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Performance Evaluation of Machine Learning Classifiers for Epileptic Seizure Detection

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Abstract— Epilepsy is a neurological disorder in the human brain, which is characterized by chronic disorders and occurs at random to interrupt the normal function of the brain. The diagnosis and analysis of epileptic seizure is made with the help of Electroencephalography (EEG). In order to detect seizure, this study aims to construct an automatic seizure detection system to analyze epileptic EEG signals. The CHB-MIT Scalp EEG dataset is used for the experiment purpose. The Welch Fast Fourier Transform is applied to convert time-domain signals to frequency-domain. The statistical features are extracted from both time and frequency domains. The ANOVA based feature selection is used to select the most significant features. Data under-sampling and over-sampling techniques are used to balance the data. Eight machine learning algorithms, including Decision Tree, Extremely Randomized Decision Tree, Linear Discriminant Analysis, Quadratic Discriminant Analysis, Random Forest, Gradient Boosting, Multilayer Perceptron, and Stochastic Gradient Descent are used to classify the data. The highest result is recorded as 99.48% of accuracy, 99.79% of sensitivity, and 99.17% of specificity for the Extremely Randomized Decision Tree. The system might be a helpful tool for physicians to make a more reliable and objective analysis of a patient's EEG records.

Keywords— Epilepsy, Electroencephalogram, Welch Fast Fourier Transform, Data Sampling techniques, Machine Learning Algorithms

I. INTRODUCTION

Epilepsy is a neurological disorder in the human brain, which is characterized by chronic disorders and occurs at random to interrupt the normal function of the brain [1, 2]. World Health Organization (WHO) in 2017 reported that approximately 50 million people have epilepsy around the world. Three fourth of the people living with the epilepsy is not getting treatment, and they commonly suffer from stigma and discrimination [3, 4, 5]. Seizures disorder can be partial (focal) limited to one part of the brain, or they can be general that exists in all parts of the brain. In the partial seizure, the signs are partial spasm, partial numbness, involuntary behaviors of talking to himself, scratching, walking around, blinking, and chewing. In the generalized seizure, the most common type is tonic-clonic. It causes upward staring, cyanotic lips, spasticity, stiff limbs, and uncontrollable drooling [6, 7]. The diagnosis and analysis of epileptic seizure is made with the help of Electroencephalography (EEG). The physicians and scientists use EEG to study brain functions and diagnose the neurological disorder since it contains physiological information of the brain. The standard EEG signals will appear as spiking waves during seizure activities [8]. In order to detect seizure, it involves the interpretation of long EEG records by the expert physicians, which is time-consuming and need high human efforts. Thus, an automatic seizure detection system is required to reduce the volume of data for the physicians. It will help experts only to study those parts of the EEG data that is seizure affected. Some studies have been conducted on EEG signals classification into normal and seizure states. The majority of previous studies on seizure detection and prediction have concentrated on patient-specific classifiers, where a classification model is trained and tested on the same person [9, 10, 11, 12, 13]. The purpose of this work is to categorize EEG records in significant states of normal and seizure across multiple subject records, as shown in Figure 1.

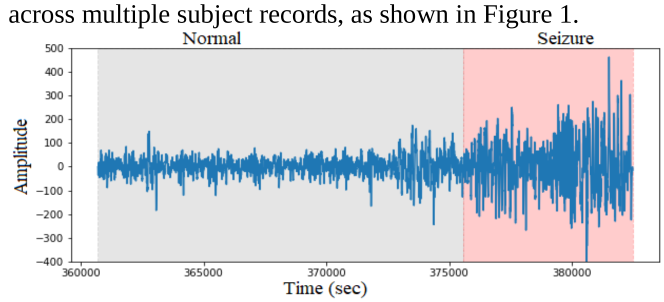


Figure 1: EEG signals classification into normal and seizure states

Section I contains the introduction, section II contain the related work, Section III explains the materials used in this work and the method with research process, section IV contain the feature generation in time and frequency domain, section V describe the data preprocessing, section VI contain the used classification algorithms, section VII describe the experimental results, section VIII contain the discussion, and IX concludes research work with future work.

