Effectiveness of Machine Learning Algorithm for classification of EEG signals in Epileptic Seizure

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Gopinath M.P
School of Computer Science and Engineering (of Aff.)
Vellore Institute of Technology (of Aff.)
mpgopinath@vit.ac.in

Krupa Gajjar
School of Computer Science and Engineering (of Aff.)
Vellore Institute of Technology (of Aff.)
krupagajjar947@gmail.com

Vrinda S.M
School of Computer Science and Engineering (of Aff.)
Vellore Institute of Technology (of Aff.)
vrindasm13@gmail.com

Nancy pal
School of Computer Science and Engineering (of Aff.)
Vellore Institute of Technology (of Aff.)
nancy.pal2020@vitstudent.ac.in

***Abstract*—In this paper, an investigation of the effectiveness of machine learning algorithms for classification of EEG signals in Epileptic seizure is performed. Machine learning techniques are based on artificial neural networks with representation learning. Learning can either be supervised, semi-supervised, or unsupervised. Deep Learning is a subset of a broader family of machine learning. Deep Learning design such as deep neural networks, deep belief networks, recurrent networks, and convolution networks is used in fields like computer vision, audio processing, drug design, medical image analysis, medical inspection and so on, where the obtained results are comparable to and in some cases outdo the human expert system. Electroencephalography (EEG) is a complicated signal and can require many years of training to be accurately interpreted. Machine learning (ML) has shown a significant effect on EEG signals due to its capacity to learn better quality representations from raw data. EEG has many application domains such as epilepsy, sleep disorder, brain-computer interfacing, cognitive and affective monitoring. Epilepsy is a chronic disease of the brain that affects all ages(more seen in young children and old age). Around 50 million people worldwide have epilepsy; it is one of the most common neurological diseases globally. The brain uses electrical signals to communicate between the brain cells; if the electrical signal is interrupted, a seizure occurs. This seizure in the brain is called as Epilepsy. Different types of seizures show different effects on humans like jerks, sudden falls, and confused state. Whenever an epileptic seizure occurs, there will be a change in brain activities, which is known as epileptiform, and these changes can easily be seen on EEG recording. Sometimes people may have epileptiform without having a seizure, so an EEG is beneficial in this case.**

***Index Terms*—Machine Learning, Epilepsy, EEG signal classification**

I. Introduction

As we all know, the brain is an integral part of the human body, and it also serves as a command center for the nervous system. It has billions of nerves and is specialized for conduction, reception, and transmission of signals. Nerve cells are very minute vessels; they communicate by creating a connection called synapses. In the brain, neurons are made up of axons, dendrites and the cell body. They transmit information from neurons to other body parts (organs, muscles, and gland cells). One of the most significant public health problems is neurological disorders, which directly affects the functionality of electrical activities in the human brain and spinal cord. Some of the nerve system diseases are Dementia, Parkinson's disease, Epilepsy, and many more; these diseases have many symptoms like confusion, paralysis, and seizures. According to the World Health Organisation (WHO), 50 million people have epilepsy worldwide, and this number is increasing every year [24]. Epilepsy is a chronic disease where the patient suffers from repeated seizures and brain dysfunction (i.e., abnormality in electrical activity in the brain); these seizures can cause mental, physical damages to patients. The only way to reduce this unfavorable effect on the patient is by keeping track of the brain's electrical activity, the development of epilepsy, and the possibility of seizure occurrence [8].Electroencephalography (EEG) is an electrophysiological method of diagnosing the imbalance in brain activity. EEG signal is a measure of currents which flow in the course of synaptic excitations of dendrites in the pyramidal neurons of the cerebral cortex [29]. These synaptic currents are generated within the dendrites, especially when the neurons are activated [2]. EEG can measure the magnetic field generated by this current in the brain, which forms an EEG signal. Electrodes attached to the scalp show the place and time of the post-synaptic potential of the cortical neurons [19]. Basically, EEG alludes to recording the brain's voluntary electrical activity during the course of time, as it will be recorded from several electrodes placed on the scalp. EEG is the most prominent method to diagnose epilepsy. It is also used to diagnose other diseases like sleep disorders, insomnia, coma, Alzheimer's stroke, depth of anesthesia, and many more.

Monitoring epilepsy on patients is done mainly to differentiate epileptic seizures from the non-epileptic one [23].

