Machine Learning Based Model For Seizure Detection Using Eeg Signals

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Abstract
Epilepsy is a disease of grave concern these days due to the negligence in its treatment in many parts of the world. Its detection and diagnose requires high skill, large amount of time and money. Thus, due to lack of treatment, epilepsy which can be diagnosed with simple epileptic drugs turn refractory. This can be avoided if it is detected at an early stage. Also, the data received after a patient undergo EEG is quite complex. Visualizing that data in an effective way and knowing important timestamps in a recorded EEG signal can help one save time and increase accuracy of detection. An automated system utilizing conventional machine learning is thus proposed in this study that uses features extracted from EEG signals. We have used a seizure detection model and visualized data and the result using various python libraries. Seizure detection is a model which is able to identify the presence of abnormal activities in the brain. Seizure prediction is a model which is able to predict in advance if he/she is going to face seizures in coming time by just studying the EEG signals of present state of that patient. Supervised Machine learning (random forest classifier) was employed to analyze recorded EEG signals for epilepsy detection. Data in the datasets was visualized using matplotlib. Classifier was visualized using Graphviz and pydot. Random forest model predicted epilepsy with a good accuracy of 96.87 %, Sensitivity came out to be 98.4 % and Specificity was 90.7 %.

Keywords: Epilepsy, Epileptic Seizures, Random Forest, Supervised Machine Learning, EEG Signals

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Introduction

Epilepsy is a dangerous neurological disease that may lead to various types of seizures in an individual, (Hossain et al., 2019) twitching and jerking movements of various body parts (like: eye, leg, and arm), extreme happiness like mood just before a seizure, consciousness loss and other psychological symptoms. It affects people of all ages and cause of this perilous disease is unknown in more than 50% (Ullah et al., 2018)of the world cases which makes it further a matter of concern. Seizures are mainly of two major types – Generalized and Focal seizures. Generalized seizures influence both of the cerebral hemispheres of the brain and is consecutively (Nafea & Ismail, 2022) more lethal whereas the focal seizures influence only a portion of the brain. It has generally been absorbed that for the matter to be worse, focal seizure is usually followed by a generalized seizure. Electroencephalogram (EEG) (Emami et al., 2019) is the most readily available, acceptable and economical technique to detect brain activity by placing some electrodes on the scalp area of a person. Thus, it is one of the most scientific ways of conforming various types of brain disorder including epileptic seizures. EEG detects mainly four types of brain signals: (Hossain et al., 2019) alpha, beta, theta and delta and consequently helps in distinguishing between the brain signals of healthy and epileptic person. EEG's simply record the brain waves without giving any extra sensation. These recorded signals are then studied by highly qualified neurologist who may take several hours to few days to differentiate between healthy and epileptic signals. In reality, (İnce et al., 2021; Vidyaratne & Iftekharuddin, 2017) several hours and even days may be consumed for EEG recording to record seizure occurrence, for example: Ambulatory EEG for long term surveillance of a person and inpatient video EEG monitoring or scalp EEG for tracking the same for few hours. This may be quite expensive for a normal individual and when more time is invested in this EEG detection, the cost may rise even higher and this also cause complications in manual analysis of the EEG brain signals.

According to the official site of World Health Organization, every year, almost 5 million people are found to be identified with epileptic seizures yearly. (*Epilepsy*, n.d.) And in middle-and-low-income countries, people per 100000 who are confirmed with epileptic seizures are 2.8 times than those detected in the high-income countries. People (especially in the low-income countries) experience treatment gap, low accessibility to the anti-epileptic medicines due to lack of resources. Drug treatment is beneficial in treating most of the cases but some cases need the intervention of expensive surgeries. Drug treatment can be done if this epilepsy is detected at an early stage. There are mainly four types of phases in seizures (Jiwani et al., 2022).

Interictal period is a crucial period as illustrated in figure 1 and this is the phase if identified by the neurologist, then, seizures can be prevented. (Varshney et al., 2022) Thus, this phase is also referred to as subclinical seizure. For detection purpose in this stage, EEG technique is required but lack of money and requirement of more human resource investment through extensive manual recording, observation and analysis of signals recorded pose an economical barrier for a person especially from middle-and-low-income countries as discussed above.

