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Classification of epileptic seizure dataset using different machine learning algorithms

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ABSTRACT

Seizure associated with abnormal brain activities caused by epileptic disorder is widely typical and has many symptoms, such as loss of awareness and unusual behavior as well as confusion. In this paper, a classification of the Epileptic Seizure dataset was done using different classifiers. It was shown that the Random Forest classifier outperformed K- Nearest Neighbor (K-NN), Naïve Bayes, Logistic Regression, Decision Tree (D.T.), Random Tree, J48, Stochastic Gradient Descent (S.G.D.) classifiers with 97.08% Accuracy, ROC = 0.996, and RMSE = 0.1527. Sensitivity analysis for some of these classifiers was performed to study the performance of the classifier to classify the Epileptic Seizure dataset with respect to some changes in their parameters. Then a prediction of the dataset using feature selection based on attributes variance was also performed.

1. Introduction

Seizures associated with abnormal brain activities caused by an epileptic disorder, which is a disorder of the brain Central Nervous System (C·N·S.), are very common and have many symptoms, such as loss of awareness, unusual behavior and confusion. These symptoms lead in many cases to injuries due to falls, biting one's tongue. Detecting a possible seizure beforehand is not an easy task. Most of the seizures occur unexpectedly, and finding ways to detect a possible seizure before it happens has been a challenging task for many researchers. Applying classification algorithms, which is the method used in this paper, can help determine whether someone will have a seizure or not. Many researchers have worked on understanding the brain's electrical activities and dynamic properties and identifying the nonlinear deterministic of the dynamics found in seizures [1]. Others described the dynamic brain system using a set of differential equations [2]. In addition, Nonlinear Time Series Analysis (N.T.S.A.) has been used in the literature to describe electroencephalograms (E.E.G.s) based on brain activities [3–5]. Many studies have been conducted on the E.E.G.s of patients with diseases, such as Parkinson's [6], depression [7], and Alzheimer's [8]; those of healthy patients [9–11]; and those of patients with epilepsy, which is our interest in this work [12–22]. These studies have provided a unique understanding of the dynamic system of the human brain.

The results obtained from epilepsy-related papers are categorized in terms of epileptic seizures [17,22] and the brain activities of healthy volunteers [23]. Using these two cases, researchers were able to identify and model the nonlinearity of human brain behavior. In addition, it was found that a slight change to the brain's dynamic system parameters results in different physiological brain states [24,25] and might cause brain dysfunction [26–28] or another issue [29,30]. Furthermore, epileptic seizures remain a challenging aspect for many investigators [13,17–20].

The aim of our study is to determine the most suitable classification algorithm to classify the epileptic seizure dataset to determine whether a person would have a seizure by applying different classification techniques and to study the behavior of the classification algorithm with respect to changes to the classification parameters.

2. Related work

A number of researchers have addressed topics related to epileptic seizures. In Ref. [31], the authors proposed a method to enable the comprehensive characterization of E.E.G. time series signals to improve the classification of the signals. In Ref. [32], an epilepsy detection algorithm to detect epileptic seizures from E.E.G. signals based on a neural network method was proposed. In Refs. [33–37], the authors studied the classification of E.E.G. signals using wavelet coefficients. They combined a neural network's adaptive capabilities with the quantitative approach of fuzzy logic and the invariant transformation of the probability density function; analyzed the subbands of E.E.G. signals in terms of the delta, theta, alpha, beta and gamma; and applied multiresolution decomposition and an artificial neural network, respectively. A special

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	0	X1	X2	X3	X4	X5	X6	X7	X8	...	X172	X173	X174	X175	X176	X177	X178	y
0	X21.V1.791	135	190	229	223	192	125	55	-9	...	-31	-77	-103	-127	-116	-83	-51	4
1	X15.V1.924	386	382	356	331	320	315	307	272	...	146	152	157	156	154	143	129	1
2	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	...	48	19	-12	-30	-35	-35	-36	5
3	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	...	-80	-77	-85	-77	-72	-69	-65	5
4	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	...	-12	-32	-41	-65	-83	-89	-73	5

5 rows × 180 columns

Fig. 1. Sample view of the epileptic seizure dataset.

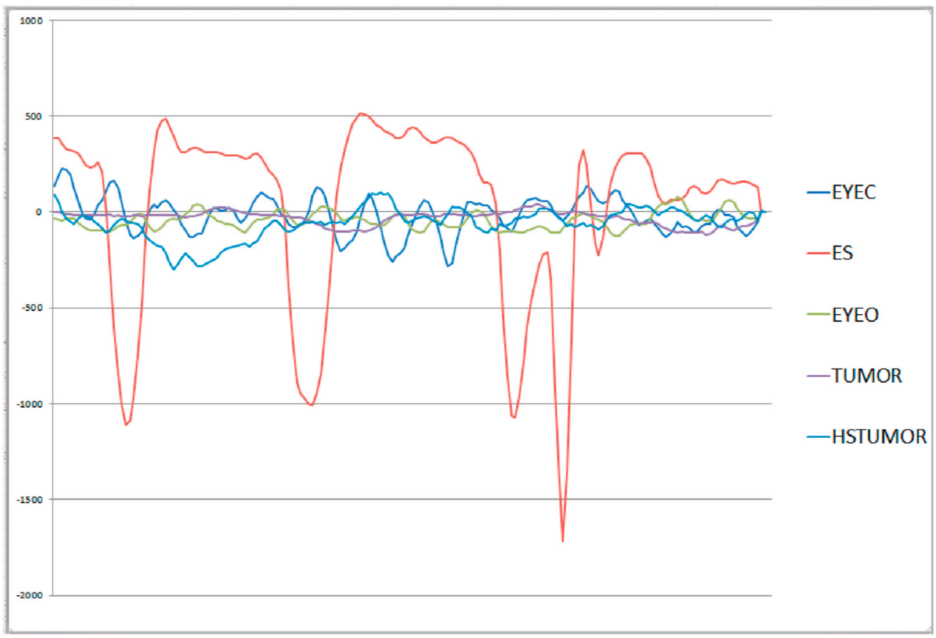

Fig. 2. Brain waveforms for different cases.

