Detecting Epileptic Disease using Machine Learning

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***Abstract*—Timely detection of epileptic seizures through electroencephalography (EEG) analysis can facilitate prompt treatment. This paper reviews machine learning techniques like support vector machines (SVMs), random forests, and logistic regression and ensemble learning for automated seizure detection using EEG signals[17]. The core ideas behind these models are discussed along with their applications for epilepsy detection based on existing literature. Feature extraction plays a vital role in model performance, with time-domain, frequency-domain, and time-frequency domain features proposed. Standard evaluation metrics like accuracy, precision, recall, and F1-score along with AUC and ROC are reviewed for each model. Key challenges include variability across patients, imbalanced datasets, generalizability across seizure types, and validation in real-world settings. Promising future directions involve deep learning for enhanced feature learning, multimodal systems combining EEG with other signals, focus on patient-specific tuning, testing across diverse datasets, and enabling real-time seizure detection. [14]**

***Index Terms*—SVC, Logistic Regression, Accuracy, Precision, F1 Score, Random Forest, Ensemble Learning, AUC, ROC**

I. Introduction

Epilepsy is one of the most common chronic neurological disorders, affecting around 70 million people worldwide (Seethalakshmi et al., 2022)[9]. It is characterized by recurrent, unprovoked seizures originating from abnormal excessive electrical discharges in the brain (Gotman, 1982)[2]. Electroencephalography (EEG) provides valuable insights into brain activity and is commonly used for detecting and analyzing epileptic seizures (Subasi, 2007)[3].

Automated seizure detection through analysis of EEG signals has the potential to enable timely medical intervention and improve treatment outcomes (Pandey and Mohanty, 2018)[4]. Machine learning techniques have been widely explored for EEG-based seizure detection, including support vector machines (SVMs), artificial neural networks (ANNs), and more recently deep learning models like convolutional neural networks (CNNs) (Roy et al., 2019)[5].

Feature extraction from EEG signals is a crucial preprocessing step for applying machine learning. Commonly used features include time-domain features like Hjorth parameters (Khan et al., 2011)[6] and frequency-domain features derived through Fourier and wavelet transforms (Wang et al., 2013)[8]. Models developed using patient-specific tuning have shown improved detection accuracy (Brinkmann et al., 2016)[7].

Overall, machine learning applied to EEG signals demonstrates immense potential for automated real-time epileptic seizure detection and monitoring. This can significantly improve diagnosis and enable timely therapeutic interventions for epilepsy patients. However, real-world clinical validation remains limited. Further research with larger patient datasets is needed to develop generalized systems for clinical adoption.

II. Literature Review

Dhondiyal et.al[10] describes SVM which is used to measure the epileptic disease. The dataset is coolected from kaggle which has 11500 rows and 178 columns. The target value(y) varies from 1-5, in which 1 signifies siezure value and 2-5 signifies non-siezure patients. They have also calculated the accuracy of 82%, precision of 100%, Recall of 10% and F1 score of 10%. Seethalakshmi et.al[9] uses wireless sensor to detect and monitor epileptic disease. They used SVM, and used feature extraction and Feature Ranking to extract features from EEG data. Grassberger and Procaccia methods are used as basic foundation in this review article, which leads to 5% greater accuracy than with FuzzyEn or HE.

