Epileptic Seizure Detection using EEG Signals

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***Abstract*—Epilepsy is a common neurological disorder which can be diagnosed by neurologists or physicians by using electroencephalogram or EEG signals. Since the manual examination of EEG for this purpose is very time consuming and requires trained professionals, it calls for the need of an automatic seizure detection method. In this study, time and frequency domain features are extracted from the EEG signals after preprocessing the raw EEG data and then using machine learning algorithms such as Logistic Regression, Decision Tree, Support Vector Machines, etc. to detect generalized seizures in the Temple University Hospital (TUH) corpus. A detailed account of the TUH dataset is also given. This work summarizes and compares the results of each of the algorithm trained, in terms of the performance metrics. Using the proposed approach, SVM obtained the highest accuracy of 92.7% in binary classification.**

Keywords—EEG, Epileptic Seizure, Machine Learning, Feature Engineering, TUH, Binary Classification

I. Introduction

One of the severe and common health issue comprises of neurological disorders. Epileptic seizures is a grave ailment that is the ranked fourth among the most common brain disorders. Everyday activities of the patient of epilepsy are impaired and it poses a great risk of accidents or even elevate the chances of early death. what further worsens the condition and makes the controlling and management of epileptic seizures even more challenging is the significant shortage of experienced neurologists, particularly in underdeveloped countries. It is estimated that almost 70% of patients with epilepsy may be treated with suitable therapy [1], if diagnosed early and proper care is given.

A brief sudden irregular, self-sustained electrical discharge that usually lasts for a few couple of minutes in the cerebral networks causes an epileptic seizure (ES). These seizure attacks are quite unpredictable and it is hard to foresee the duration and severity of the attack. As a result, patients and their caretakers are apprehensive about accidents and potential dangers as a result of these incidents. Therefore, early detection of epilepsy events is critical for avoiding and mitigating their negative repercussions.

Neurologists prescribes EEG of the brain to determine the onset of such seizure episodes. Because of its low cost and technological capability of recording brain activity for long periods of time, EEG has proven to be an essential tool. In the EEG test, the brain waves are picked up by electrodes, which are small sensors placed on different areas of the patient's head. The electrodes are able to record the electrical activity from small areas of the brain, therefore each electrode outputs an electrical signal that varies over time. These recordings are difficult to study manually since they are complex biological signals. The EEG is the combination of all the electrodes signals in one single "chart", where a signal for each electrode being (y-axis) varied over time (x-axis) can be seen. Fig. 1 shows an example of an EEG, which in this case presents some epileptic activity. EEG has a poorer spatial resolution than functional MRI but gives a better temporal insight into brain activity. The number of electrodes used can range from one to a few dozen and the way they are positioned on specific section of a patient's head, each electrode monitors the activity of separate region of the brain. To address the issues related with manual analysis of EEG recordings, like constant access to neurologists for long duration of EEG recordings and precise identification, machine learning methods are employed to automate the investigation and classification of EEG data for automatic detection of epileptic seizures [2].

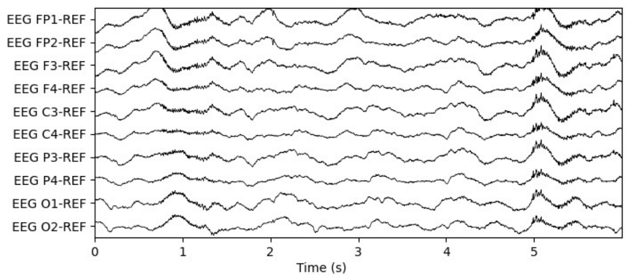

Fig. 1. EEG Signal of a patient

The EEG recordings of the epilepsy can be subdivided into four states - pre-ictal (immediately prior seizure), ictal (during a seizure), post-ictal (immediately following a seizure), and interictal (in-between seizures) [3]. For EEG data processing, five frequency bands are often examined: Delta (up to 4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–26 Hz), and Gamma (26–100 Hz). EEG has a frequency range of 1 Hz–100 Hz and an amplitude range of 10 V–100 V. The features obtained on this frequency-domain transformed signal is basically fed as an input to machine learning models, while Deep Learning models automate this feature training.