type of recurrent neural network for automatic epileptic seizure detection was proposed. The correlation measures for E.E.G. signals and actual data were proposed in Ref. [38,39]. In Ref. [40–42], different entropy estimators were applied to the E.E.G. signals of epileptic and normal subjects to detect epileptic seizures. In Ref. [43], the authors proposed an eigenvector feature extraction method using pattern recognition for E.E.G. signal detection, and a new hybrid automated identification system for E.E.G. signal classification was presented in Ref. [44]. A feed-forward method using a back-propagation N.N. was used for E.E.G. signal classification in Ref. [45], and Principal Component Analysis (P·C.A.) was used to detect epileptic seizures in Ref. [46]. In Refs. [47], the authors proposed a multilayer perceptron neural network-based classification method for epilepsy treatments, and a multidomain feature extraction method for seizure detection was presented in Ref. [48]. The authors in Ref. [49] proposed time-frequency analysis for the detection of epileptiform activities in E.E.G. signals, and authors in Ref. [50] proposed basis-based wavelet packet entropy for the feature extraction of E.E.G.s for a seizure detection algorithm. An advanced A.I. technique was used for automatic epileptic seizure detection using E.E.G. signals in Ref. [51], and the authors in Ref. [52] proposed subband nonlinear parameters for seizure detection using E.E.G.s Recently, epilepsy detection using the DWT and the K-NN classifier was proposed in Ref. [53]. In addition, more recently, the authors in Ref. [54] performed automated epileptic seizure detection and prediction using the discrete wavelet transform and wavelet packet decomposition, and a method for the classification of E.E.G. signals to detect epileptic seizures was proposed in Ref. [55]. Hybrid machine learning methods used to detect epileptic seizures were presented in Ref. [56], robust machine learning classification techniques applying different feature extraction strategies to detect epileptic seizures were proposed in Ref. [57], and convolutional neural networks for epileptic seizure prediction were proposed in Ref. [58].

To the best of our knowledge, a comparative analysis for the classification of epileptic seizure datasets for the possible classification of seizures with classifier sensitivity analysis has not been performed, and this will be the main contribution of this work.

The remainder of this paper is organized as follows. Section 3 describes the preparation of the epileptic seizure dataset, section 4 introduces the predictive methods and discusses the results, and section 5 gives a further discussion. Section 6 presents the conclusion.

3. Preparation of the epileptic seizure dataset

The epileptic seizure (E.S.) dataset used in this paper is taken from Ref. [1], and the dataset is organized as follows:

The dataset consists of 11,500 samples, each with 178 features, and the samples are normally distributed. The samples are categorized into five different classes Y = {1,2,3,4,5} based on the following criteria:

a) Class 5 - eyes open when recoding the E.E.G. signal, and this will be given the label E.Y.E.O. in this paper
b) Class 4 - eyes closed when recording the E.E.G. signal, and this will be given the label E. Y.E.C. in this paper

Table 1
Number of cases per class.

Class	Class Description	Abbreviation used	Number of cases	Binary case
1	Recording of seizure activity	ES	2300	2300
2	the tumor was located	TUMOR	2300	9200
3	the E.E.G. activity recorded from the healthy brain area	HSTUMOR	2300	
4	eyes closed	EYEC	2300	
5	eyes open	EYEO	2300	

Table 2
Different classifiers' results.

Classifier Method	Accuracy (%)	ROC	MAE	RMSE	Time (s)
K-NN (N = 1)	95.23	0.882	0.0477	0.2183	0.01
Naive Bayes	95.73	0.959	0.0427	0.206	0.29
J48	94.82	0.901	0.0543	0.226	10.35
Random Forest	**97.08**	**0.996**	0.0667	**0.1527**	17.03
Random Tree	93.86	0.900	0.0614	0.2478	0.32
Logistic Regression	81.93	0.529	0.2963	0.3884	3.67
SGD	81.92	0.549	0.1808	0.4252	4.22
Decision Table	91.97	0.922	0.1286	0.2554	22.04

c) Class 3 - Yes, a brain tumor was identified after recording the E.E.G. from the healthy brain area, and this will be given the label H·S.T.U. M.O.R.
d) Class 2 - E.E.G. signal was recorded where the brain tumor was located, and this will be given the label TUMOR
e) Class 1 - Recording of seizure activity, E.S.

Each sample had 178 features indicating the brainwave measurement per second for the different mentioned cases. Fig. 1 shows a sample view of the epileptic seizure dataset, and Fig. 2 shows a sample of the waveform of each class.

It is worth mentioning that only samples associated with class 1 had an E.S, and therefore, our analysis will take a binary shape for E.S. and non-ES cases, which contain classes {2,3,4,5}.

Table 1 shows the number of cases for the used classes, and we can see that all classes have the same number of samples.