To assist an individual to detect epilepsy at a very early stage (so that matter doesn't worsen in future), many automated systems have been developed. Classification method of supervised machine learning has labels defined and are of fixed number and type. Supervised learning is a very popular machine learning technique in which models are trained using pre available data. Then, the machine is fed with test data. Supervised learning (Fergus et al., 2015) allows us to be specific in output and defining labels as an epitome of decision extent is set up. The machine is trained from already available data thus, result is likely to come and very accurate too. Classification technique recognizes certain type of output categories from the given target variable. It identifies how the data is labeled and we receive an ordinal output. Random forest classifier used takes comparatively less time for training. (Zhang et al., 2018) It is also more suitable for large and complex data providing better efficiency as compared to other classifiers.

For visualization purposes, various libraries of python like matplotlib, seaborn, graphviz, and pydotplus are used. Here, graphviz and pydotplus were used extensively for visualizing classifiers' functioning and its result. Visualization helps in fast processing of data. Data visualization using python is used in various businesses for effectively sealing the deals in less time as it helps in better managing and examination of information. It also allows for simple yet precise investigation of information and thus helps in easy perception of that information. One can easily discover relationships in the data, its elements and consequently effortlessly achieve required adjustments and get the required realizations.

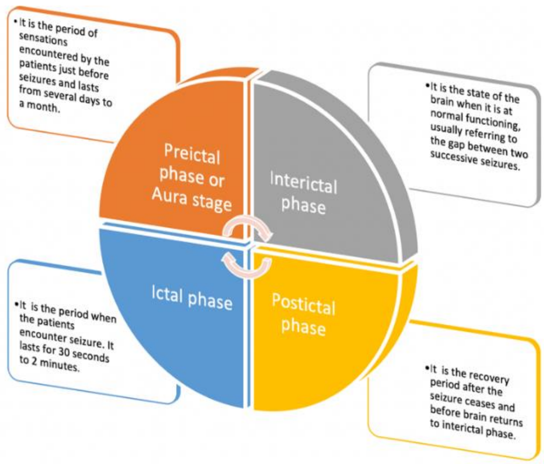

Figure 1. Phases of seizure and their description is given in this diagram

Human retina has a superpower to transmit data at very high rates, thus, visualization is a powerful technique to communicate and make others understand large amount of and complicated data which otherwise without visualization may not be communicated properly and require more time. Trends and causes can be easily conveyed, and predictions can be easily done with the help of visualization techniques.

A lot of papers published by other authors were reviewed and a review of all the existing solutions was taken for quick epileptic seizure detection decision and easy visualization by the client.

Many publishers have used CNN based approaches, that is, deep learning to predict seizures, visualized data and compared results by data visualization techniques using various python libraries. Prediction results of deep learning are quite close to that of expert epileptologists as visual ability to recognize signals of these CNN models give quite human like results. Thus, there has been a lot of discussion to replace conventional way, that is supervised ML with approaches such as deep CNN. But Supervised ML is more flexible as feature extraction and its analysis is handy and easy. Data in deep ML is sometimes quite difficult to interpret and results depend highly on quality of data.

In one such literature review (Nafea & Ismail, 2022), Supervised ML and deep ML have been compared by probing through EEG signals for diagnosing epileptic seizures. In conclusion, both techniques have their own advantages and disadvantages. Thus, need on the use of Deep Learning in collaboration with Machine Learning for detecting this major disease has been emphasized by the author.

Another technique presented by (Temko et al., 2014) uses audification of EEG signals for detecting epilepsy. It includes extracting only some ruling EEG frequencies and analyzing only those to detect seizures. Other techniques used are: algorithm based on Short Time Fourier Transform (Birjandtalab et al., 2017), random-forest classification algorithm, Long short-term memory (LSTM) and CNN Naïve Bayes, Support Vector Machine (SVM) (Hopfengärtner et al., 2014; Jiwani et al., 2022; Mardini et al., 2020), Linear Discriminant Analysis (LDA) (Mardini et al., 2020), variational modal decomposition (VMD) and a deep forest (DF) model, pyramidal one-dimensional convolutional neural network (P-1D-CNN), 1D CNN-LSTM (Ullah et al., 2018; Xu et al., 2020), decision tree (DT) (Varshney et al., 2022), shallow artificial neural network (ANN) (Hopfengärtner et al., 2014; Varshney et al., 2022), K-Nearest Neighbors (KNN) (Hopfengärtner et al., 2014), and convolutional neural networks(Emami et al., 2019).