Electrical disturbances that disrupt the neural signal are called artefacts. They might occur due to improper electrode positioning or faulty tools being used and other natural artifacts could be Cardiac Activity, Line Noise, Myogenic Activity, Ocular Artefacts, etc.

The given actions must be taken in order, to detect seizure utilizing EEG data

- Pre-processing of the obtained raw EEG data.
- Extracting the features from the time and frequency domains for learning patterns to differentiate the seizure activity from normal.
- Using machine learning classifiers to do binary classification of the patterns seen - seizure or normal.

The epileptic seizures are of varying types having distinct sources or origin. This study focusses only on generalized seizures. Generalized (or non-focal) seizures are those which have a wide onset and spreads rapidly over the entire brain, unlike focal seizures which remains concentrated only in their specific region of origin. Generalized seizures exhibit less intra-patient and inter-patient variability than other seizure types [4].

II. LITERATURE SURVEY

The goal has been to automate the epileptic seizure detection process to reduce the burden of neurologists and increase the efficiency and accuracy of the predictions. Consequently, a large number of papers have been published using different algorithms of machine learning, fuzzy logic and end to end DL models to classify, detect or predict seizures on separate EEG datasets such as Bonn University Electroencephalogram dataset, CHB-MIT, data corpus of Temple Hospital University (TUH) and so on. Furthermore, the literature survey gives the direction of the research, which methods to avoid or take, future improvements to be attempted and captures the characteristics to determine seizures depending on the separate EEG databases. The main reason behind this is the fact that EEG recorded under various scenarios has distinct properties.

Epilepsy seizure detection is not a simple straightforward problem, it requires a series of procedures and experts to carry out these steps smoothly and accurately. The EEG data is not directly fed as the input to the machine learning models, instead the time, frequency and time frequency domain features are extracted from it to be sent as input. After extracting the optimal features from the raw EEG signal, an appropriate machine learning algorithm, such as KNN, SVM, LSVM [5], etc. is applied on the input features for detection of seizure from the normal background EEG data.

A remarkable work employing statistical measures such as EEG spike of multiple signals with an initial attempt in a research paper published [6]. Electroencephalogram is non-stationary signal, that means it varies with time statistically. Both spatial and time related statistics can be found in EEG waves. Feature extraction using Fast Fourier Transform (FFT) and Wavelet Transform (WT), emerged as an efficacious tool to extract the most critical information from EEG in the last two decades. In the last several years, extracting features either directly from pre-processed EEG signal or applying Fast Fourier Transform and Wavelet Transform for it has been proven to be an effective approach for obtaining the most relevant details and data from EEG. Hand-engineered frequency features were acquired from the records in [7]. Following that, classic ML methods such as random forests, k-nearest neighbor, and hidden Markov models were applied, as well as deep learning approaches were used like CNNs. The accuracy score of KNN was 58.2% while Random Forest attained better result, i.e., 68.3% accuracy [7]. An approach builds on Hidden Markov Models (HMM) achieved an accuracy of 73.9%.

There is a lack of studies concerning seizure detection on large dataset, for example, TUH corpus, using the conventional machine learning algorithms on a wide variety of time and frequency features and drawing the comparisons of accuracies among them and with deep learning models. This imbalance could establish unfair comparisons and inferences being drawn, which could ultimately lead to false impression of one algorithm having edge over the rest. It is wrong to assume that deep learning approach will always give better results than feature-based ML algorithms as for some applications the case might be opposite. For instance, the research carried out on detecting diseases from electronic health data in [8] proves that logistic regression can compete with the DL algorithms in terms of result accuracy.

