

Prediction of Epilepsy Seizures by Machine Learning Methods

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Abstract : According to the Globe Health Organization (WHO), more than 50 million people throughout the world are living with a diagnosis of epilepsy, making it perhaps of the most widely recognized neurological issue. Epileptic seizures are a leading cause of hospitalization and mortality across the globe. Accurate and prompt diagnosis is more crucial than ever given the increase in epileptic seizures all through the globe and their effect on individuals' lives. Epilepsy, cancer, diabetes, heart disease, thyroid disease, and many more are only some of the diseases for which machine learning approaches are being applied in prediction and diagnosis. Epilepsy is one ailment that may be treated early on to save a person's life. The main objective of this research is to use feature label extraction to the dataset in order to obtain the best ML models for epileptic seizures. In order to predict epilepsy, we used the techniques of logistic regression, SVM, linear SVM, KNN, and RNN in this study. The models employed in this research are accurate to varying degrees and have attributes including precision, recall, f1-score, and support. This study demonstrates that the model is able to accurately predict the occurrence of epilepsy. Our discoveries demonstrate that involving Examination highlight extraction in the dataset, the Regional Neural Network (RNN) model with 99.9998 % Training data accuracy and 97.78% Test data accuracy and 100% prediction probability of epilepsy seizure produces the best results and also the feature characteristics of RNN is better as compared to other models used in current research work.

Keywords: Epilepsy, Seizures, Detection, Machine Learning, EEG.

I. INTRODUCTION

In excess of 50 million individuals overall experience the ill effects of epilepsy, which is perhaps of the most well-known neurological problem (WHO) [1]. A chronic, noncommunicable brain disorder called epilepsy can cause unexpected seizures by affecting the central nervous system [2] [3].

A seizure, often called an epileptic seizure, is an impermanent neurological problem of the cerebrum that may be set off by an abnormal increase in the activity of certain nerve cells in the brain [4]. There are many persons of different ages who are affected by this neurological illness. [5]. The prevalence of this condition is one percent worldwide [6].

Epilepsy can be brought about by various circumstances, including veins, mind diseases, cerebrum growths, nourishing lacks, pyridoxine lack, and issues in calcium digestion. Research is essential to fully comprehend the processes that lead to epileptic diseases in order to correctly diagnose epilepsy [6].

Diagnostic methods include magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), ultrasound, and electroencephalography (EEG). MRI, CT scans, and ultrasounds can't be utilized for long-term detection and are pricey. However, EEG testing may be employed for long-term detection since it is inexpensive. The most accurate method for diagnosing epilepsy is consequently EEG. [7].

When treating epileptic cases, the EEG offers a plethora of physiological and pathological information that is helpful, such as determining the epileptogenic zone for presurgical evaluations [8]. Neurologists' physical examination of EEG recordings is currently the main method used for EEG diagnosis. Long-term EEG visual scoring takes a lot of time and is tedious. Therefore, the automated recognition technique is beneficial to neurologists when they examine EEG data or records.

Over the past two decades, machine learning (ML), the sub-field and underpinning of artificial intelligence (AI), has made significant progress. To uncover the underlying characteristics of data and intrinsic relationships, machine

learning (ML) employs algorithms as well as ideas from mathematics and computer science. The discipline of illness diagnostics presently makes extensive use of it. Today, AI techniques are being utilized to check or recognize different difficult ailments, including as thyroid, malignant growth, diabetes, coronary illness, and epilepsy. A person's life can be saved through early diagnosis and treatment of illnesses like epilepsy [9].

However, predicting probable seizures is a difficult task. The majority of seizures happen suddenly, making it difficult for researchers to identify possible seizures in advance of their occurrence. The approach described in this article will make it easier to tell if someone is experiencing a seizure or not [10].

The comparison of five different types of ML models for the detection of epileptic episodes was the primary objective of this work. SVM, Linear SVM, KNN, and Regional Neural Networks are some of the machine learning (ML) models that will be tested (NN). Accuracy, precision, and specificity were measured for each model and compared. A total of 11500 samples were used to generate and assess the ML models, and the data used for this study came from the open-source database Physionet. This paper's goal was to determine which ML model was the most reliable and which attributes were best for building classifiers. The project's secondary goal is to use these findings as a springboard for studies in the future to assess if it is plausible to foster a convenient seizure identification gadget utilizing further developed ML models.

