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Research Article

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Seven Epileptic Seizure Type Classification in Pre-Ictal, Ictal and Inter-Ictal Stages using Machine Learning Techniques

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Abstract

Background: *Epileptic Seizure type diagnosis is done by clinician based on the symptoms during the episode and the Electroencephalograph (EEG) recording taken during inter-ictal period. But main challenge is, most of the time with the absence of any attendee, the patients are unable to explain the symptoms and not possible to find signature in inter-ictal EEG signal.*

Aims: *This paper aims to analyze epileptic seizure Electro-encephalograph (EEG) signals to diagnose seizure in pre-ictal, ictal and inter-ictal stages and to classify into seven different classes.*

Methods: *Temple University Hospital licensed dataset is used for study. From the seizure corpus, seven seizure types are pre- processed and segregated into pre-ictal, ictal and inter-ictal stages. The multi class classification performed using different machine and deep learning techniques such as K- Nearest Neighbor (KNN) and Random Forest, etc.*

Results: *Multiclass classification of seven type of epileptic seizure with 20 channels, with 80-20 train-test ratio, is achieved 94.7%, 94.7%, 69.0% training accuracy and 94.46%, 94.46% 71.11% test accuracy by weighted KNN for pre-ictal, ictal and inter-ictal stages respectively.*

Conclusion: *Seven epileptic seizure type classification using machine learning techniques carried out with MATLAB software and weighted KNN shows better accuracy comparatively.*

Keywords: Seizure Classification, TUHEEG, ABSZ, CPSZ, FNSZ, GNSZ, SPSZ, TNSZ, TCSZ, Random Forest, KNN, EEG

Introduction

Epilepsy is a disease affecting the brain and characterized by repetitive seizures caused by erratic electrical discharge in the brain. An epilepsy is a chronic disease caused by excess electrical discharge in the brain causing involuntary behavioral changes such as loss of consciousness and convolutions. In low and middle-income countries, nearly 80% of epileptic patients live with three-fourth of these people facing either a treatment gap or shortage of anti- seizure medicines. As such, the occurrence and frequency of epileptic events is unpredictable which makes it difficult to diagnose and treat. Most of the time patient visit outpatient department (OPD) with a history of epileptic episode [1]. Clinician diagnose based on EEG recording taken on the time of hospital visit i.e. inter-ictal stage along with the onset symptoms observed. But, main challenge is, un- predictive nature of occurrence of seizure makes leads most of the time patients experience without any attendee and because of which the onset symptoms could not be explained. At the same time for non-interactive epilepsy requires expertize to interpret inter-ictal EEG as looks same as normal person's EEG and end up giving EEG report as "normal". This results in trial and error based treatment. Neurologist prescribe some set of medicines predicting some type based on whatever information shared by patient and attendee and then change the medicine in consecutive visits. As inter-ictal EEG looks same as EEG of non-epileptic person, also noise and various artifacts like movement of body parts during acquisition put challenge to even experts to diagnose from those readings. On the other hand anti-seizure drugs (ASDs) has adverse side effect.

Seizure basically having four stages namely, pre-ictal, ictal, post-ictal and inter-ictal. Pre-ictal is just before the occurrence of seizure, ictal is onset and post-ictal is just after the patient come out of the episode. Whereas inter-ictal stage starts after around 10 minutes of onset and last till the next occurrence of seizure. The pre-ictal stage usually involves dizziness, headache and nausea and followed by the stage of intense electrical activity in the brain called the ictal region. Then comes the post-ictal region where the patient returns to baseline conditions along with symptoms like disorientation, drowsiness and headache. Figure 1 depicts pre-ictal, ictal and post-ictal stages of epileptic seizure, where inter-ictal representation along with non-epileptic EEG is shown in Figure 2.

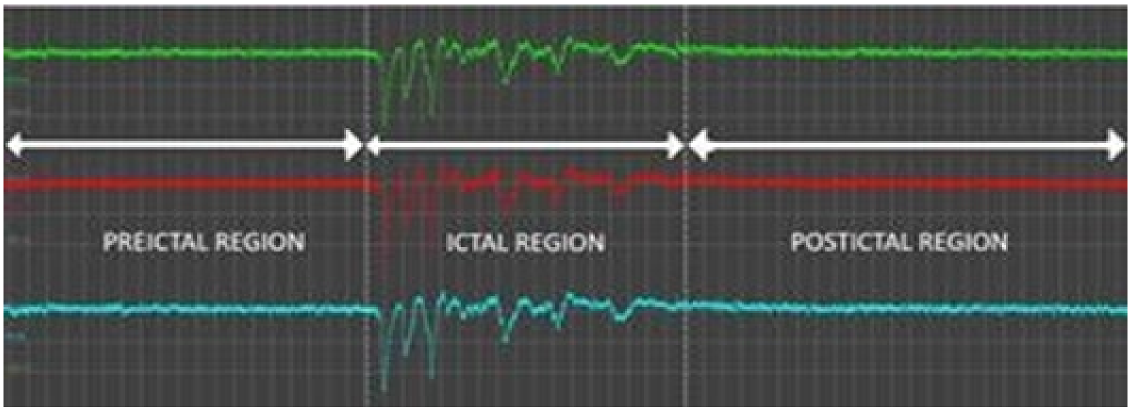


Figure 1: EEG signals with pre-ictal, ictal, post-ictal stages of epileptic seizure

