

## Comparing The Effect of Under-Sampling and Over-Sampling on Traditional Machine Learning Algorithms for Epileptic Seizure Detection

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### Abstract

Epilepsy disease, a neurological disorder that causes recurrent and sudden crises, occurs at unforeseen times. This study presents the classification of electroencephalogram signals for epileptic seizure prediction. The performances of the machine learning algorithms were evaluated on the dataset extracted from electroencephalogram signals. The dataset consists of brain activities for 23.5 seconds of 500 individuals with each has 178 data points for one second, and totally of 11500 pieces of information. In this study, since the aim was to develop a model to predict epileptic seizure, the problem was transformed into a two-class problem by combining target categories except than epileptic seizure. Since combined target categories made the dataset unbalanced, Random Under Sampling and Random Over Sampling methods were applied to prevent the machine learning algorithms from overfitting the dominant class. Thus, each of the three datasets was divided into training and test sets by ratios of 60/40, 70/30, 80/20. The performance of the several machine learning algorithms were evaluated and discussed through three different scenarios. Overall results showed us that Random Forest algorithm offered superior performance than others for all scenarios in terms of accuracy, sensitivity and specificity metrics.

**Keywords:** Epileptic seizure, machine learning, unbalanced and balanced dataset, over sampling, under sampling.

### 1. INTRODUCTION

Epilepsy is a recurring neurological disorder that comes true by sudden seizures [1]. Seizure is an instantaneous electrical activity fluctuation in the brain which influences the people for a short period in general [2]. Epileptic seizure may arise from many factors such as genetic susceptibility or physical damage on brain and result in death [3]. The prediction of seizures as early as possible before occurrence helps improving patient's life quality and their safety [4]. This study presents the performances of machine learning algorithms on Electroencephalogram (EEG) signals for epileptic seizure prediction.

A lot of studies performed on classification of EEG signals in literature. Sharif and Jafari made use of Optimum Pointcare plane to derive features from the time series and obtained a series of Pointcare samples. In order to score dynamic changes in seizure estimation, they sent the characteristics chosen from ictal rules as input data to the Support Vector Machine classifier [1]. Caplan et al. performed a study on clinical diagnosis and management of seizures of children. In their study, they discussed two case studies that address the difficulties that health professionals face during management of children with convulsions [2]. Kocadagli and Langari presented an efficient procedure in

order to early detect the epileptic seizures. This procedure consists of three steps: a) extracting of features, b) reducing dimensionality of features, c) classification [3]. Chu et al. presented a new approach for seizure prediction, including the use of scalp electroencephalograms based on attractor state analysis. This approach is the first in terms of spectral feature's use which was obtained from macroscopic dynamics of the brain [4]. Mohammadpoory et al. used weighted visibility graph and entropy characteristics for detecting epileptic seizures automatically from EEG signals. They presented a study for classifying these signals using Decision Tree, K-Nearest Neighbor, Support Vector Machine and Naive Bayes [5]. Wan et al. performed a study to identify epileptic seizures in selected regions using complex Morlet wavelet transform based on Shannon-entropy and matching pursuit methods based on adaptive-genetic-algorithm [6]. Kiral-Kornek et al. developed a prospective seizure prediction system using Harnessing deep learning algorithm on a large longitudinal and continuous dataset. They analyzed intracranial electroencephalography data of ten patients with this system. In addition, to form infrastructure of a wearable device, they deployed the system on a low power neuromorphic chip [7]. Hassan and Subasi employed a novel signal processing technique for automated epileptic seizure screening method. Six spectral moments were extracted using this technique. In order to identify