4. Classification methods

The machine learning predictive and classification methods used in this work are presented as follows:

4.1. K-Nearest Neighbor (K·N·N.)

A Nearest Neighbor (NN) classifier calculates the distance classified using the Euclidian distance between two vectors, test and training. The image's vector representation is given by:

$$d_1(I_1, I_2) = \sqrt{\sum_p |I_1^p - I_2^p|^2}$$

For the k-Nearest Neighbor (K·N·N.) classifier, I_1 and I_2 represent subjects *1* and *2*, respectively; d_1 is the distance and $\sum$ is the summation of all available elements. Instead of finding the closest single image for prediction, we find the top k closest images in the training set before predicting the label (class) of the test image.

4.2. Logistic regression

We use the following logistic model to explain this algorithm and to see how the coefficient can be estimated from data. Given two predictors in models x_1 and x_2 and a binary class Y, a linear relation between x_1 and x_2 and the log-odds of the response of Y, p (*response of* Y), is given by:

$$log_b \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

This method is used to estimate β_i that can be used to predict true and false values. This model performs the best when data separation is available in terms of the positive and negative values of the data set elements.

4.3. Decision tree

Different types of decision rules can be implemented based on the characteristics of the data set:

4.3.1. Decision tree J48

For a unified variable associated with the dataset.

4.3.2. Random tree

For a random rule seeking to answer the mentioned questions to classify the dataset.

The following parameters are available from the Weka software used to simulate the decision tree: seed = 1, where the seed is used to randomize the data when reduced error pruning is used; confidence factor = 0.25, where the confidence factor is used for pruning (smaller values incur more pruning); number of folds = 3, which determines the amount of data used for reduced error pruning; and batch size = 100.

4.4. Random forest

A random forest classifier is a collection of multiple random tree classifiers; and, usually, an average of all trees' classification results will be used to represent the performance of the random forest classification. Randomness is introduced to these trees in two different aspects:

a. A random number of rows for each tree containing the original dataset element
b. A random number of columns, or decision branches, for each tree

The following parameters are available from the Weka software used for the simulation of the decision tree: seed = 1, where the seed is used to randomize the data when reduced error pruning is used; number of execution slots = 1, which indicates the number of execution slots (threads) to use to construct the ensemble; bag size percent = 100, which represent the size of each bag as a percentage of the training set size; batch size = 100, which is the preferred number of instances to process if batch prediction is performed; and the number of iterations = 100, which is the number of trees in the random forest.

5. Results and discussion

The results obtained for using different classifiers for the classification of the epileptic seizure dataset and possibly some changed parameters for a given classifier are presented in this section. One of the challenges faced during the implementation is working with a large dataset with a large number of attributes (features), 178. As presented in the feature extraction (selection section) section, feature reduction can be applied for the close prediction of elliptic seizure cases with some selected features.

5.1. Used classifiers

The results for the 10-fold cross-validation method for different classifiers for the classification of the epileptic seizure dataset are shown as follows:

Table 2 indicates that the random forest classifier using the cross-validation method outperforms all other classifiers used for the

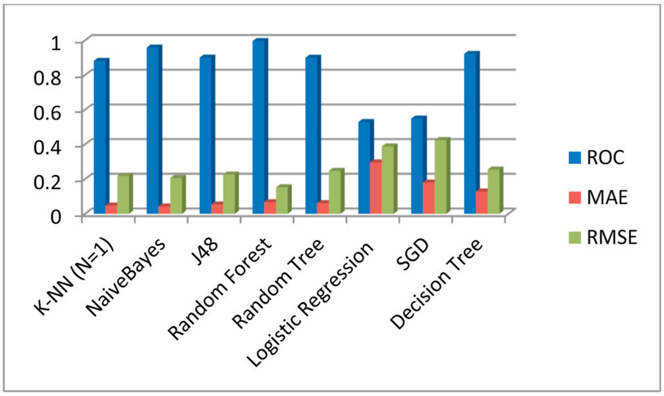

Fig. 3. Classification results.

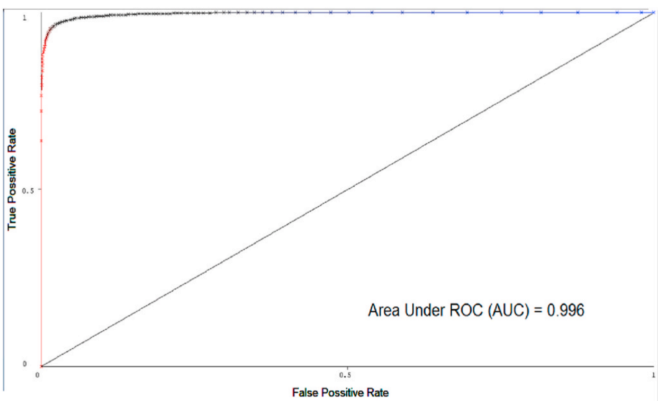

Fig. 4. R.O.C. curve for the Random Forest Classifier.

Table 3
Accuracy and R.O.C. value for the K.N.N. Classifier for Different Values of k.

k Value	Accuracy	R.O.C.
1	95.234	0.882
3	93.547	0.936
5	92.695	0.922
7	92.122	0.928
9	91.71	0.29

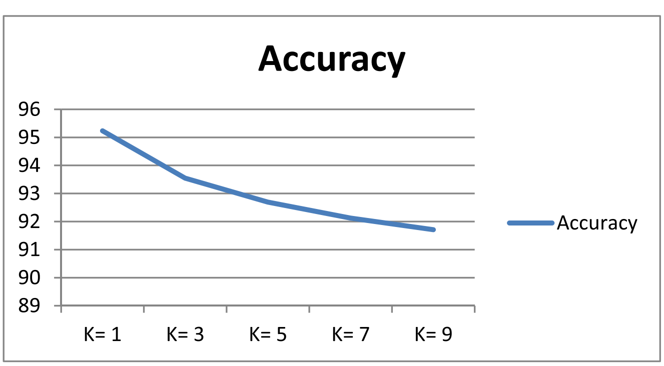

Fig. 5. Accuracy Performance with Respect to the Value of k in the K-NN Classifier.

classification of the epileptic seizure dataset. The classifiers used along with random forest classifier are the K-NN with N = 1, the naive Bayes classifier, the J48 classifier, the random tree classifier, the logistic regression classifier, the Stochastic Gradient Descent (S.G.D.) classifier

Table 4
Random forest classifier with the training set.