III. DATASET

In this study, the Temple University Hospital (TUH) EEG corpus have been used. It is one of the largest dataset publicly available (Neural Engineering Data Consortium [9]). The complete dataset contains about 16,986 sessions from 10,874 unique subjects with an equal ratio of male and female participants. It was collected using the internationally accepted American Clinical Neurophysiology Society (ACNS) standard 10-20 system in which 21 electrodes on the scalp are evenly distributed shown in Fig. 2. Average Referencing (AR) montage recordings for the electrodes from the corpus were taken.

Table I. Patient information in dataset

File	*Age (Years)*	*Gender*	*Seizure Duration (Seconds)*	*Background Duration (Seconds)*	*Total Duration (Seconds)*
1	47	Female	101	1011	1112
2	55	Female	80	189	269
3	38	Male	18	2393	2411
...	…	…	…	…	…
...	…	…	…	…	…
57	28	Female	17	584	601
58	20	Male	298	2	300

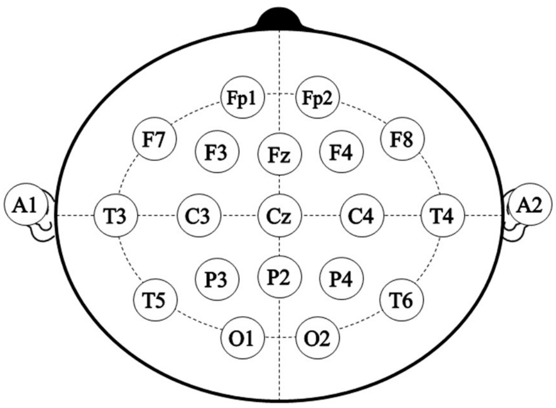

Fig. 2. ACNS map of the International 10-20 system

Annotations for the sessions are provided in separate files in the corpus. These annotation files are time-synchronous event (tse) files and use term-based annotations which applies to all the channels, shown in Fig. 3.

```
nedc_000 [1]: cat 00000492_s003_t004.tse
version = tse_v1.0.0
0.0000 10.2775 bckg 1.0000
10.2775 35.7775 gnsz 1.0000
35.7775 102.2525 bckg 1.0000
102.2525 142.9800 gnsz 1.0000
142.9800 339.0000 bckg 1.0000
```

Fig. 3. Format of a Time-Synchronous event file

First and second line of the annotation file defines the specific version of time-synchronous event (tse) file and current version of dataset. The values on the following lines describe the events in four values – the start time of the event in seconds, the stop time of the event in seconds, the label of the event, and probability of that label. The last value is 1.0 because these filles are annotated manually [10].

In our subset of the corpus, 58 session files are used which are stored in edf format (European Data Format). All the recordings in our subset are sampled at a frequency of 256 Hz and all of them have 21 common channels. There is only one particular type of seizure in our dataset which is generalized seizure (gnsz). Generalized seizures occurs in most if not all parts of the brain. The other annotation is background (bckg) which are other non-seizure cerebral signals.

In the 58 edf session files of our subset there is only generalized seizure and background events. Total duration of all the seizure events in the files is approx. 16,048 seconds and that of non-seizure events is approx. 17,027 seconds. From Table I, it can be observed that the dataset contains EEG recording of patients of different ages with varying duration of seizures. The data in the TUH corpus is clinical grade, i.e., it is inconsistent across various session for e.g., number of channels can differ from session to session. In our subset, data from 21 common channels from the EEG session was used.

IV. Methodology

The proposed approach of generalized seizure detection using EEG signals follows the workflow as shown in Fig. 4. The methodology is divided into four stages after extracting the data.

