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EMD-CNN Based Classifier to Detect Schizophrenia from EEG Signals

Rosu Varkeyachan Padayatty, Thasneem Fathima N.K, Mohanraj V

***Abstract:** The United Nations has designated schizophrenia (SZ) as a serious mental illness that affects 20 million people globally. Hallucinations, delusions, and incredibly chaotic thought and behavior are some of the symptoms. SZ has an impact on a person in all facets of his life and makes it challenging to go on. Traditionally, a skilled psychiatrist uses thorough and incisive patient interviews to make the diagnosis of SZ. This procedure takes a long time and could lead to mistakes. Therefore, the purpose of our effort is to assist physicians in making diagnoses effectively. In this work two different methods for the detection of SZ is compared and the results are analyzed. In the first method Local binary pattern which is a computationally simple andproven technique in image processing is modified and madecapable to be applied to the 1D EEG signal and histogram based features were extracted from it.Using the histogram features a feature matrix is formulated. The obtained matrix is used to train various machine learning models using the classification learner toolbox in matlab and K- nearest neighbour with medium kernel obtained a comparatively better training accuracy. Further this model is tested and an overall accuracy of 83.3 % is obtained. In the second method the EEG signals were decomposed using empirical mode decomposition (EMD). EMD is one of best signal processing technique that handle the nonlinear, nonstationary and aperiodic signal like EEG. EMD is performed to decompose the signal into various Intrinsic mode functions (IMF). Then differential entropy, a stastistical feature used to determine the randomness measure of a signal were extracted from the EEG signals. Further a feature matrix is formulated and it is trained andtested on the renowned deep learning model, the convolutional neural network. CNN performed well on theEEG data and an overall accuracy of 86 % is obtained. From the results we can see that the deep learning model (CNN) outperformed the machine learning model (K-NN) and is good and robust in detecting SZ using EEG signals.*

***Keywords:** Electroencephalogram_(EEG), Schizophrenia (SZ), Healthy Control (HC), K-nearest Neighbor (KNN), Local Binarypattern (LBP), Intrinsic Mode Function (IMF), Empirical Mode Decomposition (EMD),1 Dimensional Convolutional Neural Network (1D-CNN).*

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I. INTRODUCTION

SZ is a typical neurological condition that primarily affects adults. Schizophrenia affects about 28 million people worldwide, or 1% of the total population (SZ). The American Psychiatry Association states that SZ patients exhibit illusions (hallucinations), slurred speech, delusions, and other symptoms [1]. SZ prognosis necessitates ongoing financial strain and medicine [2]. The effectiveness of early SZ identification has been hampered by the absence of standardized tests and techniques. Electroencephalogram (EEG) signals offer substantial information for the diagnosis of SZ [5]. The EEG signals are non-invasive, inexpensive, and non- radioactive when compared to other techniques as fMRI, CT, PET, MEG, and FNIRS. As a result, they are frequently employed these days to identify brain abnormalities [6]. EEG signals are basic electrical voltages that are produced as a result of continuous electrical activity of the brain [7]. They are non-linear, non- stationary and periodic signals. The potential benefits of this study are outlined as:- 1.To analyse the EEG signals using 1D Local binary pattern and to extract histogram-based features from it in order to formulate a feature matrix. Classification of the feature matrix using classification learner tool box in MATLAB to find out the suitable classifier [8]. To decompose the EEG signals into Intrinsic mode functions (IMF) using empirical mode decomposition (EMD) and to extract Differential entropy (DE) feature in the IMF domain. The formulated DE matrix is classified using 1D Convolutional neural network (CNN) Comparison of the 2 methods mentioned above and toarrive at a conclusion.

II. LITERATURE SURVEY

So far so many researchers have proposed different methods for the classification of SZ signals from EEG [10]. Kim et al used the spectral analysis across the five EEG bands for classification [1]. Suily et al used statistical methods to extract features in the IMF domain and it was further selected using Kruskal Wallis test [9]. Further the feature matrix was classified using several machine learning classifiers. Johanassen et al utilized Regression based analysis. The Time-frequency data were extracted from 5 EEG bands and classified using SVM classifier [6]. Boostani et al extracted Auto regressive model parameters, band power and fractal dimension features and classification were done using LDA [2]. Singh et al used variational mode decomposition to extract features. Six features were calculated and statistical significance test was conducted to find the best SZ biomarker [3]. Z.Dvey et al used a single electrode approach for classifying SZ from the EEG signals [4]. We can see that some methods failed to take into account appropriate EEG channels that could transmit crucial information for the detection of SZ. Additionally, because the original EEG data was non- stationary and aperiodic in some instances, the feature extraction methods chosen were not the best option for obtaining representative features from the data. So in thispaper we compare 2 methods namely the local binary pattern using machine learning classifier and empirical mode decomposition with deep learning classifier to find out the best classification system that discriminates SZ from Healthy control subjects [11].