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epileptic seizures from EEG signals, train and test datasets obtained from these extracted features were fed as input data to the ensemble learning based linear programming boosting machine learning algorithm [8]. A new automatic seizure method was proposed by Truong et al. that classifies interictal, ictal and early ictal periods of intracranial electroencephalogram signals by using Random Forest classifier [9]. Jia et al. proposed a method using full ensemble empirical mode decomposition for detecting epileptic seizures from electroencephalogram signals. This method includes the stages of classification of statistical properties extracted from growth curve by Random Forest algorithm using 10 - fold cross - validation technique [10]. Tawfik et al. carried out seizure detection on hundreds of actual EEG signals with Weighted Permutation Entropy and Support Vector Machine classifier based model. They tested the performance of the model using sensitivity, specificity and accuracy measurements [11]. In order to detect epileptic seizures, Gajic et al. automatically classified EEG signals by utilizing wavelet transform and statistical pattern recognition methods. The study includes three phases: wavelet transform based feature extraction, b) scatter matrices based feature dimension reduction c) classification by quadratic classifiers [12]. Acar et al. classified multi-channels EEG data using attributes they obtained in both time and frequency domains of seizure and non-seizure periods [13]. On the other hand, there are many studies in the literature that uses Bonn dataset. In this study, the problem was handled out in two classes by considering four target labels out of five as non-epileptic seizure. Some of the studies in the literature that considers problem with two classes as epileptic seizure and non-epileptic seizure are as follows. Tzallas et al. proposed a method which classifies the features extracted in the time-frequency plane using artificial neural network [14]. Guo et al. presented a method which classifies the features extracted by wavelet transform multiresolution decomposition using artificial neural network [15]. Orhan et al. proposed a decision support system for epilepsy treatment using Multi-Layer Perceptron (MLP). They decomposed EEG signals into frequency sub-bands using discrete wavelet transform (DWT). Then, they clustered the wavelet coefficients using K-means, and probability distributions of wavelet coefficients to the clusters were used as input to the MLP [16]. Gandhi et al. used important features of EEG signals such as entropy, energy and standard deviation computed by wavelet functions in different sub-bands for training Probabilistic Neural Network [17]. Nicolaou et al. used permutation entropy values as feature to classify the EEG signals using SVM [18]. Fu et al. extracted spectral entropies and energy features using Hilbert marginal spectrum analysis and put into the support vector machine for seizure detection of EEG signals [19]. Samiee et al. extracted features using rational discrete short time Fourier transform (DSTFT) and passed them to multilayer perceptron classifier to separate seizure from non-seizure data [20]. A general regression neural network with K-fold cross-validation were used by Swami et al. to classify feature vectors of EEG signals utilizing features based on statistical measurements [21]. Jaiswal and Banka used Local Neighbor Descriptive Pattern

and One-dimensional Local Gradient Pattern for feature extraction and classified the features with different machine learning algorithms [22]. Sharma et al. calculated fractal dimensions following analytic time-frequency flexible wavelet transform and fed to least-squares support vector machine classifier with 10-fold cross validation [23]. The aim of this study is to compare the effects of RUS and ROS methods which are applied to eliminate the imbalance problem in the two-class dataset used in the estimation of epileptic seizure on traditional machine learning algorithms. The rest of the paper was designed as follows. Section 2 addresses the dataset and presents the methods used in this study. Section 3 gives experimental results and discussions. Finally, the study is concluded in Section 4.

## 2. MATERIALS AND METHODS

### 2.1. Data

In this study, experiments were conducted on a public epileptic seizure dataset [24] containing 11500 instances. Each data represents the value of the EEG recording at a different point in time. The original dataset consists of recordings of 500 individuals each with 23.6 seconds brain activity recordings and represented by 4097 points divided into 23 parts each containing 178 points. Therefore, the number of attributes is 178 and the target is a categorical variable including numbers between 1 and 5. Information of each categorical value for output was listed in detail below.

1. Seizure activity recordings,
2. EEG signal recording from tumor area,
3. Region of tumor in brain is identified and EEG activity recorded from healthy brain area.
4. Patient had their eyes closed when recording the EEG signal.
5. Patient had their eyes opened when recording the EEG signal.

All subjects in classes 2, 3, 4 and 5 are subjects without epileptic seizures. Only subjects falling in class 1 are with epileptic seizure.

### 2.2. Machine Learning

Machine learning is away used to make inferences from data to learn new tasks by utilizing learning algorithms based on mathematical and statistical methods. Machine learning algorithms perform learning from the training data and then performance of the trained model is measured over test data. Algorithms used in this study were mentioned below briefly.

#### 2.2.1. Random Forest (RF)

RF algorithm [25] builds a forest of combined decision trees and classifies data is by selecting most voted decision tree of the forest. Once all trees have been created, each tree in the ensemble selects a class and the top-rated class provides the last decision for classification [26].