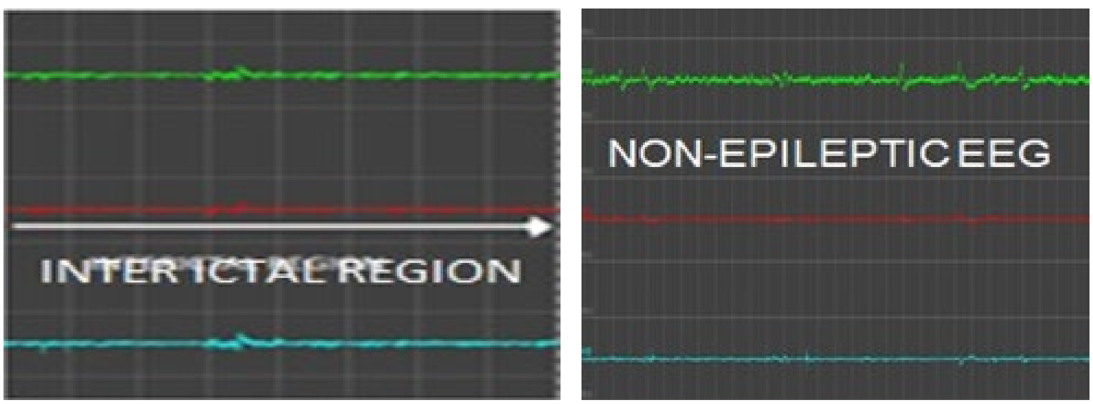


Figure 2: Inter-ictal region with non-epileptic EEG

With the advent of machine learning and Deep learning and its increasing popularity in healthcare application makes it possible to classify majorly a) seizure-seizure free and b) different types of seizure but it's done in ictal period having high frequency EEG signal with spikes makes classification little simple. There are many works available in seizure- seizure free classification. Researchers uses different pre- processing techniques for accuracy enhancement. In literature different mathematical models are used as pre- processing techniques like empirical mode decomposition (EMD), ensemble EMD, dissimilarity based frequency distribution, based on high order statistical parameter tuning, feature extraction based on discrete wavelet transform (DWT), composite multiscale dispersion entropy, etc. [2-8]. For the ever-growing demand for correct diagnosis, various algorithms are developed [9]. For segment wise seizure classification transfer function approach is adopted [10]. Increasing acceptability of artificial intelligence in the field of medical diagnostic, seizure classification from unprocessed EEG signals are carried out [11]. Various machine learning algorithms like support vector machine (SVMs), using auto regression feature, using Bayesian regularized shallow neural networks, bagging based ensemble frame work, using extreme gradient based classifier, is used. Predominant usage of deep learning techniques are witnessed [12-20]. Based on domain invariant deep representation, autonomous deep feature extraction, convolutional neural networks (CNN), recurrent neural networks (RNN) etc. deep learning algorithms are used. To enhance accuracy one or more algorithms are clubbed together, such as CNN with long- short memory (LSTM), CNN with empirical WT, etc. [21-27].

Seizure type detection also slowly became research interest [28,29]. Different machine learning, deep learning methods are explored with and without pre- processing of EEG signals. RNN, LSTMs, K nearest neighbour (KNN), SVMs with different transforms like discrete cosine transform (DCT), Hilbert transform (HT), etc. are used as feature extractor based on their energy compaction, using recurrence plots, based on dictionary learning and sparse representations, using Random forest (RF) classifier, using different layers of CNN, transfer learning, using deep batch normalization, using neural memory networks, etc. are tried out with different researcher using cleaned and raw data from different datasets [30-42]. Slowly real time clinical diagnostics is tried out [43]. But most of the literature available classification is done in ictal stage EEG signal and very less exploration in inter ictal or other stages can be found because of its similarity with non-epileptic EEG [13,44,45].

It is clear from the literature that multi class seizure classification in pre-ictal, inter-ictal has not been paid much attention. Therefore, this paper focuses on epileptic seizure type classification based on pre-ictal, ictal and inter-ictal stages using machine learning algorithms. To the best of the author's knowledge, multi class classification for seven different types in pre-ictal, ictal and inter-ictal is tried out for the first time. In this paper first section discusses introduction along with relevant supportive literatures, section 2 describes methodology and includes information about dataset, pre- processing techniques adopted and also the different machine and deep learning techniques used for classification. Section 3 deals with results and discussion followed by conclusion for the study.