II. RELATED WORK

Epileptic seizure detection and classification is seen as a challenging task for a long time, which requires a solution. EEG has been used as a tool for the diagnosis and analysis of epileptic seizure. Many studies were carried out for seizure detection, where researchers mainly focused on feature extraction methods for the analysis of EEG signals. Automatic classification of epileptic seizure is proposed by Jimmy Ming-Tai [7]. In this study, they used maximum amplitude, and Standard Deviation (SD) features in time-domain. Additionally, maximum and mean values of energy in each sub-band from the converted signal using Fast Fourier Transform (FFT) in frequency-domain were considered as efficient features. They achieved 99.48% accuracy using Multilayer Perceptron classifier (MLP). Harpale et al. [14] proposed a time/frequency domain feature extraction approach. In this work, statistical features, such as mean, coefficient of variation (COV), root mean square (RMS), and kurtosis were extracted in time-domain. The Power Spectral Density (PSD) of Fourier Transform, and Pattern Adapted Wavelet Transform in frequency-domain were considered as sufficient features. The Fuzzy classifier was applied. The results presented were with 96.48% of seizure classification accuracy, 96.52% true positive rate (TPR), and 0.352 of false positive rate (FPR). In [15] work, an automated whole-brain seizure detection method is presented. In this study, the raw EEG data was filtered using second-order Butterworth filters. Then median, variance, RMS, skewness, kurtosis, and sample entropy features were found as significant features in the frequency-domain. Several classifiers were used to detect seizure from data. The K-nearest Neighbor classifier (K-NN) classifier performed well and obtained a sensitivity of 88%, specificity of 88% and 93% for the area under the curve (RUC). The use of classification algorithm is another focus for the epileptic seizure detection. Many previous studies attempted to use powerful yet simple machine learning algorithms to detect epileptic seizure. The Shanir et al. [16] proposed an automatic seizure detection system using Local Binary Pattern (LBP) and K-NN. The classifier obtained 99.7% accuracy, 99.8% specificity, and sensitivity of 99.2% respectively. Patient non-specific strategy for seizure detection is reported by Orosco et al. [17]. In this study, the Linear Discriminant Analysis (LDA) and Neural Network (NN) classifiers were trained on the extracted features from Stationary Wavelet Transform (SWT). For patient-specific, the LDA and NN classifiers obtained on average sensitivity of 92.6% and 79.9% respectively. For patient non-specific on average sensitivity of 87.5%, and specificity of 99.9%. In [18] patient-specific method is presented based on K-means unsupervised clustering method to cluster the EEG data into two separate clusters of seizure and normal data. The algorithm achieved 91.43% accuracy. Hosseini et al. [19] proposed a random ensemble learning for EEG seizure detection and classification in cloud infrastructure. The extracted time/frequency-based features space was split into sub-spaces through random selection. Then the combinations of classifiers (Support Vector Machines (SVM), Multilayer Perceptron Neural Network (MLP) and Extended K-nearest Neighbors (k-NN)) were applied on each subspace to classify the input data into seizure and non-seizure. The majority voting method was used to select the output with the maximum number of votes from the classifiers. The result of the proposed method was found to be 0.97 of accuracy, 0.98 of sensitivity, 0.96 of specificity, 0.04 of false positive, and 0.02 of false negative ratios, respectively.

III. MATERIALS AND METHODS

A. Data Source

The dataset from the Children's Hospital Boston [20] consists of scalp EEG recordings from patients is used in this work. The dataset, grouped into 23 cases, from 22 patients of 5 males, and 17 females recorded at various time and stored in 654 .edf files with intractable seizure. The files are having from one to four hours' recordings of digitized EEG signals with 256 sampling rate of and 16-bit resolution. The EEG data is recorded in 23 channels using international10-20 system of EEG electrode positions and nomenclature. For the experiment, 15 subjects' data and only the files having seizure records are used as shown in table 1.

