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Different Approaches for the Detection of Epilepsy and Schizophrenia Using EEG Signal Analysis

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Abstract - *Electroencephalogram (EEG) data can be used to extract information using machine learning and deep learning methods. The research is primarily concerned with how they might be used to identify mental illnesses like schizophrenia and epilepsy. We present two methods for diagnosing epilepsy, the first approach is to utilize the Welch power spectral density for feature extraction and multiple classifiers (Kernel SVM, Naive Bayes, Random Forest) for the classification approach using the datasets offered by the Zenodo organization. We also present a different method called ChronoNet (second approach), in which each 1D convolution layer makes use of numerous filters with progressively longer durations. The next phase involves stacking layers of feed-forward-connected deep gated recurrent units (GRUs) on top of one another. When applied to the data from the Temple University Hospital EEG Corpus using the Keras framework, the suggested ChronoNet design (with five 1D convolution layers of varying filter size) produced an accuracy of roughly 97.20%. Using the data from the Repository for Open Data for EEG in Schizophrenia, we present two methods for diagnosing schizophrenia here. While the second method uses Keras to generate a Convolutional Neural Network (CNN), the first method extracts features using extractors including mean, standard deviation, kurtosis, skewness, and root mean square as well as Logistic Linear Regression Classifier. For epochs = 10, we were able to attain a maximum accuracy of 85.11% in the instance of schizophrenia for the second approach.*

***Key Words*: EEG, Welch Power Spectral Density, ChronoNet, schizophrenia, epilepsy, Keras.**

1. INTRODUCTION

A person's life may be seriously in danger as a result of an epileptic seizure. The neurological disorder known as epilepsy is brought on by the improper discharge of brain neurons. The most important tool for the diagnosis of epilepsy is the Electroencephalogram (EEG), which demonstrates how epileptic seizures manifest as distinct, typically rhythmic signals that frequently precede or coincide with the initial observed changes in behavior. Schizophrenia is a mental illness that causes a variety of challenges with daily activities. People with schizophrenia have hallucinations, delusions, and a disconnection from reality. A person's mental capabilities and overall behavior suffer from schizophrenia. A non-invasive, cost-effective method of assessing someone's brainwave activity is the electroencephalogram (EEG).

Due to the immense labor involved in identifying seizures by human experts and the large number of epilepsy patients, numerous attempts have been made to develop automatic seizure detection systems. Four methods are used to identify seizures, with the best classification results being produced by random forest (RF), decision tree (DT) algorithm C4.5, SVM+RF, and SVM+C4.5[1]. Estimated entropy and sample entropy obtained by WPD are used as features, while SVM and extreme learning machine are employed as classifiers, in [2] for the goal of detecting epileptic episodes. In order to minimize the number of variables, WPD and kernel PCA (KPCA) are also utilized in [3]. Due to exceptional achievements [4-5], deep learning techniques, particularly CNNs, have recently garnered substantial attention in the field of EEG signal processing.

Schizophrenia has a variety of symptoms, including formal mental illnesses and disruptions in thought flow or sequence. In terms of risk factors, complications, clinical manifestations, course, response to treatment, and functional result, schizophrenia is a severe and complicated mental condition. It currently ranks as one of the major causes of disability worldwide, affecting a lot of people. In the analysis of EEG signals in schizophrenia patients, classification is an important goal. The effectiveness of first-generation entropy measures, including approximate (ApEn), sample (SampEn), and fuzzy entropy (FuzzyEn), in terms of the classification of EEG signals is calculated [6]. The accuracy of the classification of the healthy and schizophrenic patient was assessed using Support Vector Machines (SVMs), Decision Trees, k-Nearest Neighbor Classifiers, Random Forest Classifier Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) in the feature classification state [7].

This study provides two comparative analyses: first one is to discriminate between healthy and epileptic patients (using two methodologies) and the second one is to differentiate between healthy and schizophrenic patients (utilizing two methods).

The first comparison analysis presented in this paper is to distinguish between healthy and epileptic individuals utilizing two approaches. The first method involves categorizing epileptic seizures using features extracted in the frequency domain from the Welch power spectral density. The mean, standard deviation, minimum value, and maximum value of the epoch signal fluctuations were measured using the datasets available from zenodo organization. These measurements were used to train a classifier (kernel SVM, Random Forest, Naive Bayes, Decision tree) to calculate its accuracy, loss, confusion matrix, sensitivity, and specificity. In terms of the Nigerian data, kernel SVM provides the highest levels of accuracy among the classifiers which is significantly higher than the accuracy of the relevant work [8]. The second approach uses a novel recurrent neural network (RNN) architecture named ChronoNet. We implemented five convolutional layers in the ChronoNet, which improves accuracy (97.20%) in Keras by roughly 6.2% more from a related work [9] drawing ideas from 1D convolution layers [10] gated recurrent units [11], inception modules [12], and densely linked networks [13]. In this study, we compared the accuracy rates of these two techniques involved in Approach I (Differentiating between Epileptic and Healthy People).