The rest of this paper is organized as follows. Materials and methods are explained in Section 2. Experimental results are found in Section 3, followed by the conclusion in Section 4 [12].

III. MATERIALS AND METHODS

A. Dataset Used

The Kaggle website is where the dataset for this study is available.it can be accessed at: https://www.kaggle.com/broach/button-tone-sz/home. The dataset's specifications are described in [23]. The dataset consists of 81 patients, of which 49 have SZ and 32 are healthy controls. Among the eighty-one subjects, fourteen are female and sixty-seven are male. Theiraverage age is 39 years old, and they have an average of 14.5 years of schooling. Each patient underwent three button presses tasks in order to examine the corollary discharge [15]. In this study, HC and SZ are distinguished using EEG data based solely on the first criterion. This is due to the fact that SZ subjects did not produce the same press-button tone as Healthy controls did. The acquired EEG data is referred offline to averaged earlobe electrodes and sampled at 1024 Hz. The dataset is subjected to a number of preprocessing procedures in the sequence listed below [13].

B. Method I

The first technique employed in this work creates afeature matrix by using a local binary pattern to extract histogram features from the EEG signals of both SZ and HC subjects. A block diagram for easy understanding is shown in fig 1 Then Leveraging Matlab 2021's classification learner toolbox, the feature matrix is classified [15].

i. Local binary pattern

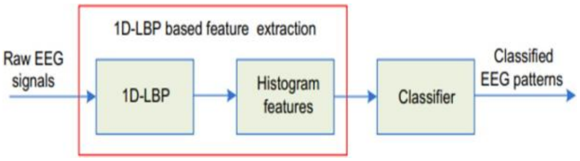
Ojala first presented the local binary pattern in 1996. 2- D image processing has made substantial use of local binary patterns (LBP). LBP has been demonstrated to be a computationally efficient, discriminative texture descriptor in [17]. The idea behind the aforementioned applications is that a collection of texture patterns can adequately characterize an image. Our goal is to create a framework for 1-D LBP signal processing and show how it can be used to solve the schizophrenia identification challenge. As seen below, the LBP signal is determined.A binary code is created for each data sample of a signalby thresholding its value with the value of the centre sample. This process is applied iteratively to the full signal [16].

$t = P_i - P_c$

$$LBP(x) = \sum_{i=0}^{P} F(t)2^i = 1 \; where$$

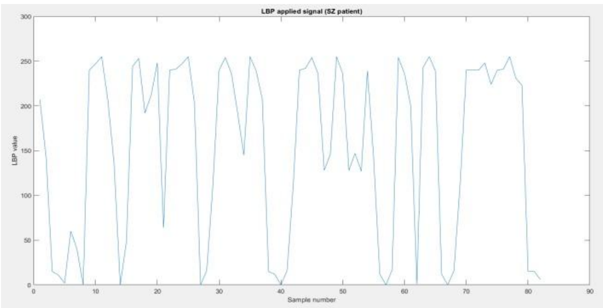
$$F(t) = \begin{cases} 0, & t < 0 \\ x, 1, & t \geq 0 \end{cases}$$

Where P_i is the amplitude of the neighbor sample and P_o is the centre sample value. P/2 adjacent samples were taken into consideration as being before and after the centre sample Pc for each sample of the signal [14]. Then thecentre sample is subtracted and thresholded against the neighbor values.The LBP signal thus formed has values ranging fro 0 to 256. Each LBP value has a unique pattern that it matches to. The LBP signal's histogram, which was created, displays the frequency with which each of these 256 distinct patterns emerges in a particular signal. By splitting the data into intervals known as bins,histograms plot the data.

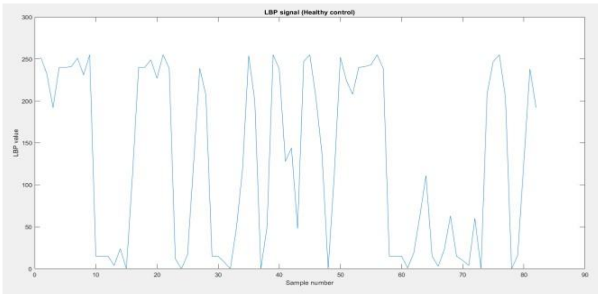


[Fig.1: Method 1 Block Diagram]

The frequency with which various LBP values appear inthe given signal is shown by histogram features generated from the LBP signal. In this work, EEG samples up to 12 min duration is considered. The samples are divided in to 12 frames of one-minute duration each [18]. The sampling frequency of the EEG signal is 1024 Hz. Using the sampling frequency, the no: of samples per frame is calculated and LBP [19].