Table 1: Patients Data from CHB-MIT Scalp EEG Dataset

Patient	Gender	Age (Years)	Total Seizure Files	Total used Files
chb01	Female	11	7	6 seizure files
chb02	Male	11	3	3 seizure files
chb03	Female	14	7	7 seizure files
chb04	Male	22	4	3 seizure files
chb05	Female	7	5	5 seizure files
chb07	Female	14.5	3	3 seizure files
chb08	Male	3.5	5	5 seizure files
chb09	Female	10	3	1 seizure file
chb10	Male	3	7	7 seizure files
chb11	Female	12	3	3 seizure files
chb15	Male	16	14	9 seizure files
chb16	Female	7	6	6 seizure files
chb17	Female	12	3	3 seizure files
chb19	Female	19	3	2 seizure files
chb22	Female	9	3	3 seizure files

B. Research Process

The methodology of this study is described in Figure 2. It includes the stages of signal filtering and segmentation, feature extraction, data preprocessing and classifier construction.

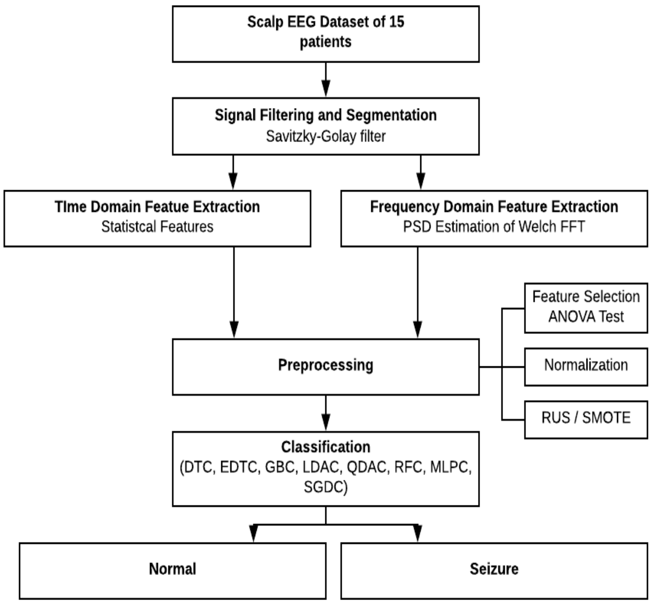
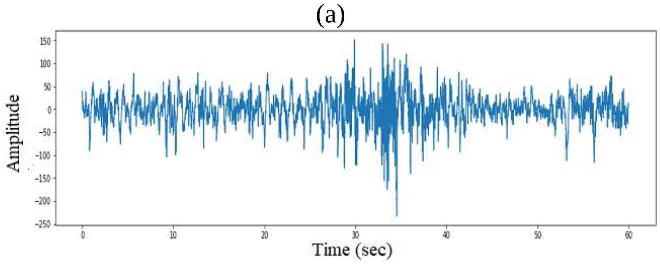


Figure 2: Research process

C. Signal Filetering and Segmentation

In this study, 6 channels (T8-P8, F3-C3, FP2-F8, F7-T7, P8-O2, T7-P7) are extracted for the experiment from multi-channel EEG data (23 channels in this case) from 15 subjects as it holds the most regular epileptic seizure activities, and has less noise compared to other channels [20, 21]. After extraction of the T8-P8, F3-C3, FP2-F8, F7-T7, P8-O2, and T7-P7 channels, the Savitzky-Golay filter is applied on each second of the EEG data to remove noise from the EEG signals [7]. The noise is unwanted signals added to the original signal during recordings, such as eye movement or muscle tightening. Figure 3 presents an original 60 seconds EEG signal record and the filtered signal by the Savitzky-Golay filter. Additionally, only the beginning 60 seconds of ictal data is used from each seizure record file that lasts longer than 60 seconds due to the outliers containing in the records [15].