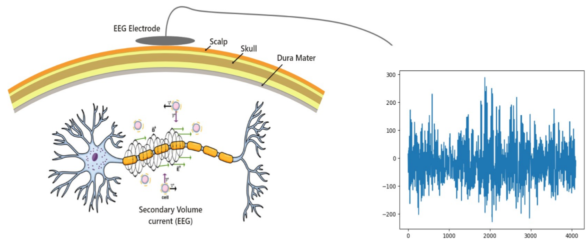

Fig. 1. Diagram of neuron activity during the EEG test

This is purely a painless technique that can be performed without the removal of any hair from the scalp. In comparison to MRI scans, EEG provides low temporal resolution [32]. Epilepsy causes the sudden electrical discharge of a particular part of the brain. The patient might feel some sensation and gradual loss of awareness with some change in behavior, which is spontaneous [7]. EEG signals are capable of tracking this electrical imbalance in the human brain. Due to the evolution of technology in recent decades, we can save the digital recordings of the EEG signal and their analysis. This analyzed data can be fed as an input to any automatized seizure detection system to identify the seizure from the fed data. Analysis of the EEG signals involves pre-processing, feature scaling, and classification of signals [21].In the pre-processing stage, the primary focus is on removing noise, enhancing the signals and thresholding, etc. After this stage, feature scaling is done where vector size can be reduced. At the end comes the classification step; here, it will test the feature vector and classify it in the best possible way based on the hidden layers. In this framework, we look at machine learning approaches to detect epileptic seizures [12]. The algorithms used in this work are Support Vector Machine (SVM), Least Squares Support Vector Machine (LS- SVM), Na¨ıve Bayes, K-nearest neighbors (KNN), Long Short Term Memory (LSTM) and Artificial Neural Network (ANN) [20]. An analysis was done on each of these algorithms in detail and compared them based on f1-score, specificity, sensitivity, recall, precision, and accuracy. The rest parts of the paper are assembled as follows: Section 2 deals with the literature survey; in the next section, we discuss the data set which we have worked on; in section 4, we speak about the proposed methodology. Finally, we discuss the result and the conclusion in section 5 and section 6, respectively

II. Literature Review

EEG Signals are proved to be one of the most effective methods for accelerating the study of cognitive development due to its non-invasive and low-cost methodology. Because of which early prediction of several brain diseases such as Alzheimer's, Autism, sleep-disorder, depression, stress, epilepsy seizure detection has become extensively possible and attracted many researchers for further study. One of the well-known technique involves net/saline or cap/gel systems. Using these two techniques, EEG tests are recorded during specific tasks like calculating, reading, or in the rest position (eyes open/ eyes closed). These computerized EEG signals are composed of multiple sine waves at different frequencies investigating several factors such as signal frequency distribution, EEG signal amplitudes, spatial coordinates of specific phenomena occurrence, the morphology of the waveform, waveform for similar regions of the brain, the symmetry between the brain hemispheres (voltage symmetry, frequency symmetry), the occurrence model of the waveform (random, sequential, continuous) and reactivity (change in the individual's state and subsequent changes in an EEG parameter). Afterward, these components are compared, and artifacts (movement of muscles and heart, blinking, or other neural activities) are removed to reduce the attrition rate as it may also distort the signal. Data used for the prediction should be consistent with the subject's gender, age, and conditions.

Current research on EEG Signal Classification focuses on the effectiveness of machine learning algorithms in comparison with other state-of-the-art methods. Researchers have proposed several algorithms to improve the detection classification of EEG signals. Such as Support Vector Machine, Deep CNN, and many more. The data set is taken from the University of Bonn, which is commonly used by several researchers. This literature describes several briefly studied methodologies proposed by researchers in this subject.

Marzieh Savadkoohi and Timothy Oladduni used a machine learning approach for epileptic seizure prediction using electroencephalogram (EEG) signals [25].They used EEG recorded signals from five healthy participants with eyes open and eyes close and intracranial EEG recordings from five epilepsy patients. Their study used various feature extraction techniques like Butterworth filter for time-domain analysis, Fourier transformation for frequency domain, and Wavelet transform for the time-frequency domain. They compared their results achieved from training support vector machine (SVM) and k-nearest neighbors (KNN) algorithms based on various feature extraction techniques. They achieved a maximum accuracy of 100%, sensitivity of 100% and specificity of 100% in the SVM algorithm and an accuracy of 99.5%, sensitivity of 99%, and specificity of 100% in the KNN algorithm for classification of epileptic and non-epileptic patients and showed that SVM has a slight edge over KNN. They proposed a reliable and efficient detection of epileptic seizure using EEG signals, and it is flexible, so can be modified easily for a different range of frequencies.

