Hybrid ensemble learning framework for epileptic seizure detection using electroencephalograph signals

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ABSTRACT

An automated method for accurate prediction of seizures is critical to enhance the quality of epileptic patients While numerous existing studies develop models and methods to identify an efficient feature selection and classification of electroencephalograph (EEG) data, recent studies emphasize on the development of ensemble learning methods to efficiently classify EEG signals in effective detection of epileptic seizures. Since EEG signals are non-stationary, traditional machine learning approaches may not suffice in effective identification of epileptic seizures. The paper proposes a hybrid ensemble learning framework that systematically combines pre-processing methods with ensemble machine learning algorithms. Specifically, principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE) combined along k-means clustering followed by ensemble learning such as extreme gradient boosting algorithms (XGBoost) or random forest is considered. Selection of ensemble learning methods is justified by comparing the mean average precision score with well known methodologies in epileptic seizure detection domain when applied to real data set. The proposed hybrid framework is also compared with other simple supervised machine learning algorithms with training set of varying size. Results suggested that the proposed approach achieves significant improvement in accuracy compared with other algorithms and suggests stability in classification accuracy even with small sized data.

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1. INTRODUCTION

Epilepsy is one of the most prevalent and chronic neurological disorder affecting over 50 million individuals worldwide of all ages, according to World Health Organization (WHO) in 2019 [1]. Early effective diagnosis, treatment will help 70% of epileptic patients to live seizure free. Electrical instability in the cortical region of the brain characterizes epilepsy as transient, abrupt, and periodic. Method to detect brain signals non-invasively is through electroencephalograph (EEG) and study of EEG recording is cumbersome and non-derivable, so an automated seizure detection system recognizes specific EEG sections to review and analysis [2].

In [3] the author discusses an approach for seizure prediction and detection in the time, frequency and time-frequency domains using techniques like Independent Component Analysis (ICA) and Principal Component Analysis (PCA). A classifier using a multilayer perceptron neural network (MLPNN) is proposed in [4]. Additional studies utilize random ensemble learning approach [5]. Most recently extreme gradient boosting [6] is considered. There is lack of assessment in existing approaches in the ensemble learning framework. To address above limitations, this paper proposes in; i) A hybrid ensemble learning extracts significant features and processes as epileptic seizures; ii) Pre-processing involves dimensionality reduction techniques to extract features and apply on machine learning (ML) algorithms. Accommodates linearity and non-linearity between features through PCA and stochastic neighbor embedding (t-SNE) methods; iii) A gradient based ensemble machine learning method, XGBoost [6] is presented which combines the predictive analysis of multiple learning approaches and minimizes the error in sequential manner. Dataset is acquired from UCI ML library to demonstrate [7]. Results suggest that the proposed hybrid approach shows similar or improved MAP score when conpared with frequently used techniques. Varying size of training set between 0.2 to 0.8 achieves between 93-95% MAP score allowing selection of smaller training size to further improve efficiency through speed. The remainder of the paper is structured as: section 2 examines related works, section 3 details proposed hybrid framework, section 4 reviews existing ML methods, section 5 describes data to assess the proposed approach. Section 6 provides conclusion and future scope.

2. METHODS

Various transforming approaches have been recommended for automatic seizure identification, analysis, and recognition [8]. Discrete wavelet transform (DWT) based methodologies with neural networks, Fourier are preferred and used in [9]. Frequency domain studies on feature extraction of epileptiform episodes are prevalent. Power spectral density (PSD) can be calculated using parametric approaches [10]. When precise results were difficult to classifiy, genetic algorithm was constructed in [11].

Using time-series analysis, ime-domain attributes for feature extraction is done. Exponential energy with classes of entropy like Shannon, Renyi and energy-based features in [12] is taken. Different decomposition methods like wavelet transform are applied through time-frequency analysis. Discrete cosine transform (DCT) with wavelets as coslets are efficient in identifying low frequency components over multi-resolution scale [13]. Alterations in brain states are found by nonlinear methods [14], entropy and approximation entropy (ApEn) are extracted as features and linear classifier is used. In [15] intrinsic mode functions (IMFs) using emphirical mode decomposition (EMD) are got and the IMF's energy, instantaneous area, coefficient of variation and fluctuation index as characteristics are used. Error as linear prediction error energy (LPEE) is got by approximation of EEG signals in [16].