II. LITERATURE SURVEY

This section of the study is devoted to a number of researchers who have talked about epileptic seizures and utilized AI techniques to anticipate them. Here, we examine some recent research on the identification of epileptic episodes in EEG data.

By using the discrete wavelet transform (DWT) technique, Hamad et al. were able to extract features that were then utilized to train an SVM using a radial basis function (RBF) kernel function. The key feature subset and the appropriate SVM parameters were chosen using the grey wolf optimizer (GWO) to accurately categorize EEG data.[11].

In order to decompose signals and calculate statistical measurements, Swami et al. used the dual-tree complex wavelet transform (DTCWT). After training a general regression neural network classifier with all of the statistical measurements, the model's accuracy was 95.24% [12].

To isolate EEG information into various sub-groups and therefore extrapolate factual information from them, Sharmila & Geethanjali largely used discrete wavelet transforms (DWT) in 2016. Utilizing the statistical information received from the DWT, the classifier is trained. Two classifiers are then used to classify the signals and determine whether or not they are epileptic. The two classifiers employed in this study are the KNN and Naive Bayes classifiers. In this examination, the viability of 14 unique two-class blends for recognizing epilepsy is broke down. The aftereffects of the exploration showed that, for most dataset blends, The Innocent Bayes classifier accomplishes the most noteworthy exactness while using the least amount of processing time to identify epileptic episodes. [8].

Al-Mustafa 2020 used several machine learning methods to classify an epileptic seizure dataset, including RF, DT, K-NN, Naive Basis, Logistic Regression, Random Tree, J48, and Stochastic Gradient Descent (SGD). The Random Forest classifier produced results with 97.08% accuracy [8].

Principal component analysis (PCA) was utilised by Usman et al. in 2019 to classify epileptic seizures using support vector machines, and the suggested model had an average sensitivity of 93.1% [9].

In 2019, Nandy et al. employed an SVM classifier to categorise epileptic seizures using a Bayesian optimization approach to optimise the hyper-parameters of the SVM. Additionally, they compared the results using linear discriminant analysis (LDA) and quadratic discriminant analysis (QLDA). The SVM classifier demonstrated 97.05% accuracy in their article [7].

III. MATERIALS

3.1. SYNOPSIS OF DATASET

This work used the epileptic seizure dataset from the University of Bonn, which is available on the UCI Machine Repository website [6]. There are 100 signals in each of the five classes in this dataset, which are numbered from 1 to 5, and each signal lasts for 23.6 seconds. Classes 5 and 4 were collected from five healthy people who alternated between having their eyes open and closed. Five individuals with epilepsy were used to record the other three groups (3, 2, and 1). When there is not an epileptic episode, the two classifications 3 and 2 were recorded (The patient's epileptogenic area was where the class 3 were recorded from the pre-seizure hippocampus contralateral side of the equator, and the class 2 were acquired.) And during convulsions, the class 1 was registered.

All EEG signals are inspected at 173.61 hertz and recorded using a 128-channel framework and a 12-bit simple to-computerized converter. Approximately 11,500 examples are included in the collection, and each one has a normal distribution across its 178 properties. Classes 2, 3, 4, and 5 patients are all without history of epileptic seizures. Epileptic seizures were only experienced by class 1 persons

[13]. As a result, our analysis will have a binary structure with classes 2,3,4,5 for both epileptic seizure and non-epileptic seizure cases. Each of the classes used is represented by the number of cases in Table 1, and as can be seen, there are an equal number of samples for each class. Figure 1 provides an example presentation of the epileptic seizure dataset.

Table 1 lists the dataset's description and the quantity of each class's cases.