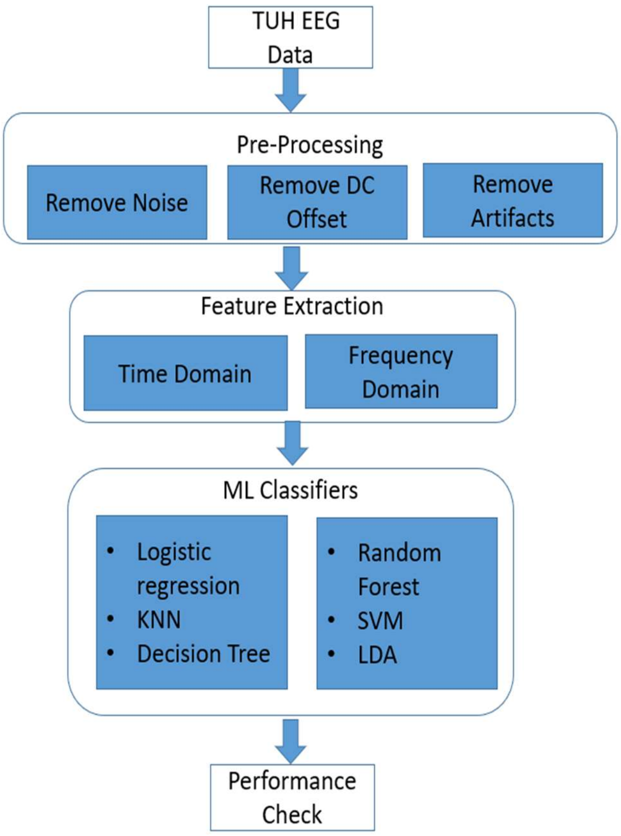

Fig. 4. Workflow of proposed methodology

A. Preprocessing

Pre-processing of EEG signal is done to remove noise, bad/artefact data, or to modify the data. In pre-processing, poor data is removed which might be generated by bad electrodes, body movements, eye blinking, along with noise generated by electrode movements or static discharge. These artefacts or noise can be removed from EEG segments by filtering the signal.

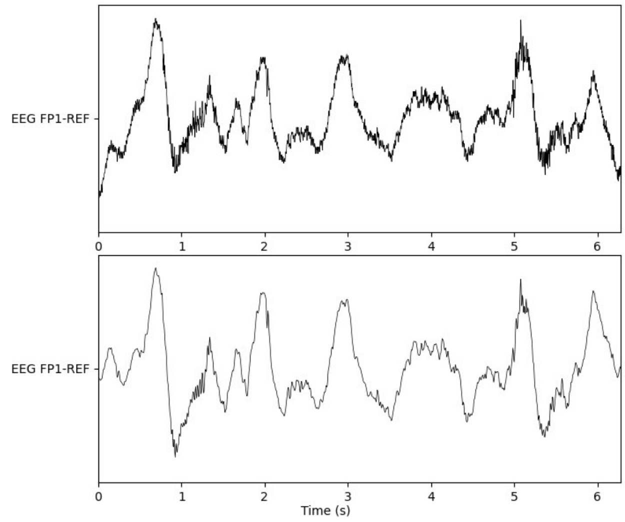

Fig. 5. EEG signal of a single channel before and after filtering

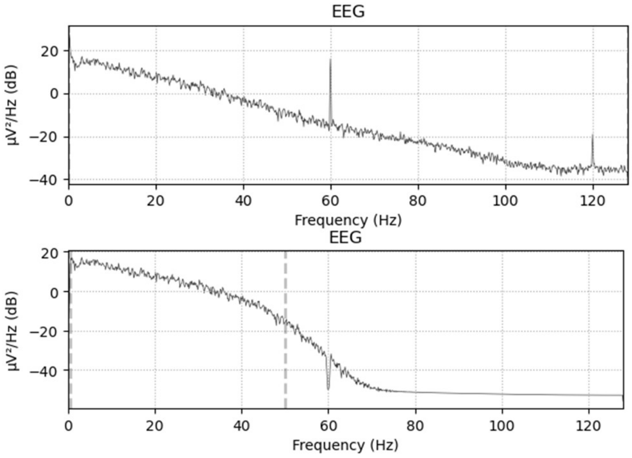

Fig. 6. Power Spectral Density plot of single channel EEG signal before and after filtering

Filters are used to attenuate a signal of a certain frequency. These artefacts or noise can be removed by filtering frequencies over 50 Hz. In the proposed methodology, data was separated and stored as seizure data and background data, and the signal was passed through a notch filter of 60 Hz. A 4th order Butterworth filter configured with passband from 0.5 Hz to 50 Hz was used which only allows signals with desirable frequency components, i.e., from 0.5 Hz to 50 Hz, to pass. The rest of the signals were filtered out. The resulting EEG signal, shown in Fig. 5 and Fig. 6, is free from noise or artefacts.