(a)



(b)

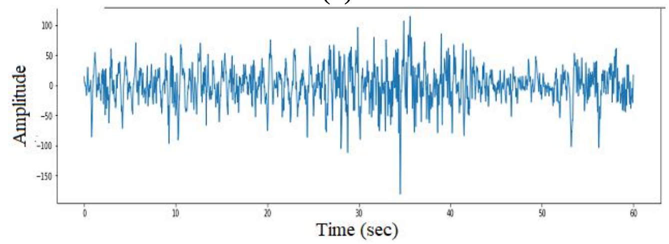


Figure 3: The EEG signal ((a) and (b) describes before and after filtering of signal using Savitzky-Golay filter)

D. Welch Fast Fourier Transform

Fast Fourier Transform (FFT) is a high-speed algorithm for calculating discrete Fourier transforms. In this study, Power Spectral Density (PSD) is estimated using Welch FFT approach. Welch based FFT is an effective non-parametric signal processing method in the frequency domain. The advantages of this method are the enhanced speed with reduction in computations time and storage over all other available methods in real-time applications [22, 23]. The procedure for PSD computation based on the Welch FFT is specified as follows:

1) The input signal $X(t)$ is divided into N overlapping segments.

$$X(t) = X\left(t + (N-1)D\right), \quad t = 0,1,2,...,L-1 \tag{1}$$

Where, $X(t)$ denotes the data segments with the starting point of these segments D of length L and N number of such segments.

2) For each segment of length L a modified periodogram is calculated. The procedure is a specified data window $W(t)$, $t = 0,1,2,...,L-1$ is applied on each segment.

3) Discrete Fourier transforms based on FFT is used to the windowed data.

$$A_N(n) = \frac{1}{L}\sum_{t=0}^{L-1} X_N(t)W(t)e^{-2Nitn/L} \tag{2}$$

Where $i = (-1)^{1/2}$

4) Each periodogram (in this case N modified periodograms) of new windowed data segment is estimated

$$I_k(f_n) = \frac{L}{V}|A_N(n)|^2, \quad k = 1,2,3,...,N \tag{3}$$

Where

$$f_n = \frac{n}{L}, \quad n = 0,1,2,...,L/2$$

and

$$V = \frac{1}{L}\sum_{t=0}^{L-1} W^2(t)$$

5) Finally, taking the average of periodograms to obtain PSD

$$PSD(f_n) = \frac{1}{N}\sum_{k=1}^{N} I_k(f_n) \quad (4)$$

IV. FEATURE GENERATION

A. Time Domain Features

Maximum amplitude, mean, standard deviation (SD), coefficient of variation (COV), root mean square (RMS), skewness, and kurtosis statistical features are extracted in time domain based on the literature review. The literature reports that maximum amplitude, mean, SD, COV, RMS, skewness, and kurtosis have the most potential to separate epileptic from non-epileptic EEG signals.

B. Frequency Domain Features

FFT method is applied to convert time domain EEG signal to the frequency domain. In this study, the PSD using Welch's method FFT is calculated by dividing the data into overlapping segments of a Hanning window with one-sided spectrum for each EEG window of length 1 second (each of 256 segments). The obtained spectrum is divided into Delta signal (δ: 0 Hz–4 Hz), Theta signal (θ: 4Hz–8 Hz), Alpha signal (α: 8–13 Hz) and Beta signal (β: 13–30 Hz) sub-bands. Then the statistical features, such as mean, SD, RMS, skewness, kurtosis are extracted in each sub-band of (δ, θ, α, β) and complete frequency bandwidth as features for epilepsy classification in the frequency domain. Figure 4 shows EEG signals after using FFT on raw EEG data with none-seizure activities.

(a)

(b)

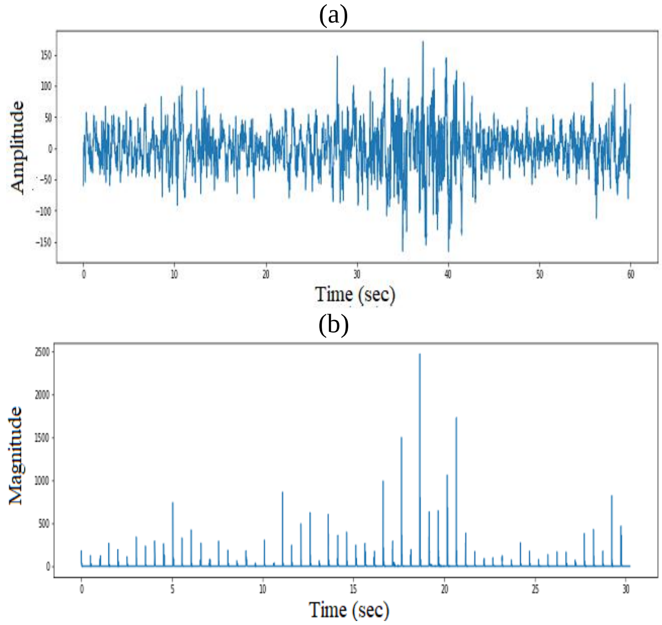


Figure 4: EEG Signal ((a) and (b) represents signal charts before and after Welch FFT)

