Comparative Analysis of Different Supervised Machine Learning Models for Recognizing Epilepsy in Children

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ABSTRACT

As we all know, Children are the future of every country, so it's the vital fact that every country in this world wants to reduce the mortality rate of children in their country and improves their health also. By doing this, that particular country can enhance and develop in many ways like building unity, increase economic prosperity and political stability and many more. So, it's a prime responsibility of every country in world wide web to take major steps for enhancing children health. Manual assessment of Epilepsy detection from electroencephalogram (EEG) waveform is very old-dated technique and mainly depends on the knowledge level of healthcare expert. Out of 100 cases, approximately 30 cases are wrongly interpreted due to the lack of automated approach and advancements in this field. The prediction methodology of EEG signals seems more powerful and accurate as scientists and researches moves towards the computational methods and techniques in order to take boom in healthcare industry. This paper presented a comparative analysis of several supervised machine learning models in order to recognize epilepsy in children using EEG data. Authors has taken the total 40 EEG signals of normal children and epileptic children. For generating statistical feature values (mean, median, mode and standard deviation) of experimental EEG signals, power spectral and fuzzy entropy techniques have been used. For classification part, five supervised machine learning algorithms (AdaBoost, support vector machine, naïve bayes, random forest and K nearest neighbor) were used. Experiments were carried out on the CHB-MIT scalp EEG database, channel FP1-F7 on 256 HZ data sampling rate. Results are generated by visualizing and evaluating the computed statistical EEG feature values using heat map and lift curve respectively. Performance evaluation has been performed on the basis of different classifiers used by other researchers. On the basis of classification results, authors conclude that 100% accuracy is achieved by analyzing different supervised machine learning models for detecting epilepsy in children.

Keywords: Epilepsy; seizures; power spectral density; fuzzy entropy; AdaBoost; Support vector machine; naïve bayes; random forest and K-nearest neighbor.

1. INTRODUCTION

Epilepsy is a neurological disorder which is found in central nervous system (CNS) of human brain and a major cause of mortality in whole world. Every year millions of people die due to this disorder. Epilepsy is a disorder generated by the disturbance of brain in which signals of the brain fire abnormally which leads to seizures also. There are various reasons of seizure due to brain unconsciousness, movements due to jerks, double minded in all these cases patients consists symptoms of totally blank sometimes or not responding for certain period of time. In some cases, these neurological disorders (epileptic seizure) are really dangerous and life threatening which leads to sudden death also or serious injuries. These situations are very difficult to handle when it occurs and patient are exposed to critical surroundings like driving or swimming. So, the recognition of this disorder related to brain are very important at early stage so that precautions can be taken on time leads to reduced risks [1]. An accurate detection and recognition of epileptic seizures are very conventional and prominent challenge in front of health care professionals from the last 40 years approx. [2]. The detection of these neurological disorders is compromised sometimes due to the imbalance and fluctuating behavior of seizures, this may lead to even death of subject [3].

An accurate detection of seizures due to brain disorder at very primary stage can reduce the over effects of hard epileptic medicines because many seizures are detected wrongly as this disorder also arises on paper due to residues of normal EEG recordings [4]. The visual observation of signals is very prominent and traditional method of epilepsy detection used by healthcare professionals, but sometimes it may not be easy to detect epilepsy from normal EEG signals because both signals show no discharges. That is why this conventional observation of signals has certain drawbacks as approximately 30% subjects are wrongly detected as epileptic but in actual, they don't have [5].

The accuracy of this process is directly dependent on the occurrence of discharges found in the EEG signals and moreover on the expert knowledge of the doctor. Lot of research has already been done for improving the rules and steps in order to detect seizures prediction algorithms dependent on long term observation with computational modeling and multimodal recording system [6-7]. To provide advancements with the amalgamation of machine learning algorithms leads to the introduction of several automated techniques and methods in order to detect EEG seizures. Although it is really tough to predict epilepsy from the recording which is in actual seizure free. For classification of EEG signals, authors of this paper employed the five supervised machine learning models (AdaBoost, SVM, NB, RF and KNN [8-11].