Machine Learning is the method in which the computer is trained to use predefined data and learn from it. It is then expected to give accurate outcome when same type of test data is fed in it (Hopfengärtner et al., 2014; Jiwani et al., 2022; Mardini et al., 2020; Nafea & Ismail, 2022).Many researchers have started using Machine Learning methods to solve their problems faster and because low-cost processing and memory are at our disposal. Because of the availability of Machine Learning approaches, it is now feasible to study and analyze huge datasets to reveal the patterns and trends which might not be visible to the naked eye. Machine Learning's perceptive action is based on some predefined procedures or algorithms that allows it to learn from the previously available data. Machine Learning needs data that is already prepared in the form of spreadsheets and then the methods of Machine Learning find the hidden patterns and trends. Deep Learning allows automatic data extraction with the help of multi-layer structures. Even though Machine Learning has a lot of techniques for classification and the results are good, but (Ullah et al., 2018; Xu et al., 2020) Deep Learning is taking over since it can automatically extract the data whereas for Machine Learning, the data needs to be extracted and arranged in a proper manner. Building a model for epileptic seizures comprises multiple steps, which includes data collection, data preprocessing, finding a suitable approach and the last stage being assessing the performance of the applied approach. EEG signals are acquired with the help of special equipment in which the electrodes are positioned on the head of humans. The data consists of different recordings for each electrode. These obtained recordings are called recording channel, which is then used in preparing the dataset. The data preprocessing step involves the cleaning of data like removing unwanted signals or noise from the obtained signals, etc.

In contrast to how (Nafea & Ismail, 2022) Machine Learning utilizes the raw data; Deep Learning uses a network which learns by discovering intricate structures in the data they experience. Deep Learning uses several non-activation units which are distributed over multiple layers. It involves a hierarchical data structure, in which data is fed into each level, the level then performs feature extraction and feature selection processes automatically on the data and then the data is fed into the next level. The final layer is like a classifier as the activation division represents the selection that needs to be constructed by utilizing the raw data.

Materials and Methods

Dataset Used

The dataset which has been used for the classification is given by University of Bonn, Department of Epileptology, Germany. (Andrzejak et al., 2001) The patients are classified into two categories only i.e., epileptic patients and non-epileptic or healthy patients. 'y' is the target variable and contains output for 500 patient data. 'y' shows on of the output {1,0} as shown in Figure 2.

X1, X2, ……., X178 are explanatory variables that correspond to EEG signal recording at different point of time. Subjects categorized under 0 are healthy people with non-epileptic signals. Only those categorized under 1 are epileptic. Thus, dataset is multivariate and attributes are of integer type. 11500 instances consist of 178 attributes.

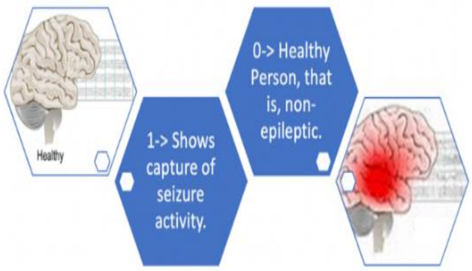

Figure 1. Meaning of outputs in target variable 'Y' is depicted in this diagram

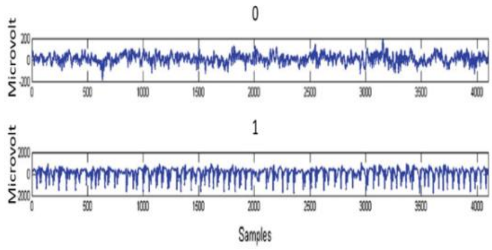

Figure 2. Visualization of EEG signals of healthy and epileptic patients is depicted in this graphical diagram (Clearly the amplitude of a epileptic EEG is very high)

Methodology

In this work, Machine Learning Algorithms have been used to classify epileptic and healthy patients and the EEG signals in the two cases have been visualized. The data is classified using random forest classifier available in the Machine Learning methods and the accuracy of classifier is calculated. In addition to this, the classified data is also visualized with respect to different
parameters to make it easy for the people to understand the result.