Method used	Accuracy %	ROC	MAE	RMSE	Time (s)
Cross-Validation	97.08	0.996	0.067	0.153	17.03
50% training	97.061	0.995	0.072	0.156	0.17
60% training	97.196	0.996	0.072	0.154	0.14
80% training	97.478	0.996	0.067	0.153	16.92

Table 5
Parameter changes of the S.G.D. classifier with respect to learning rate.

L.R.	Accuracy %	ROC	MAE	RMSE	Time (s)
0.01	81.923	0.549	0.1808	0.4252	4.47
0.02	81.809	0.546	0.1819	0.4265	4.09
0.04	81.522	0.539	0.1848	0.4299	4.07
0.08	81.913	0.549	0.1809	0.4253	4.02
0.1	81.965	0.551	0.1803	0.4247	3.98
0.2	81.617	0.542	0.1838	0.4287	3.96

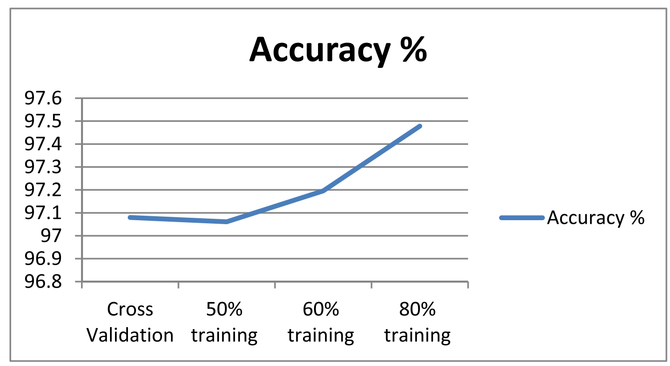

Fig. 6. Accuracy Comparison when using the Training/Testing Method.

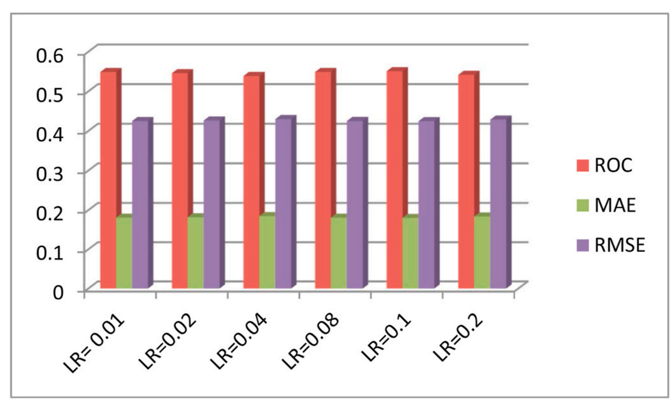

Fig. 7. Visual representation of the results in Table 5.

Table 6
Parameter changes of the S.G.D. classifier with respect to the regularization parameter.

1/λ	Accuracy %	ROC	MAE	RMSE	Time (S)
10,000	81.923	0.549	0.1808	0.4252	4.47
5000	81.852	0.547	0.1815	0.426	4.09
2500	81.922	0.549	0.1808	0.4252	4.11
1250	81.808	0.546	0.1819	0.4265	4.2
1000	81.904	0.548	0.1810	0.4254	4.07

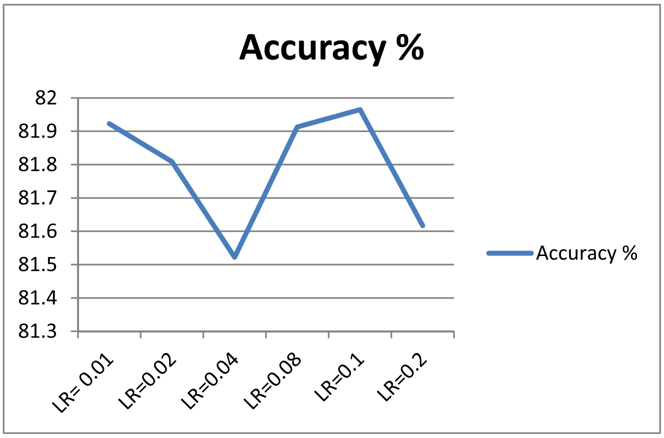

Fig. 8. Accuracy in percentage for the S.G.D. Classifier with Different L.R.s.

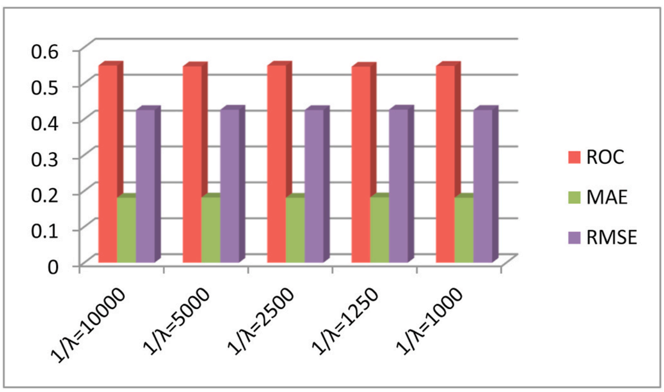

Fig. 9. Visual representation of the results in Table 7.

