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Performance Comparison of Various Classifiers For Classification of Seizure

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***Abstract*— As in the absence of proper technology lot of time is waste in the identification of brain signal as seizure and non-seizure. Generally a lot of tests are performed to catch the disease or to actually know whether the patient is cured or healthy. These tests results in congregate or cluster of huge number of records. Whereas many diagnostic process could result in the mesh up of the actual diagnosis process and create difficulty in obtaining the genuine result specially when there is lot of test performed. These problems could be neutralized by using classifiers for the classification of record. So there are lot of classifiers are available called as SVM (square vector machine), k-NN (k- nearest neighbours), discriminate classifier and many like these. In this study we gave a resemblance of the classifiers on the basis of their accuracy sensitivity and specificity.**

***Index Terms*— SVM – support vector machine, k-NN – K-nearest neighbour, EEG – electroencephalography, EMD – Empirical mode decomposition, IMF – Intrinsic mode function**

I. Introduction

The objective of this study is to discover the behaviour of varying classifier with help of MATLAB tool on EEG data set of five different persons with different attribute. The devastated problem in the analysis of neural signals or brain signals is to optimize the correct diagnostic process of certain useful knowledge. For better treatment, many processes are followed that results in clustering of huge data and performing this whole process is necessary for the sake of the effective diagnosis. However at other side of coin, performing these diagnosis result in the colossal collection of diagnostic records which makes the treatment hectic and make us unable to conclude the final result. These type of problems can be cured by having the knowledge of the classifiers technique which could further lead to extract final report with the help classifier. So we have number of classifiers which we can use generally known as SVM (square vector machine), k-NN (K- nearest neighbours), discriminate classifier and many like these. In this study we gave a resemblance of the classifiers on the basis of their accuracy sensitivity and specificity. Classifier covers a huge range of procedure which is impossible to define without vagueness. The pluck out of necessary records from massive collection of data and its concurrence is often beneficial using classifier. Our objective of this work is to analyse the behaviour of varying classifiers for a collection of large data.

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EEG data set of 5 random people with different attribute is used in this work to clarify the variation between the classifiers. Therefore the classifier with best accuracy, swift process and with large potential will be propound for the classification of huge number of records or data set of neural signals or brain signals or for other general application. The three classifiers that we used (i.e. SVM (support vector machine), k-NN (K-nearest neighbour) and discriminate classifier) are well defined in MATLAB. The data we have used in this work have 100 data values in all 5 sets named Z, O, F, N and S. These data sets are publically available and used by many scholars for their research so we have well defined results for our demonstration. Apart from these classifiers our work involved EMD algorithm along with AM (amplitude modulation) and FM (frequency modulation) feature extraction technique. This feature extraction technique is already used by our honourable scholars Mr. Ram Vilas Pachori and Mr. Varun Bajaj in a paper title "classification of seizure and non-seizure EEG signal using EMPIIRICAL MODE DECOMPOSITION which is also involved the data set that we have used in this work. The paper is further assigned as: data set description, feature extraction method and parameters, description of classifiers and comparison. Finally at last conclusion of the paper.

II. Data Set

The data set used in this work is known as bonn data set which is publically available online[1]. In this data set used here has 5 subset i.e. Z, O, N, F and S each having 100 single channel EEG signals of 23.6 seconds duration each. The signals are picked from sequential multichannel EEG signal taken from visual inspection for article facts. These subsets have different attributes some are extra-cranially recorded like Z and O whereas some are recorded intra-cranially like N, F and S. Extra-cranial recordings are acquired from five diseased free person with their eyes open and closed in order from surfaced EEG recording. The subset F have been acquired in non-ictal recordings from five volunteers in the epileptogenic zone. Whereas, subset N acquired from the hippocampal formation of the opposite part of the brain. The final subset have recorded some ictal activities therefore the subset S contains recording of seizure signals. That means we have only one seizure signal subset and four different seizure free subsets whose sampling frequency (fs) is 173.61 Hz. In our paper we have made two classes one is ictal containing only S subset and other is ictal free containing 4 subsets Z, O, N and F and the Fig contains recordings from each signal.

