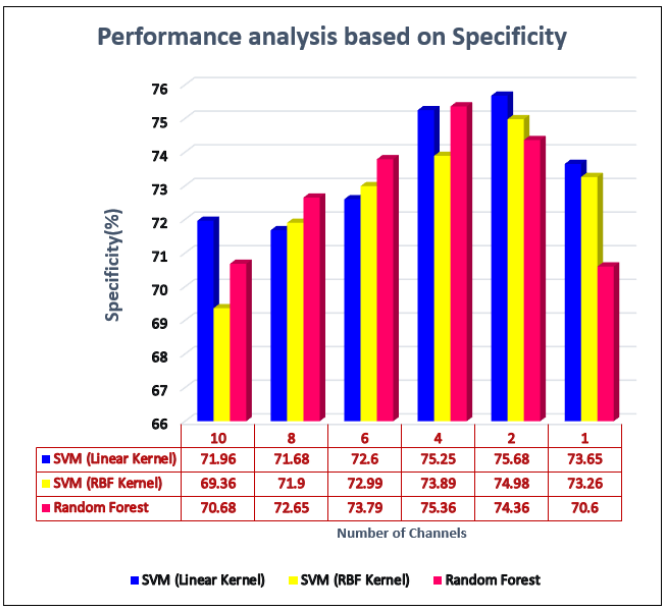
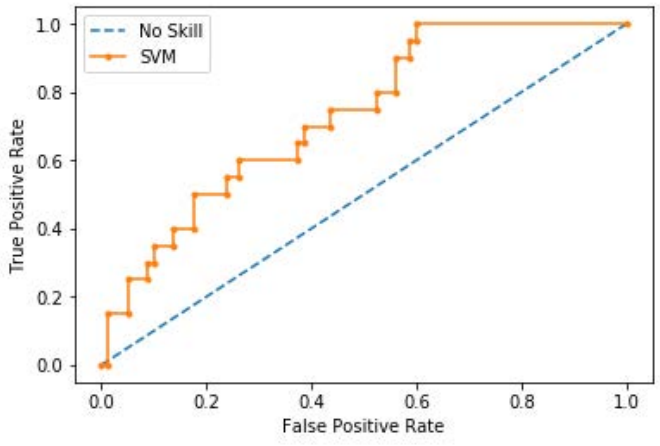


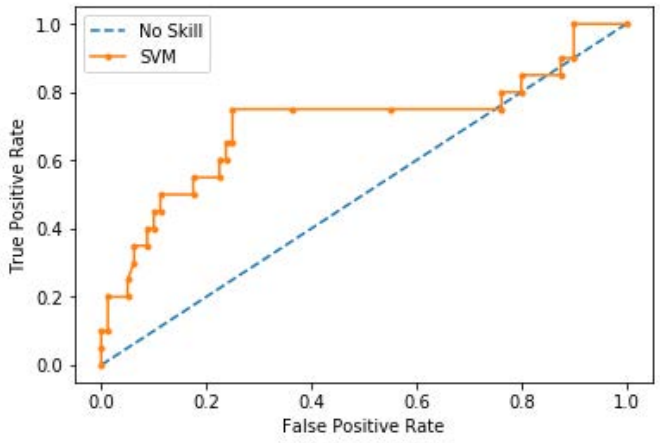
Fig. 4: Specificity-based performance study of SVM and RF classifiers

G. Experiment and Results

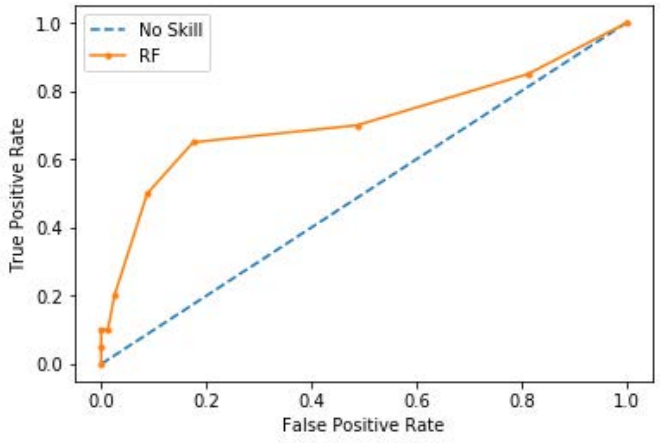
1) Data Description: In this work, an EEG database, currently accessible online, is used [18]. The database contains five subsets of the EEG recordings (noted as Z, O, N, F, and S), each with 100 singular-channel EEG recordings, with a duration of 23.6 s. After visual inspection for artifacts, these signals were selected from continuous multichannel EEG recording. Among all the subsets Z and O were recorded extracranially, while subsets N, F, and S were recorded intracranially.