Artificial neural networks are extensively used in the modeling of non-linear system [17], [18]. Ren and Wu [19] Convolutional deep belief neural network and Übeyli [20] Lyapunov exponent and probabilistic neural network (PNN) is used to classify. Currently, deep learning in seizure detection is being implemented and in combination with machine learning have shown remarkable performance. In [21], deep learning has received a wider scope of learning temporal patterns. Recurrent neural networks (RNN) can also be used for EEG analysis [22]. In recent years, ML algorithms are used for EEG signal acquisition, noise removal as signal pre-processing and finally classifying EEG signals.

3. THE PROPOSED HYBRID ENSEMBLE LEARNING FRAMEWORK

Epilepsy is a neurological disorder generating electrical actions and can be recorded. A need for developing automatic systems to evaluate and diagnose is essential. To address the challenges encountered by non-stationarity of signals, we propose a hybrid ensemble learning framework to improve the classification accuracy regardless of the time-varying frequency in data or sample size and the steps are as:
- Step 1: Denoising: For raw EEG data, 0.3 Hz frequency range is selescted by applying band pass filters.
- Step 2: Data Preparation: EEG data is highly unstructured with high variance and hence standardization is a requirement in machine learning algorithms. To achieve zero mean and unit variance, the standard scaler approach is applied and performing operations independently and mathematically expressed as:

$$Z = \frac{x-\mu}{\sigma} \qquad (1)$$

where μ and σ are mean and standard deviations of a sample x.
- Step 3: Train/Test Split: Training and testing subsets are considered. Training subset is recommended to have 60-80% of the filtered data.
- Step 4: Dimensionality Reduction: PCA and t-SNE are found to be efficient in removing less significant features and to accommodate linearity and non-linearity between features in compressed domain.
- Step 5: Clustering: k-means clustering partitions into k clusters with reference to the centroid.
- Step 6: Ensemble Learning: Selected features from Step 5 are then fitted through XGBoost technique. Because of the better computation speed and accuracy XGBoost is considered better than Random Forest classifier.

In the proposed boosting technique few layers are generated, and hypothesis is drawn with fewer split trees, but in bagging techniques, trees are allowed to grow to its maximum extent. PCA and k-means clustering techniques are applied capturing both spatial and spectral information in reduced feature space. These features are subjected to distinctive learning process using KNN, Random Forest approaches and further classified.

4. MACHINE LEARNING ALGORITHMS

Algorithms considered as part of the hybrid framework is summarized. Best accuracy and slight delay in detecting seizures is the aim of the models. Using biological datasets for better results can be achieved by realizing reasonable and important patterns It also describes other supervised and unsupervised ML methods presented and compared among PCA, logistic regression, k-nearest neighbors (KNN), artificial neural network (ANN), random forest, and XgBoost. Data Preprocessing is the first step involved as the first step. Here the raw data must overcome noise from human body in the form of noise due to electrical field and other interferences. This is modelled as per the need of algorithm. Once preprocessing is done, classification techniques are implemented to categorise as epileptic or non epileptic. It also aids in reviewing the classification performance metrics and the results are compared ahead.

4.1. Principal component analysis

The primary applications of the exploratory data analysis method (PCA) are feature extraction and dimensionality reduction [23] and is expressed as:

$$u_1^T S u_1 = \frac{1}{N}\sum_{n=1}^{N}(u_1^T(x_n - \bar{x})^2) \quad (2)$$

where $u1$ is a D-dimensional vector $\bar{x}$ is mean of the sample set, S is the data covariance matrix, and N is the size of the sample space. In (2), the projected variance $u_1^T\, S\, u_1$ is maximized with respect to u_1.