### 2.2.2. Logistic Regression (LR)

LR is a technique from field of statistics used for binary classification [27]. For example, classifying whether an email is a spam or not, classifying whether a cell with cancer or not. This algorithm uses linear equation with independent predictors. The output of the algorithm is taken into between 0 and 1 using sigmoid function. To predict class values a logarithmic loss function is used to calculate the cost for miss classifying [28].

### 2.2.3. Linear Discriminant Analysis (LDA)

LDA is a classification method first proposed by Fisher [29] in 1936. Maximum class discrimination is achieved by finding the component axes that maximize both the variance of data and separation between multiple classes [30].

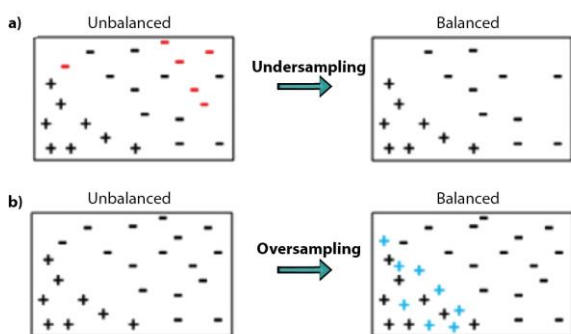
### 2.2.4. Diagonal Linear Discriminant Analysis (DLDA)

DLDA belongs to the family of Naive Bayes classifiers and arises in a Bayesian setting where the distributions of each class share a common covariance matrix and are assumed to be multivariate normal. Different from LDA, DLDA classifier sets the off-diagonal elements to zero in the pooled sample covariance matrix [31].

### 2.2.5. Support Vector Machines (SVM)

SVM is a classification algorithm based on statistical learning theory. The mathematical algorithms in SVM were originally designed for binary classification, and then generalized for classification of multi-class and non-linear data. It is based on the definition of the hyper-plane that can optimally distinguish two classes from each other [32].

### 2.3. Balanced Dataset



**Figure 1.** Random sampling a) Under-sampling b) Over-sampling [34].

Any dataset which has unbalanced data distribution leads to negative situations in machine learning. When a dataset does not represent all classes of data equally, the model might overfit to the class that's represented more in the dataset and become oblivious to the existence of the minority class. It might even give a good accuracy but it fails miserably in real life. There are different methods to eliminate the negative

effects of unbalanced datasets on machine learning methods such as collecting more data, resampling based on under-sampling and over-sampling. While Random Under Sampling (RUS) method eliminates the instances of majority class (Figure 1.a), and Random Over Sampling (ROS) method generates the instances to be added into minority class (Figure 1.b) [33-34]. The unbalanced distribution in the dataset is discarded by applying RUS or ROS methods.

### 2.4. Performance Metrics

In our study, performances of the machine learning algorithms were evaluated using accuracy, sensitivity and specificity measures. The accuracy value (Acc) indicates the percentage of success of the model in terms of true classification. Sensitivity (Sen) and specificity (Spe) are the ratio of positive and negative classification, respectively. While the sensitivity value indicates the success rate of classification of patients, specificity value indicates the success rate of classification of non-patients [35]. Equations of these metrics are given below;

$$Acc = (TP + TN)/(TP + FN + TN + FP) \quad (1)$$

$$Sen = TP/(TP + FN) \quad (2)$$

$$Spe = (TN)/(TN + FP) \quad (3)$$

where TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative. True positive is the number of patients who are correctly classified as having epileptic seizure and TN is the number of non-patients who are correctly classified as not having epileptic seizure. Likewise, FP is the number of non-patients who are incorrectly classified as having epileptic seizure and the FN is the number of patients who are incorrectly classified as not having epileptic seizure.