[Fig.2: LBP Applied Signal – SZ]



[Fig.3: LBP Applied Signal – HC]

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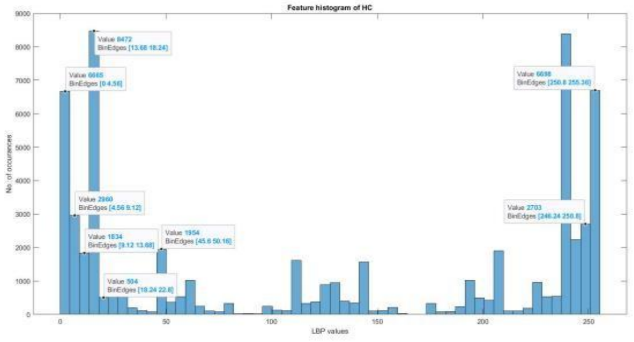
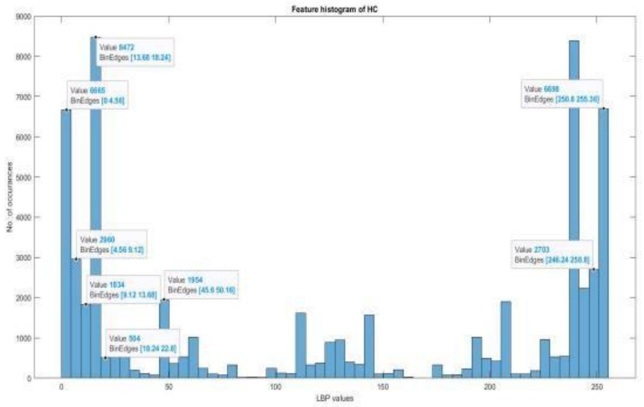


[Fig.4: Histogram Plot of HC]



[Fig 5: Histogram Plot of SZ]

Histogram features are extracted per frame. The LBP code for extracting histogram features is developed in MATLAB and the number of neighbours is selected as 8. The bin size for extracting histogram features are selected as 56. Likewise, histogram features for both the Healthy control subjects and Schizophrenia subjects were calculated and a feature matrix is formulated. The figure 2 and 3 shows the LBP applied signal of both HC SZ. The histogram that is obtained for both the cases are shown in fig 3 and 4. The LBP values ranging from 0 to256 are divided into 56 bins to get the histogram. If we look to the fig 6.5 we can see that 1 st bin edge is from 0to 4.56 and these values occurred 6316 times in the LBPsignal. Likewise, there are 56 bins [20].

ii. Classification

Classification learner toolbox available in matlab 2021 is used to classify the obtained histogram feature matrix. All the machine learning classifiers available in tool box were trained on the data. Out of that the Medium K-NN showed the best training performance The tuning parameters are shown in table [21].

Table 1: Tuning Parameters Used for Meduim K-Nn

Parameter	Values
Number of neighbors	10
Distance metric	Euclidian
Distance weight	Equal
Standardize data	True

C. Method II

The second method adopted in this work utilizes the empirical mode decomposition to decompose the non linear , non stationary EEG signals into Intrinsic mode functions .Then differential entropy feature is extracted from the EEG signals in IMF domain to analyze the randomness measure contained in the signal. Subsequently the differential entropy matrix is classifiedusing 1D convolutional neural network.

i. Empirical Mode Decomposition

The decomposition method known as empirical mode decomposition is used to acquire meaningful temporal frequency information out of EEG data. The non- stationary and non-linear EEG signals are broken down by EMD into intrinsic mode functions (IMF). The idea of EMD is to find the right time scales to display the physical properties of the signal. The intrinsic mode functions (AM-FM components) used in the EMD approach are used to breakdown the non-linear, non- stationary EEG signals (IMF). The signal itself contains these IMFs either directly or indirectly. The instantaneous frequency of each IMF is known. Any complex data set may be broken down using EMD into a limited number of well-behaved Hilbert Transform-satisfying "intrinsic mode functions," which are finite and frequently simple. As a result, Hilbert-Huang transformations is another name for this technique [22].