The Bonn University data is in the form of a spreadsheet. Machine Learning is suitable for such kind of datasets because:

- Machine Learning algorithms typically use simpler and more linear algorithms.
- Machine Learning algorithms require significantly smaller amounts of data to make fairly accurate decisions.
- A Machine Learning model can be easily trained on a personal computer.

As depicted in Figure 4, the feature extraction is done while processing the EEG signals which are obtained. But the feature extraction from the EEG signal required for training the model has already been done by Bonn University and in this work, that extracted data is used by the model to further predict whether the patient is epileptic or not. In the work, 70 percent of the data has been used in training the model and 30 percent of data is used for testing the model.

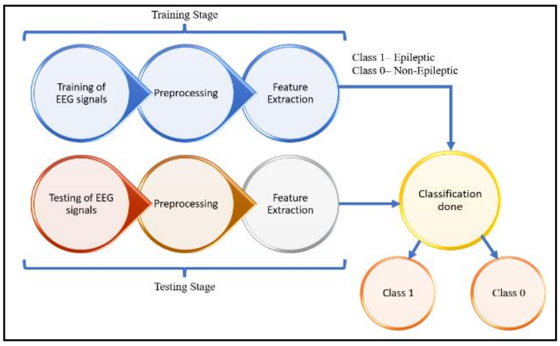

Figure 3. Steps employed to make a random forest classifier are illustrated in this diagram: 70% data of the dataset was used for training and the rest 30% was used for training the model.

The feature prediction step of Machine Learning approach is done in two parts in background-(a) feature extraction and (b)feature selection. Through the (a) step, raw EEG signals are converted to understandable form. It is important that the data is non-redundant and discriminative so that they can be meaningful for the Machine Learning model and can be utilized to the full extent. In the (b) step, all the extracted information from EEG signals is further divided into dependent and independent variables corresponding to each patient. Then, random forest model is made using Python library sklearn and final prediction is performed. Finally, performance of this applied model is assessed through various parameters and importance of features is extracted for better understanding.

The prediction is done with the help of algorithms of Supervised Machine Learning. In Supervised Machine Learning, models are first fed with predefined data for training and all the algorithms are defined for the model. From the supervised Machine Learning algorithms, random forest classifier is used. Random forest is a classifier which contains several decision trees for several subsets of data and the average of the result of each decision tree is calculated which is the result. The data is classified in two categories i.e., ‘0’ and ‘1’. ‘0’ represents the patients that are non-epileptic or healthy or have shown no signs of epileptic seizures. ‘1’ represents the patients that are epileptic or have shown signs of epileptic seizures.

After the classification of the dataset, the mean absolute error is calculated for the dataset. Mean absolute error is the meaning of the difference between test value and predicted value for all the data. This is calculated to get the value of accuracy and precision of the model.

The accuracy of the model is calculated to know how efficiently the model is predicting the epileptic and non-epileptic patients based on data provided to it. Then the importance of each feature of the database is calculated. This is done to recognize at which instant the EEG signals are affecting the prediction of the model or to get the peaks in the dataset which will be deciding parameters whether the person is healthy or epileptic. A confusion matrix has been plotted between the test and the predicted values of the result of the model. A confusion matrix is a table which visualizes and summarizes the performance of an algorithm and helps in understanding the efficiency of algorithm more. With the help of confusion matrix, the specificity and sensitivity of the model are also calculated.

Results and Discussion (12 pt Bold)

All the prediction models that have been used in the past or are being used are analyzed based on three parameters – accuracy, sensitivity, and specificity. Accuracy of a model describes whether the predicted values match the test values of the predicted and how much the predicted values are disturbed due to the noises present in the input values. It is calculated by taking the difference between test values and the predicted values.