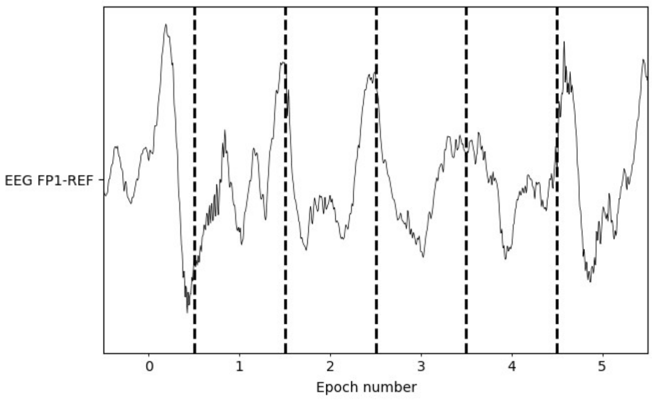

Fig. 7. Windows of a single channel EEG signal

A long EEG recording can be interpreted better by splitting the recording into segments of ideal window size. After filtering, the EEG signals are separated into EEG segments using fixed length windows of 1 second, as shown in Fig. 7. Windowing can help to simulate artificial stationarity of the signal. From these windows, time domain and frequency domain features can be extracted.

B. Feature Extraction

The next stage is extracting the patterns or features from the windows of EEG data of all 21 channels. These features which are used as input for different ML classifiers in next stage, are categorized by feature domains – time, frequency and time-frequency domains. Various time and frequency domain features have been considered, which have been listed. Time domain features are derived from the electroencephalogram data in the time domain. The features acquired from the Discrete Fourier Transform (DFT) of EEG signal comes under frequency domain features. The time domain features are given as follows.

1. Kurtosis – It measure the non-Gaussianity of the wave. Kurtosis describes the amount of peakedness of a distribution. It denotes the sharpness of the peak of a curve and helps to determine if the curve is more or less high as compared to the normal curve. The higher it is, the more sharply peaked the density function is. The lower it is, the flatter the density function is. It is sensitive to outliers. For a time-series, *X*, Kurtosis is given by

$$F^{(t)} = \frac{1}{N}\sum_{n=1}^{N}(X[n] - \mu)^4 \quad (1)$$

where, $\mu = \frac{1}{N}\sum_{n=1}^{N} X[n]$

2. Skewness – It is used as basic statistics which defines the degree of asymmetry or distortion of the waveform that deviates from symmetrical curve or normal distribution of a data. A curve is said to be skewed if it is shifted either to the left (left-skewed) or right (right-skewed) from its original bell curve.