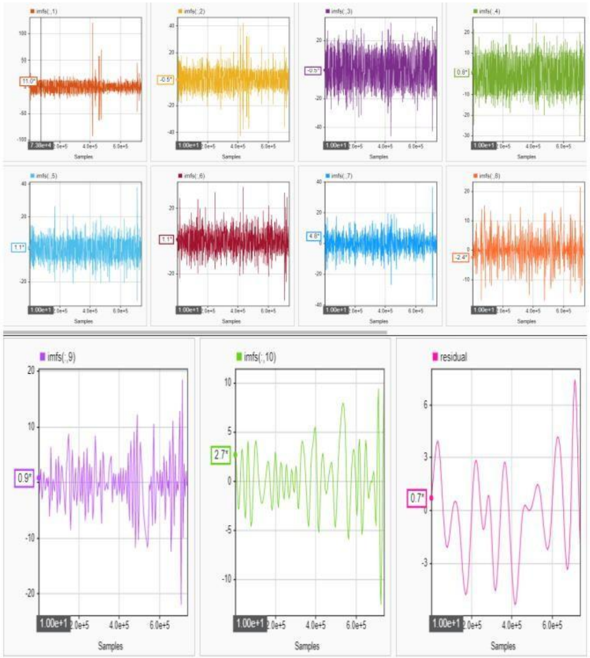
The following two requirements must be met by IMFs.

1. The number of extrema and zero crossings in the entire data set must be identical or differ by no more than one.
2. The mean value of the envelope produced by the local maxima and minima is indeed 0.

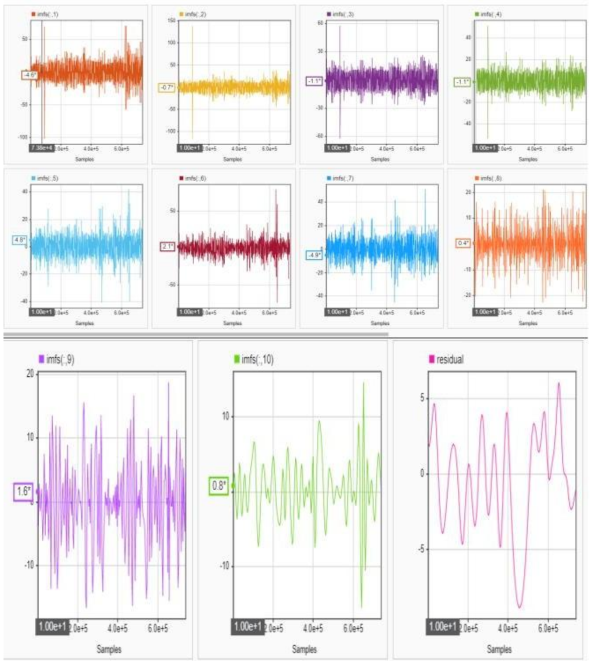
EMD is a screening process that is iterative. We extract one IMF from the signal, subtract it from the original signal, and continue the operation until we acquire a residual from which no additional IMF can be retrieved. As a result, it functions as a filter. The first filter takes the highest frequency component, followed by the next higher frequency, and so on.The total of all IMFs can be used to reconstruct a signal [23].

f(t)= Σ IMF + residual where f(t) is the original signal. Sum of all IMFs and the remaining residue resembles the original signal. The iterations are continued until a stopping criterion is reached that is the standard deviation between the consecutive IMFs should lie between 0.2 & 0.3.

The empirical mode decomposition of both the healthy controls and schizophrenia patients are carried out in MATLAB 2021a. IMFs and the residual obtained for a Healthy subject and SZ patients is shown in figures 5 & 6 respectively. 10 IMFs were obtained per subject per channel. From the 30 obtained IMFs, entropy analysis is carried out in IMF domain to determine the randomness measure of both HC and SZ.



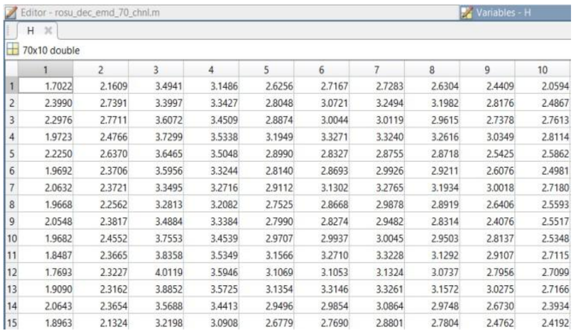
[Fig.6: IMF S Obtained for A HC Subject]