2. LITERATURE SURVEY

Children are the future of every country, so it's a prime most responsibility of medical experts of each and every country to provide the accurate and timely detection and treatment to youngsters. For this Electroencephalogram (EEG) is a popular and effective tool in medical field used by professionals to investigate the electrical activities generated in brain in order to collect useful data of epilepsy. Researchers shows a comparison of epilepsy detected in children with powerful method known as cerebral palsy (CP) in order to control peers. They conclude that children had a more risk of epilepsy if they have cerebral palsy rather than their peers. For this work, authors have taken the data from Quebec hospital [12]. Random deaths of children due to epilepsy triggering substantial concerns in their families. Scientists unable to find the exact cause of sudden death of children due to this neurological disorder, but their research provided them a result that those children had a cardiac and some respiratory abnormalities between seizures. Several treatments are in limelight to avoid this issue like surgeries, neurological therapies, diet modifications etc. in order to reduce the tragic deaths of children [13]. A histopathological detection of FCD1A has been performed on 19 children aged between 0.2 to 10 years. All suffering from daily seizures problem and found presence of drug from disease onset. Authors successfully identified the section of those young children who had drug resilient from epileptic seizure onset [14].

In paper [15], research was illustrated based on extraction of data from 1114 children (from 6 months to 18 years), to analyse the severity of seizures. Results are surprising, 50% reduction had noticed those underwent on ketogenic diet. Moreover, adverse effects had been showed by gastrointestinal symptoms. So, authors of this paper conclude that adopting kito diet is very important step towards the epilepsy treatment. It's really a big challenge in front of clinicians to correctly detect the epilepsy especially the cases of drug obstructive epilepsy. A study has been done by authors of paper [16] based on polymorphism concept using data of 93 children range between 1.5 to 14 years based on binary regression model. Their findings showed the direct connection between ABC2 gene polymorphism concept with higher rated of drug obstructive epilepsy in children. There are different reasons and different genetic history of every child for showing seizure symptoms. The study revealed the quantifiable aspects of epilepsy and seizure issues of children with the outset of presenting neuroscientists related to clinical investigation [17]. Analyse the concerns, worries and issues of epileptic parents when they are planning to increase their family or planning a child. Their concerns are really an obvious thinking, because they don't want to see the same health problem in their children. Total 477 couples underwent the study while planning a kid to avoid any abnormality in their unborn kids. This interesting study conclude that higher age women are more likely to give birth to the child have brain disorder [18].

On the basis of facts provided by International League Against Epilepsy (ILAE) in year 2014, subjects with one unraised or unprovoked seizures, medical experts must categorize the recurrence risk in order to recognize if the conditions for detection of epilepsy had been met or antiseizure tablets or medicines are required. Remote symptomatic etiology was well thought out to be one of the best analysts for seizure recurrence. It is also considered to the best tool among all available prediction tools in market [19]. There is research performed on Beijing Children's hospital on epileptic seizures after 15 days of those children who underwent brain injury. The main motive of this study is to explore risk associated factors of seizures that can avoid its repetition. This study was done on 108 subjects on the basis of regular monitoring of EPTS using prophylactic groups using logistic regression method. The conclusion is the children with fever on admission time of hospital are more chances to develop EPTS [20]. In Ontario, study was done on children for epilepsy surgery or medical therapy for sick and week children using inverse probability weighting technique with balanced weights demonstrated the long-term financial benefits of epilepsy surgery rather than medical therapy for health care system using real world global data [21].

After performed literature review, it was found that every scientist used different classifiers and methods for evaluating EEG signals and showed their accuracy also. So, it's a vital fact that everyone needs to be a method for accurately detection of EEG signals to control the death rate globally. Motivated by this, authors of this paper have extracted EEG signals for feature extraction and then applied this on different five supervised machine learning classifiers discussed in this work and also presented a comparative and as well as recent study for diagnosis of epilepsy.

3. Data Set and Research Methodology

3.1. Data Set Used

The data source of this research is CHB-MIT scalp EEG database. 1 hour EEG recording has been taken of normal and epileptic children of male and female both genders between the age of 1 to 19 years. Data analysis and simulations are carried out on MATLAB software. All EEG signals were sampled at 256 HZ frequency with 16-bit resolution record per sample. Types of EEG data recording of normal and epileptic children have been used in this paper is shown in Table 1.