III. Related work

The encephalography has undergone massive progress during 100's of year. The existence of electrical currents in the brain was discovered in 1875 by an English physician Richard Catton. In 1924 Hans Berger, a German neurologist, used ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. It is a neurological disorder which effects about 1% of world's population. There are almost 1% of the world's population is suffering from epilepsy involving brain tumor, brain injury, strokes and substance of anarchy. There are numerous work available or carried out on the diagnosis of various kind of disease like the work done by R. B. Pachori and Varun Bajaj gives a technique for the classification of EEG signal, their work is based on the extraction of signal using EMD method[2] and then processed the signal by applying AM and FM parameter and finally they classify the extracted signal using LS-SVM i.e. least square support vector machine[3]. R. B. Pachori has numerous work on diagnosis of EEG signal by using different parameters. The methodology used is classification using fractional linear prediction, local binary patterns, study based on phase space representation of IMF[4]. Similarly apart from using EMD as a filter time frequency analysis is also carried out by Alexandros T. Tzallas, Member, IEEE, Markos G. Tsipouras, and Dimitrios I. Fotiadis, Senior Member, IEEE[5] under title Epileptic seizure detection in EEGs using time-frequency analysis, in this work EEG signal is extract out using many time frequency based algorithm and finally classified using ANN classifier by dividing the data into three classes class I Z and S subset class II Z, N and S and class III includes all the data sets Z, O, N, F and S and the average accuracy obtain for each class is 94.27, 94.68 and 80.33 respectively. In our work we have the data into several classes and processed them by using different classifiers and tried to obtain better accuracy, sensitivity and specificity.

IV. Methodology

A. Empirical Mode Decomposition[2]

The empirical mode decomposition method is highly preferred as it is a flexible and data dominated process and it does not need any requirements like linearity and signal's stationarity. As the result of this method, the non-linear and non-stationary signal x(t) is decompose into the sum of intrinsic mode function. There are several earmark extraction method are proposed using EMD[8], in all these methods firstly the EMD of each signal is classified along with IMF (Intrinsic Mode Function) of each signal then various methodology is used to further classify these signal and to make categorization easy.

EMD algorithm [9] for signal x (t) can be defined as-

- From the given set of EEG records stratify the maxima and minima.
- By merging maxima and minima independently, engender upper and lower envelopes.

Appraise sectional average as –

$$a(t) = \frac{[e_m(t)+e_l(t)]}{2}$$

Extract IMF $h_1(t)$ = x(t) – a(t).

Now we applied Hilbert transform on all the IMF obtained by repeating above algorithm. The analytic signal z(t) of any real IMF is defined as -

$$z(t)= A(t)e^{-j\emptyset(t)} \quad (1)$$

Where,
A(t) = signal amplitude

B. By analysis of Amplitude Modulation and Frequency Modulation bandwidth [6]

The EEG record is decomposed by using Empirical mode decomposition and its IMF is obtained by using above algorithm. Then the bandwidth of the signal is estimate of the expansion in frequency for the time period of records use, this spread in frequency is due to aberration from the average frequency or due to differences in amplitude and blend of the one and the other. To appraise amplitude modulation bandwidth and frequency modulation bandwidth [10], first we appraise the centre frequency of IMF as follows –

$$w = \frac{1}{E}\int \frac{d\emptyset(t)}{dt} A^2(t)\,dt \quad (2)$$

Where
W = centre frequency
E = energy signal
The band width of analytical imf is defined as-

$$B^2 = \frac{1}{E}\int (w-\langle w\rangle)^2 |Z(w)|^2\,dw \quad (3)$$

It can be further expressed as –

$$B^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right) dt + \frac{1}{E}\int \left(\frac{d\emptyset(t)}{dt} - \langle w\rangle\right)^2 A^2(t)$$

It shows that the signal's bandwidth has some terms, depending on extent and phase respectively. Therefore bandwidth by virtue of amplitude modulation and by virtue of frequency modulation are defined as –

$$B_{AM}^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right)^2 dt \quad (4)$$

$$B_{FM}^2 = \frac{1}{E}\int \left(\frac{d\emptyset(t)}{dt} - \langle w\rangle\right)^2 A^2(t)\,dt$$

Therefore the total bandwidth is given as –

$$B = \sqrt{B_{AM}^2 + B_{FM}^2} \quad (5)$$

Later on, LSSVM (least square support vector machine)[3], k-NN and discriminate classifier is used to evaluate the effectiveness of the bandwidth parameters to detect ictal and ictal free EEG records.