4.2. t-distributed stochastic neighbor embedding

PCA fails to visualize non-linear properties of the data, so tSNE is used as an alternate where distance between two data points is converted to known probabilities using gaussian distribution function. If ‘i’ & ‘j’ are any two data points, eucledian distance between ‘i’ & ‘j’ are converted to probabilities of high and low dimensions using following gaussian distribution equations.

$$p_{j/i} = \frac{exp\left(-\|x_i - x_j\|^2/2\sigma_i^2\right)}{\sum_{k\neq i} exp(-\|x_i - x_k\|^2/2\sigma_i^2)} \quad (3)$$

$$q_{j/i} = \frac{\exp\left(-\|y_i - y_j\|^2\right)}{\sum_{k\neq i}\exp\left(-\|yi - y_k\|^2\right)} \quad (4)$$

where $p_{j/i}$ and $q_{j/i}$ are probability values for high and low dimensional data. When distance between 2 points is increasing, their probability is decreasing so the 2 points shall not fall in the same cluster. Hence, the cost function is considered to minimise probability using KL divergence and is computed using following equation.

$$C = \sum_i KL\,(P_i \,||\, Q_i) = \sum_i \sum_j p_{j/i}\,\log\frac{p_{j/i}}{q_{j/i}} \quad (5)$$

4.3. K-means clustering

This is an unsupervised learning technique, where attribute and label are not used for prediction, instead looks for features and then classifies. Here, groups are based on data features having similar qualities. Kabir *et al*. [24] used a K-means clustering approach to cluster the EEG signal. This algorithm uses Euclidean as the metric. Steps followed by k-means algorithm are given: i) Centroids are created by randomly selecting k (i.e., 2) points as cluster centers; ii) Estimating the distance with respect to each centroid, data point is allocated to the nearest cluster; iii) Evaluating the average of the allocated points a new cluster center is found; vi) Iterate steps 2 and 3 till none of the cluster allocations alter.

4.4. Logistic regression

Statistical regression model [25] for categorical responses is logistic regression, which models the log odds ratio of the posterior probability of categorial response as linear model of the explanatory variables, x denotes a vector of explanatory variables and y Є {0,1} denotes binary output. The logistic model is given as:

$$\log \frac{p(y=1/x)}{1-p(y=\frac{1}{x})} = \beta_o + \beta^T x \quad (6)$$

where β0 is the intercept, and $\beta \in R^p$ is a vector of coefficients for the p variables. In general, let (x1, y1), ………, (xn, yn) be a training sample. The model parameters are identified by maximum likelihood estimation, where the log-likelihood for *n* observations is:

$$\mathcal{L}(\beta_o, \beta_o) = \sum_{i=1}^{n} [y_i - (\beta_o + \beta^T x_i) - \log(1 + \exp(\beta_o + \beta^T x_i))] \quad (7)$$

4.5. Support vector machine

SVM algorithm classifies the data using hyperplane to tackle linear and nonlinear classification and regression problems [26]. Assuming the data is linearly separable, the decision function is:

$$\mathrm{y(x)} = \mathrm{w^T} \emptyset(x) + \mathrm{b} \quad (8)$$

where Ø(x) denotes the fixed feature-space transformation, w is HTE M-dimensional vector, and *b* is the bias parameter. The numerical value of *w* and *b* of the optimal separating hyperplane is:

$$Min\ Q(w, b) = \frac{1}{2} \|w\|^2 \quad (9)$$

subject to $y_i(x) = w^T \emptyset(x) + b \geq 1$, for i=1……, M

4.6. Naive Bayes

By calculating the likelihood that the data in question (x) belongs to class C, the Naïve Bayes technique applies the Bayes theorem to the solution of classification issues. Mathematically expressed as:

$$P(C|X = x) = \frac{P(X = x|C)\, P(C)}{P(X=x)} \quad (10)$$

where *P(X = x|C)* is the conditional probability, *P(C)* is the state probability of class C, and *P(X = x)* is the normalizing density. Let *Yi* be a discrete valued variable with discrete or real valued attributes, *Xi* for *i* = 1, 2 ,…….., *n* and *Y* be the desired output probability distribution for each instance of *X* to be classified.