[Fig.7: IMFS Obtained for A SZ Subject]

ii. Entropy Analysis

Entropy is a term borrowed from physics which definesthe amount of disorderliness or randomness in the system. In this work differential entropy is taken as the discriminating feature for the classification of healthy controls from schizophrenia patients. DE is defined as the entropy of continuous random variables and the specific calculation formula: h(x) = − Z x f(x)log(f(x)) dx where x is a random variable and f(x) is the pdf of x Entropy measures are widely used in disease diagnosis from EEG signal. When compared to healthy people, those with pathological disorders of the brain exhibit various levels of unpredictability in their EEG patterns. According to studies on entropy-based assessments of SZ condition, the EEG signal for SZ is less random thanHC, in comparison. This is because patients with SZ have diminished cognitive abilities, which causes their EEG patterns to be less random. Previous studies have demonstrated that entropy analysis in the IMF domain had a higher level of discriminating power when used toidentify the SZ condition in a multichannel EEG data. Due to the lack of a dataset, the applications of entropy measurements in schizophrenia identification are restricted. Through this research, we presumptively compute the randomness measure in the domain of the Intrinsic Mode Functions (IMF). The differential entropyof all the subjects are calculated in IMF domain in MATLAB 2021a and a feature matrix is formulated. The sample entropy values obtained for a healthy control subject & a Schizophrenia patient is shown in figure 7 & 8 respectively. Then this feature matrix is classified using deep learning algorithms. This is explained in the next section.



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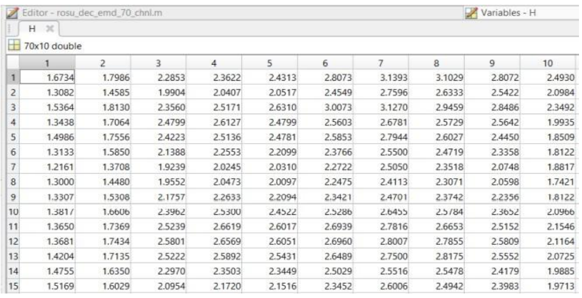
H

70x10 double

	1	2	3	4	5	6	7	8	9	10
1	1.7022	2.1609	3.4941	3.1486	2.6256	2.7167	2.7283	2.6304	2.4409	2.0594
2	2.3990	2.7391	3.3997	3.3427	2.8048	3.0721	3.2494	3.1982	2.8176	2.4867
3	2.2976	2.7711	3.6072	3.4509	2.8874	3.0044	3.0119	2.9615	2.7378	2.7613
4	1.9723	2.4766	3.7299	3.5338	3.1949	3.3271	3.3240	3.2616	3.0349	2.8114
5	2.2250	2.6370	3.6465	3.5048	2.8990	2.8327	2.8755	2.8718	2.5425	2.5862
6	1.9692	2.3706	3.5956	3.3244	2.8140	2.8693	2.9926	2.9211	2.6076	2.4981
7	2.0632	2.3721	3.3495	3.2716	2.9112	3.1302	3.2765	3.1934	3.0018	2.7180
8	1.9668	2.2562	3.2813	3.2082	2.7525	2.8668	2.9878	2.8919	2.6406	2.5593
9	2.0548	2.3817	3.4884	3.3384	2.7990	2.8274	2.9482	2.8314	2.4076	2.5517
10	1.9682	2.4552	3.7553	3.4539	2.9707	2.9937	3.0045	2.9503	2.8137	2.5348
11	1.8487	2.3665	3.8358	3.5349	3.1566	3.2710	3.3228	3.1292	2.9107	2.7115
12	1.7693	2.3227	4.0119	3.5946	3.1069	3.1053	3.1324	3.0737	2.7956	2.7099
13	1.9090	2.3162	3.8852	3.5725	3.1354	3.3146	3.3261	3.1572	3.0275	2.7166
14	2.0643	2.3654	3.5688	3.4413	2.9496	2.9854	3.0864	2.9748	2.6730	2.3934
15	1.8963	2.1324	3.2198	3.0908	2.6779	2.7690	2.8801	2.7804	2.4762	2.4192

[Fig.8: Sample DE Values Obtained for A Healthy Subject]