(a) ROC curve for SVM (Linear Kernel)



(b) ROC Curve for SVM (RBF Kernel)



(c) ROC curve of Random Forest

Fig. 5: ROC curve for all three classifiers

On the dataset from the Bonn site, we used Fuzzy Entropy, Distribution Entropy, and Sample Entropy to analyze 5-s EEG. We found that it performed well at differentiating between interictal, ictal, and ictal from interictal EEG, but Sample Entropy had trouble with one of the three classification issues

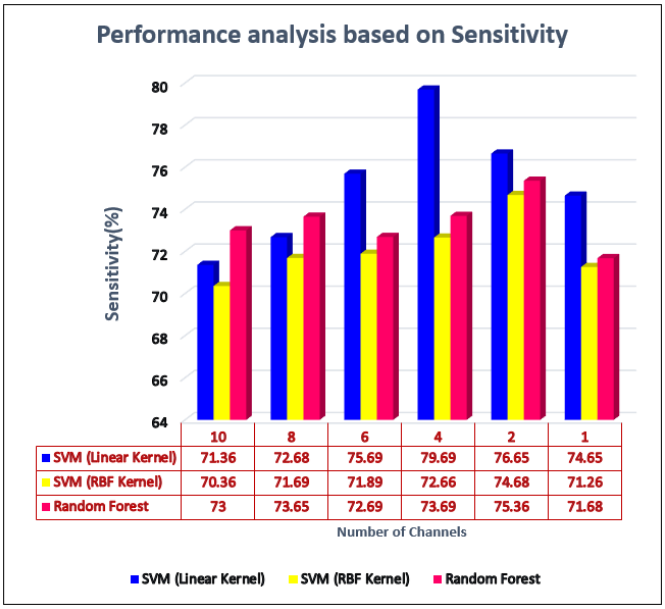


Fig. 6: Sensitivity-based performance study of SVM and RF classifiers

and we have mentioned that Distribution Entropy may still use a technique for switching analytical frames if it uses a 1-s EEG segment. Create an entropy-focused short-term Electroencephalogram classification model based on the preceding findings that are appropriate for clinical settings and may be used to start evaluating epileptic diseases or epileptic therapies for epileptic patients. Which entropy works best actually depends on the classifier. For example from Table 1, we can see that for Linear Kernel SVM Fuzz Entropy is giving the best results on the other side with Random Forest Distribution Entropy giving the best results among the three entropies. Also, the classifiers' performance depends on the number of channels. In Table 1 the performance with the different number of channels has been shown.

2) Experiment 1- Entropy Features Survey : In a contrast to the Sample Entropy in this study, we will apply the Fuzzy Entropy and Distribution Entropy techniques. Additionally, although Approximate Entropy is defined for short data times, it wasn't included owing to the measure's bias (particularly for short-term data). As far as we know there is no systematic study is available for the application of various types of entropy or dynamic entropy to the biological signal which is highly constrained. Finding the ideal entropy and minimum features to get maximum performance is still a challenge. Two protocols must be established in order to do this: E entropy a single window with lengths ranging from 1 to 23 s and ii) a multi-window entropy based on protocol measurements E with overlap (l = 1 s) with lengths spanning from 1s to a certain range x. The capacity to tell apart between: will be used to determine whether the procedure is more successful. Regular EEGs are created from interictal and ictal EEGs, while ictal EEGs are created from interictal EEGs.

3) Experiment 2-Classification Process between seizure and non-seizure : From the following datasets in which, for each window size, we obtain entropy values for all the 500 signals classified as Z, F, N, O, and S in different tabs. Now, we apply various classification algorithms like Least Square Support Vector Machine using different kernels and Random Forest In all of these, the 'S' data values are classified as that of seizure patients whereas all the other four data values are classified as being from non-seizure patients who are healthy.

4) Results: The ROC curve for SVM and RF has been shown in Figure 3. (a), (b) and (c). It has been noticed that the linear kernel is performing better than the RBF kernel. When we tested the dataset with the Random Forest classifier it gave better results than the RBF kernel but the linear kernel outperformed both of the classifiers in most of the cases. We are saying most of the cases because we have noticed for some number of channels RF is performing better. So we can say that RF and SVM (Linear Kernel) are good classifiers for this kind of experiment. Figures 3, 4, and 5 have shown the performance analysis of both of the classifiers based on accuracy, sensitivity, and specificity.

Conclusion and Future Scope

The proposed artifact removal method works well with our framework and successfully removes noise from the data. Nonlinear characteristics have been shown to be critical for this type of research. Furthermore, the inclusion of several week-long classifiers distinguishes and verifies the study. The cognitive framework that has been used in this paper can be improved in such a way that it can be utilized in real-time, also for medical purposes. An alarm system or sensor can be installed with the machine and it will help the medical practitioners understand the information quickly. More clinical datasets can be tested with this algorithm to understand whether it is good for all or not. Designing new gadgets like smartphones or robots to assist epileptic patients can also be possible if a new algorithm or advanced method has been incorporated. Here we have considered the machine learning method only, while the deep learning method can be used to extract features for the seizure and it may help to make the process much faster. A more hierarchical structure can be used using several entropies and deep learning methods. It may minimize the time and computational cost as well as the uncertainty or overfitting of the model. Subject variability issues or intensity measurement can be addressed in the future for further improvement.

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