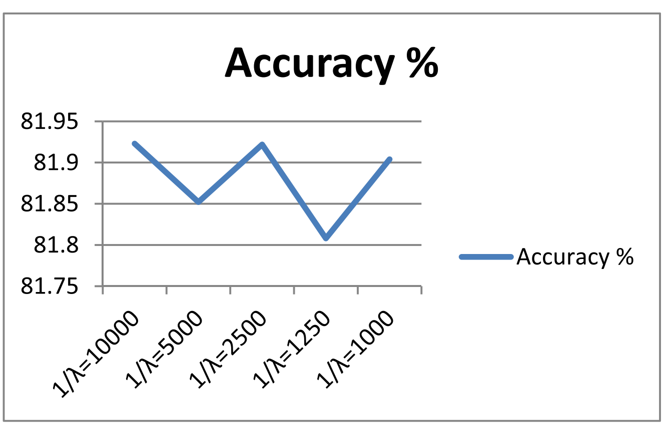

Fig. 10. Visual representation of the results of Table 6.

Table 7
Parameter changes of the S.G.D. classifier in terms of the loss Function.

Loss Function	Accuracy (%)	ROC	MAE	RMSE	Time (s)
SVM	81.923	0.549	0.1808	0.4252	4.47
Logistic Regression	80.8522	0.523	0.2827	0.3954	5.62

and the decision table classifier. The results show that the random forest outperforms these classifiers with an accuracy of 97.08%, an R.O.C. equal to 0.996, and an R.M.S.E. of 0.1527. The graph of the results is

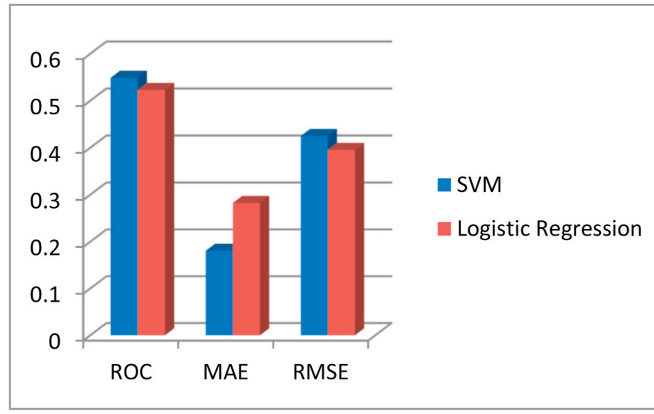

Fig. 11. Visual representation of the results of Table 7.

shown in Fig. 3.

Fig. 4 shows the R.O.C. curve for classifying the epileptic seizure dataset using the random forest classifier.

Fig. 4 shows the R.O.C. value for the random forest classifier for an AUC value of 0.996 with an accuracy of 97.08% compared to the other classifiers used for comparison.

5.2. *Parameter sensitivity for some classifiers*

We will present some parameter sensitivities for some classifiers, such as the k value for the K-NN classifier and the change of the training/test samples for the random forest classifier to assess the results of the classifiers due to these changes.

5.2.1. *K-Nearest Neighbors*

The K-NN classifier with different ks was tested to demonstrate the classifier output for the given epileptic seizure dataset, and the following results were obtained for the accuracy and the R.O.C. values.

Table 3 shows that the accuracy decreases as the value of k increases for the K-NN classifier. The accuracy changes from 95.234% to 91.71% as k changes from 1 to 9, respectively. Fig. 5 shows a representation of the obtained results.

5.2.2. *Random forest*

We select the random forest classifier instead of cross-validation as the training/test method and change the percentage of test samples to study the accuracy of the classifier and other performance metrics. Table 5 shows the performance of the mentioned classifier.

Table 4 presents some changes in the performance of the classifier when using the random forest method selection instead of the 10-fold cross-validation method for training/testing. We can note some close performances for the 80%/20% training/testing method in terms of the R.O·C, M.A.E. and R.M.S.E. of 0.996, 0.067 and 0.153, respectively; furthermore, we can also see the outperformance of 80% training compared to cross-validation with the method achieving an accuracy of 97.478% compared to 97.08% for the cross-validation method. Fig. 6 illustrates the accuracy enhancement presented in Table 4.

5.2.3. *Stochastic Gradient Descent (S.G.D.)*

In this section, we will change some of the parameters associated with S.G.D. and assess the classifier performance based on the changes of these parameters.

5.2.3.1. Learning rate (L.R.). The learning rate is a configurable parameter that influences the convergence of the algorithm. The following results were obtained by setting $\lambda = 0.0001$ and using the support vector machine as a loss function.

Fig. 7 shows a graph of the performance of the S.G.D classifier based

Table 8
Comparison of the feature extraction results.