Rahib Abiyev and his companions considered deep learning based on the convolutional neural network to increase the identification system's performance of an epileptic seizure [1].They applied a cross-validation method in the design phase of the system. They have set the results side by side between machine learning approaches (SVM-Support Vector Machine, NN-Neural Network) and deep CNN (10-fold validation). They acquired an average accuracy rate of 98.67%, sensitivity of 97.67%, and specificity of 98.83%. The fundamental advantage they obtained from their model is its simple structure that

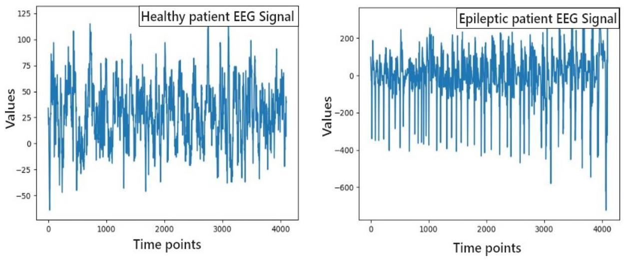

Fig. 2. Sample EEG signal belonging to Non-epileptic and Epileptic sets in the dataset.

combines the extraction of features and classification stages in the body of deep learning and also faces complications by increasing the number of convolutional layers in the deep learning structure.

Milena Cukic and his teammates illuminate the effectiveness of non-linear measures with Higuchi fractal dimension and sample entropy in detecting depressive disorder when applied to EEG [6].They performed their study on various machine learning algorithms like Multilayer Perceptron, Logistic Regression, Support Vector Machines with the linear and polynomial kernel, Decision Tree, Random Forest, and Naïve Bayes classifier, to distinguish EEG signals between a healthy person and a depression diagnosed patient. They achieved the average accuracy per feature set of 89.90% in HFD, 95.12% in sample-EN, and 94.77% in HFD + sample-EN, including the maximum average accuracy obtained by using multiple perceptrons of 97.56%, random forest of 93.49%, and naïve Bayes 90.24%. They demonstrate that feature extraction methods are useful for further investigation with larger sample sizes towards potential diagnostic applications in psychiatry.

III. Dataset description

The dataset used to classify the epileptic seizures was downloaded from an openly available platform constructed by Andrzezak et al. at the University of Bonn [4]. This dataset comprises EEG signals of five healthy patients and five patients with epilepsy. Firstly the electrodes are placed on the patients' scalp to record the EEG signals [5]. The EEG signals were recorded with two conditions; first, with eyes closed and then with eyes opened. This dataset has five folders, namely A, B, C, D, E and F. Each folder contains 100 EEG signals with a sampling rate of 173.61 Hz and 0.53-40 Hz as bandpass filter settings.

In the dataset, folders A and B have healthy patients' data with their eyes opened and closed, respectively. Folder C contains EEG signals of patients who had full control after the epileptic zone resection, and folder D has data from the same region in the opposite brain hemisphere. Folder E is the only set that has data of epileptic patients during seizure.

This dataset contains 100 samples from folder E, class-1/Minority class(Epileptic samples), and 400 samples by combining the folders A,B,C and D, which is class-0/Majority class(Non-epileptic sample). By comparing the number of samples in each class, it is clear that the dataset is imbalanced. This imbalanced dataset will be biased towards the majority class, which directly affects the performance of the model. So to avoid the inclination towards the majority class, the balancing of data becomes necessary. There are many strategies to deal with imbalanced data; one is the Synthetic Minority Oversampling Technique(SMOTE) method. This method duplicates the data by randomly increasing the samples of minority class for uniform class distribution. Linear interpolation technique generates these duplicate training samples by randomly selecting one or more k-nearest neighbors. Once the data oversampling is done by applying this technique, the data is ready for further analysis.