V. Training and Classification

Different types of method are implemented which combines features and classifiers. The author approaches the multi-class problem as a set of classification problem in such a way one can assemble together diverse features and classifiers approaches custom-tailored to parts of the problem, which handles a simple three class problem. One classifiers consisting of three classes each classes will be used as base learner, and each classifier will be trained images, Each class will receive a unique ID.

A. Classification of data

Stratification of remotely discerned signal records is used to earmark homogeneous levels with compare to groups with kindred characteristics, with the objective of perspicacious multifarious objects from each other within the data. Class denotes level. Classification will be done on the basis of spectral or spectrally defined features, such as destiny, texture etc. in the feature space, it can be said that classification separates the feature space into several classes based on a decision rule.

Common classifier approaches that we are used in this work for the classification of our EEG data are as follows:-

a) Support Vector Machine classifier

Support Vector Machine (SVM) is a supervised learning algorithm[7] developed by Vladimir Vapnik and it was first heard in 1992, introduced by Vapnik, Boser and Guyon in COLT-92[8]. For many years Neural Networks was the ultimate champion, It was the most effective learning algorithm. SVM has so many useful application in real world problems which can be defined as text and image classification, hand-writing recognition, data mining, bioinformatics, medicine and bio sequence analysis and seven stock market.The Support vector machine (SVM) use to determine a separating hyperplane to identify different classes of data to maximize the margin and minimize the categorization error. By this methodology we determine the ictal and ictal free signal, as in non-seizure signals, it is observed that the changing rate of amplitude envelops of IMFs is large in number and the amplitude modulation bandwidth is larger with respect to the IMFs of seizure EEG record. Whereas the changing rate of frequency modulation components of IMF are less in number in seizure EEG records and the value of frequency modulation bandwidth is lower with respect to the IMFs of non-seizure signals.Therefore we can conclude that the total bandwidth of the IMFs of ictal EEG record is smaller as compares to the IMFs of the non-ictal EEG records.

b) K-nearest neighbor (k-NN) classifier:-

In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN for short)[9] is a parameter used for regression and classification.In all conditions, the input is inclusion of the k nearest training examples in the feature space. The output rely on whether k-NN is considered for classification or regression:

- Class membership is the output in k-NN classification. Any object is classified on the basis of majority support of their neighbors, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is easily entrust to the class of that single nearest neighbour.
- For the object the outcome is the property value in k-NN regression. This value is the average of the values of its k nearest neighbors.

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms.

***c)** Discriminate Classifier*

Gene expression data on p genes for n tumour mRNA samples may be summarized by an n x p matrix X D 4xij5, where xij denotes the expression level of gene (variable) j in mRNA sample (observation) i. The expression levels might be either absolute (e.g., oligonucleotide arrays used to produce the leukaemia dataset) or relative to the expression levels of a suitably denotes need common reference sample (e.g., the lymphoma and NCI 60 data sets are produced using cDNA micro arrays). The samples of mRNA belongs to the same identified classes(e.g., follicular lymphoma), the data for each observation consist of a gene expression profile xi D 4xi11::: 1 xip5 and a class label yi, that is, of predictor variables xi and response yi. For K tumour classes, the class labels yi are denotes need to be integers ranging from 1 to K, and nk denotes the number of observations belonging to class k. Note that the expression levels xij are in general highly processed data; the raw data in a microarray experiment consist of data profiles, and important pre-processing steps include data analysis of these processed data's and normalization. The data that is available publically, 'n' the number of tumours is hardly below 100 and on the other hand, 'p' the number of genes is in number of thousands. In the comparison of prediction methods, the number of genes will be substantially reduced by identifying a subset of genes whose expression levels are associated with tumour class.