Classes	Class Description	The Patient State	The Number of cases	Binary case
1	Patients with epilepsy have their seizure activity monitored.	General epilepsy (with seizures)	2300	2300
2	In epileptic individuals, the tumor was found.	Partial epilepsy (without seizures)	2300	9200
3	Epileptic individuals with a healthy brain area were used to capture the EEG data.	Partial epilepsy (without seizures)	2300	
4	eyes closed	Healthy	2300	
5	eyes opened	Healthy	2300	

Out[2]:

	Unnamed	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X170	X171	X172	X173	X174	X175	X176	X177	X178	y
0	X21.V1.791	135	190	229	223	192	125	55	-9	-33	...	-17	-15	-31	-77	-103	-127	-116	-83	-51	4
1	X15.V1.924	386	382	356	331	320	315	307	272	244	...	164	150	146	152	157	156	154	143	129	1
2	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	-85	...	57	64	48	19	-12	-30	-35	-35	-36	5
3	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	-87	...	-82	-81	-80	-77	-85	-77	-72	-69	-65	5
4	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	-21	...	4	2	-12	-32	-41	-65	-83	-89	-73	5
...
11495	X22.V1.114	-22	-22	-23	-26	-36	-42	-45	-42	-45	...	15	16	12	5	-1	-18	-37	-47	-48	2
11496	X19.V1.354	-47	-11	28	77	141	211	246	240	193	...	-65	-33	-7	14	27	48	77	117	170	1
11497	X8.V1.28	14	6	-13	-16	10	26	27	-9	4	...	-65	-48	-61	-62	-67	-30	-2	-1	-8	5
11498	X10.V1.932	-40	-25	-9	-12	-2	12	7	19	22	...	121	135	148	143	116	86	68	59	55	3
11499	X16.V1.210	29	41	57	72	74	62	54	43	31	...	-59	-25	-4	2	5	4	-2	2	20	4

11500 rows x 180 columns

Figure 1: displays an example perspective on the epileptic seizure dataset.

IV. METHODOLOGY AND PERFORMANCE ANALYSIS

Our study seeks to use the feature engineering approach to the dataset in order to identify the most effective Machine Learning (ML) models for predicting epileptic episodes.

These stages will be discussed in the sections that follow. Figure 2 shows a high-level diagram of all the proposed models.

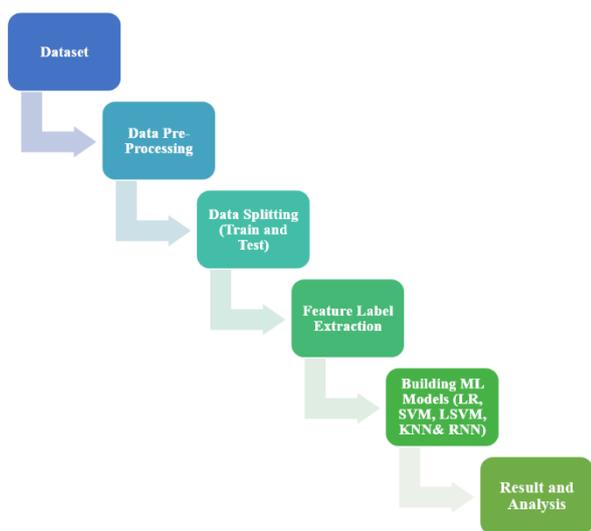


Figure 2: Proposed Model

4.1 DATA PREPROCESSING

Data preparation is one of the most important and necessary machine learning phases. When employing machine learning algorithms in a data collection, this method is crucial for successful, accurate, and dependable prediction outcomes. [14]. Information planning is a system that involves putting crude, unedited information in an organization that is appropriate for the classification procedure.

Real-world data is frequently incomplete, unreliable, lacking in particular behaviors or patterns, and/or erroneous in various ways. An established method for resolving such problems is preprocessing data. Pre-processing is done on raw data to get it ready for further processing. The expression "under testing" alludes to a gathering of strategies for reestablishing factual equilibrium to the class dissemination of a grouping dataset having an unbalanced class distribution. Our dataset was standardized using the

Feature Engineering method. We utilized 70% of the information for approval and preparing after normalizing the dataset using the suggested methodology, and 30% of the data for testing.

There are no missing values in our dataset (NAN). Table 1 shows that there is an issue with an unbalanced class distribution in the binary class; to fix this, we use under sampling techniques.

4.2 FEATURE LABEL EXTRACTION

By generating new attributes from the existing ones in the dataset, the element extraction stage looks to lessen the quantity of traits. This new, dense list of capabilities ought

to act as a rundown of most of the information and elements in the first dataset. The original set can be combined to create a condensed version of the key features [15].