IV. Methodology

This section discusses the steps involved in data preprocessing, feature scaling, and then data classification as shown in Fig. 3. (flowchart). Here, the data is prepared for feeding it into the machine learning model. Data preprocessing plays a vital role in any machine learning project, as data cleaning will remove the unwanted anomalies and inconsistency from the data, making it ready to feed into our various models for further processing [10]. After this step, the data is split into train and test sets, later the model is trained using train sets and check the model's prediction capabilities and performance using the test sets. There are independent features available in the data that has to be standardized. We call this normalization process of our data Feature scaling. Once the normalization of data is done using this technique, the data is ready to be fed into various machine learning algorithms like SVM, ANN, KNN, LSTM, Naive Bayes, and LS-SVM. The models are trained by fitting the pre-processed data into it. After the training phase, machine learning models are ready to get tested from the test dataset, and the most efficient model is found based on various measure factors like F1-score, accuracy, specificity, sensitivity, precision, recall, and confusion matrix.

The dataset used has 4096 columns as there are 4096 data points in the sample signal with a frequency rate of 173.61Hz. As there are 500 samples combining both of Epileptic and Non-epileptic patient EEG Signals. The model's output will be classified in the form of 0 and 1, where 0 means the patient is healthy and 1 means the patient has epilepsy.

A. K-nearest Neighbors

K-NN(nearest neighbor) is also a supervised learning model used for classification and regression [11].It presumes that there exists closeness between similar objects. K-NN articulates these assumptions being true enough to make the algorithm more efficient. The output of k-NN depends on its usage, whether used for classification or regressions [3]. K-NN starts by loading the data and initializes the value of k, which is nothing but the number of neighbors. For each example in the data, it calculates the distance between the query data or

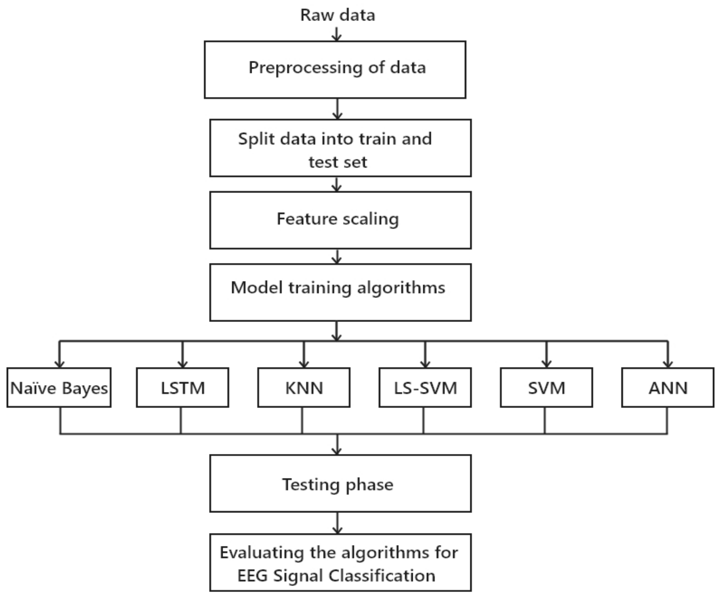

Fig. 3. Flowchart of the operations performed in EEG signal classification

current data, adds the distance, and indexes the example into the ordered collection. Further sort the collection based on their indices by the distances. It then picks the first k entries from the sorted collection and takes those selected k entries labels. If the algorithm is used for regression, it will return the mean of those k labels, or if it is used for classification it returns the mode value of k labels, but if k=1, it is assigned to a single nearest neighbor.

B. *Support Vector Machine (SVM)*

SVM or support vector machine is a supervised learning model used for the classification of data or regression problems. The points in space are used to represent the data, further mapped to categorize or divide by a clear gap as large as possible [22].It creates a line, or we can say

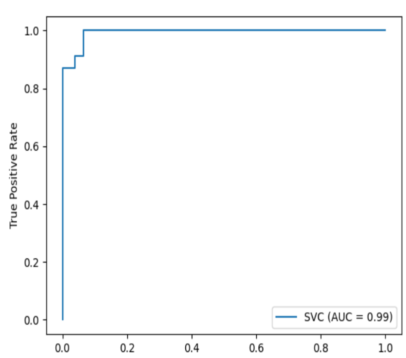

Fig. 4. AUC graph of SVM

a hyperplane, to distinguish the data into different classes. According to the SVM algorithm, we find the closest points to the hyperplane from both the classes, which are called support vectors [34].The distance between support vectors and the hyperplane is called a margin. In performing linear classification SVM works better in non-linear classification, which uses a trick called kernel trick (i.e., inferring the data point in large dimension feature space and the hyperplane calculated by the SVM) always a straight line [31].