4.7. K-nearest neighbor

Classification and regression are done by nonparametric method and entire data is utilized for training. KNN captures the idea of similarity like distance, proximity, or closeness and grouping is done by fixing a number to K value. Euclidean distance is used to estimate the distance between an unknown sample and point. The distance is calculated wrt origin and the sample values of EEG sample. Based on distance, features are extracted and sorted in ascending order. If K=1, the unknown sample is classified wrt the nearest sample from the training set. KNN's ability to be updated with new datasets and to function well is its unique property. From the sorted array, the upper k rows are selected.

4.8. Random forest

Random forest is a cluster of decision trees built to be more robust and limits overfitting and errors. The feature selection is random and is known to perform better, when features are categorical, so random forest (RF) is apt when large number of variables are present. The test features should pass through the rules of each tree and later the algorithm returns the predicted target. Ensemble bagging or averaging multiple randomly chosen trees from the dataset allows the random forest technique, which is not typically thought of as a boosting kind.

4.9. Proposed ensemble learning: XG boost technique

Ensemble machine learning technique uses gradient descent method to combine analytical analysis of various learning approaches to learn seizure features more optimally, it can be developed by training a model through same learning algorithm or diverse learning algorithms. Ensemble learning can be broadly classified into Bagging and Boosting. Bagging method trains the model by splitting the train data randomly into different trees and average of these trees are considered for final prediction. Besides bagging, boosting technique generates trees sequentially based on the relevance feedback in closed loop. Subsequent tree learns from its predecessor and aggregates the response for final classification. Unlike random forests which possess low bias with high variance will have parallel decesion trees, XGBoost will produce sequential decision trees as shown in Figure 1. XGBoost will initially have high bias and low variance to obtain decision trees (along with week classifiers) at different levels by regularly updating feature weights. Finally, weak classiifers are combined to reduce the bias level and increase the classifier efficiency. Low bias decision tree will have fixed levels (e.g. 3 to 4).

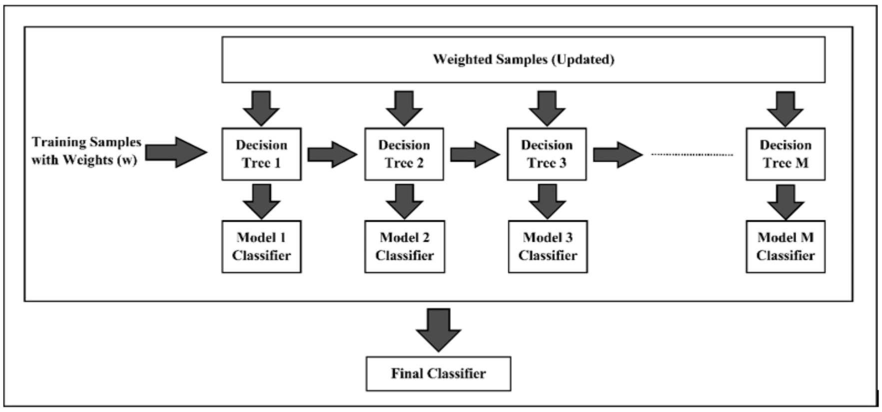

Figure 1. Block diagram of XGBoost model showing sequential decision trees

5. RESULTS AND DISCUSSION

This section uses numerical examples to show the efficiency of the algorithms. EEG dataset obtained from the UCI ML repository [7] is subjected to ML techniques and contrasted based on MAP score. The EEG waveform of various classes of UCI ML repository [7] is also demonstrated in Figure 2. For each of the methods, MAP score demonstrates Random Forest and XGBoost being best in Table 1. The train and test size is varied from 0.2 to 0.8 samples in steps of 0.1 and MAP scores of various ML techniques using PCA+k-means and tSNE+k-means with varying training set is demonstrated and inferred in Table 2 and 3.