Methodology

The methodology followed in this work is as shown in Figure 3

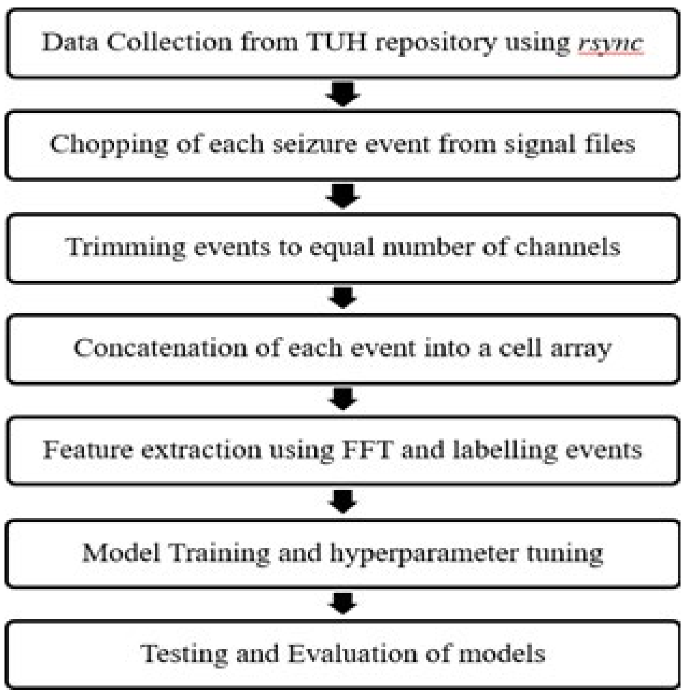
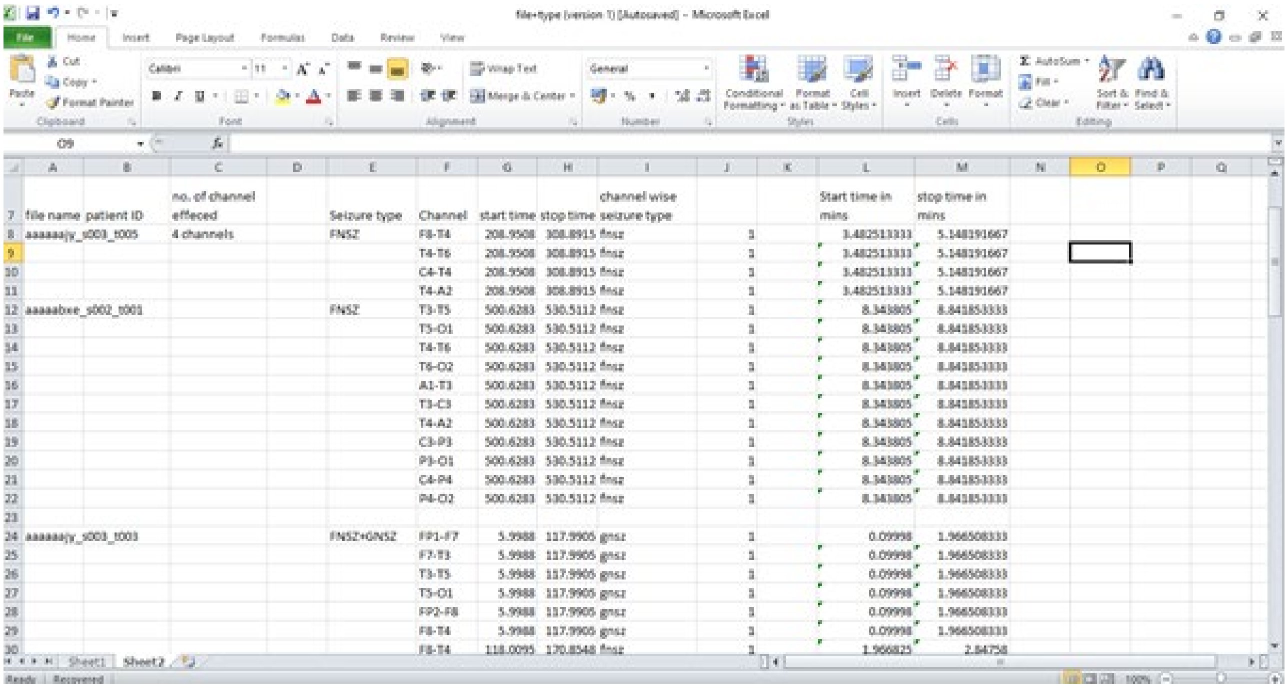