Suppose the data point of n dimension vector or list of n elements belongs to one among two classes, and now a decision should be made on which class does the new data point belongs to. For that, we can check whether separate such points in (n-1) dimensional hyperplane [16]. For supervised learning, the data should be labeled; if it is not labeled, then the unsupervised learning approach is used, which maps the data in a group using natural clustering and maps the new data into the previously created group [15].

C. *Naive Bayes*

Na¨ıve Bayes is efficiently used when there are a large number of data and quite a few variables in trained data because it provides a faster solution than other classification algorithms [26].Na¨ıve Bayes uses the Bayes theorem(or Bayes law or Bayes rule) as its classification technique. It belongs to the family of statistical classification. Na¨ıve Bayes classifier assumes that the probability of an event with a particular feature might be related to the event [9].Bayes theorem is a simple technique based on an assumption of independence among predictors for constructing a classifier; it calculates posterior probability P(a|b) from P(a), P(b) and

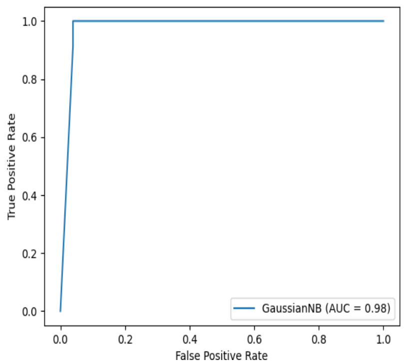

Fig. 5. AUC graph of Naive Bayes

P(b|a).

$$P(a|b) = \frac{P(b|a).P(a)}{P(b)} \tag{1}$$

$$P(a|b) = P(b_1|a).P(b_2|a).P(b_3|a)...P(b_n|a).P(a) \tag{2}$$

Where

- P(a|b) is the posterior probability of class (a, target) given predictor (b, attributes).
- P(a) is the prior probability of class.
- P(b|a) is the likelihood which is the probability of predictor given class.
- P(b) is the prior probability of predictor.

D. Least-square Support Vector Machine(LS-SVM)

The basic idea of LS-SVM is to minimize the sum of squared errors from the objective functions, and it adopts the equality constraints [14].It is also called a least sure in the SVM version, which is also a supervised learning model used to analyze data and recognize patterns using classification and regression. LS-SVM belongs to kernel-based learning algorithms. Due to equality type constraints, the solutions should have to follow solving the set of linear equations instead of SVM's quadratic equations. In this paper, after the analysis, it was clear that LS-SVM gave better results than the SVM technique. From the obtained results, LS-SVM is approaching the highest accuracy than any other algorithms implemented in this paper.

E. Artificial Neural Networks (ANN)

ANN is part of artificial intelligence that designs to stimulate the process of information, similar to the neurons present in the human brain [27]. The connections in Artificial Neural Network act like a synapse in the human brain which transmits signals to other neurons. Connections are referred to as edges that contain weight that will keep getting optimized in the training phase. The strength of the signal depends on the

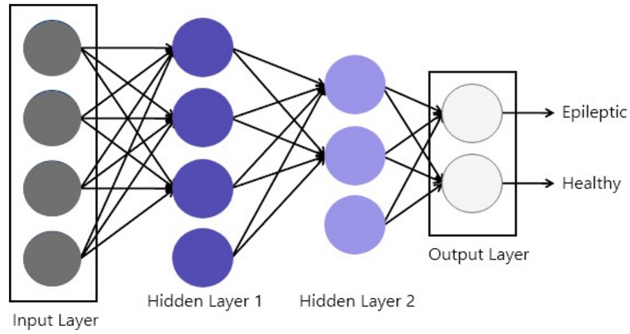

Fig. 6. ANN Network

weight of the edges. It is a core simplified model based on a biological neuron that allows us to capture the information that how neuron functions. This artificial neuron also referred to as the perceptron [18].

It takes inputs from the input layer and feed it up to the hidden layer as there are several hidden layers before the output layer [13]. The number of neurons at the input layer is equal to the number of features present in the dataset of the EEG signal [28]. In this framework, Two hidden layers are implemented where each layer performs different transformations depending on their respective input. Traversal of signal proceeds from the input layer and passes through the hidden layers computing the sum of inputs of the non-linear functions and finally reaches the output layer of the artificial neural network [33].