Velvizhy et al[11] uses three models - MPL, CNN, SVM combinations for detecting epileptic seizures from EEG signals. The hybrid combinations used for this study are SVM+Cnn, MLP+CNN, and SVM+MLP+CNN. The dataset was collected from CHB-MIT which includes 23 patients. This research helped in diagnosing the particular area of the brain with seizure leading to hiring accuracy and identifies the firing location from the brain. To minimize information loss, it is imperative to undertake future efforts aimed at enhancing the suggested system's ability to detect restricted diffused partial seizures. Moreover, incorporating novel methodologies is essential to improve the precision of identifying the firing region of seizures within the brain. J.M et. al[12] Numerous alternative classification strategies and algorithms are documented in the literature, including artificial neural networks (ANN), random forests (RF), and support vector machines (SVM).The dataset comprises recordings from 23 participants, including five males aged between 3 and 22 years, and seventeen females aged between 1.5 and 19 years. The classification performance achieved with HG-RF surpassed that of other methods, boasting an accuracy rate of 97.32%, a sensitivity of 94.52%, and a specificity of 97.19%. This paper leads to delve deep into online epilepsy detection. B.B et al[13] The generated .csv file serves as a dataset for seizure detection, utilizing XG-Boost to ascertain the presence of an impending seizure during the prediction phase. Analytical features are initially extracted from each brain signal to form the characteristic vector. Based on these features, XG-Boost distinguishes between seizure signals and healthy signals. he code is tested with an existing dataset encompassing individuals experiencing seizures at various stages, namely ictal, preictal, and inter-ictal.In the ictal stage, the proposed method achieves a detection accuracy of 88%. For the pre-ictal stage, the accuracy is 84%, and for individuals with epilepsy in the inter-ictal stage, the accuracy reaches 91%. The proposed method demonstrates time efficiency in seizure detection, with potential for further improvement through the addition of more surface electrodes, extended data collection, and the integration of powerful ensemble algorithms. The recordings were collected at the Neurology & Sleep Centre in Hauz Khas, New Delhi.The available downloadable dataset consists of fifty MAT files, each containing a single EEG time series data lasting for 5.12 seconds with 1024 samples. Chekhmane et al[14] The detection of epileptic seizures relies on the wavelet transform in conjunction with the Support Vector Machine (SVM) and Multilayer Perceptron Neural Network (MLPNN) for automated disease identification. The results obtained from SVM and MLPNN demonstrate accuracies of 99.5% and 100%, respectively. The publicly available data utilized in this study is sourced from Andrzejak. The complete dataset comprises five sets (A, B, C, D, and E), each containing 100 single-channel EEG segments lasting 23.6 seconds. Sets A (open eyes) and B (closed eyes) are extracranial data taken from five healthy subjects. Sets C, D, and E are intracranial data collected from five epilepsy patients. Sets C and D contain EEG activity measured in seizure-free intervals from the epileptic hemisphere and the opposite hemisphere of the brain, respectively. Set E exclusively comprises data from the epileptic seizure state. Islah et al[15] The experiment involved testing the Isolation Forest algorithm and Logistic Regression using various ratios of outliers to random samples within the interictal training set.Outlier-based sampling demonstrates superior performance compared to standard sampling methods for imbalanced classes, achieving high accuracy, sensitivity, lower false positives, and short latency.To further investigate this success, a subsequent study could explore repeating the process with outliers from different anomaly detection algorithms, allowing for a comprehensive head-to-head comparison.[16]

III. Materials and Methods

A. EEG

Electroencephalography (EEG) is a critical technological component that enables brain-computer interface (BCI) and neurofeedback (NFB) applications. (Debener et al, 2019)[17]. Electroencephalogram (EEG) is one of the most vital tools for diagnosing and analyzing epilepsy. Manual detection of epileptic seizures from EEG is a tedious and time-consuming task that requires neurologists' expertise. It is crucial to provide a prompt and accurate diagnosis so that patients can start treatment as soon as possible(Liu et al, 2012)[20]. Prior research on EEG classification and interpretation is based on the idea that dynamic temporal and spectral alterations in EEG signals reflect brain response times. As a result, wavelet transforms are very effective for capturing even the smallest changes in EEG data. Processing EEG signals is often challenging owing to their nonstationary and nonlinear characteristics. Thus, automated techniques for detecting epileptic episodes are being extensively researched (Golovoko et al, 2007)[21]. EEG measures electrical signals generated by neuronal firing within the brain and detected via electrodes placed at strategic scalp locations. The electrode impulses are acquired and stored in a recording device connected to the electrodes through cables (Tzallas et al., 2009) [22]. The universally accepted technique for positioning electrodes in EEG recordings is the 10-20 system. It refers to the notion that actual inter-electrode spacings are 10% or 20% of the head's front-back or right-left distance (Silva et al, 2021) [23].

B. Dealing with unbalanced data

Machine learning shows promise for seizure detection from EEG data. However, classification is challenging due to imbalanced data and complex EEG patterns. This paper proposes an integrated technique using principal component analysis (PCA) and ML classifiers to improve seizure detection with imbalanced data. Unlike typical use of top principal components, they extract both high- and low-variance components, hypothesizing the latter may better capture implicit patterns for the minority class. Various ML models are trained on PCA component combinations. Results show selective components outperform using all EEG attributes, indicating overfitting reduction and more accurate seizure detection is possible without all complex data. The proposed integrated PCA-ML approach is statistically significant. In only 150 PCA-transformed attributes versus thousands of EEG readings, performance improves - fast processing for clinical adoption. The novel handling of imbalanced data and assessment of component combinations advance epilepsy study.[19]

C. Logistic Regression

Logistic regression is a popular algorithm for binary classification tasks. The key idea is to model the probability P(Y=1—X) - that is, the probability of the output Y being 1 given the input features X.