5.1. Experimental procedure and MAP score

The UCI-ML EEG dataset [7] consists of 11,500 samples with 179 data points of duration 1s collected involving 100 individuals subjected to 23.6 seconds of recording. The last column represents the response variable as label Y Є {1,2,3,4,5} and the remaining columns denote explanatory variables X Є {x1,…x178}. Data categorized into Y Є 1 are patients with epileptic seizure (i.e Class 1) and Y Є 2,3,4,5 are non epileptic (class 2,3,4,5) as demonstrated in Figure 2. The UCI-ML EEG dataset is split into train and test samples, pre-processed and significant features extracted by applying PCA or t-SNE in conjunction with kmeans clustering. Extracted features are processed and classified through ensemble learning methods including random forest and XgBoost. Performance is evaluated using the MAP score and results are recorded for each instance. These results are validated using K-fold cross validation.

The average precision mean iscalculated using the average precision (AP) as its unit.

$$AP = \sum_{i=0}^{i=n-1}[Recall(i) - Recall(i+1)] * Precision(i) \quad (11)$$

In (11), *n* denotes number of thresholds and recall(n)=0, while precision(n)=1.

5.2. Comparison of MAP score

To calculate the efficiency of the suggested method, existing approaches in assessing EEG data is identified from the literature, where we split *x%* of the dataset into training and the remaining as testing. The dataset goes through two stages of processing:

- (S.1) Feature extraction with PCA followed by k-means clustering.
- (S.2) Random Forest and XGBoost is applied on features selected from step (S.1) and MAP scores are computed.

Table 1 reports MAP score. Results of proposed approach are highlighted, and all methods achieved a MAP score of ~ 80% and higher. While LDA, logistic regression, PCA, and SVM exhibits an improvement in the score with a difference of 2% or higher, ANN, Naive Bayes, and KNN achieve similar scores. However, proposed ensemble learning approaches have a higher MAP score, suggesting high classification accuracy.

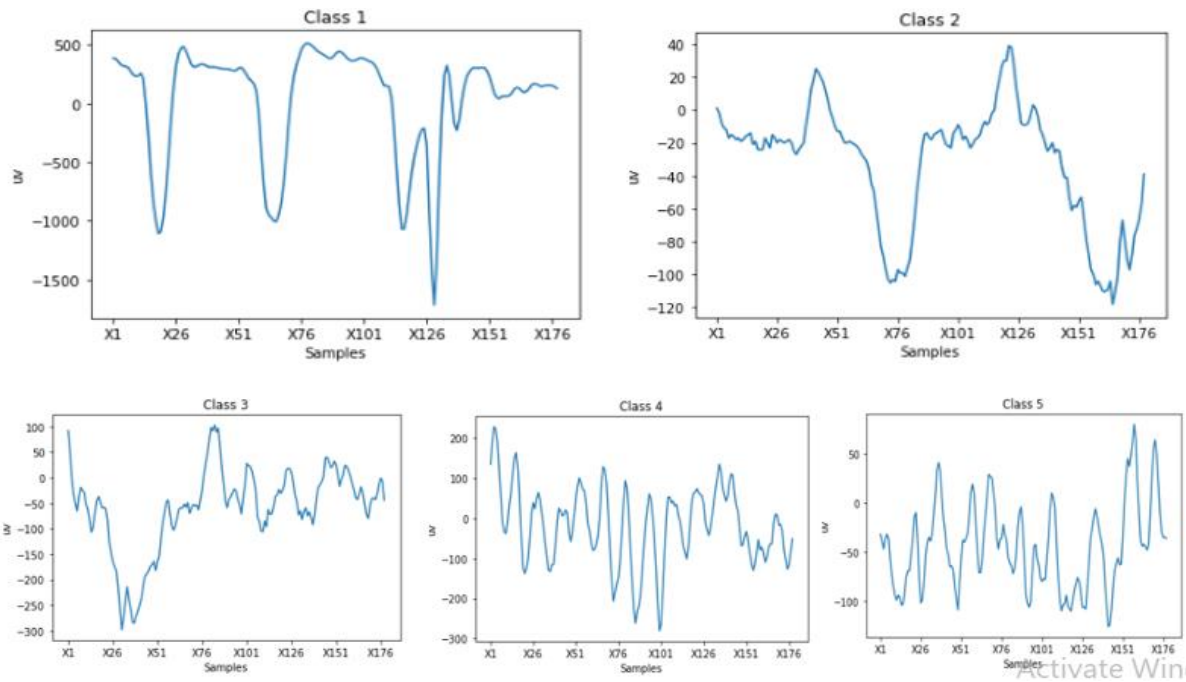

Figure 2. EEG signals depicting 5 different classes with samples

Table 1. Comparison of suggested and existing approaches using MAP scores on data from epileptic seizures