As we have said, our data set has 178 characteristics, and utilizing all of them for training would need a very long training time. Therefore, in our study, we extracted and reduced the features.

These features are extracted for the proposed algorithm

- TP (True-Positive): If someone has seizures and they are appropriately identified as seizures.
- TN (True-Negative): The individual is in fact normal, the classifier also identified the incident as a non-seizure.
- FP (False-Positive): Inappropriate discovery occurs after the classifier classifies a healthy person as a case of seizures
- FN (False-Negative): Inaccurate discovery occurs after the classifier classifies a person experiencing "seizures" as a regular person. In the field of health informatics research, this is a major issue.

$$F1 - Score = \frac{TP}{TP + 1/2(FP + FN)} \quad (1)$$

$$Accuracy = \frac{(TP + TN)}{(TP + FN + FP + TN)} \quad (2)$$

4.3 BUILDING ML MODELS

This article employs a number of helpful machine learning methods and approaches for estimate and classification:

4.3.1 Classical ML

A. Logistic regression

Logistic regression classifier (LRC) is one of the most common multivariate analysis models used in biomedical applications for analyzing binary outcome data [20], [21]. The choice of the explicative variables that should be included in Logistic regression classifier is perhaps of the most frequently elaborate multivariate consistent model in biomedical applications for the investigation of double result information (LRC). Illustrative factors for the strategic relapse model are chosen for incorporation in view of earlier epilepsy information and the factual connection between the variable and the rate of epilepsy. Cox relapse and the LRC have been utilized in late examinations to gauge the typical repeat chance of ictal asystole and its deciding variables in epilepsy patients, to classifier the basic non-antiepileptic drug signs of mental and direct optional impacts rate, and to develop time to first EEG seizure in quite a while [16]. Logistic regression models are

built using epilepsy history data and the statistical relationship between the variable and the incidence of epilepsy [17].

The algorithm of Logistic regression ML model for training and testing the dataset and along with that model interpretation is carried out.

B. SVM

Supervised machine learning is known as SVM. In 1963, Vapnik and Chervonenkis made the SVM official for the first time. The SVM searches for a perfect hyperplane capable of isolating samples of any class. Hyperplanes with maximum margins may be used to discover groups that can be separated linearly. On the other hand, on the off chance that the information can't be directly isolated, they might be migrated to a greater space (i.e. feature space). This conversion is known as the kernel function. The nearest points on the hyperplane make up the support vectors. The smallest distance between them all, as well as the locations in that class, is the separation from a class to a hyperplane [18]. Additionally, grouping or regression may be done using the hyperplane. SVM classifies compounds that are not supported by data and can also classify instances by placing them in certain groupings. For each given group, Hyperplane will play out the partition to the closest training facility until the detachment is complete. The algorithm of SVM ML model for training and testing the dataset and along with that model interpretation (LIME) is carried out.

C. Linear SVM

To this day, the linear SVM remains the most used supervised machine learning approach across all three major application domains: classification, regression, and estimation. Using a training set of data that distinguishes one class from another, the computer learns a number of hyperplanes in this method. The optimum hyperplane for classification is the one with the largest margin between members of one class and those of another [19]. The kernel function in a Linear SVM classifier transforms the input into the required space of dimensions [20]. The algorithm of Linear SVM ML model for training and testing the dataset and along with that model interpretation (LIME) is carried out.

D. KNN

One supervised learning method that is widely applied in classification research is K-NN. It is a nonparametric, fundamental approach that categorizes input space objects based on the closest samples [21]. The k-nearest neighbour's method is so named because it is so close to the data that has to be categorized, even though the number of neighbour's is indicated with k. Both classification and regression issues are intended to be addressed by the KNN Classification approach. The KNN algorithm [18] is one example of a complex algorithm that requires substantial time investment to master.

K-NN is a learning algorithm that works by measuring the distance between samples; every time the system comes across a new sample of data, it measures the distance across all samples in the new data. After this is calculated, the k nearest neighbors are found from the training data and compared to the instances in the new example's training data to establish the class labels [22]. The algorithm of KNN ML model for training and testing the dataset and along with that model interpretation (LIME) is carried out.