It uses the logistic sigmoid function to squeeze the probability prediction to between 0 and 1. The model parameters are learned by maximizing the likelihood of the training data through numerical optimization. Mathematically, the logistic regression model is[28]:

P(Y=1—X) = 1 / (1 + exp(-wT X - b))

where:

- X - Input feature vector
- w - Learned weight vector
- b - Learned bias term

The optimal w and b are learned by maximizing the likelihood or log-likelihood of the training data. This turns the logistic regression training process into an optimization problem that can be solved using gradient ascent.

In a nutshell, logistic regression provides a clean probabilistic framework to predict binary outcomes from feature data. The use of optimization algorithms for model fitting makes it easy to implement as well.[28]

D. SVM

Support vector machines (SVMs) are a powerful machine learning technique for classification, based on statistical learning theory. They achieve good generalization performance in practice. The key idea behind SVMs is to find a hyperplane that maximizes the margin between classes. Intuitively, a larger margin allows for better discrimination between classes, leading to improved generalization on unseen data. This connection between large margins and generalization capability can be leveraged to enhance other classification algorithms like decision trees.[18] The model demonstrates high accuracy. The dataset was split into 70% train data to fit the model, and 30% test data to evaluate it. Since the data is labeled, model training is straightforward - it learns decision boundaries from examples. Support vector machines (SVMs) create optimal hyperplanes to categorize data, fixed at maximal margin from examples. So new epileptic EEG can be reliably classified based on past training[24].

E. Random Forest

Random forest builds an ensemble of decision trees for classification and prediction. Unlike a single decision tree, a random forest averages votes from multiple trees to determine the final output class. Specifically, it trains a number of decision trees on random subsets of features from the data. Each constituent tree is like a set of if-else rules that partitions the feature space into regions and assigns them class labels. The branching decisions, made based on cut-off thresholds for features at each node, can be visualized as a tree flowchart. Individual trees may overfit, but aggregated together, random forests can integrate over many distinct partitioning solutions. This strategy combines predictions from a diverse set of models to yield high generalization capability - properly classifying new unseen data at a robust level of accuracy. The randomness injected both in subsampling training data and features evaluated at splits increases coverage of the feature space for reliable predictions.[24].

F. Ensemble Learning

This paper [25] presents a patient-specific algorithm using supervised learning to detect seizures from long intracranial EEG (iEEG) recordings. It processes fixed 5s iEEG segments, since seizures last 10s to minutes. A two-step ensemble approach is proposed. First, Logistic Regression classifiers are trained on 1s subsegments via cross-validation. Then a meta-classifier combines predictions from the 1s classifier set to classify 5s segments by majority vote. Dividing longer episodes enables training on short seizure events. Ensembling multiple classifiers improves robustness. So the system can reliably detect epileptic events by learning from labeled examples, without needing real-time warning.

IV. Flow Diagram

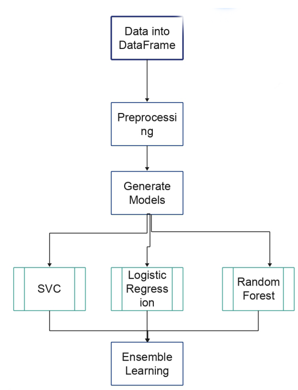

Fig. 1. Flow diagram for the problem statement

V. Results & Discussion

A. Balance in dataset

The dataset used for this epilepsy classification problem contains an equal number of EEG recordings from epileptic patients (positive class) and healthy people without epilepsy (negative class). The dataset consists of EEG recordings collected from 20 total subjects, split evenly with 10 healthy people and 10 epilepsy patients.