The sensitivity of prediction model, also called true positive rate or probability of detection, is defined as the probability of a model to give the right prediction for an entire group with the same predictions. It is basically the probability of the model to not miss the epileptic patients that are present in the entire dataset. It is calculated by taking the ratio of true positives in the confusion matrix to the total number of predicted outcomes.

Specificity of prediction model, also called true negative rate, is defined as the probability of a model to give the negative prediction for the entire group of negative observations. It is basically the probability of the model to give true negative for the dataset. It is calculated by taking the ratio of true negatives in the confusion matrix to the total number of predicted outcomes.

With the help of the confusion matrix depicted in figure 5 that is obtained after the classification is done with the help of random forest classifier, the accuracy, sensitivity and specificity of the classifier model can be calculated. The prediction model of Supervised Machine Learning using random forest classifier has achieved an accuracy of 96.87%, specificity of 90.7% and sensitivity of 98.4%.

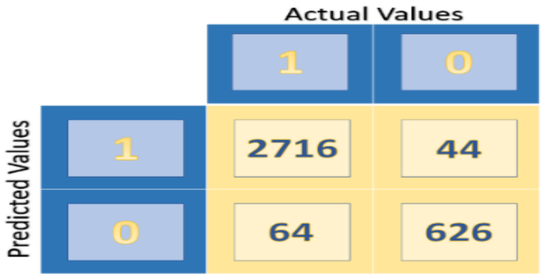

Figure 4. Confusion matrix depicting actual and predicted values for healthy and epileptic patients by the classifier

Our accuracy is better than many random forest classifications done previously in many studies. (Edla et al., 2018) Edla have used Brain Computer Interface (BCI) using random forest classifier and its proposed model has an accuracy of 75%. (Fraiwan et al., 2012) Fraiwan used random forest classifier after extracting features with Renyi's entropy to get an accuracy of 83%. (Donos et al., 2015) Donos also used a random forest classifier to get an accuracy of 93.84%. This is also depicted using figure 6. The figure 7 graphs represents the number of patients in each category. Only category 1 patients are epileptic. The patients of other categories are non-epileptic. So, according to this graph, only 2300 records out of 11500 records show that the person is epileptic and has undergone epileptic seizure. The rest 9200 patients are healthy and have shown no signs of epileptic seizures during the time when the data is taken.