Figure 3: Flow of work carried out



file name	patient ID	no. of channel effeced	Seizure type	Channel	start time	stop time	channel wise seizure type		Start time in mins	stop time in mins
aaaaaajy_s003_t005		4 channels	FNSZ	F8-T4	208.9508	308.8915	fnsz	1	3.482513333	5.148191667
				T4-T6	208.9508	308.8915	fnsz	1	3.482513333	5.148191667
				C4-T4	208.9508	308.8915	fnsz	1	3.482513333	5.148191667
				T4-A2	208.9508	308.8915	fnsz	1	3.482513333	5.148191667
aaaaabxe_s002_t001			FNSZ	T3-T5	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				T5-O1	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				T4-T6	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				T6-O2	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				A1-T3	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				T3-C3	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				T4-A2	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				C3-P3	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				P3-O1	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				C4-P4	500.6283	530.5112	fnsz	1	8.343805	8.841853333
				P4-O2	500.6283	530.5112	fnsz	1	8.343805	8.841853333
aaaaaajy_s003_t003			FNSZ+GNSZ	FP1-F7	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				F7-T3	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				T3-T5	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				T5-O1	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				FP2-F8	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				F8-T4	5.9988	117.9905	gnsz	1	0.09998	1.966508333
				F8-T4	118.0095	170.8548	fnsz	1	1.966825	2.84758

Figure 4: TUHEEG Seizure corpus information

Table 1: Seizure Types and Description

Seizure code	Name	Description	Pre- Ictal		Ictal		Inter-ictal	
			Samples	NE	Samples	NE	Samples	NE
[a]ABSZ	Absence Seizure	On EEG, absence discharges are noticed. Symptom: Loss of consciousness	271989	18	96568	56	745239	46
[a]CPSZ	Complex Partial Seizure	Staring blank and daydreaming is the symptoms also loss of awareness regarding their surroundings.	317195	28	28	52	753664	46
[b]FNSZ	Focal Seizure	Starts in one part of the brain, but can spread to other parts i.e. become Generalized.	426127	28	324887	55	786432	48
[b]GNSZ	Generalized Non Specific Seizure	Generalized seizures which cannot be further classified. Symptoms: unconscious-ness with spasms, stiffening, etc.	323400	22	447487	54	712084	44
[a]SPSZ	Simple Partial Seizure	Awareness is not affected. It affects body muscles.	298618	18	541405	52	786432	48
[a]TNSZ	Tonic Seizure	Stiffening of muscles.	353294	28	1089507	52	786432	48
[a]TCSZ	Tonic-Clonic Seizure	First stiffening followed by body jerking (Grand Mal)	411635	28	240279	45	700249	44

*NE= number of events

Seizure Types and Descriptions

Epileptic seizure is mainly having four major types, namely, Fibril, generalized, partial and unclassified. They are subdivided into total 20 different classes. In this work, seven types of seizures have been chosen, which have different symptoms during onset of seizure attack. Two manifestations are used i.e. electro clinical and electrographic. For representing Electro clinicala is used and for electrographicb is used. Seizure types and description is narrated in Table 1.

Dataset

The dataset used in this work is taken from Temple University Hospitals EEG Repository, specifically TUH EEG Seizure Corpus (TUSZ) as shown in Figure 4 [42]. The repository contains 16986 sessions from 10874 unique subjects. The number of EEG channels varies from 20 to 31. The signals are of varying lengths (3,00,000 columns). The 10-20 electrode configuration was used.

Pre Processing

The obtained EEG recordings were then preprocessed be- fore feeding into machine learning models. Since each file had a varying number of channels (from 21 to 30 channels), the first 18 channels from all files were taken and labelled for the type of seizure. Duration of signal for ictal region was directly taken from the corpus information shown in Figure 1. For inter-ictal regions, duration between the stop time of one event and start time of the next chronological event of the same file were taken as start and stop times. The duration of signal before the first event of each file is taken as the pre-ictal duration.

Feature extraction using Fast Fourier Transform (FFT)

For feature extraction of each signal, FFT as in Equation
(1) Was performed on each signal and the power spectrum was analyzed. The frequencies in the signal with maximum power were extracted as features and appropriate labels (type of seizure each for ictal, preictal and interictal) were added.

$$X(K) = \sum_{n=0}^{N-1} x(n)e^{\frac{2\pi Kn}{N}} \quad (1)$$

The features extracted above were fed into multiple classification algorithms to find the models giving better results. Of these, the models showing better performance can then be tuned to improve performance. These models are explained as below.