Table 1. Types of EEG Data Recording (Normal & Epileptic Children)

Type of EEG Data Recording	Data Source	Gender	Age
Normal Children 1 hour Recording	CHB-MIT	M & F	1 -19 Years
Epileptic Children 1 hour Recording	CHB-MIT	M & F	1-19 Years

The flow chart of proposed methodology by the authors of this work has been illustrated in Figure 1. The automated system contains three steps as feature extraction using power spectrum, feature reduction using fuzzy entropy and classification using supervised machine learning algorithms. Authors used the five machine learning models (AdaBoost, SVM, NB, RF and KNN) for classifying EEG signals which is represented in Figure 2.

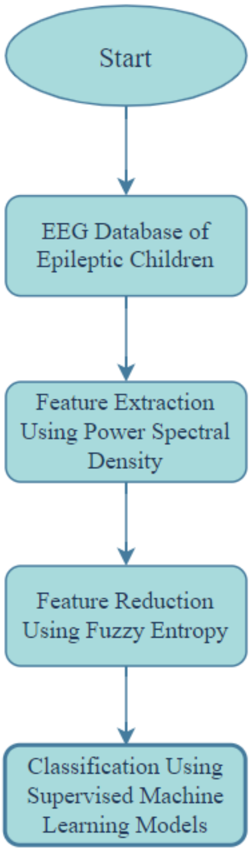

Figure 1. Flowchart of Proposed Comparative Analysis

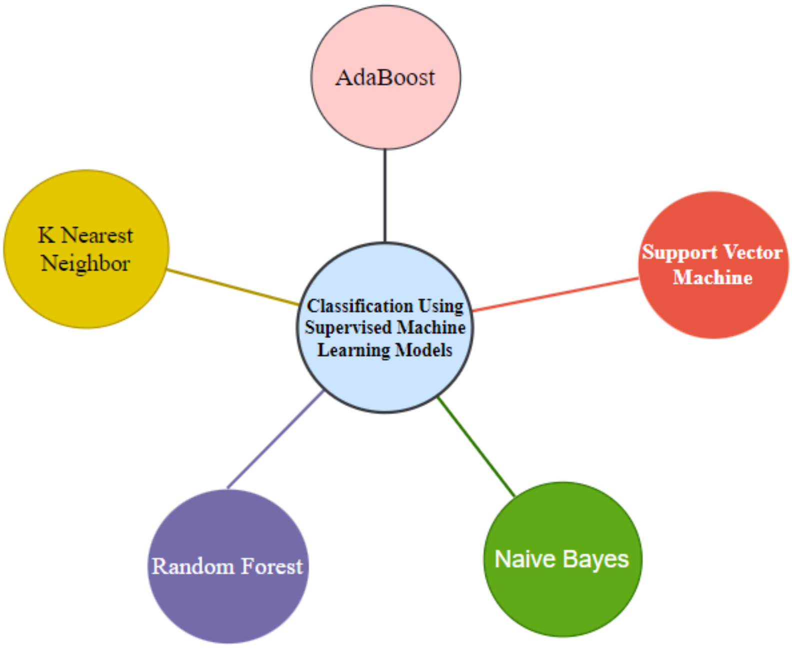

Figure 2: Classification Using Different Supervised Machine Learning Models

3.2. Feature Extraction and Feature Reduction

Firstly, features are extracted from EEG signals of normal and epileptic children using power spectral method. Then those extracted features are reduced using fuzzy entropy technique and then finally classification has been performed using five supervised machine learning algorithms. Power spectral method is used in this work for estimating the statistical feature values like mean, median, mode and standard deviation of sample EEG signals obtained from CHB-MIT database on channel FP1-F7. The sampling frequency of the experimental EEG signals of normal and epileptic children was 256 HZ. Welch method is chosen for power spectral calculation for this research work by firstly dividing the time series data into possible segments, then calculates each segment on specific period and then finally averaging the statistical features of sampled EEG signals. Once authors obtained the values of mean, median, mode and standard deviation, employed these values to classifiers for generating the results of this work using supervised machine learning models. Now, feature extraction is needed at this point of time after calculating SF values of EEG signals. Algorithm of Fuzzy entropy has been used for finding the score values of extracted features and then used those features for training and testing the signals using confusion matrix concept.

3.3. Classification

The SF values of EEG signals are used for training and testing the neural network model. AdaBoost, SVM, NB, RF and KNN supervised machine learning models are used for data classification work.