F. Long short Term Memory (LSTM)

Long short time memory(LSTM) is nothing but an artificial recurrent neural network which is basically used in a deep learning approach. LSTM has feedback connections that help it process the single data points and the entire sequence of data [30].It is widely used to classify, process, and make predictions based on a time series of data. The basic LSTM unit contains cells, an input gate, an output gate, and a forget gate. The input shape consists of 4096 as we have 4096 data points from EEG signal for one sample data of a patient with a class output as an epileptic or non- epileptic patient. LSTM uses a dropout

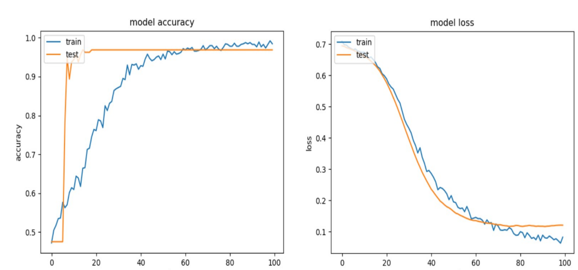

Fig. 7. Accuracy and Loss graph of LSTM

Classifier	Sensitivity	Specificity	Confusion Matrix	Precision	Recall	Accuracy	F1-Score
SVM	100	86.95	23 3 0 77	96.25	100	99.85	93.02
Naïve Bayes	96.10	91.30	21 2 3 74	97.36	96.10	90.25	89.36
LS-SVM	100	34.78	8 15 0 77	83.69	100	100	51.61
LSTM	100	76.62	59 18 0 83	82.17	100	97.5	90.22
ANN	100	78.26	18 5 0 77	93.90	100	95	87.80
KNN	100	47.82	11 12 0 77	86.51	100	98.45	64.70

Table. 1. Classification Results (Note: The results in the table are in percentage.)

regularization method where input and recurrent connections to LSTM units are probabilistically excluded from activation and weight updates while training a network. LSTMs can be used to learn features from EEG signals, and then dense layers can be used for classification. To model the temporal characteristics of the brain activities, RNNs and LSTMs appear to be the best choice in tools [17]. The primary advantage gained by LSTM is from its cell memory unit as compared to standard recurrent units.

V. Experimental Analysis

The EEG dataset used in this paper has the sample data of 500 patients, from which 400 samples are from the non-epileptic patients and 100 from epileptic patients. As the dataset is imbalanced, the linear interpolation technique(SMOTE) is applied to equalize the samples.

The two different classes are represented as epileptic(1) and non-epileptic (0) for the algorithms used. The split ratio splits training and testing data. This data is applied to various machine learning algorithms(SVM, LS-SVM, KNN, LSTM, Naive Bayes, and ANN). Parameters like accuracy, confusion matrix, precision, recall, specificity, sensitivity, and f1 score were obtained and are tabulated in Table. 1.

$$precision = \frac{TP}{TP + FP} \tag{3}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$recall = \frac{TP}{TP + FN} \tag{5}$$

$$specificity = \frac{TN}{TN + FP} \tag{6}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{8}$$

where, TP = True Positive,
TN = True Negative,
FN = False Negative and,
FP = False positive.

VI. Conclusion

In this paper, we have assessed a model that predicts if a person has epilepsy or not. The EEG dataset was analyzed, which comprises data of non-epileptic patients and epileptic patients. This data has a sampling rate of 173.61 Hz and consists of 4096 points of data. The data was first preprocessed to remove the noise signal, and then feature scaling was done to select and determine the most necessary data to be classified. The dataset used is imbalanced as the number of non-epileptic samples is greater than the number of epileptic samples.

So the dataset was balanced and then used for further computation. Hence we consider the results based on the F1-score rather than just the accuracy. The chosen data was then fed to different machine learning algorithms like Na¨ıve Bayes, LSTM, KNN, LS-SVM, SVM, and ANN classifiers and the following accuracy was obtained 90.25%, 97.5%, 98.45%, 100%, 99.85%, and 95% respectively. Other parameters like confusion matrix, specificity, sensitivity, recall, precision, and accuracy were also found and tabulated in the above section.

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