V. DATA PREPROCESSING

A. Feature Selection

Feature selection is also known as variable selection, where most dominant features are selected, and the dimension of data is reduced. The advantages of feature selection are low computational cost, response time, and high accuracy of the machine learning algorithms [24, 25]. Analysis of variance (ANOVA) hypothesis test is an appropriate feature selection method for non-stationary EEG data [14, 26]. ANOVA test is a statistical test based on variance used to compare the variation between two or more means of samples of the data [27]. In this work, ANOVA F-distribution is an appropriate feature extraction method used to select the most dominant features from two categories of features (Normal and seizure). F-distribution is measured as the ratio between-group variance and within-group variance. There is an inverse proportion between F-value and P-value. If the F-value is large, then the P-value is considered to be small. The features are selected based on the significance level for P-value, which is normally 1% or 5% [28]. In this study, the significance of time and frequency domain extracted features are decided using a 5% level of significance for P-value. If the P-value of a feature is less than 0.05, then it is relevant and can be considered for classification.

B. Normalization

Normalization is a data preprocessing scaling technique to convert continues data into discrete and find new range from an existing range [29]. It will help for better classification of the problem [30]. In this work, Min-Max a linear normalization technique is used and the data is normalized or ranged between 0 and 1. The method is mathematically described as follows.

$$Normalized(X) = \frac{X - \min(X)}{\max(X) - \min(X)}$$

C. Data Sampling

Data sampling techniques are used to imbalance data. The purpose of data sampling is to balance when there is a vast difference between the ratio of positive and negative samples of a dataset. It helps machine learning classifiers to avoid misclassification problems. After signal segmentation, the data has 300,175 normal activities and 3582 seizure activities, as shown in Figure 5, which is an imbalanced dataset. This research applies Random Under-Sampling and Synthetic Minority Over-Sampling techniques to balance the dataset.

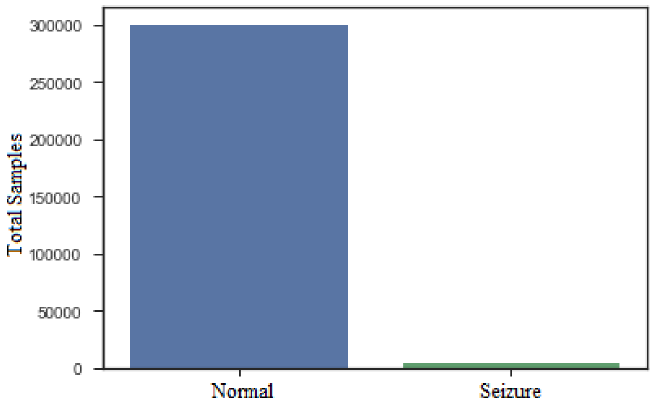


Figure 5: The original data

1. Random Under-Sampling Technique (RUS): The instances from the majority classes would be randomly removed until there is a balanced ratio between minority and majority classes. This approach decreases the majority class by randomly selecting data points from the majority class [31]. In this study, from 300,175 normal activities, 3582 samples are randomly selected to balance the ratio between normal and seizure activities. Figure 6 shows the data after applying RUS technique.