3.3.1. AdaBoost

The very basic and popular idea behind this supervised machine learning method is to adjust the weights (data) of classifier in such a way for training that sample of experimental data in each and every iteration ensures the accurate detection of unusual patterns [22]. AdaBoost have numerous benefits and higher accuracy rather than other supervised machine learning algorithms. AdaBoost designed in such a way that it performs best when work with SVM and shows better performance than support vector machine especially on the problems which are facing non balanced classifications [23-24].

3.3.2. Support Vector Machine

This supervised machine learning method is used for binary (0 & 1) and several other problems of regression and classification issues in which targeted data is necessary for training. This model depends upon the fixed sample theory that avoids random variations of data that mislead the classification process [25]. SVM technique has been employed by numerous researchers in healthcare diagnostic field and found to be best for classification of high dimensional data values. Figure 3 illustrates the architecture of SVM classifier. I1, I2…..In are the input vectors, SV (I1,I), SV (I2,I),……..SV (In,I) are represents the non-linear mapping of data depends on the support vectors and W1Alpha 1, W2 Alpha 2……..WnAlphan are the weights and F(I) is decision function [26-28].

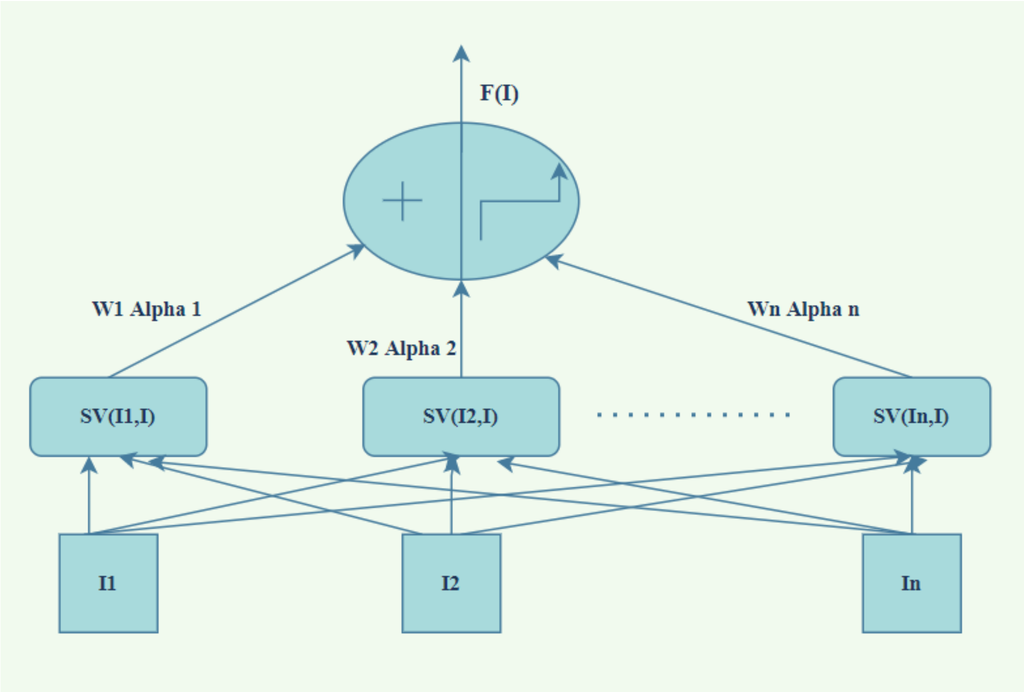

Figure 3: SVM Classifier

3.3.3. Naïve Bayes

Naïve Bayes is the most prominent, simple and easy to implement supervised machine learning classifier which is totally uses the concept of Bayes theorem based on one simple concept that classify the features in such a way that each and every pair of features are treated as independent [29]. This classifier sometimes estimates probabilities and create their own self hypothesis for understanding the behaviour of features in experimental data [30]. Naïve bayes is extremely fast learning classification algorithm for training the classifier by predicting the classes of unknown data sets [31].

3.3.4. Random Forest

This supervised machine learning algorithm is broadly used in classification as well as regression related problems [32]. This algorithm works on building the decision trees on the basis of extracted samples taken from data and perform classification using their majority votes and calculate average in regression related problems [33]. Many times, it uses collaborative learning which is a method that adds several classifiers in order to provide solution to the mathematical and complex classification problems [34].