The training set is comprised of 10 of these subjects - 5 healthy and 5 epileptic. For each of the 10 training subjects, there are 40 associated EEG data files per person. This results in a total of 400 data files capturing single electrode brainwave measurements in the training set, with a sampling frequency of 250 - 256 Hz. [27] This Figure shows how balanced the dataset is, where H in green represents healthy people and E in red represents Epileptic patients:

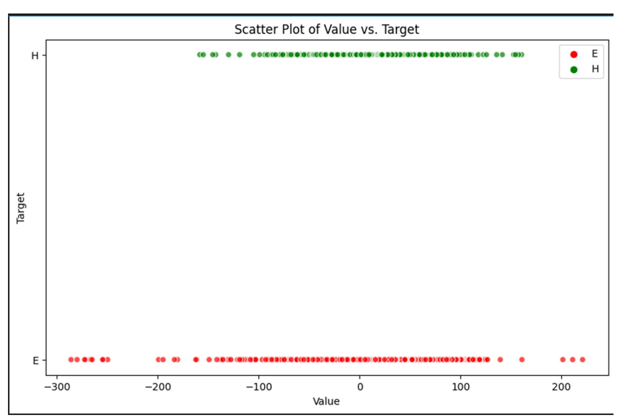

Fig. 2. Balance in Dataset

B. Data Loading and Preprocessing

- Dataset : This epilepsy diagnosis dataset[27] was generated in 2020 with the goal of building machine learning

models to predict epilepsy from EEG signals. It overcomes certain limitations faced by the older University of Bonn epilepsy dataset.
The key aspects are:

1 It uses surface EEG recordings exclusively, unlike University of Bonn which had a mix of inter-cranial and scalp recordings.
2 The recording settings match those of the University of Bonn dataset in terms of sampling frequency (250, 256 Hz), bandpass filtering and signal duration
3 Data was collected from 15 patients - both healthy individuals and those with generalized and focal epilepsies. By standardizing the recording methodology and using only surface EEG, this dataset enables training generalized models. The consistent recording settings also allow fair comparisons to existing research benchmarks. Using signals from both healthy patients and those with established epilepsy aids in building detection systems that can handle real-world variability.

Overall, the dataset advances epilepsy diagnosis research through its robust collection methodology and coverage of diverse EEG signals. The availability of focal and generalized seizure EEGs, in particular, facilitates building automated tools for fine-grained classification.

- Code walkthrough : The data[27] consisting of EEG signal values across multiple text files is loaded into a Pandas dataframe.The file names are extracted and stored in the 'FileName' column while the signal values are stored in the 'Value' column.
Preprocessing steps involve:

1 Removing everything after the underscore from file names to generalize them
2 Converting the values to float datatype.
3 Grouping by file name and aggregating values into lists
4 Adding a label column indicating 1 for epileptic (E) patients and 0 for healthy (H) based on file name

```
print(df)

          FileName   Value
0       E10_1.txt    8.61
1       E10_1.txt    4.38
2       E10_1.txt   -5.18
3       E10_1.txt  -13.98
4       E10_1.txt  -19.05
...           ...     ...
7995  TrainH5_9.txt   22.51
7996  TrainH5_9.txt   23.05
7997  TrainH5_9.txt   22.71
7998  TrainH5_9.txt   22.92
7999  TrainH5_9.txt   21.91

[8000 rows x 2 columns]
```

Fig. 3. Dataframe

These steps structure the raw data into an analysis-ready dataset(Fig:3) with file identifiers, eeg values, and binary labels.

C. Exploratory Data Analysis

- Missing values : The dataframe is checked by using a isnull().sum() operation to check if there are any emply or missing values in the dataset. The result we saw was that there were no missing values in the dataset.

```
Total number of null values: 0
```

Fig. 4. Missing values

- data types: The datatype of the column that is in the dataframe is object type and we cannot perform direct operation on this object type, so this need to be converted to float type for implementing different models.
- Feature details like Min and Max: Now, to get more insights on data, finding the min and max value is crucial, as it can provide the range in which the value is lying in between.

```
Minimum value: -0.00
Maximum value: 99.10
```

Fig. 5. MinMax

D. Model Building

This paper presents with 4 models that are used to train the dataset and prediction. Each prediction Multiple supervised learning models are trained and evaluated. These models are namely Logistic Regression, SVC, Random Forest and Ensemble Learning.

- Logistic Regression: The model's performance varies across different folds, with accuracies ranging from 16.67% to 83.33%. The average accuracy of 50% suggests that, on average, the model is making correct predictions half of the time. This information indicates that there may be room for improvement in the model's performance on this dataset, as the accuracy is relatively modest.