Method	Time (s)	Precision	Recall	F-Measure	ROC	MAE	RMSE	RAE (%)
All features	0.30	0.957	0.957	0.957	0.959	0.0427	0.206	13.32
Var>25,000	0.46	0.957	0.957	0.957	0.959	0.043	0.2066	13.44
Var>26,000	0.23	0.956	0.957	0.957	0.961	0.0433	0.2072	13.52

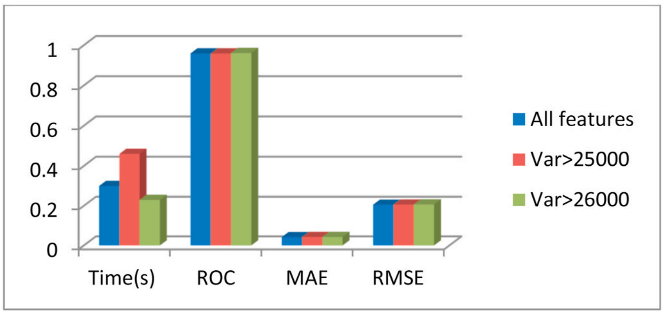

Fig. 12. Visual representation of some of the results of Table 8.

on the changes in the R.O·C, M.A.E, and R.M.S.E. for different L.R.s, as presented in Table 6. We can see that changing the L.R. does not have a large impact on the S.G.D. classifier when classifying the epileptic seizure dataset.

Fig. 8 shows the changes in the accuracy as the L.R. changes. The highest accuracy of 81.965% is achieved for LR = 0.1 over the provided range.

5.2.3.2. Regularization parameter (c = 1/λ). The regularization parameter is a parameter in the S.G.D. that influences over fitting by making the training weights small, where λ is the penalty term. The following results were obtained by setting LR = 0.01 and using the support vector machine as a loss function.

Fig. 9 shows a graph of the performance of S.G.D. as represented by the R.O·C, M.A.E, and R.M.S.E. for different values of 1/λ presented in Table 6. We can see that changing 1/λ does not have a large impact on the S.G.D. classifier when classifying the epileptic seizure dataset.

Fig. 10 shows the changes in the accuracy as 1/λ changes. A maximum accuracy of 81.922% is achieved when 1/λ = 2500 for the provided range.

5.2.3.3. Loss function (L.F.). There are different types of loss functions associated with the S.G.D. classifier model. We will examine the classifier performance when changing the L.F. from the support vector machine (SVM) to the logistic regression loss function when LR = 0.01 and λ = 0.0001.

We can see from Table 7 that the SVM achieves better performance than the logistic regression loss function for the S.G.D. classifier, achieving accuracy of 81.923%, ROC = 0.549, and MAE = 0.1808. The visual representation of Table 7 is given in Fig. 11.

5.3. Feature extraction and epileptic seizure prediction

The variance threshold feature selection method was applied on the available attributes for two different thresholds, Var <25,000, and Var <26,000. It was found that only 172 and 148 features were relevant, respectively; and similar, if not slightly better, classification results were obtained using the naive Bayes classifier for prediction using the epileptic seizure dataset, as seen in Table 8.

Table 8 shows the mentioned results. We can see that working with only 148 features out of 178 gives acceptable results, achieving a classification precision of 0.956, a recall of 0.957, an F-measure of 0.957, a receiver operating characteristic curve (R.O·C.) of 0.961, a Mean Absolute Error (M.A.E.) of 0.0433, a Root Mean Square Error (R.M.S.E.) of 0.2072, a Relative Absolute Error (R.A.E.) 13.52%, and a better processing time of 0.23 s. Fig. 12 shows the visual representation of some of the results.

6. Conclusion

In this paper, the epileptic seizure dataset was classified using different classification. It was shown that the random forest classifier outperformed the k-Nearest Neighbors (K-NN), naïve Bayes, Logistic Regression, Decision Tree (D.T.), Random Tree, J48, and Stochastic Gradient Descent (S.G.D.) classifiers with 97.08% accuracy, an ROC = 0.996, and an RMSE = 0.1527. Additionally, sensitivity analysis was performed for the K-NN, random forest, and S.G.D. classifiers to study the performances of the classifiers at classifying the epileptic seizure dataset when some parameters change, such as the value of k for the K-NN classifier; the training set/testing set splits for the random forest and the learning rate, regularization parameter and the loss function for S.G.D. The results show that by changing some classifier parameters, one enhances the classification performance. For example, the random forest classifier attains an enhanced accuracy of 97.3487% when changing the training/testing split, an enhanced accuracy of 81.965% is attained when changing the learning rate of the S.G.D. classifier to 0.1, and an enhanced accuracy of 81.923% is attained when changing its regularization parameter to 10,000. Finally, using the naïve Bayes classifier feature extraction method based on the variance of the available attributes in the epileptic seizure dataset shows that good classification accuracy can be achieved using only 148 features out of the 178 features that can be used for the prediction of epileptic seizures.

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Availability of data and material

The Epileptic Seizure dataset used in this work was obtained from the publicly available dataset: https://archive.ics.uci.edu/ml/datasets/Epileptic%2BSeizure%2BRecognition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Andrzejak RG, Lehnertz K, Rieke C, Mormann F, David P, Elger CE. Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: dependence on recording region and brain state. Phys Rev E 2001;64:061907.
[2] Ott E, Sauer T, Yorke JA. Coping with chaos. New York: Wiley; 1994.