Machine Learning Algorithms

Bagged Trees

To reduce variance of a statistical learning method, bagging or bootstrap aggregation, is a procedure in general. In this bagged tree (BT) method, using B bootstrapped training sets, B regression trees is constructed and the resulting predictions is averaged. Due to deep growth of trees and non-pruned nature, high variance with low bias can be observed in each individual tree, towards reducing variance averaging the BT is used. The predicted value for an observation is the mode (classification) or mean (regression) of the trees. The difference between BT and Decision Trees (DT) is that BT may contain multiple trees, each having different features, terminal node counts, data, etc., where DT contains single tree. Bagged Trees consist of the following steps.

- Sample m data sets D_1, D_2, …., D_m from training set D with replacement.
- For each D_j train a classifier $h_j(x)$ where x represents features.
- The final classifier is given by equation (2)

$$h(x) = \frac{1}{m}\sum_{j=1}^{m} h_j(x) \quad (2)$$

The Advantages of Bagged Trees are:

- It can reduce the variance within the algorithm (helpful with high-dimensional data).
- It is easy to implement.
- It forms a strong learner yielding better performance.

Disadvantages of Bagged Trees are:

- The algorithm is computationally intensive.
- It is difficult to interpret (Low explain ability).

K-Nearest Neighbours

The KNN algorithm works on the assumption that similar data points tend to be situated closer to each other in a plane, seen in Figure 5. This classification algorithm works by classifying data points based on their ‘K’ nearest neighbours. For example, if the value of K is taken to be 1, the data will be assigned the class of its closest neighbour. In Figure 5, blue hexagon is the test sample, two concentrated circles represent K=3 and K=5 nearest neighbours. In this example for K=3, has 2 red balls close to the test sample whereas green only one ball so, in this case, test sample is classified as red class. In the other hand for K=5, 3 green balls are present compare to 2 red balls. Therefore, for K=5, the test sample will be classified as green class. Because of this ambiguity, researcher prefer to have K=1, most of the time shows better result, compare to any value of K. the nearest neighbours are found based on Euclidean distance as in Equation (4).

The largest probability of an input x being assigned to a class is given as in Equation (3):

$$P(y=j \mid X=x) = \frac{1}{K}\sum_{i\in A} I(y^{(i)} = j) \quad (3)$$

The distance metric is given by the Euclidean distance as follows (where p=2):

The distance metric is given by the Euclidean distance as follows (where p=2):

$$d(x,x') = \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2 + (x_3-y_3)^2 + \cdots + (x_N-y_N)^2} \quad (4)$$

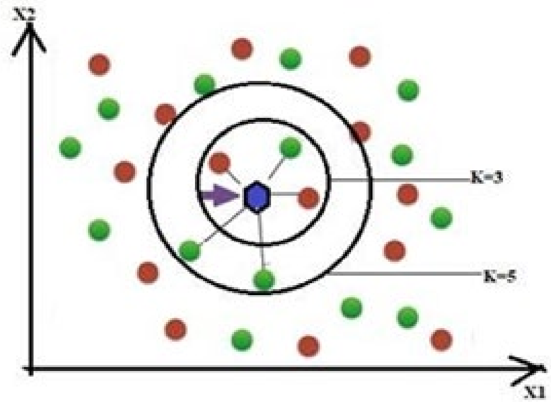


Figure 5: K-Nearest Neighbour Algorithm

Commonly used distance metrics are the Euclidean, Manhattan and Minkowski metrics. d(p,q) is the distance between points p and q as shown in Equation (5), Equation (6) and Equation (7) respectively. Here n is the number of dimensions of train set and pi and qi are the values of the ith dimensions of data point's p and q respectively.

Euclidean distance metric

$$d(p,q) = \sqrt{\sum_{i=1}^{N}(p_i - q_i)^2} \qquad (5)$$

Manhattan distance metric

$$d(p,q) = \sum_{i=1}^{N} |p_i - q_i| \qquad (6)$$

Minkowski distance metric

$$d(p,q) = (\sum_{i=1}^{N}|p_i - q_i|)^{1/p} \qquad (7)$$

The Merits of KNN are:
- Implementation is simple.
- To the noisy training data, it is robust
- For large training data, it can be more effective.

The Demerits of KNN algorithm are:
- Determination of the value of K is complex some time.
- High computation cost because for all the training samples the distance between the data points need to calculate.
- Standardization required for training sets.