$$F^{(t)} = \frac{1}{N}\sum_{n=1}^{N}(X[n] - \mu)^3 \quad (2)$$

where, $\mu = \frac{1}{N}\sum_{n=1}^{N} X[n]$

3. Approximate entropy [11] – Entropy quantifies the uncertainty or unpredictability of a non-stationary EEG signal. It can be used in variety of ways to measure the randomness of a series of data. One of the entropy measure is approximate entropy, which gives a measure of the constancy and variation in time series, that are generated by comparing the template vector's similarity patterns. A windowed signal is defined as a template vector of size m.
4. Sample Entropy [11] – It is based on similar concept as that of approximate entropy with some modification. It is better than approximate entropy in two ways – it is easy to implement (relatively) and independent of the length of data. There is also a little computational difference between the two.
5. Hjorth parameters (Mobility and complexity) – These are the nonlinear parameters which are used to capture the spectral properties of EEG signals in the time domain [12]. Hjorth mobility is a measure of a quantity that is proportional to the spectral density of power spectral density of a signal. It is determined as the ratio of the Spectral Density of a signal derivative to the Spectral Density of the signal. Hjorth complexity denotes the difference between the signal and a pure sine wave. The signal's complexity is determined by the ratio of a signal derivative's mobility to the signal's mobility.
6. Singular Value Decomposition (SVD) Fisher Information – Fisher information measure provides a unique way for analyzing nonlinear dynamical systems such EEG signals. It offers a convenient way for signal analysis that may be utilized as an automated detector. As a result, Fisher's information was used to obtain physical information from a signal generated by a nonlinear dynamical system. These systems are either deterministic or chaotic in nature. Fisher information provides regular states a greater value and disordered states a lower value.
7. Singular Value Decomposition (SVD) Entropy – SVD of a rectangular matrix $A = U\sum V^T$, where $\sum = diag(\sigma_1, \sigma_2, \ldots, \sigma_m)$ consisting of singular values of *A*.

$$SVD\ Entropy, E(X) = -\sum_{j} \tilde{\sigma_j}\ log\tilde{\sigma_j} \quad (3)$$

where, $\tilde{\sigma_j} = \sigma_j / \sum_{i}^{m} \sigma_i$ which is normalized singular value [13]. The larger singular values are from the EEG signals with seizure and smaller values are from the normal EEG signals. An EEG signal with seizure has a lower SVD entropy value than a normal EEG signal.
8. Hurst Exponent – It gives a measure of time-series memory. A cumulative deviate series (or partial time series) of a time-series X is given by

$$z[t] = \sum_{j=0}^{t}(X[j] - \bar{X}) \quad (4)$$

$$HE.\log m = \log\left(\frac{R(m)}{S(m)}\right) \quad (5)$$

where, $\bar{X} = \left(\frac{1}{m}\right)\sum_{i=0}^{m-1} X[i]$, $S(m)$ is the standard deviation of the partial time series and $R(m) = \max(z[t]) - \min(z[t])$.
9. Fractal dimension – The complexity of a signal can be found out by using its fractal dimension. Higuchi and Katz dimension can be used on a time-series to calculate its fractal dimension in time domain [14].

The frequency feature domain features are as follows.

1. Band Energy – Energy of some specified frequency ranges are collected to assess the pattern of EEG signal.
2. Spectral Edge Frequency (SEF) – It is the frequency under which α percent of the total power is contained. It is denoted as SEFα. Most of the power of a typical EEG is contained within 0 Hz to 40 Hz, $P_{40\,Hz}$. Hence, the frequency below which 50 percent of the total power is contained can be used [15].

$$f_{50} = \min\left\{\dot{f} \,|\, \sum_{f=0}^{\dot{f}} p_f > P_{40\,Hz} \,.\, 0.50\right\} \quad (6)$$

3. Spectral Entropy [13] – It indicates the uncertainty of the random process from the frequency distribution. For a time-series, *X,*

$$SE(X) = -\sum_{n} X[n] \log_2 X[n] \quad (7)$$

4. Power Spectrum – Power contained in different frequency bands of the EEG signal are calculated and used as features.

$$\delta_r = \frac{1}{P_s} \sum_{f_r=0.5\,Hz}^{4\,Hz} p_{f_r}\,;\ \vartheta_r = \frac{1}{P_s} \sum_{f_r=4\,Hz}^{8\,Hz} p_{f_r}\,; \quad (8)$$

$$\alpha_r = \frac{1}{P_s} \sum_{f_r=8\,Hz}^{13\,Hz} p_{f_r}\,;\ \beta_r = \frac{1}{P_s} \sum_{f_r=13\,Hz}^{30\,Hz} p_{f_r}\,; \gamma_r = \frac{1}{P_s} \sum_{f_r=30\,Hz}^{50\,Hz} p_{f_r}$$

Where, p_{f_r} is the power of frequency f_r and P_s is the total power.