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H

70x10 double

	1	2	3	4	5	6	7	8	9	10
1	1.6734	1.7986	2.2853	2.3622	2.4313	2.8073	3.1393	3.1029	2.8072	2.4930
2	1.3082	1.4585	1.9904	2.0407	2.0517	2.4549	2.7596	2.6333	2.5422	2.0984
3	1.5364	1.8130	2.3560	2.5171	2.6310	3.0073	3.1270	2.9459	2.8486	2.3492
4	1.3438	1.7064	2.4799	2.6127	2.4799	2.5603	2.6781	2.5729	2.5642	1.9935
5	1.4986	1.7556	2.4223	2.5136	2.4781	2.5853	2.7944	2.6027	2.4450	1.8509
6	1.3133	1.5850	2.1388	2.2553	2.2099	2.3766	2.5500	2.4719	2.3358	1.8122
7	1.2161	1.3708	1.9239	2.0245	2.0310	2.2722	2.5050	2.3518	2.0748	1.8817
8	1.3000	1.4480	1.9552	2.0473	2.0097	2.2475	2.4113	2.3071	2.0598	1.7421
9	1.3307	1.5308	2.1757	2.2633	2.2094	2.3421	2.4701	2.3742	2.2356	1.8122
10	1.3817	1.6606	2.3962	2.5300	2.4522	2.5286	2.6455	2.5784	2.3652	2.0966
11	1.3650	1.7369	2.5239	2.6619	2.6017	2.6939	2.7816	2.6653	2.5152	2.1546
12	1.3681	1.7434	2.5801	2.6569	2.6051	2.6960	2.8007	2.7855	2.5809	2.1164
13	1.4204	1.7135	2.5222	2.5892	2.5431	2.6489	2.7500	2.8175	2.5552	2.0725
14	1.4755	1.6350	2.2970	2.3503	2.3449	2.5029	2.5516	2.5478	2.4179	1.9885
15	1.5169	1.6029	2.0954	2.1720	2.1516	2.3452	2.6006	2.4942	2.3983	1.9713

[Fig.9: Sample DE Values Obtained for A Healthy Subject]

iii. Classification

Python is used to do classification, and Google Collaboratory is utilized. The back end also makes use of the Tensor Flow 2.0 library. It uses a 1D Convolutional neural network The CNN, or convolutional neural network, is a popular deep learning model used for categorization problems. When it comes to signal classification problems, we must employ 1D CNN instead of the more well-known 2D CNN model that is often used in image classification problems. A 1D CNN with 4 hidden convolution layers, maxpooling, batch normalization, 2 fully linked layers, and a dropout layer is used in this study. The sigmoid function is used in theoutput layer. The activation function that is used is the ReLU. The optimizer that is used in this model is the ADAM optimizer.

IV. EXPERIMENTAL RESULTS

The performance of the classification models implemented using both the Method I & Method II was evaluated using the following performance evaluation

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parameters. They are Accuracy, Recall, Precision, False Alarm rate, specificity, F1 score, Confusion matrix and ROC plot.

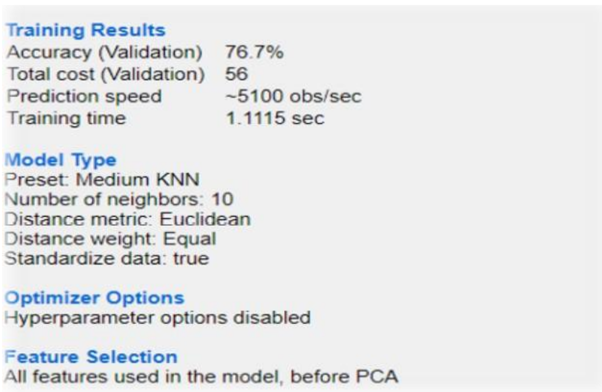
A. Method 1

In the first method,after obtaining the LBP histogram feature matrix ,it was classified using classification learner toolbox in matlab. The models were trained by employing 10 fold cross validation. Table 2 shows the training results obtained in matlab for the various modelsthat is trained. From Table 2 it is clear that medium K-

Table 2: Method 1 -Training Results

	Model Training results		
Sl. No	Name of the Model	Subtype	Accuracy
1	Decision tree	fine	71.7
		medium	70.4
		coarse	70.0
2	LDA		58.3
3	Logistic regression		59.6
4	Naive bayes	Gaussian	54.6
		Kernel	71.7
5	SVM	Fine gaussian	73.3
6	K-NN	fine	70.8
		medium	76.7
		cubic	65.8
7	Ensembled bagged tree		71.7
8	Ensembled boost tree		70.8
9	Neural Networks	single layered	70.8
		bi layered	72.9
		tri layered	74.6