[3] Rombouts SARB, Keunen RWM, Stam CJ. Investigation of nonlinear structure in multichannel EEG. Phys Lett A 1995;202:352.
[4] Lopes da Silva FH, Pijn JP, Velis D, Nijssen PCG. Alpha rhythms: noise, dynamics and models. Int J Psychophysiol 1997;26:237.
[5] Pritchard WS, Duke DW, Krieble KK. Dimensional analysis of resting human EEG II: surrogate-data testing indicates nonlinearity but not low-dimensional chaos. Psychophysiology 1995;32:486.
[6] Pezard L, Jech R, Ruzicka E. Investigation of non-linear properties of multichannel eeg in the early stages of Parkinson's disease. Clin Neurophysiol 2001;112:38–45.
[7] Nandrino JL, Pezard L, Martinerie J, El Massioui F, Renault B, Jouvent R, Allilaire JF, Wildlo cher D. Decrease of complexity in EEG as a symptom of depression. Neuroreport 1994;5:528.
[8] Jeong J, Chae TH, Kim SY, Han SH. Nonlinear dynamic analysis of the EEG in patients with Alzheimer's disease and vascular dementia. J Clin Neurophysiol 2001;18:58.
[9] Soong ACK, Stuart CIJM. Evidence of chaotic dynamics underlying the human alpha-rhythm electroencephalogram. Biol Cybern 1989;62(55).
[10] Stam CJ, Pijn JPM, Suffczynski P, Lopes da Silva FH. Dynamics of the human alpha rhythm: evidence for non-linearity? Clin Neurophysiol 1999;110:1801–13.
[11] Jing H, Takigawa M. Topographic analysis of dimension estimates of EEG and filtered rhythms in epileptic patients with complex partial seizures. Biol Cybern 2000;83:391–7.
[12] Andrzejak RG, Widman G, Lehnertz K, Rieke C, David P, Elger CE. Epileptic process as nonlinear deterministic dynamics in stochastic environment: an evaluation on mesial temporal lobe epilepsy. Epilepsy Res 2001;44:129–40.
[13] Iasemidis LD, Pardalos P, Sackellares JC, Shiau D-S. Quadratic binary programming and dynamical system approach to determine the predictability of epileptic seizures. Combi. Optimization 2001;5(9).
[14] Theiler J. On the evidence for low-dimensional chaos in an epileptic electroencephalogram. Phys Lett A 1995;196:335.
[15] Babloyantz A, Destexhe A. Low-dimensional chaos in an instance of epilepsy. Proc Natl Acad Sci USA 1986;83:3513.
[16] Mormann F, Lehnertz K, David P, Elger CE. Mean phase coherence as a measure for phase synchronization and its application to the EEG of epilepsy patients. Physica D 2000;144:358.
[17] Frank GW, Lookman T, Nerenberg MAH, Essex C, Lemieux J, Blume W. Chaotic time series analyses of epileptic seizures. Physica D 1990;46:427.
[18] Lehnertz, Elger CE. Can epileptic seizures be predicted? Evidence from nonlinear time series analysis of brain electrical activity. Phys Rev Lett 1998;80:5019.
[19] Le Van Quyen M, Martinerie J, Navarro V, Boon P, Have MD, Adam C, Renault B, Varela F, Baulac M. Anticipation of epileptic seizures from standard EEG recordings. Lancet 2001;357:183.
[20] Martinerie J, Adam C, Le Van Quyen M, Baulac M, Clemenceau S, Renault B, Varela FJ. Epileptic seizures can be anticipated by non-linear analysis. Nat Med 1998;4:1173.
[21] Lehnertz K, Arnhold J, Grassberger P, Elger CE. Chaos in brain. Singapore: World Scientific; 2000.
[22] Iasemidis LD, Sackellares JC, Zaveri HP, Williams WJ. Phase space topography of the electrocorticogram and the Lyapunov exponent in partial seizures. Brain Topogr 1990;2:187.
[23] Theiler J, Rapp P. Re-examination of the evidence for low-dimensional, nonlinear structure in the human electroencephalogram. Electroencephalogr Clin Neurophysiol 1996;98:213.
[24] Stam CJ, van Woerkom TCAM, Pritchard WS. Use of non-linear EEG measures to characterize EEG changes during mental activity. Electroencephalogr Clin Neurophysiol 1996;99:214.
[25] Rapp PE, Bashore TR, Martinerie JA, Albano AM, Zimmermann ID, Mees AI. Dynamics of brain electrical activity. Brain Topogr 1989;2(99).
[26] Jelles B, van Birgelen JH, Slaets JPJ, Hekster REM, Jonkman EJ, Stam CJ. Decrease of non-linear structure in the EEG of Alzheimer patients compared to healthy controls. J Clin Neurophysiol 1999;110:1159.
[27] Stam CJ, van Woerkom TCAM, Keunen RWM. Non-linear analysis of the electroencephalogram in Creutzfeldt-Jakob disease. Biol Cybern 1997;77:247.
[28] Nandrino JL, Pezard L, Martinerie J, El Massioui F, Renault B, Jouvent R, Allilaire JF, Wildlo cher D. Decrease of complexity in EEG as a symptom of depression. Neuroreport 1994;5:528.
[29] Pijn JPM, Velis DN, van der Heyden MJ, DeGoedde J, van Veelen C, Lopes da Silva FH. Nonlinear dynamics of epileptic seizures on basis of intracranial EEG recordings. Brain Topogr 1997;9:249.
[30] Mormann F, Lehnertz K, David P, Elger CE. Mean phase coherence as a measure for phase synchronization and its application to the EEG of epilepsy patients. Physica D 2000;144:358.
[31] Gautama T, Mandic DP, Van Hulle MM. Indications of nonlinear structures in brain electrical activity. Phys Rev E 2003;67:046204.
[32] Nigam VP, Graupe D. A neural-network-based detection of epilepsy. Neurol Res 2004;26:55–60.
[33] Güler I, Übeyli ED. Adaptive neuro-fuzzy inference system for classification of E.E. G. signals using wavelet coefficients. J Neurosci Methods 2005;148:113–21.