Weighted KNN

The weighted K-Nearest Neighbours (WKNN) algorithm differs from the conventional KNN algorithm (as in Figure 6) as weights are assigned to classes, and the decision is reached depending on the weights. The data points located close to the query point are assigned higher weights. The results obtained from this model are easy to interpret. The weighted Euclidean distance d between points pi and qi with weight wi is calculated as in Equation (8).

$$d(p,q) = \sqrt{\sum_{i=1}^{N} wi\ (p_i - q_i)^2} \qquad (8)$$

The Advantages of weighted KNN algorithm are:
- Gives importance to closer neighbours
- No training period (Instance-based learning)
- It is easy to implement

Disadvantages of weighted KNN are:
- Sensitive to noise, missing data and outliers
- Does not work well for high dimensional data
- Needs feature scaling

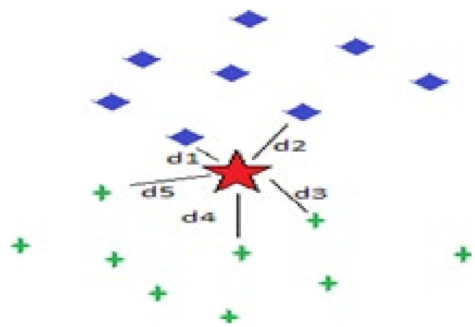


Figure 6: Weighted K nearest Neighbours

Subspace KNN

In random subspace method, the features ('attributes', 'independent variables', 'predictors') are sampled randomly unlike BT. In this, it replaces, for each learner. Informally, to avoid over focusing on feature by individual learner, which appear highly predictive/ descriptive in the training set. But, at the same time, it fails to be as predictive for points outside that set. For this reason, for high-dimensional problems where the number of features is much larger than the number of training points, random subspaces are an attractive choice. Selection of subspace is mathematically shown as in Equation (9) and Equation (10) The process is pictorially represented by Figure 7.

- Given a set of N points in an n-dimensional feature space

$$\{(x_1, x_2, \ldots\ldots x_n) \mid x_i \text{ is real for all } 1 \leq i \leq n\} \qquad (9)$$

- We consider the m-dimensional subspaces

$$\{(x_1, x_2, \ldots\ldots x_n) \mid x_i\ 1 \text{ for } i \in I, x_i{=}0 \text{ for I not belongs to I}\} \qquad (10)$$

Where I is an m-element subset of {1, 2… n} and m<n.

The advantages of Subspace KNN (SKNN) are:
- Gives different results for each subspace
- Avoids overfitting issues. Better performance.

Disadvantages of Subspace KNN are:
- Not suitable when data contains irrelevant features
- Difficult to interpret.

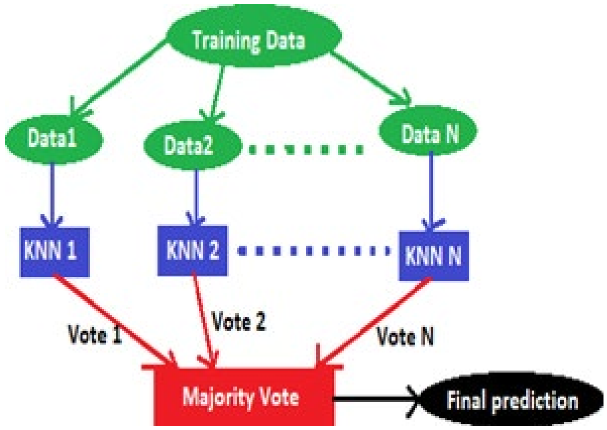


Figure 7: Subspace K nearest Neighbours

Random Forest

A Random Forest (RF) algorithm can be used for classification as well as regression, as in the case of Support Vector Machines. The algorithm works by creating decision trees and assigning new data points to the category that wins the majority of votes, as described in Figure 8. This model finds applications in many sectors and is often used for high-dimensional data.

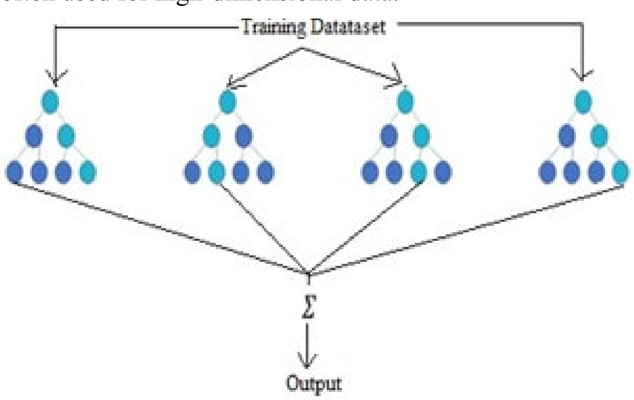


Figure 8: Random Forest Algorithm

Results

The pre-processed signal passed through classifier app for multi class classification without hyper parameter tuning. Seven class classification accuracy in percentage for pre- ictal stage is shown in Figure 9,, for ictal stage is shown in Figure 10 and inter-ictal stage is shown in Figure 11. The models selected based on accuracy more than 60%. The models selected are SVM Kernal, Cosine KNN (CO KNN) Cubic KNN (Cu KNN), Medium KNN (MKNN), Subspace KNN (SKNN), BT, WKNN, Fine KNN (FKNN).