3.3.5. K-Nearest Neighbors

KNN is a very popular classification method which does not involve any assumptions or parameters for sampling the frequency of experimental data. Mainly this method involves the selection of closest samples in search space [35]. Finally, this method, classifies the samples by deciding its nearest K neighbors, and labelled accordingly on the basis of closest neighbor [36-37]. Figure 4 shows the KNN classifier that how it samples the data into two classes of class A and Class B [43].

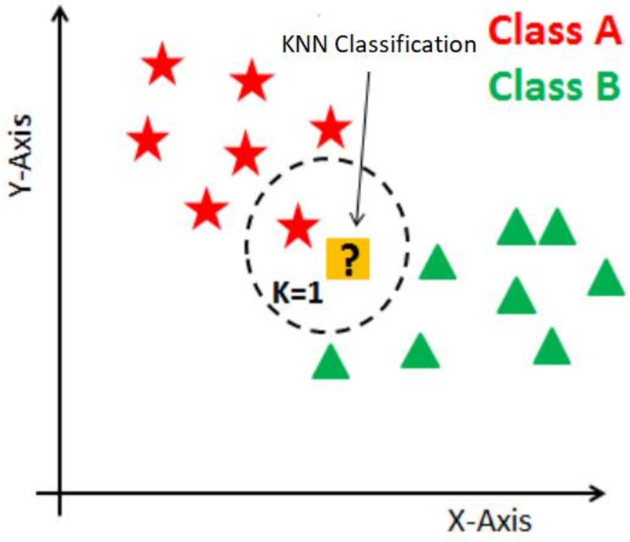

Figure 4: KNN Classifier [43]

RESULTS AND DISCUSSION

On the basis of proposed technique in this paper, generated results are found to be easy and accurate for showing clear separation between normal and epileptic children. This work proposed the automated approach of PSD and fuzzy entropy for feature extraction and feature reduction and used five supervised machine learning classifiers (AdaBoost, SVM, NB, RF and KNN) for classification of EEG signals. The extracted feature values are used to calculate the statistical feature values (mean-Me, median-Md, mode-Mo and standard deviation-St Dev) of experimental EEG signals (normal & epileptic). Table 2 depicts the statistical feature values of EEG signals of 20 normal children and Table 3 illustrated the statistical feature values of EEG signals of 20 epileptic children using the FP1-F7 channel.

Table 2. Statistical Feature Values of 20 EEG signals of Normal Children

SF Values of 20 Normal EEG Signals	SF Values			
EEG Statistical Features	Me	Md	Mo	St. Dev.
Records	Channel (FP1-F7) of Normal Children			
NC1	0.476891	0.386556	0.044610	0.015825
NC2	0.471142	0.393749	0.092717	0.027466
NC3	0.523510	0.334482	0.027502	0.280877
NC4	0.452626	0.386113	0.037877	0.037457
NC5	0.433569	0.203743	0.115533	0.082802
NC6	0.498769	0.396462	0.041087	0.028548
NC7	0.477566	0.391295	0.081558	0.083450
NC8	0.487542	0.390200	0.048969	0.028867
NC9	0.450547	0.360078	0.027077	0.052971
NC10	0.472637	0.314426	0.096736	0.079914
NC11	0.512667	0.321631	0.126822	0.180214
NC12	0.514504	0.387177	0.144781	0.099055
NC13	0.573667	0.390445	0.095006	0.021656
NC14	0.576104	0.250217	0.124043	0.040450
NC15	0.497331	0.290428	0.189110	0.142498
NC16	0.534695	0.205287	0.135435	0.098500
NC17	0.545065	0.390485	0.142167	0.054749
NC18	0.570649	0.214096	0.160813	0.077175
NC19	0.565480	0.297863	0.193565	0.058770
NC20	0.552748	0.300013	0.128579	0.099611