4.3.2 Neural Network

A. Regional Neural Network

RNNs are a type of network structure made up of many linked components called neurons, each of which performs a very straightforward function and has an input and an output. In general, neural networks develop their capabilities through a learning process. In reality, they find the legislation that supports them by analyzing data and the process of transmitting it across a network. These networks are really programs that attempt to simulate human behavior:

- a. More knowledgeable as a result of time and more exposure to the environment.
- b. Capable of making logical inferences in addition to doing computations.
- c. Offer a workable resolution under new circumstances.

Regional neural networks are computer architectures that are designed after the human brain. RNN is composed of several linked unit operations that work together to process data. As a result, they frequently produce favourable outcomes. There are network layers and organization undertakings that form the RNN; the organization layers are the information layer, the secret layer, and the result layer. All of the attribute values for the data mining model's inputs are decided by the input neurons [23]. A considerable number of new advances in the field of Artificial Intelligence have been accomplished by deploying Regional Neural Networks, including Voice Recognition, Image Recognition, and Robotics. The algorithm of RNN ML model for training and testing the dataset and along with that model interpretation (LIME) as is carried out.

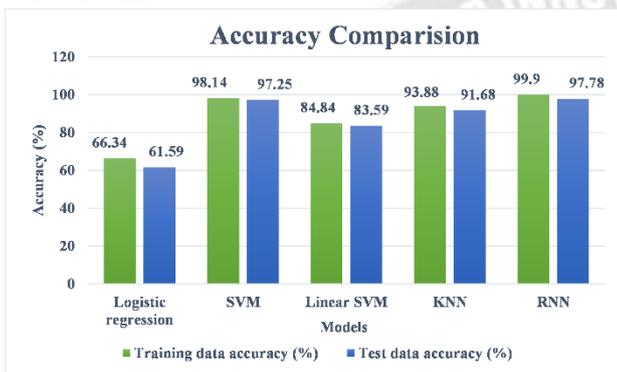
V. RESULTS AND DISCUSSION

5.1 ACCURACY OF ML MODELS' TEST AND TRAINING DATA COMPARISON

Table 2: Accuracy of machine learning models on training and test data

ML Models	Training data accuracy (%)	Test data accuracy (%)
Logistic regression	66.34	61.59
SVM	98.14	97.25
Linear SVM	84.84	83.59
KNN	93.88	91.68
RNN	99.90	97.78

In this part, It is examine the results of applying a few classifiers to the epilepsy informational collection and the effectiveness of the orders by means of feature label extraction. Using feature label extraction and dividing the dataset into 70% for preparing and 30 percent for testing, Table 2 and Graph 1 compare many ML models. Table 2 shows that the best results are achieved by the RNN Classification algorithm, which achieves an exactness of 99.90% in preparing information and 97.78% in test information. The KNN and SVM algorithms, which achieve an accuracy of 93.88% and 98.14% in training data and 91.68% and 97.25% in test data, respectively, come in second and third.



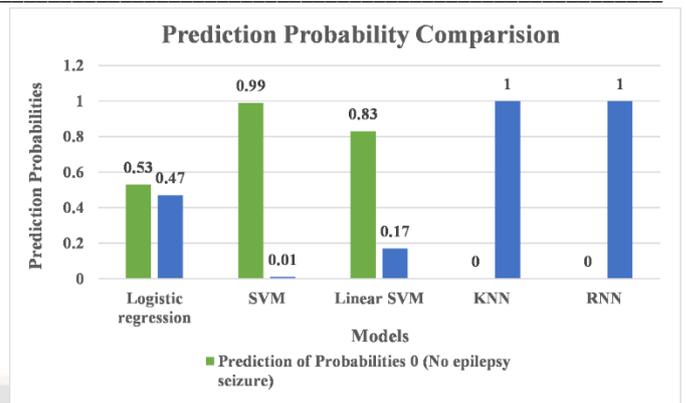
Graph 1: Comparison of the different ML Models

5.2 MODEL INTERPRETATION (LIME) AND PREDICTION OF PROBABILITIES OF DIFFERENT ML MODELS

Table 3: Prediction of probabilities of different ML models

ML Models	Prediction of Probabilities	
	0 (No epilepsy seizure)	1 (Epilepsy seizure)
Logistic regression	0.53	0.47
SVM	0.99	0.01
Linear SVM	0.83	0.17
KNN	0.0	1
RNN	0.0	1

Table 3 and Figure 2 provide a comparison of several ML models trained on the same dataset by allocating 70% of the data to training and 30% to testing using feature label extraction. From Graph 2 it is see that RNN ML model and classification algorithm is best for prediction of probability of epilepsy seizure with 100% probability. Also KNN model also prediction epilepsy seizure with 100% probability but KNN accuracy is less as comaped to RNN and SVM.