C. Machine Learning Classifiers

After extracting features of the EEG signals, the following supervised classification models were used.

1. Logistic Regression – It is a linear classifier which fits the input to a logit function to predict the probability of an event occurring. It is an effective and straightforward machine learning algorithm which is used regularly.

2. K-Nearest Neighbours (KNN) – The KNN algorithm uses the defined distance metric to find n samples from the dataset which are most similar to a datapoint and classifies them as nearest neighbours by giving a class label to the samples using a majority vote. KNN classifier can be used with the Manhattan distance, with p=1, or the Euclidean distance, with p=2.

$$d(x_i, x_k) = \left(\sum_{j=1}^{D} \left| x_{i,j} - x_{k,j} \right|^p \right)^{\frac{1}{p}} \quad (9)$$

The classifier is highly adaptable when unused data is available, however overfitting is a problem in KNN because of dimensionality, in which the feature space gets significantly scattered as the dimensions of the feature space grows.

3. Decision Tree Classifier – In their most basic form, decision trees basically pose a series of questions to split data points into nodes (bins). The data or information is divided into features whichever is able to acquire most information by an algorithm that begins at the root of the tree. All the samples of a certain node are grouped in the same class by repeating the algorithm. To minimize overfitting due to a deep tree, a node limit, or tree depth, is frequently specified. The difference between parent node's impurity and the sum of its child node's impurities is calculated to split by using the information gain. When the child node's impurity is low, information gain is significant.

4. Random Forest Classifier – Random Forest combines the output of various decision trees and computes an outcome. It is a frequently used machine learning algorithm. An uncorrelated forest of decision trees is constructed by random forest by using feature randomness and bagging technique as it is an extension of the bagging method. There are three key hyperparameters in a random forest that must be specified before training such as the size of the nodes, the number of trees, and the number of characteristics sampled. Random forest can be used to solve problem of classification or regression.

5. Support Vector Machine – The Support Vector Machine (SVM) is another frequently utilized discriminative technique. SVM separates the data point belonging to different classes by finding a hyperplane with largest margin of separation. Features in the feature vector are considered as data points in the high-dimensional space. During training, the model tries to split the classes using the optimum values of w, the positive class datapoints are grouped behind the positive hyperplane and negative-class datapoints are grouped behind the negative hyperplane.

$$w^T x_i \geq 1 \ if \ y_i = 1 \quad (10)$$

$$w^T x_i < -1 \ if \ y_i = -1 \quad (11)$$

Support vectors are a subset of training data. To compute the ideal separation hyperplane, support vectors are chosen to optimize the model. A hard separation margin can be created for data which can be linearly divided, and the decision boundary's support vector is a datapoint on the edge of a class.

6. Linear Discriminant Analysis – LDA is a dimensionality reduction approach. In supervised classification, LDA is a frequently used approach. It is used to find differences in groups, such as separating two or more classes. Higher-dimensional characteristics are projected onto a lower-dimensional region in this approach. Using Bayes' rule, class conditional densities are shaped to the data by generating a linear decision boundary. The covariance matrix is presumed to be the same for all classes by the LDA model and fits a Gaussian density function to each class. In this study, the eigenvalue decomposition was employed as the solver for the classifier.

D. Evaluation Metrics

All classifiers that have been considered were assessed using a cross-validation approach. Performance is calculated on the part of dataset that was not used for training the classifier. The performance evaluation of each model was done by the following metrics on each held-out dataset.