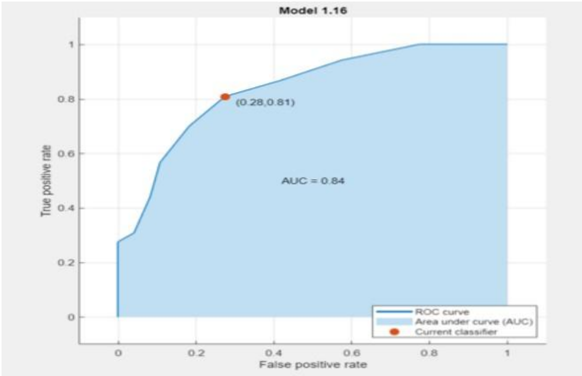
NN achieved the best training accuracy. Figure 9 shows the training details of Medium k-NN. The number of neighbours used was 10 and the distance metric used is euclidian distance. Figure 10 shows the ROC plot for the training data. It can be sen than the area under the curve is 0.84 which is a good score. Figure 11 shows the confusion matrix. The validation accuracy and other performance metrics obtained during testing for medium K-NN is shown in Table 3. From the Table 3 we can see that during testing medium K-NN has obtained an overall accuracy of 83.33 %. The difference between training and validation accuracy obtained from Tables 8.1 ans 8.2 is around 8.25 % which indicates that the model is not over-fitting on the data.



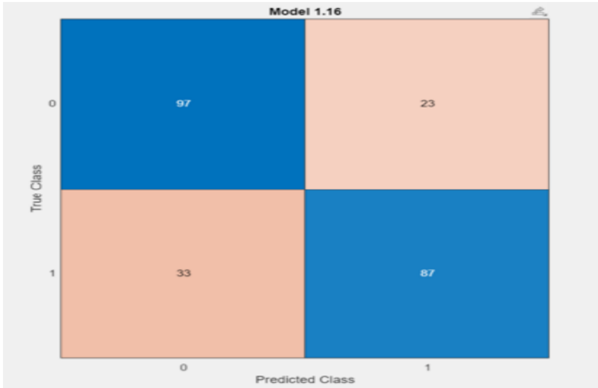
[Fig. 10: Training Details of Medium K-NN Classifier]

B. Method 2

In method II, Empirical mode decomposition (EMD) is done on the subjects to decompose into Intrinsic mode functions (IMF). The number of IMF s obtained per



[Fig.11: ROC Plot for Training Data-Medium K-NN]



[Fig.12: Confusion Matrix for Training Data -Medium KNN]

Table 3: Medium K-Nn Validation Results

Medium K-NN Testing Results		
Sl. No	Evaluation Parameter	Percentage
1	Accuracy	83.33
2	Recall	78.5
3	Specificity	90.0
3	Precision	91.6
4	False positive rate	10.0
5	F1-score	84.5

Subject per channel is 10. A sample plot of the IMFs obtained for a HC subject and a SZ subject is shown in figure 5 and 6. Further differential entropy feature was extracted from all the subjects and a feature matrix was formulated and it was classified into HC and SZ by using 1D CNN. The sample differential entropy values obtained in MATLAB for both HC and SZ subjects are given in fig 7 and 8 for reference. EMD and feature extraction was carried out in MATLAB and classification was done in python. During classification,80 percent data was used for training and 20 percent data was used for testing. The training details obtained in python for 1D CNN is shown in figure 12. The training accuracy is obtained as 95.56 percent for theproposed 1D - CNN model. The performance metrics obtained for the proposed classifier is shown in Table 4.From the table it can be seen that 1D CNN has obtained an overall validation accuracy of 86 percent for.

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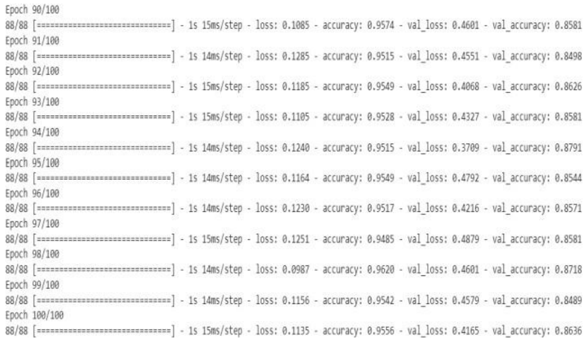