Graph 2: Prediction of probabilities of different ML models

5.3 FEATURE EXTRACTION REPORT OF USED MODEL IN PRESENT RESEARCH WORK

Table 4: Feature extraction values of model used in work

Classification model	Precision		Recall		F1- Score		Support	
	0	1	0	1	0	1	0	1
Logistic Regression	0.82	0.24	0.67	0.41	0.74	0.30	2753	697
SVM	0.98	0.95	0.99	0.91	0.98	0.93	2753	697
Linear SVM	0.83	0.93	1.00	0.23	0.91	0.36	2734	716
KNN	0.91	1.00	1.00	0.60	0.95	0.75	2753	716
RNN	0.99	0.98	1.00	0.93	0.99	0.96	2753	697

Performance of the classifications using feature label extraction is evaluated, as are the results of applying several classifiers to categorize the epilepsy data set. Classification Techniques are compared in Table 4 and Graph 2 by employing feature label extraction and allocating 70% of the dataset to preparing and 30% to testing. As per Table 4, the RNN model with 99% accuracy for no epilepsy seizure and 98% precision for epileptic seizure displays the best outcome, followed by the SVM and the KNN with 98% and 91% precision for no epilepsy seizure, and 95% and 100% precision for epilepsy seizure, respectively. Along with that the output values of RNN such as Recall, f1-score and support for no epilepsy and epilepsy seizure are better as compared to other models used in present research work as shown in Table 4 and Graph 3.

Table 5: Results comparisons between our study and several research papers

Research studies	Methods	Best method	Accuracy
Almustafa [24]	RF, DT, K-NN, Naïve Bayes, Logistic Regression, Random Tree, J48 and Stochastic Gradient Descent (S.G.D.)	RF	97%
Nandy et al., [25]	SVM classifier for classification, Linear Discriminant Analysis (LDA) and Quadratic Linear Discriminant Analysis (QLDA) for comparison	SVM	97%
Usman et al., [9]	PCA for feature extraction and SVM classifier to classification	SVM	93.1%
Swami et al., [12]	Used dual-tree complex wavelet transform (DTCWT) for decomposition of signals and calculate statistical measurements, and general regression neural network classifier for classification	Neural network	95%
This paper	Logistic regression, SVM, Linear SVM, KNN, RNN (Neural Network)	Neural network	99%

Table 5 contrasts the findings of our work with those of previous studies on the categorization of epileptic seizures.

VI. CONCLUSION

One of the main causes of illness and mortality worldwide today is epileptic seizures. It's critical to have an accurate and early diagnosis given the global increase in epileptic seizures and their impact on people's lives. Using the feature label extraction method on the dataset, this article set out to identify the most effective classification ML approaches for epileptic episodes.

In this study, we use the feature label extraction approach in the dataset to apply Logistic regression, SVM, Linear SVM, KNN, and RNN ML algorithms to the task of predicting epilepsy, and we evaluate the classifiers' performances with the use of interpretation LIME. Using the dataset's feature label extraction, it has been shown that the RNN with a 99.90% accuracy produces the best result. In addition, the KNN and SVM, algorithms with 93.88 % and 98.14% training data accuracy and 91.68% and 97.25 test data accuracy respectively, shown the best result. Also The RNN model, with 99% precision for no epilepsy seizure and

98% precision for epilepsy seizure, outperforms the SVM and KNN, which have 98% and 91% precision for no epilepsy seizure and 95% and 100% precision for epilepsy seizure, respectively.

It is also concluded that RNN model is best for Prediction probability of Epilepsy seizure with 100% probability as compared to other ML models.

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