## 3. RESULTS AND DISCUSSION

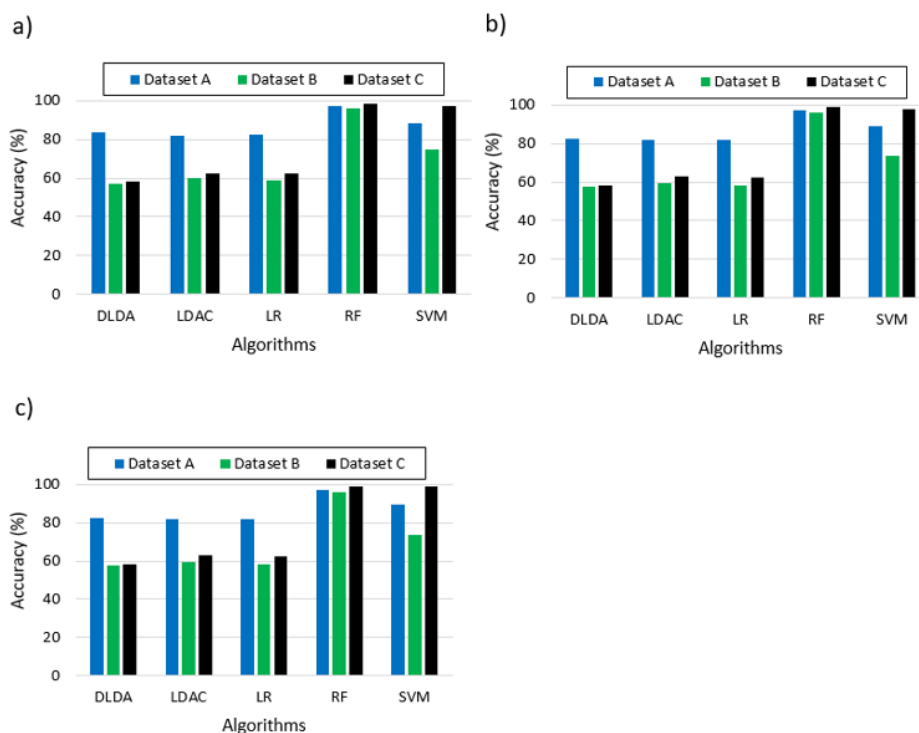
The dataset consists of 500 individuals which have 4097 data points for 23.5 seconds. Firstly, original target values were labeled as either 1 or 0. If the output variable “y” is 1, the subject has disease. If the output variable contains any of 2, 3, 4 and 5 values, it means the subject does not have disease. This transformation for all subjects were carried out on the original dataset. So, the dataset including two classes, normal and epilepsy was obtained. After obtaining labeled dataset, RUS and ROS methods were applied on the original dataset and two additional datasets were obtained. While the original dataset was named as Dataset A, other two datasets obtained after ROS and RUS methods were named as Dataset B and Dataset C, respectively. The information about these datasets were given in Table 1.

**Table 1.** The information about the datasets.

Datasets		
Dataset A	Dataset B	Dataset C
True 2300	True 2300	True 9200
False 9200	False 2300	False 9200

Then, experimental studies on these datasets were carried out over three different scenarios. According to these scenarios, training and test datasets were prepared by dividing all

datasets with ratios of 60/40 (Scenario 1), 70/30 (Scenario 2) and 80/20 (Scenario 3), respectively.



**Figure 2.** The performances of learning algorithm; a) The results considering 60% train and 40% test data, b) The results considering 70% train and 30% test data, c) The results considering 80% train and 20% test data.

The RF, LR and SVM algorithms were implemented using the sklearn library in Python environment, and the DLDA and LDA algorithms using the mlpy library. While applying algorithms, the number of trees for RF was selected as 100, “lbfgs” was used as solver for LR, the regularization parameter was selected as 0.1 for DLDA, and core function for SVM algorithm was selected as 'poly'. There were no parameters used for LDA. All parameters other than the parameters specified for the relevant algorithms were used with the predefined values used in the related libraries. The performances of learning algorithms on the datasets were evaluated considering Acc, Sen and Spe metrics. Experimental studies showed that RF had the best success among all algorithms. SVM algorithm showed the closest performance to RF. As seen in Table 2, RF gave 97.11%, 96.09% and 98.49% accuracies on Scenario 1 for the Dataset A, B and C, respectively. Moreover, this classifier gave

similar performances for Scenario 2 and 3 on all databases obtained by the RUS and ROS methods. When the results obtained with RF were analyzed, it was seen that while the sensitivity of this classifier was increased on datasets obtained with RUS and ROS methods, its specificity was decreased slightly. However, since the decrease of Spe value on the dataset obtained by the RUS method was higher compared to the ROS method, a better Acc was obtained with the ROS method. Situations that are valid for Scenario 1 are also valid for Scenario 2 and Scenario 3. Figure 2 clearly shows that the success on Dataset C was increased with only RF and SVM algorithms for all scenarios compared to the successes achieved with the original dataset. On the other hand, while performance of RF was decreased slightly on Dataset B, performance of SVM was quite decreased for all scenarios.