Table 3. Statistical Feature Values of 20 EEG signals of Epileptic Children

SF Values of 20 Epileptic Signals	SF Values			
EEG Statistical Features	Me	Md	Mo	St. Dev.
Records	Channel (FP1-F7) of Epileptic Children			
EC1	0.470220	0.401238	0.070202	0.041913
EC2	0.495947	0.400865	0.087645	0.017226
EC3	0.430004	0.399466	0.140226	0.033757
EC4	0.501423	0.200159	0.053124	0.007067
EC5	0.510981	0.378193	0.047918	0.009809
EC6	0.480787	0.201469	0.095669	0.013466
EC7	0.439475	0.393043	0.204336	0.045813
EC8	0.451784	0.397507	0.200159	0.035122
EC9	0.581703	0.201354	0.099815	0.011780
EC10	0.598169	0.206390	0.038832	0.017948
EC11	0.483635	0.202826	0.304351	0.094504
EC12	0.468903	0.395805	0.226313	0.122579
EC13	0.466953	0.394635	0.312938	0.117146
EC14	0.501557	0.397230	0.195654	0.082304
EC15	0.532235	0.388787	0.168488	0.102868
EC16	0.584321	0.398868	0.124924	0.042114
EC17	0.516350	0.392420	0.198231	0.087943
EC18	0.538869	0.394478	0.169164	0.034547
EC19	0.456673	0.275962	0.218959	0.220349
EC20	0.458644	0.297677	0.208426	0.135997

Once getting the SF values of EEG signals of normal and epileptic children, features are reduced by using the fuzzy entropy method on the basis of signal variations of extracted features. Finally, the SF reduced values are employed into the 5 classifiers namely AdaBoost, SVM, NB, RF and KNN for training and testing the signals. Approx. 70% data are used for training purpose and rest 30% were utilized for testing results. Table 4 shows the performance evaluation using different classifiers. This table 4 also presented the other researchers work in the same field. Table 5 shows the comparison of our selected models on the basis of machine learning performance metrics on AUC, CA, F1, precision and recall parameters. Authors of this paper, also presented a confusion matrix evaluation using different classifiers in Figure 5 to strengthen the outcome of this research. In Figure 6, authors clearly shown a visualization of epileptic & normal children using heat map technique on the basis of statistical feature values of experimental signals. For evaluation purpose, Lift Curve technique is used, Figure 7 and Figure showing the lift curve of epileptic children and normal children respectively. Performance evaluation of five supervised machine learning models is illustrating in Table 4.

Table 4. Performance evaluation using different classifiers

Reference	**AdaBoost**	**SVM**	**NB**	**RF**	**KNN**	**Our Findings**
41	94.58%	88%	0	0	0	0
39		88.60%	91.16%	0	89.23%	0
40		0	0	75.00%	0	0
42		0	0	0	78.31%	0
38		0	87.50%	0	0	0
Our Findings		0	0	0	0	100%

Table 5: Comparison of selected models on the basis of machine learning performance metrics

Model	AUC	CA	F1	Precision	Recall
AdaBoost	1.000	1.000	1.000	1.000	1.000
Support Vector Machine	0.985	0.900	0.899	0.917	0.900
Naïve Bayes	0.991	0.925	0.925	0.926	0.925
Random Forest	1.000	0.950	0.950	0.955	0.950
K Nearest Neighbor	0.910	0.775	0.763	0.845	0.775