VI. RESULT

After applying these methodology the output obtained will be as 8 data values of bandwidth of amplitude modulation and 8 data values is of bandwidth of frequency modulation which is then concatenate to form a 100 x 16 matrix from each subset and then from this matrix different data for testing and training is selected for e.g. if we have processed F subset from the above methodology and obtained 100 x 16 data matrix then from this matric we will select 80 x 16 data as data for training purpose and 20 x 16 data for testing purpose. Same technique is performed on the other subsets too for obtaining different training and testing data as 80 % , 70 % , 60 % and 50% and then classified the data using different classifiers i.e. SVM with different kernel function then by k-NN classifier and finally with discriminate classifier and obtain its accuracy error sensitivity and specificity of different combination of seizure and non-seizure (seizure free) sub set i.e. different 'class' starts with FS, NS, FNS, ZS, OS, ZOS and ZONFS and tried to obtain the best accuracy among all and also defined the average accuracy of all the classifier so that we can identify the best classifier and then that can be used in future without any doubt. The methodology used in this paper breaks nonlinear and non-stationary signal into a set of AM-FM component of narrow band by using the EMD algorithm. After applying EMD methodology we obtain the AM-FM IMFS which smooth the way for calculation of bandwidth. After obtaining the bandwidth due to frequency modulation and amplitude modulation, we have processed that data using various classifiers i.e. SVM, k-NN and discriminate classifier. Obtain the accuracy, error rate, sensibility and seizure dataset and with three set of training data as 80%, 70%, 60% and 50%. The accuracy of each combination of dataset with different training data is shown using bar graph as in Fig 2, 3 and 4. As shown in Fig below it can be easily said that the SVM classifier with highest accuracy of 97.5% and with lowest accuracy of 65% is best among all classifiers**.** Whereas K-nn classifier is worst among all as its highest obtained accuracy for all class and training data is 81% only also its lowest accuracy is 53.75%.