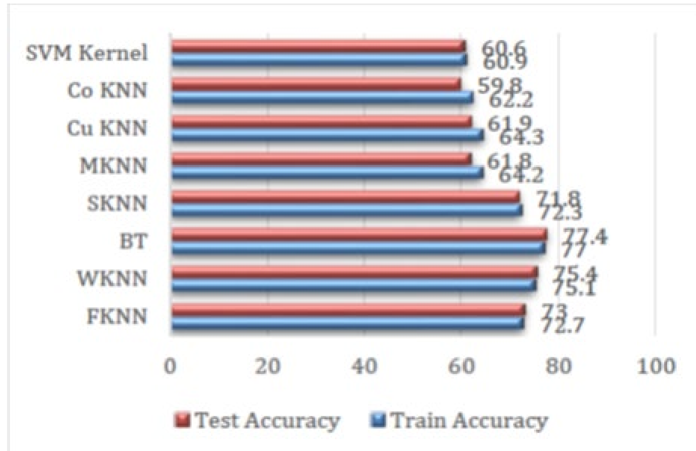


Figure 9: Seven Class classification in Pre-ictal stage

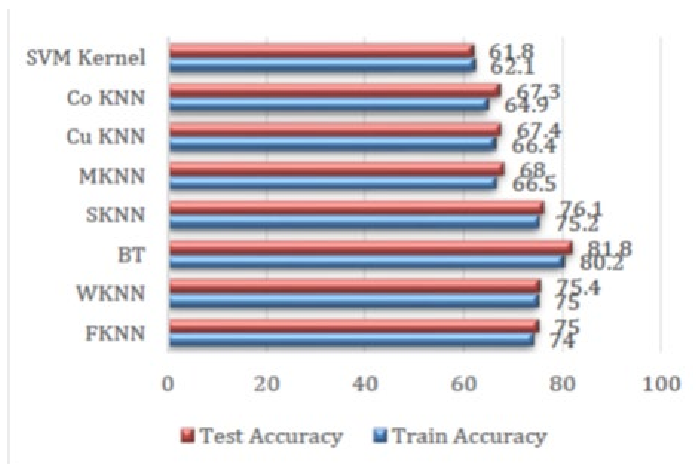


Figure 10: Seven Class classification in ictal stage

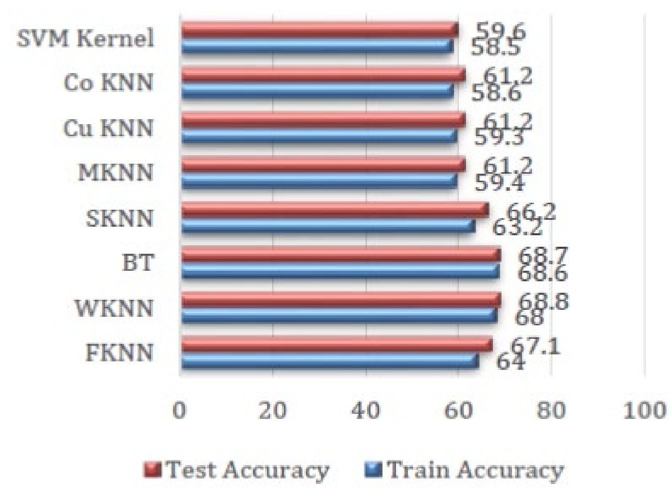


Figure 11: Seven Class classification in Inter-ictal stage

This experiment used 80-20 train-test ratio. The maximum test accuracy obtained 77.4%, 81.8%, 68.7% for pre-ictal, ictal and inter-ictal stages respectively by BT model. The train and test accuracy in percentage of all the three stages is shown in Figure 12 and Figure 13 respectively.