**Table 2.** The performance results of learning algorithms.

Scenario	Learning Algorithms	Dataset A			Dataset B			Dataset C		
		Performance metrics (%)			Performance metrics (%)			Performance metrics (%)		
		Acc	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe
0% Training, 40% Testing	DLDA	83.87	30.5	97.59	57.12	45.88	68.14	58.29	51.49	65.22
	LDAC	81.91	12.43	99.78	60.27	40.18	79.98	62.64	46.14	79.47
	LR	82.39	16.15	99.43	59.08	41.6	76.21	62.61	48.4	77.11
	RF	97.11	91.92	98.44	96.09	97.26	94.94	<b>98.49</b>	<b>99.62</b>	<b>97.34</b>
	SVM	88.59	46.97	99.29	74.67	49.18	99.68	<b>97.28</b>	<b>95.35</b>	<b>99.26</b>
0% Training, 80% Testing	DLDA	83.68	29.28	97.28	57.54	47.08	67.87	58.62	50.04	67.19
	LDAC	82.32	12.03	99.89	61.96	42.27	81.41	63.59	48.37	78.76
	LR	82.7	14.64	99.71	59.42	43.0	75.65	63.03	49.02	76.99
	RF	97.04	91.74	98.37	95.14	97.23	93.08	<b>98.77</b>	<b>99.82</b>	<b>97.72</b>
	SVM	88.78	46.52	99.35	73.77	48.1	99.14	<b>98.1</b>	<b>96.81</b>	<b>99.38</b>
0% Training, 20% Testing	DLDA	82.7	29.42	96.34	57.93	46.2	69.72	58.1	50.35	65.92
	LDAC	81.78	11.09	99.89	59.35	41.21	77.56	62.72	48.08	77.5
	LR	81.87	12.37	99.67	58.26	42.52	74.07	62.58	49.43	75.86
	RF	97.17	92.11	98.47	95.76	98.26	93.25	<b>98.83</b>	<b>99.62</b>	<b>98.03</b>
	SVM	89.43	50.32	99.45	73.37	47.94	98.91	<b>98.78</b>	<b>97.94</b>	<b>99.62</b>

Table 3 shows that our proposed method achieved satisfying performance compared to other studies. Only, performance

of our method was slightly lower than the performance of study proposed by Sharma et al. [23].

**Table 3.** The comparison of the studies.

Study	Method	Acc %
Tzallas et al. [14]	Time-frequency features; using ANN	97.73
Guo et al. [15]	DWT, line length feature; using ANN	97.77
Orhan et al. [16]	DWT, clustering; using MLP	99.60
Gandhi et al. [17]	DWT and energy, std and entropy features; using SVM and Probabilistic neural network	95.4
Nicolaou et al. [18]	permutation entropy values; using SVM	
Fu et al. [19]	spectral entropies and energy features; using SVM	98.80
Samiee et al. [20]	DSTFT; using MLP	98.10
Swami et al. [21]	statistical measurements; using general regression neural network	95.24
Jaiswal and Banka [22]	Local Neighbor Descriptive Pattern and One-dimensional Local Gradient Pattern; using different machine learning algorithms	98.30
Sharma et al. [23]	fractal dimensions; using least-squares SVM	99.20
<b>Proposed Study</b>	<b>ROS; using RF</b>	<b>98.83</b>

#### 4. CONCLUSION

Epilepsy, a neurological disorder that causes recurrent and sudden crises, causes a critical physical injuries or death during seizures based on many trigger factors such as genetic, physiological, brain damage, etc. The aim of this study is to compare the performance of various well-known machine learning algorithms for epileptic seizure prediction in terms of effects of unbalance and balance datasets. Into this aim, RUS and ROS methods were applied to original dataset to get balanced datasets. ROS method randomly duplicates samples of minority class in order to make the class distribution equal. However, this process increases the overfitting possibility for some machine learning algorithms. To the contrary, RUS method randomly removes the

majority class samples from the dataset, in order to make class distribution equal. Overall experiments showed that RF and SVM methods on ROS applied dataset obtained high accuracies due to not overfitting dataset. RUS method caused loss of information and decreased performance of other algorithms except than RF. RF algorithm performed well although RUS reduced the number of samples in the dataset used in this study.

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