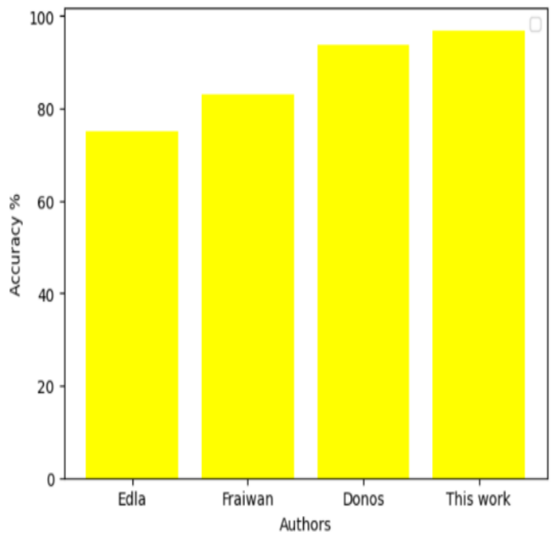

Figure 6. Comparison of this work with existing works

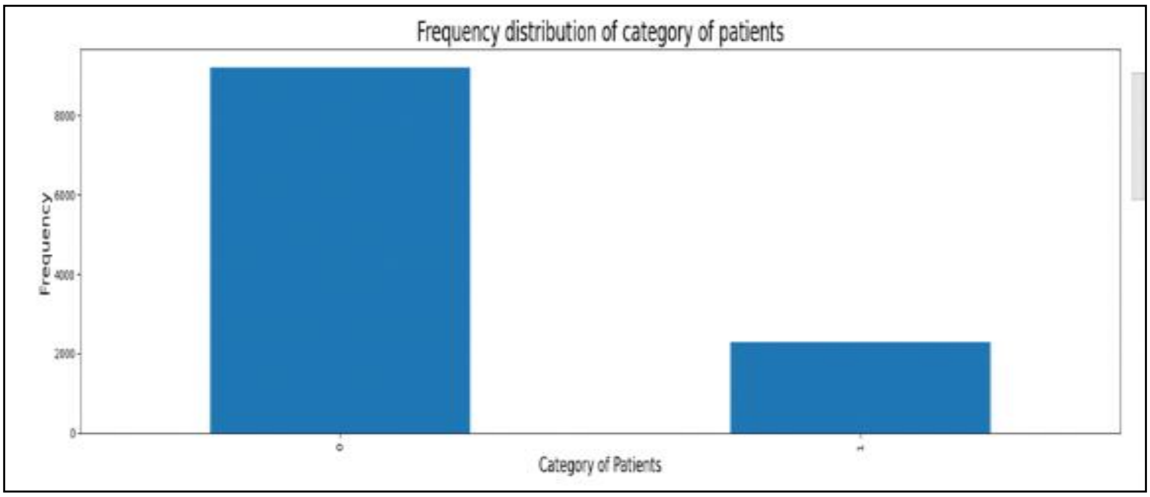

Figure 7. Frequency Distribution of Category of Patients

The category of patients is denoted by ‘0’ and ‘1’. ‘0’ denotes the patients that are non-epileptic or not showing any signs of epileptic seizures whereas ‘1’ denotes the patients that are epileptic or show any signs of epileptic seizures and require the appropriate care for it. The graph in figure 8 also shows the correlation matrix of dependent features with the independent features. The dependent features in the above graph are all the data points that have been recorded for each patient and the mean of all the data points for each patient whereas the independent feature is the category of patients whether the patients are epileptic or not. The variables with the most range are the ones that will affect the results more or have a large correlation coefficient with the category of patients. The figure 9 shows the correlation matrix between the different numerical features present in the given dataset.

Correlation matrix is basically a table consisting of rows and columns in which the correlation coefficients between the two variables are represented. Correlation coefficients talk about the strength of the linear relationship among variables. The relationship between the two variables directly depends on correlation coefficient.

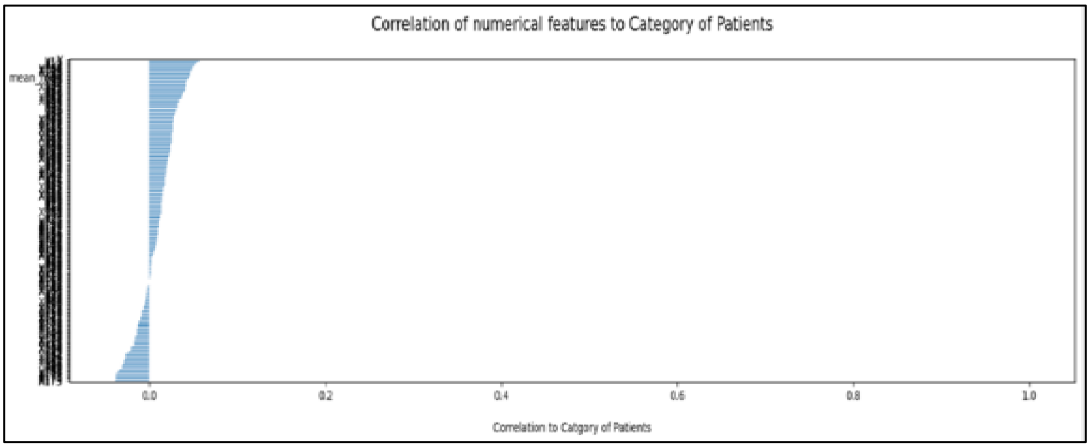

Figure 8 Correlation matrix of Dependent features to Independent Feature

In figure 9, the correlation matrix between all the features is depicted. Each feature of the dataset is correlated with all the features. Dark regions in the figure show the region where the features correlated are same and the light regions show the region where the features are not same. Correlation coefficient is greater when both the features that are correlated are same, and it is less when the features are different.