Sensitivity (or Recall) – Out of all the actual positive points, what percentage of them are predicted to be positive gives the sensitivity.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + Fals\ \ Negative} \times 100 \quad (12)$$

Specificity – Out of all the actual negative points, what percentage of them were correctly predicted to be negative gives the specificity.

$$Specificity = \frac{True\ Negative}{True\ Negative + Fals\ \ Positive} \times 100 \quad (13)$$

Precision – Out of all the points the model declared/predicted to be positive, what percentage of them are actually positive gives the precision.

$$Precison = \frac{True\ Positive}{True\ Positive + False\ Positive} \times 100 \quad (14)$$

F1 Score – It gives the harmonic mean of Precision and Recall. F1-score lies between [0, 1]. Lesser the F1-score lesser the sensibility of model.

Table II. Values of various performance metrics

Classifier	***Sensitivity (or Recall)***	***Specificity***	***Precision***	***Accuracy***	***F_1 Score***
Logistic Regression	93.39	91.16	93.30	92.43	0.9300
K- Nearest Neighbors	93.05	88.85	92.00	91.28	0.9250
Decision Tree	92.06	90.04	92.52	91.20	0.9250
Random Forest	96.40	81.15	87.65	90.01	0.9183
Support Vector Machine	93.64	91.37	93.67	92.70	0.9400
Linear Discriminant Analysis	90.08	87.77	90.65	89.08	0.9050

$$F_1\ Score = \frac{2\ \times Precision\ \times Recall}{Precision + Recall} \qquad (15)$$

Accuracy – It is simply the fraction of the total sample correctly identified. It is a very simple evaluation measure and gives the percentage of correct classification.

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \times 100 \qquad (16)$$

In equation (16),

- True Positive (TP) – Points which are actually positive, and the model also predict them as positive.
- True Negative (TN) – Points which are actually negative, and the model also predict them as negative.
- False Positive (FP) – Points which are actually negative. but the model predicts them as positive.
- False Negative (FN) – Points which are actually positive. but the model predicts them as negative.

V. Result and Discussion

In this study, the models were trained on an Asus laptop with Intel 8th Gen i7 – 8750H 2.21 GHz, 16GB RAM and Nvidia GeForce GTX 1060. Dataset was split into training (80%) and validation (20%) and used 5-fold cross-validation to select the ideal classifier. From Table II, it can be observed that all six classifier had comparable results, but Support Vector Machine obtains the highest accuracy, i.e., 92.70%, and F1 score, i.e., 0.94. Support Vector Machines (SVMs) are immune to overfitting and work well for modelling non-linear decision boundaries. Logistic regression also gave an accuracy of 92.43% and F1 score of 0.93. It is a discriminative approach to categorizes a dependent variable with a finite number of alternative values, which makes it more suitable for seizure classification.

VI. Conclusion

The normal physical and emotional health of person is disrupted by these episodes of seizures. machine learning-based techniques for EEG signal categorization have been widely used for other datasets like CHB-MIT Scalp EEG Database, Bonn University EEG database and so on to identify epileptic episodes but not much work has been reported for generalized seizure detection on TUH EEG dataset. In this study, epileptic seizure detection on TUH EEG corpus was studied, which detect seizure through six different machine learning algorithms – Logistic Regression, KNN, Decision Tree, Random Forest, SVM and LDA. The performance of all these algorithms have been compared in terms of the following evaluation metrics – sensitivity, specificity, precision, F1 score and accuracy. This system takes time-domain and frequency-domain features as input which were obtained from the EEG data of patients after preprocessing, and then predict whether epilepsy is detected or not. It can be inferred from the results in Table II that all of these classifiers are giving decent performances which are comparable, with support vector machine giving the best results. This study reports novel work with good results from ML classifiers on TUH EEG dataset. We worked with a limited amount of data in order to replicate a real-world scenario, where seizure data is highly difficult to gather.

VII. Future Work

Future works on this study could involve a research on a bigger scale, testing a higher amount of machine learning models with different parameters, using some extra pre-processing technique and additional feature extraction through time, frequency as well as time-frequency domain to improve performances, while still keeping the dataset fairly small to be more realistic. This work on TUH EEG dataset can be extended further by converting the EEG data into spectrogram/scalogram images, which can be used as inputs to the deep learning models.

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