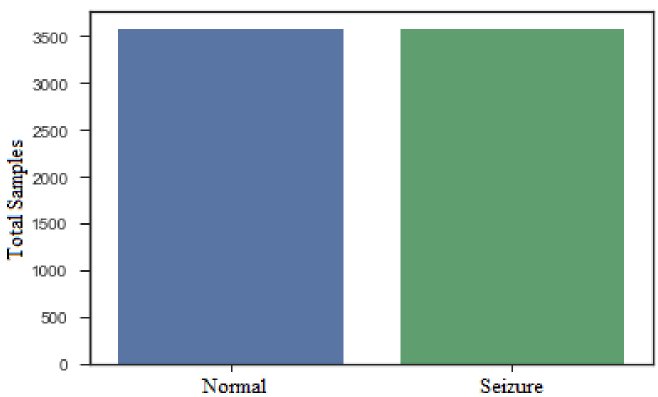


Figure 6: The data after using RUS

2. Synthetic Minority Over-Sampling Technique (SMOTE): SMOTE is an over-sampling technique to increase minority class data points [32]. The data points are randomly selected from the minority class, and new synthetic examples are created between selected and adjacent samples. In other words, SMOTE technique synthesizes the minority class samples depending on k minority class nearest neighbors. SMOTE is used on seizure activities, and the nearest neighbors parameter is set to 5. That is, in the seizure data, select an instance X and randomly select one of the instances from five seizure instances that is more adjacent to X to produce a new synthesized example. In this study, the seizure class is over-sampled to 300,175 samples to balance the ratio between normal and seizure classes. Figure 7 shows the balanced data after using SMOTE.

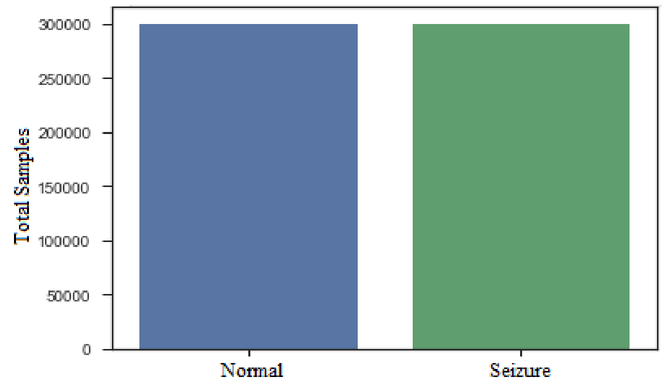


Figure 7: The data after using SMOTE

VI. CLASSIFICATION ALGORITHMS

In this study, powerful machine learning algorithms are adopted for classification purposes. These include the Decision Tree Classifier (DT) [33], Extremely Randomized Decision Tree Classifier (Extra-DT) [34], Linear Discriminant Analysis Classifier (LDA) [35], Multilayer Perceptron Classifier (MLP) [35], [36], Quadratic Discriminant Analysis Classifier (QDA) [37], Random Forest Classifier (RF) [38], Gradient Boosting Classifier (GB) [39], and Stochastic Gradient Descent classifier (SGD) [40].

VII. EXPERIMENTAL RESULTS

A. Construction of Classification

Data sampling techniques are used to balance the ratio between the samples of imbalanced data. These techniques could be divided into under-sampling and over-sampling. In order to avoid misclassification, both under-sampling and over-sampling are used to balance the data. At first, the number of non-epileptic samples is under-sampled using RUS. The 3582 samples are randomly selected from 300,175 samples to balance the dataset. Then the classifiers are constructed with DT, Extra-DT, GB, LDA, QDA, MLP, RF, and SGD. In this work, SMOTE is used on epileptic samples. It is an over-sampling technique to bring the ratio to 50:50. The 3582 samples are synthesized to balance the data. Then the classifiers are trained with the balanced data. Table 2 shows the accuracy of constructed classifiers after using RUS and SMOTE techniques. Our results show that the SMOTE performed better compared to the RUS technique. RUS reduce the size of the dataset, and it is less computationally expensive in terms of implementation than SMOTE, but it may result in loss of relevant information. The accuracy of SMOTE technique is almost 10% higher in most classifiers compared to RUS. Therefore, our recommendation is to use SMOTE. It helps to balance the data, and also there is no loss of relevant information in data.