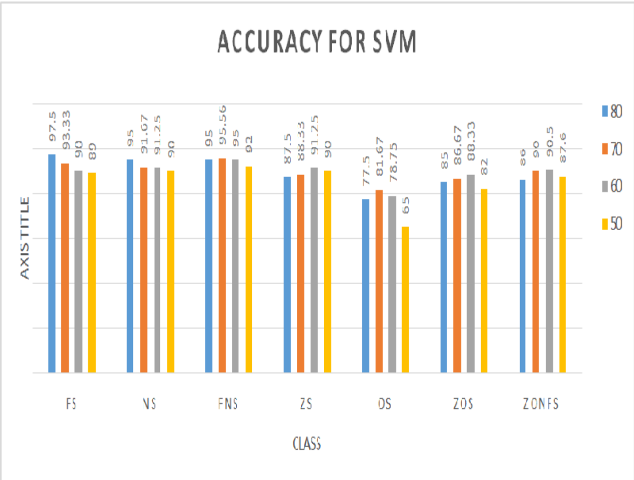

Fig 1: Accuracy of different combination of datasets using SVM classifier

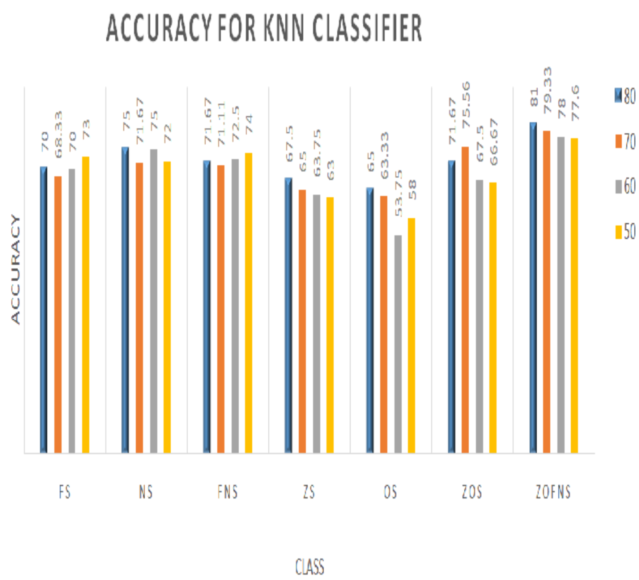

Fig 2: Accuracy of different combination of datasets using KNN classifier

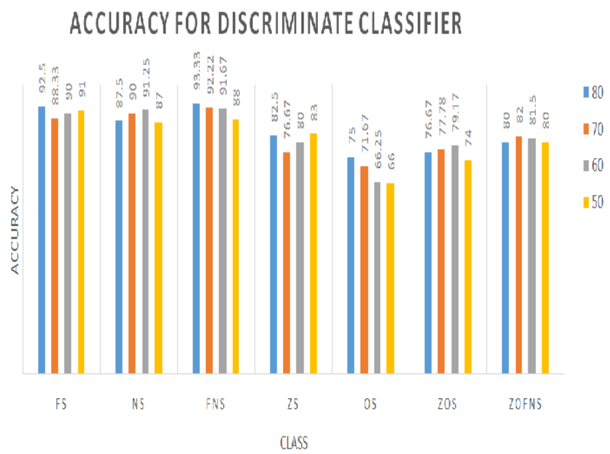

Fig 3: Accuracy of combination of different data sets using discriminate classifier

Table 1Error rate using different kernels in SVM for 80 % trainning data and FNS class

Sr. no.	Classification machine used	Kernel function	Accuracy (in %)	Error rate (in %)
1.	SVM	Linear	95	5
2.	SVM	RBF	86.67	13.33
3.	SVM	Quadratic	85	15
4.	SVM	Polynomial	88.33	11.67
5.	SVM	MLP	83.37	16.67

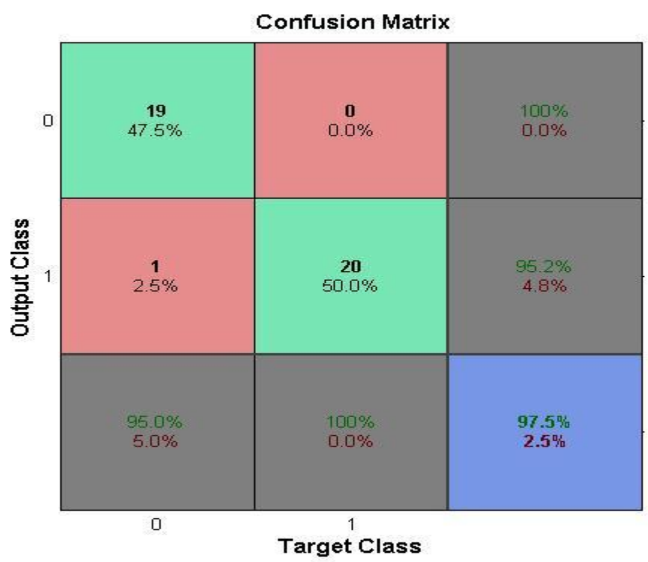

Fig 4: Confusion matrix of FS class

On the other hand discriminate classifier or classify classifier is much accurate than K-nn whereas its accuracy is little less than SVM. As it has its highest accuracy of 93.33classification of neural signal of the detection of seizure and non-seizure. Therefore SVM classifier best among all the classifier used hence SVM classifier will all its kernel function and a training data of 80 and a class FNS is shown in table 1. The best accuracy obtain with linear kernel function whereas worst accuracy is obtain with MLP kernel function. We can verify the above result with the help of confusion matrix also as the ratio of true positive and true negative is best for SVM classifier class FS for 80% training data. The ratio obtain is 19:1 and also the best result for false positive and false negative is also for same i.e. 20:1 as shown in Fig 4 of confusion matrix of class FS.

VII. Conclusion

By observing the above results it can be conclude that the beat classifier that can be used for the classification of neural signals for the detection of seizure and non-seizure is SVM classifier with outstanding accuracy up to 97.5% and with good error rate 2.5%. The above result is the outcome of the various combination of dataset i.e. class and the best result is obtained with FS class using SVM for 80% training data value and the accuracy and error obtained is 97.5 % and 2.5 % respectively. Whereas for other classification the best result is obtained for Classify discriminate classifier is 93.33 % accuracy for FNS class with 80 % training data and sensitivity and specificity of this class is 86.36 and 97.37 respectively.

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