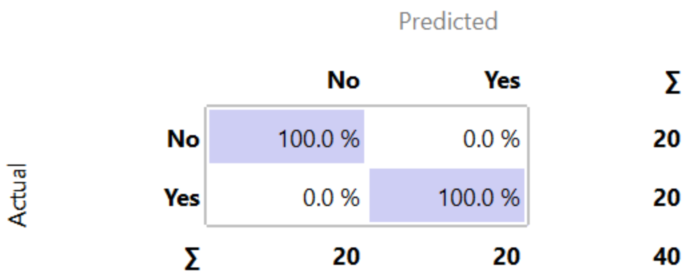

Figure 5: Confusion matrix evaluation using different classifiers

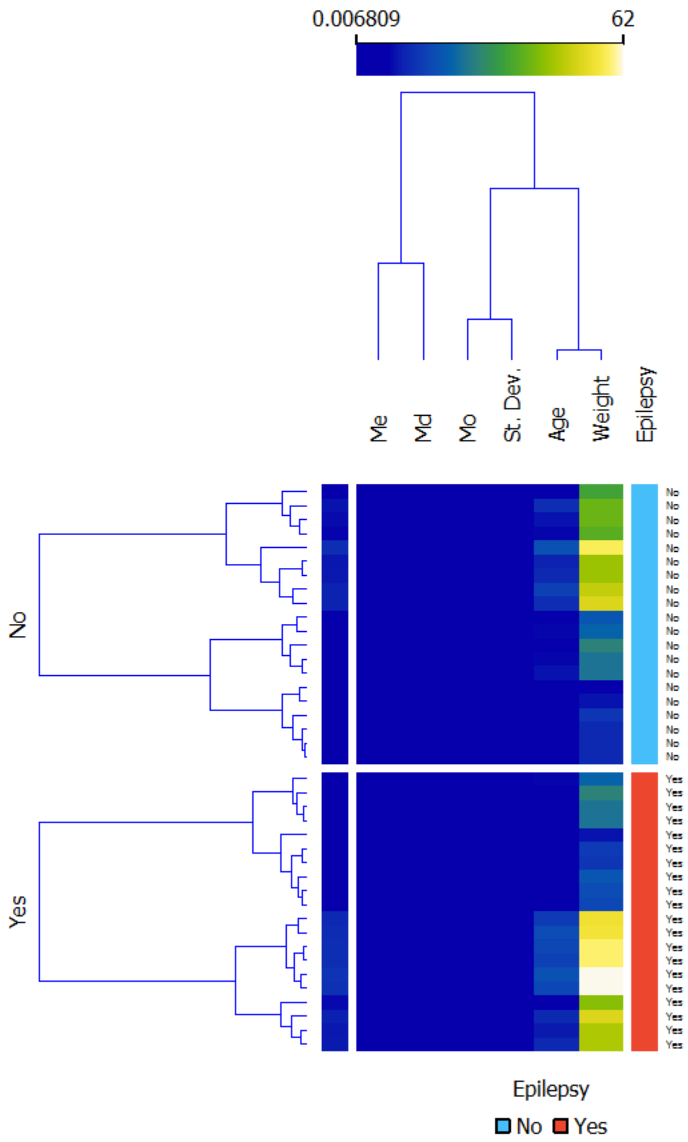

Figure 6: Visualization of Epileptic & Normal Children Using Heat Map

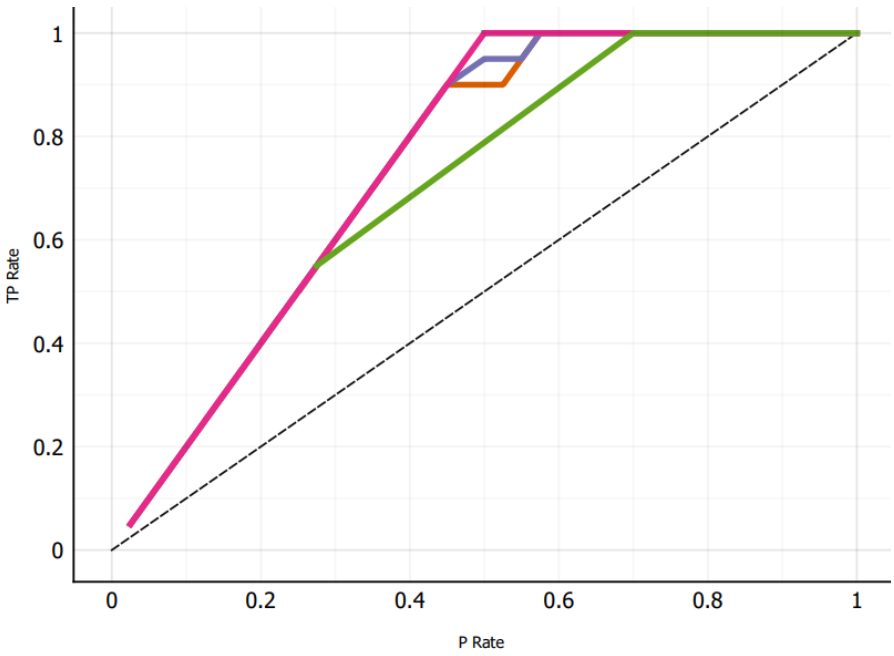

Figure 7: Lift Curve of Epileptic Children

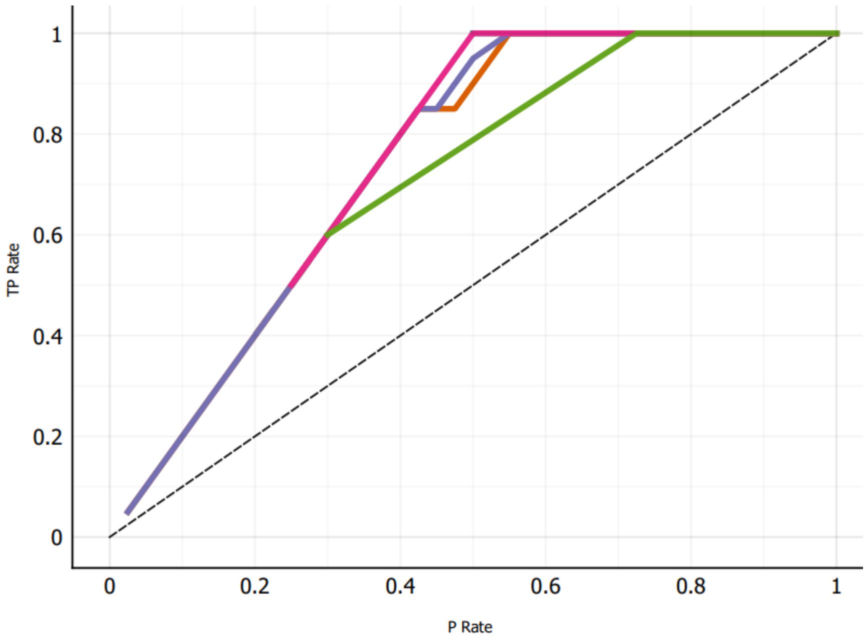

Figure 8: Lift Curve of Normal Children

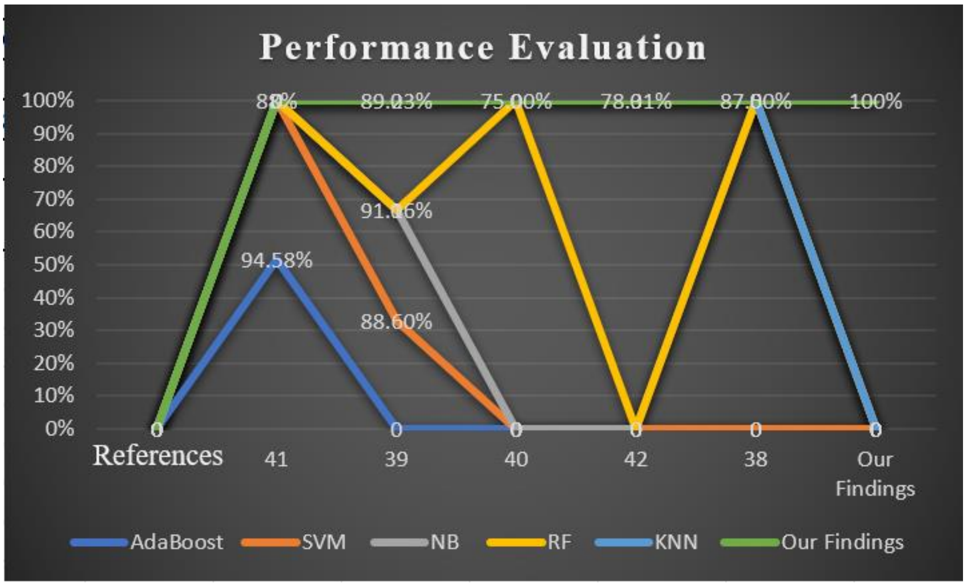

Figure 9: Performance Evaluation Shows Comparison of Different Classifiers with our findings

4. CONCLUSION

This paper presented a comparative analysis for epilepsy recognition in children based on five supervised machine learning models. PSD and fuzzy entropy techniques are used for feature extraction and feature reduction. For classification purpose, authors used the five supervised machine learning methods-AdaBoost, SVM, NB, RF and KNN in this work. On the basis of obtained statistical feature values of signals after extraction and reduction, those SF values were employed to classifiers for training and testing part. For evaluation, authors used the popular techniques like confusion matrix and lift curve showing 100% accuracy, for visualization of this research work heat map is used that clearly representing the difference between normal and epileptic children by using the statistical feature values-Me, Md, Mo and St. Dev. At last, authors also illustrating the comparison of different classifiers with our findings for accurate performance evaluation. The shown analysis in this research can be extended for real time seizure and epilepsy recognition with inclusion of ECG signals like arrhythmia detection, those combined approach of ECG and EEG detection could be a boom in healthcare industry in order to predict life threating diseases.

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