Table 2: Classification accuracy after using RUS and SMOTE

Classification	Accuracy (%) of Classifiers after Using	
	RUS	SMOTE
DT	83.07	96.54
Extra-DT	90.42	99.48
GB	90.84	95.04
LDA	76.74	78.95
QDA	71.58	64.39
MLP	80.23	99.24
RF	89.25	99.23
SGD	72.70	78.70

B. Evaluation of Classification Model

In order to determine the overall performance of each of the classifiers Stratified K-Fold cross-validation technique is used on 70% of randomly selected observations to train the algorithms and 30% of randomly selected test cases to test the algorithms. For model selection, the Grid-Search CV method is used to tune over specified parameters values for the classification algorithms. The performance and ability of classifiers are measured using several common classification indicators, such as accuracy, specificity, and sensitivity [41]. Accuracy, specificity, and sensitivity respectively evaluate the performance of eight classification models. Table 3 describes the performance of classifiers.

Table 3: Evaluation of classification models after using RUS and SMOTE

Classification	Data Sampling Technique	Accuracy (%)	Specificity (%)	Sensitivity (%)
DT	RUS	83.07	82.49	83.66
	SMOTE	96.54	95.47	97.66
Extra-DT	RUS	90.42	90.59	90.25
	SMOTE	**99.48**	**99.17**	**99.79**
GB	RUS	90.84	91.84	89.89
	SMOTE	95.04	94.70	95.39
LDA	RUS	76.74	82.66	72.71
	SMOTE	78.95	81.52	76.75
QDA	RUS	71.58	87.30	65.30
	SMOTE	64.39	91.67	58.68
MLP	RUS	80.23	89.27	74.66
	SMOTE	**99.24**	**98.69**	**99.79**
RF	RUS	89.25	91.24	87.48
	SMOTE	**99.23**	**98.93**	**99.53**
SGD	RUS	72.70	70.42	75.46
	SMOTE	78.70	81.23	76.54

VIII. DISCUSSION

This study has focused on differentiating seizure and normal activities of EEG signals across a group of 15 patients, rather than a single patient. The classification algorithms are trained using 15 subjects. Hence, the classifiers are generalized across the multiple subjects. The accuracy of Extra-DT, MLP, and RF is higher than 99%, the DT and GB classifiers having an accuracy of 96% and 95%, respectively. The remaining classifiers have slightly performed poor, which is below 79%. The result proves that Extremely Randomized Decision Tree, Multilayer Perceptron, and Random Forest are suitable methods for analyzing EEG signals.

Our work is compared with previous methods proposed for seizure detection by different researchers with the CHB-MIT EEG scalp dataset, although other methods are tested with different conditions, such as a different selection of EEG records from CHB-MIT EEG scalp dataset, different prediction horizons, etc. Table 4 shows the performance of our proposed method compared to various other studies.

Table 4: Comparison of performance with previous studies

Study	Method	Accuracy	Specificity	Sensitivity
[15]	K-NN classifier	Not shown	88%	88%
[16]	local binary pattern (LBP) operator and K-NN classifier	99.7%	99.8%	99.2%
[17]	Stationary Wavelet Transform (SWT)	Not shown	99.9%	87.5%
[19]	Random Ensemble Learning of (SVM, MLP, K-NN)	97%	96%	98%
[42]	Fourier based Spectral Analysis	Not shown	Not Shown	86.67%
[43]	Recurrent Convolutional Network	99%	99%	84%
[44]	Convolutional Neural Networks (CNNs)	Not shown	Not shown	86.29%
Proposed Work	**Welch FFT + Extra-DT**	**99.48%**	**99.17%**	**99.79%**

IX. CONCLUSTION AND FUTURE WORK

In this research, we have presented an epileptic seizure detection system based on Welch FFT and supervised machine learning algorithms. The EEG signals are processed using Welch FFT method. Statistical features are extracted in both time and frequency domains. Then ANOVA based feature selection is used to select the most important features. The under-sampling and over-sampling methods are used after feature selection to balance the EEG data. Several powerful supervised machine learning algorithms are trained with the data. The results present 99.48% of accuracy, 99.79% of sensitivity, and 99.17% of specificity using Extra-

DT classifier for seizure detection, which shows an improvement on existing studies. Future studies can be further developed by choosing more adaptive feature extraction methods and advanced machine learning algorithms.

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