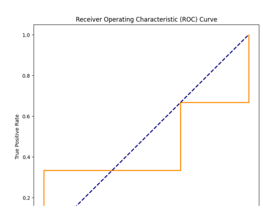

Fig. 6. Logistic regression

- Support Vector Machine (SVM): the model's accuracy varies across folds, ranging from 50% to 66.67%. The AUC values also vary, with some folds indicating poor discrimination (close to random performance). The average accuracy and AUC provide an overall summary of the model's performance,

```
Accuracy of fold 1: 0.3333333333333333
Accuracy of fold 2: 0.16666666666666666
Accuracy of fold 3: 0.8333333333333334
Accuracy of fold 4: 0.5
Accuracy of fold 5: 0.6666666666666666
Average accuracy: 0.5
```

Fig. 7. Logistic regression Accuracy

```
Accuracy of fold 1: 0.6666666666666666
AUC of fold 1: 0.4444444444444445
Accuracy of fold 2: 0.6666666666666666
AUC of fold 2: 0.3333333333333333
Accuracy of fold 3: 0.6666666666666666
AUC of fold 3: 0.0
Accuracy of fold 4: 0.5
AUC of fold 4: 0.5
Accuracy of fold 5: 0.5
AUC of fold 5: 0.6666666666666667
Average accuracy: 0.6
Average AUC: 0.3888888888888889
```

Fig. 8. SVC Average accuracy & AUC

Models	Average AUC	Average Accuracy
Logistic Regression	0.4	0.50
SVC	0.34	0.60
Random Forest	0.74	0.70
Ensemble Learning	0.62	0.66

TABLE I
COMPARISON TABLE

- Random Forest: Comparing this random forest model to the previous models, it generally has higher accuracy and AUC values, suggesting better performance in terms of both overall accuracy and the ability to discriminate between classes. With Random forest we achieve the Accuracy of 74%, which is the highest till now among the models that we used.

```
Accuracy of fold 1: 0.8333333333333334
AUC of fold 1: 0.7777777777777778
Accuracy of fold 2: 0.8333333333333334
AUC of fold 2: 0.6666666666666666
Accuracy of fold 3: 0.8333333333333334
AUC of fold 3: 0.875
Accuracy of fold 4: 0.5
AUC of fold 4: 0.625
Accuracy of fold 5: 0.5
AUC of fold 5: 0.7777777777777778
```

Fig. 9. Random Forest

- Ensemble: Ensemble model took in the three models that were previously used for evaluation. This model basically takes models and do computation on these to produce better results. Here the majority of models which were provided to ensemble were not properly accurate, thus leading to poor accuracy of the ensemble model. The below result shows how the accuracy varies after K-Fold was applied to it.

```
Fold 1:
Accuracy: 0.8333333333333334
AUC: 0.6666666666666666

Fold 2:
Accuracy: 0.6666666666666666
AUC: 0.4444444444444445

Fold 3:
Accuracy: 0.8333333333333334
AUC: 0.875

Fold 4:
Accuracy: 0.5
AUC: 0.375

Fold 5:
Accuracy: 0.5
AUC: 0.7777777777777778

Average Results:
Average accuracy: 0.6666666666666667
Average AUC: 0.6277777777777778
```

Fig. 10. Ensemble K-Fold validation

The average AUC for the ensemble model is provided below, with an average AUC of 62.78%.

VI. CONCLUSION

The random forest model had the highest average accuracy of 0.7 across the 5 folds, compared to 0.66667 for the ensemble model, 0.6 for the SVC model, and 0.3333 for logistic regression. The random forest model also had the highest average AUC of 0.744444 across the folds, indicating it had the best ability to discriminate between epileptic and non-epileptic patients. So in conclusion, of the models tested, the random forest model seems to most effectively predict whether a person is epileptic based on the provided data. It demonstrates higher predictive accuracy and ability to differentiate positive cases than the other models. Thus recommend using the random forest model for this classification task. Additional tuning of the model hyperparameters could potentially further

```
Accuracy of fold 1: 0.8333333333333334
AUC of fold 1: 0.6666666666666666
Accuracy of fold 2: 0.6666666666666666
AUC of fold 2: 0.4444444444444445
Accuracy of fold 3: 0.8333333333333334
AUC of fold 3: 0.875
Accuracy of fold 4: 0.5
AUC of fold 4: 0.375
Accuracy of fold 5: 0.5
AUC of fold 5: 0.7777777777777778
Average accuracy: 0.6666666666666667
Average AUC: 0.6277777777777778
```

Fig. 11. Ensemble: Average AUC

improve its performance. But the random forest shows promise for reliable prediction of epilepsy from the inputs compared to the other models

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