Methods	MAP Score (%)
LDA	79.20
Logistic regression	82.83
Principal component analysis	89.00
Wavelet + SVM	92.30
ANN	93.00
Wavelet+Gaussian Naïve Bayes	93.21
KNN	93.96
Random Forest Classifier	94.92
XGBoost	94.10

5.3. Performance analysis

To evaluate the efficiency of the suggested approach, other methods such as logistic regression, KNN, SVM, and naive Bayes are applied, which exhibited significant MAP score applied to UCI-ML EEG dataset with hybrid pre-processsing. Dataset is split into train and test, test size varying from 0.2 to 0.8 samples in steps of 0.1 and proposed ensemble learning model are allowed to learn from the remaining feature vectors.

Table 2 shows MAP scores of various ML techniques using PCA+k-means with varying size of train and test subsets. Numbers reported in Tables 2 is rounded down to the nearest integer. Table 2 suggests that the MAP score across different train size do not vary much suggesting consistent accuracy even when the algorithms are trained on small training subset. This is because of the stability of the pre-processing stage involving clustering and PCA, which enables selection of significant features from clusters. SVM has smaller scores compared to other methods, however, overall random forest, XGBoost, and Gaussian NB achieves over 93% MAP score consistency regardless of the size of the data set.

Table 2. MAP scores of various ML techniques using PCA+k-means with varying training set

ML Methods	MAP score (%): PCA+k-means Train size						
	0.2	0.3	0.4	0.5	0.6	0.7	0.8
SVM	74	74	73	73	72	72	65
LR	89	89	89	89	89	89	85
KNN	94	94	93	94	94	94	94
Random Forest	93	93	94	94	94	94	94
Gaussian NB	93	93	93	94	93	94	94
XGBoost 94	94	94	94	94	94	95	94

Table 3 shows MAP score of algorithms considered in Table 2 where PCA is replaced with tSNE, which handles feature extraction in data set with small sample size. It is also evident that, results with trend like results reported in Table 2. Compared individual MAP scores between the two tables, tSNE does not seem to improve the accuracy significantly. In both Table 2 and 3, smaller training set size can be selected to improve the overall computation speed.

Table 3. MAP scores of various ML techniques using tSNE+k-means with varying train set

ML Methods	MAP score (%): tSNE+k-means MAP Score (%) for Varying train size						
	0.2	0.3	0.4	0.5	0.6	0.7	0.8
SVM	65	64	63	63	62	63	62
LR	84	85	81	86	80	85	81
KNN	92	93	93	93	93	94	95
Random Forest	93	94	94	95	95	95	95
Gaussian NB	80	81	82	87	81	86	83
XGBoost 94	92	92	92	93	93	93	95

6. CONCLUSION

Due to its massively parallel and distributed structure of computation, the proposed ensemble learning technique has proved more effective in learning random patterns of seizures to provide better estimates of epilepsy in highly non-linear EEG signals. Proposed boosting type uses gradient descent method to reduce the loss and generates a single model to give better performance in comparison with bagging type and other conventional unimodel ML techniques. Moreover, the proposed hybrid framework achieved high and consistent accuracy even with small sized data. However future work suggests that using appropriate method like RNN, better accuracy can be obtained in detecting pre-ictal regions, where the preprocessing techniques or configurations of the RNN LSTM need to be adjusted. Using Genetic algorithms, dominant features to detect pre-ictal periods can be found. Appropriate methods for dimensionality reduction can be implemented to eliminate redundant features.

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