[34] Abdulhamit S. E.E.G. signal classification using wavelet feature extraction and a mixture of expert model. Expert Syst Appl 2006. https://doi.org/10.1016/j.eswa.2006.02.005. in the press.
[35] Adeli H, Ghosh-Dastidar S, Dadmehr N. A wavelet-chaos methodology for the analysis of E.E.G.s and E.E.G. Sub-Bands to detect seizures and epilepsy. IEEE (Inst Electr Electron Eng) Trans Biomed Eng 2006. https://doi.org/10.1109/TBME.2006.886855.
[36] Guo L, Rivero D, Dorado J, Rabunal JR, Pazos A. Automatic epileptic Seizures detection in E.E.G. based on line length feature and artificial neural network. J Neurosci Methods 2010;191:101–9.
[37] Srinivasan V, Eswaran C, Sriraam N. Artificial neural network based epileptic detection using time-domain and frequency-domain features. J Med Syst 2005;29:647–60.
[38] Harikrishnana KP, Misrab R, Ambikac G, Kembhavib AK. A non-subjective approach to the G.P. algorithm for analyzing noisy time series. Physica D 2006;215:137–45.
[39] Kannathala N, Rajendra Acharyab U, Limb CM, Sadasivana PK. Characterization of EEG-A comparative study. Comput Methods Progr Biomed 2005;80:17–23.
[40] Kannathala N, Choo ML, Acharyab UR, Sadasivana PK. Entropies for detection of epilepsy in E.E.G. Comput Methods Progr Biomed 2005;80:187–94.
[41] Srinivasan V, Eswaran C, Sriraam N H. Approximate entropy-based epileptic E.E.G. Detection using artificial neural networks. IEEE Trans Inf Technol Biomed 2006. https://doi.org/10.1109/TITB.2006.884369.
[42] Nicolaou N, Georgiou J. Detection of epileptic electroencephalogram based on permutation entropy and support vector machine. Expert Syst Appl 2012;39:202–9.
[43] Übeyli ED, Güler I. Features extracted by eigenvector methods for detecting variability of E.E.G. signals. Pattern Recogn Lett 2006;28(5):592–603. https://doi.org/10.1016/j.patrec.2006.10.004. In this issue.
[44] Polat K, Gunes S. Artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and FFT method based new hybrid automated identification system for classification of EEG signals. Expert Syst Appl 2008;34(3):2039–48. In this issue.
[45] Kumar Y, Dewal ML, Anand RS. Epileptic seizures detection in E.E.G. using DWT-based ApEn and artificial neural network, 8; 2014. p. 1323. https://doi.org/10.1007/s11760-012-0362-9. SIViP.
[46] Subasi A, Gursoy MI. E.E.G. signal classification using P.C.A., I.C.A., LDA and support vector machine. Expert Syst Appl 2010;37:8659–66.
[47] Orhan U, Hekim M, Ozer M. E.E.G. signals classification using the K means clustering and a multilayer perceptron neural network model. Expert Syst Appl 2011;38:13475–81.
[48] Wang Lina, Xue Weining, Yang Li, Luo Meilin, Huang Jie, Cui Weigang, Huang Chao. Automatic epileptic seizure detection in E.E.G. Signals using multi-domain feature extraction and nonlinear analysis. Entropy 2017;19:222. https://doi.org/10.3390/e19060222.
[49] Gajic Dragoljub, Djurovic1 Zeljko, Gligorijevic Jovan, Di Gennaro Stefano, Savic-Gajic Ivana. Detection of epileptiform activity in E.E.G. signals based on time-frequency and nonlinear analysis. Comput. Neurosci. 2015;24. https://doi.org/10.3389/fncom.2015.00038. March.
[50] Wang D, Miao D, Xie C. Best basis-based wavelet packet entropy feature extraction and hierarchical E.E.G. classification for epileptic detection. Expert Syst Appl 2011;38:14314–20.
[51] Paul Fergus, Hignett David, Hussain Abir, Al-Jumeily Dhiya, Abdel-Aziz Khaled. Automatic epileptic seizure detection using scalp E.E.G. And advanced artificial intelligence techniques. BioMed Res Int 2015. https://doi.org/10.1155/2015/986736.
[52] Hsu KC, Yu SN. Detection of seizures in E.E.G. using subband nonlinear parameters and genetic algorithm. Comput Biol Med 2010;40:823–30.
[53] Sharmilaasharmila Ashok, Madan Saiby, Srivastava Kajri. Epilepsy detection using DWT based hurst exponent and SVM, K-NN classifiers. Serbian Journal of Experimental and Clinical Research 2019;19(4):311–9. https://doi.org/10.1515/sjecr-2017-0043. 23.
[54] Alickovic E, Kevric J, Subasi A. Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. Biomed Signal Process Contr 2018;39:94–102.
[55] Satapathy Sandeep Kumar, Dehuri Satchidananda, Kumar Jagadev Alok. An empirical analysis of different machine learning techniques for classification of E.E.G. signal to detect an epileptic seizures. Int J Appl Eng Res 2016;11(1):120–9.
[56] Subasi Abdulhamit, Kevric Jasmin, Abdullah Canbaz M. Epileptic seizure detection using hybrid machine learning methods. Neural Comput Appl 2019;31(1):317–25.
[57] Hussain Lal. Detecting epileptic seizures with different feature extracting strategies using robust machine learning classification techniques by applying advance parameter optimization approach. Cognitive Neurodynamics 2018;12(3):271–94.
[58] Rosas-Romero Roberto, Guevara Edgar, Peng Ke, Nguyen Dang Khoa, Lesage Frédéric, Pouliot Philippe, Lima-Saad Wassim-Enrique. Prediction of epileptic seizures with convolutional neural networks and functional near-infrared spectroscopy signals. Comput Biol Med 2019;111:103355.