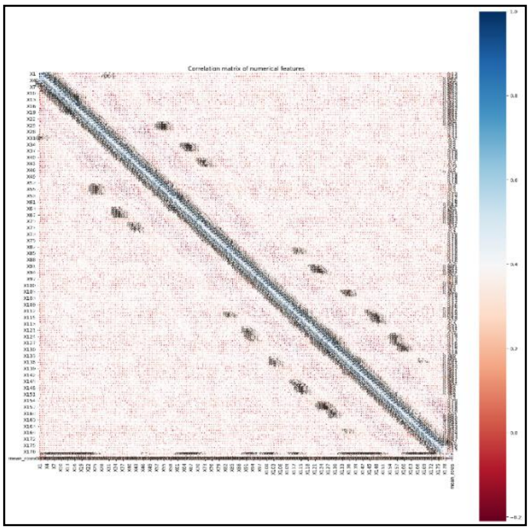

Figure 9 Correlation Matrix of Numerical Features

Important features on which prediction depends more were extracted. 'X20','X21','X28','X37',' X44', and 'X93', these variables had the highest importance of 0.02. Rest all the features except those mentioned above in the feature list of EEG, have least or no importance at all for predicting epilepsy. By finding this feature extraction, score of each feature was made clear and one can get useful insights about data. Thus, by focusing more on important features when viewing and analysing manually, time can be saved, and accuracy of detection increased. The comparative analysis of the different approaches to design a model for epilepsy detection which have been previously described as well in the research papers is given in Table 1.

Table 1. Shows Comparison of proposed work with other available methods using same dataset

Paper	Year	Analysis Method	Senstivity (%)	Specificity (%)	Accuracy (%)
Ardalan Aarabi (Aarabi et al., 2009)	2009	Furry-Rule Based System	98.7%	-	-
Andriy Temko (Temko et al., 2014)	2014	Audified Neonatal Eeg	38%	92%	98%
Yatindra Kumar (Kumar et al., 2014)	2014	Dwt Based Apen Nad Artificial Neural Network	-	-	100%
Paul Fergus (Fergus et al., 2015)	2015	Supervised Machine Learning	93%	94%	-
Lasitha S. Vidyaratne (Vidyaratne & Iftekharuddin, 2017)	2017	Vector Machine Model	96%	70%	99.8%
Lina Wang (Wang et al., 2017)	2017	Multi-Domain Feature Extraction And Non-Linear Analysis	-	-	99.25%
Shamin Hossain (Hossain et al., 2019)	2019	Deep Cnn Model	90%	91.65%	98.05%
Gaowei Xu (Xu et al., 2020)	2020	One Dimensional Cnn Lstm	98.39%	98.79%	99.39%
Wail Mardini (Hopfengärtner et al., 2014)	2020	Genetic Algorithm	98.51%	95.87%	97.47%
Varshney Y (Varshney et al., 2022)	2020	Triadic Wt	100%	100%	100%
Nasmin Jiwami (Jiwani et al., 2022)	2022	Lstm Cnn Model	100%	100%	100%
Xiang Liu (Liu et al., 2022)	2022	Variational Mode Decomposition	95.2%	98.56%	98.52%
This work	**-**	**Random Forest Based Model**	**98.4 %**	**90.7 %**	**96.87 %**

Conclusions

Epilepsy is truly very lethal, especially in the developing and under-developed countries where doctor to patient ratio is quite low and treatment gap of epilepsy is significantly observable. Its early detection is very crucial for its treatment. Taking the example of India, more than 10 million individuals are suffering from epilepsy with almost 33.33% having refractory epilepsy, its diagnosis and treatment becomes very necessary. Thus, the only way to eradicate this treatment gap is getting timely diagnosis of this disease and consulting the doctor as soon as possible. Since doctor to patient ratio is very low and it is practically not possible for a neuro-expert to diagnose this illness for such many patients, so automatic detection and visualization becomes very necessary, so that a common person can also understand about it and timely seek the advice of doctor. This will also assist the neuro-expert in analyzing the EEG signals quickly. Thus, with this automated system of supervised Machine Learning and visualizing the data with the help of python libraries, feature analysis was done and data correlation done with visualization techniques to make the understanding of EEG signals easier.

Acknowledgement

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