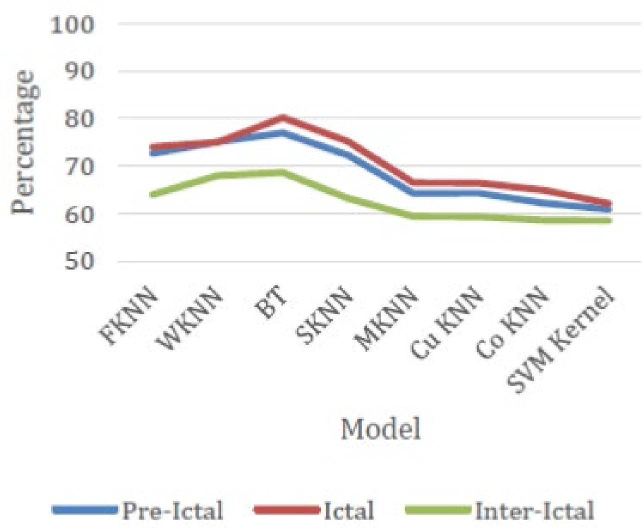


Figure 12: Training Accuracy of all three stages

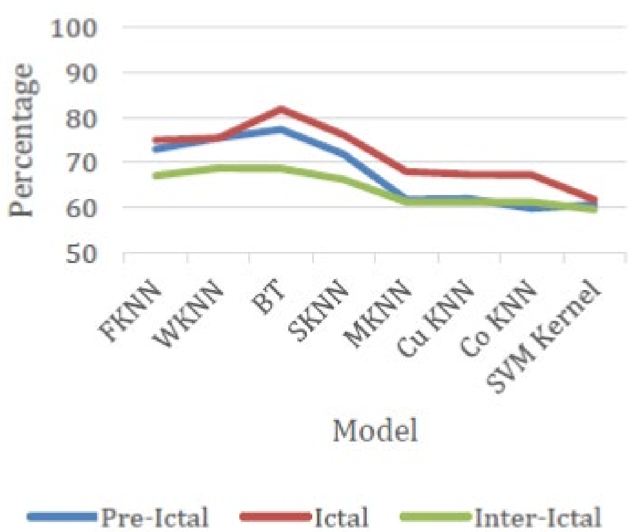


Figure 13: Test Accuracy of all three stages

It can be clearly observed that Ictal shows better accuracy in both training and testing. Pre-ictal some of the models shows at par ictal accuracy where inter-ictal without hyper parameter tuning shows comparatively low accuracy. RF is modelled and all other models are fine-tuned using hyper parameter aiming better accuracy for all the three stages. Table 2, Table 3 and Table 4 shown the fine-tuned results of train and test accuracy for pre-ictal, ictal and inter-ictal stages respectively.

Table 2: Seven Class Pre-ictal Classification

Model	Train Accuracy	Test Accuracy
WKNN	94.70	94.46
RF	75	76.8

Table 3: Seven Class ictal Classification

Model	Train Accuracy	Test Accuracy
WKNN	94.70	94.46
KNN	80.6	83.2
RF	75	76.8

Table 4: Seven Class Inter-ictal Classification

Model	Train Accuracy	Test Accuracy
WKNN	69.0	71.11
Ensemble BT	69.0	69.2
FKNN	65.1	65.2

Discussion

The best performing models were further fine-tuned for robust performance. Grid search, Random Search and Bayesian Optimization techniques were utilized to find optimal hyper parameters. Weighted KNN, Bagged Trees, Random Forest and Fine KNN were found to be the top models which improves accuracy on hyper parameter tuning. The hyper parameters for these are outlined below

- Weighted KNN: The Number of neighbours K, distance metric, weight function (equal, inverse or squared inverse) parameters of WKNN are varied.
- Fine KNN: In Fine KNN, the number of neighbours K is fixed to 1 while the other parameters are varied. Since Fine KNNs are not distance weighted, the only parameter left to vary is the distance metric.
- Bagged Trees: Hyper parameters for bagged trees include minimum leaf size (minimum number of observations per leaf), number of trees in the ensemble, and whether or not the trees need pruning.
- Random Forest: Maximum depth of trees in the forest, minimum number of observations required in any node to split it, number of trees, maximum number of features provided and fraction of dataset to be used in training and some parameters that require tuning.

With hypermeter tuning the test accuracy enhanced from 77.4% to 94.46% in case of pre-ictal, in case of ictal it improves from 81.8% to 94.46% and in inter-ictal stage accuracy increases from 68.7% to 71.11%. Though without fine tuning BT performed best but after hyper parameter tuning WKNN shows the best accuracy for all the three stages.

Conclusion

The EEG signals of epileptic seizure is collected from TUHEEG corpus [42]. With seven different type of seizure signal along with individual patient history, a new project based database is created. In this all EEG signals consider same number of channels. In the next step pre-ictal, ictal and inter-ictal stages are extracted and made three different sub dataset, each of which having seven different classes. Seven class classification of each of the stages performed using machine learning model and RF is modelled.

To improver accuracy of models, hyper parameter tuning is performed. After fine tuning WKNN gives the best result for all the three stages. Accuracy for both pre-ictal and ictal shows 94.7% and 94.46% for train and test respectively. Where for inter-ictal train and test accuracy obtained as 69.0% and 71.1% respectively.

This experimental study can gives promising aid to clinical diagnosis of epileptic seizure type and most of the patients comes in inter-ictal stage. The pre-ictal prediction of seizure can help the patients and clinician to prevent from episode.

Future Scope

Epileptic seizure is a common neurological disorder and occurrence is highly un-predictive. Therefore, most of the patients visit clinician in inter-ictal stage with vague details about the episode, makes diagnosis extremely challenging. Proper study and research in inter-ictal definitely enhance accuracy of diagnosis in clinical set up. This paper concentrates on seven different types of seizure, in future researcher can explore more types of seizures incorporating the symptoms of each type.

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