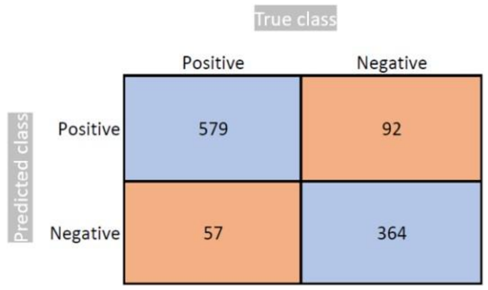
```
Epoch 90/100
88/88 [==============================] - 1s 15ms/step - loss: 0.1085 - accuracy: 0.9574 - val_loss: 0.4601 - val_accuracy: 0.8581
Epoch 91/100
88/88 [==============================] - 1s 14ms/step - loss: 0.1285 - accuracy: 0.9515 - val_loss: 0.4551 - val_accuracy: 0.8498
Epoch 92/100
88/88 [==============================] - 1s 15ms/step - loss: 0.1185 - accuracy: 0.9549 - val_loss: 0.4068 - val_accuracy: 0.8626
Epoch 93/100
88/88 [==============================] - 1s 15ms/step - loss: 0.1105 - accuracy: 0.9528 - val_loss: 0.4327 - val_accuracy: 0.8581
Epoch 94/100
88/88 [==============================] - 1s 14ms/step - loss: 0.1240 - accuracy: 0.9515 - val_loss: 0.3709 - val_accuracy: 0.8791
Epoch 95/100
88/88 [==============================] - 1s 14ms/step - loss: 0.1164 - accuracy: 0.9549 - val_loss: 0.4792 - val_accuracy: 0.8544
Epoch 96/100
88/88 [==============================] - 1s 14ms/step - loss: 0.1230 - accuracy: 0.9517 - val_loss: 0.4216 - val_accuracy: 0.8571
Epoch 97/100
88/88 [==============================] - 1s 15ms/step - loss: 0.1251 - accuracy: 0.9485 - val_loss: 0.4879 - val_accuracy: 0.8581
Epoch 98/100
88/88 [==============================] - 1s 14ms/step - loss: 0.0987 - accuracy: 0.9620 - val_loss: 0.4601 - val_accuracy: 0.8718
Epoch 99/100
88/88 [==============================] - 1s 14ms/step - loss: 0.1156 - accuracy: 0.9542 - val_loss: 0.4579 - val_accuracy: 0.8489
Epoch 100/100
88/88 [==============================] - 1s 15ms/step - loss: 0.1135 - accuracy: 0.9556 - val_loss: 0.4165 - val_accuracy: 0.8636
```

[Fig.12: 1D -CNN Training Details]

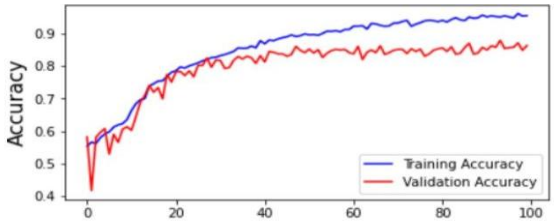
Table 4: 1d-CNN Validation Results

1D CNN Testing results		
Sl.No	**Evaluation Parameter**	**Percentage**
1	Accuracy	86.00
2	Recall	91.00
3	Precision	91.6
4	F1-score	89.00

Discriminating SZ subjects from Healthy control subjects. The confusion matrix for the validation data is shown in figure 13. Figure 14 shows a graph that shows the deviation between training and validation accuracies. Since the deviation is small, we can say that the proposed model is not over-fitting.



[Fig.13: Confusion Matrix Obtained for 1D-CNN]



[Fig.14: Training Vs Test Accuracy Plot of 1D CNN]

V. CONCLUSION

This study compares two techniques for identifying schizophrenia from EEG waves. In the first technique, histogram features were extracted after a local binary pattern was computed from the EEG signals of both schizophrenia patients and healthy controls. The classification learner toolbox in MATLAB was then used to classify a feature matrix that had been created. K-Nearest Neighbor with Medium Kernel emerged as the top classifier among several cutting-edge machine learning classifiers, outperforming the others with an overall accuracy of 83.33%. The second technique used empirical mode decomposition to analyze the non-stationary, non-linear, and non-stationary EEG signals and derive time- frequency information. A characteristic known as differential entropy was taken out of the intrinsic mode functions that were created as a result of performing EMD. The popular deep learning model, the convolutional neural network, is then used to classify the output feature matrix. Being a 1D signal, the EEG is classified using a 1D CNN. The Overall accuracy for the proposed CNN classifier was 86%, which was a solid performance. The results show that the second method performed better than the first. Therefore, we may conclude that empirical mode decomposition can concurrently extract local spectral and temporal information from non-stationary EEG signals, and CNN outperforms K-nearest neighbor classifier on the datasetchosen for this study.

A. Future Scope

The inter subject variability is present in EEG data. Even though the proposed classifier works well on the selecteddata, it may not work well when we test the model usinga different dataset. Therefore, a subject independent study will be more helpful otherwise poor generalization of the classifier model across subjects will be the consequences. Hence in future we would like to extend the research to develop a subject independent classifier for schizophrenia detection.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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