The study also presents a comparative assessment to distinguish between healthy and schizophrenic patients using two approaches: one is used to extract frequency domain features (using feature extractors like mean, standard deviation, kurtosis, skewness, and rms) and a variety of classifiers (Logistic Linear Regression, Gradient Boosting Classifiers), and the other makes use of deep convolutional neural networks (CNN) in the Keras framework. When subject base testing was conducted using our model with a 15-layered deep CNN model, we were able to reach a maximum accuracy of 85.11%, which is about 4% better than the work that was done previously [7].

2. APPROACH I: CLASSIFYING EPILEPSY USING THE WELCH POWER SPECTRAL DENSITY AND CHRONONET

2.1 Method I: Welch Power Spectral Density

In total, 212 Nigerians took part in the survey. In the dataset, there were 112(Males→67, Females→45) epileptic seizure prone patient while 92(Males→67, Females→25) people were healthy. The fourteen-channel EEG has a resolution of 16 bits and a sample rate of 128 hertz. The subjects were divided into two groups: Control (subjects who were in good health) and Epilepsy (subjects who were prone to epileptic seizures). Fig. 1 shows the EEG signal and power spectral density of one participant having an epileptic seizure. The electrode position corresponds to the global 10-20 system. The epochs' lifespan was set to ten and training-testing ratio is 80:20.

Features that correspond to various epochs within an individual were used in the analysis as input for the categorization model. The Welch Power Spectrum method contributes to the classification model's feature extraction. Four classifiers' output parameters were evaluated in comparison (Kernel SVM, Random Forest, Decision Tree, Naive bayes). The three variables considered in the performance evaluation of the suggested work are as follows: [14,15]:

Accuracy=(TN+TP)/(TP+TN+FN+FP)

Sensitivity = TP/(TP+FN)

Specificity= TN/(TN+FP)

F1 Score: The F1-score, is a measure of a model's accuracy on a dataset.

F1 Score=$(2*(Recall*Precision))/((Recall+Precision))$

Where, TP = true positive

FN = false negative,

FP = false positive

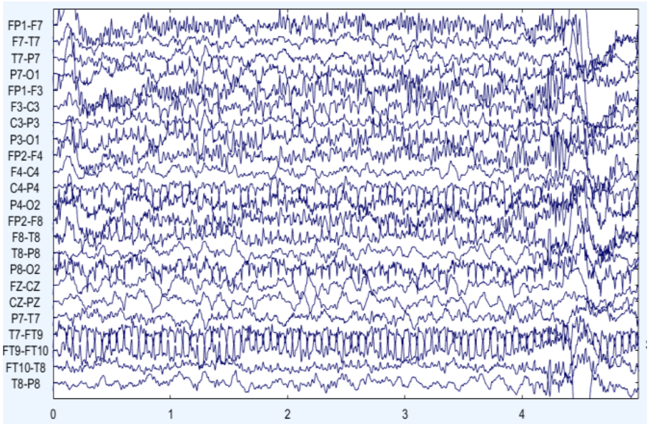
TN =true negative

The proportion of accurately identified seizure time periods to non-seizure time periods is considered accuracy. Sensitivity assesses how well seizures are recognized over time. The percentage of correctly identified non-seizure segments is what is meant by "specificity." A classifier with a high level of specificity can quickly identify segments that are seizure-free. The flowchart in Fig. 2 displays this method. The values of the aforementioned parameters for the different classifiers used on the Nigerian dataset are shown in Table 1. The ROC curve (receiver operating characteristic curve) represents the model's overall performance.

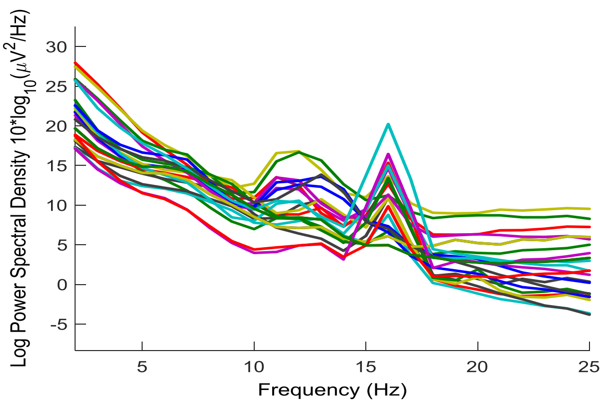
A ROC curve is shown along with the value of AUC (Area Under Curve) for the best performing classifier in Fig. 3.

Five-fold cross validation is used here for the validation purpose. Five-fold accuracies [0.99198026,0.99198026, 0.99136336 0.99136336,0.99136336]. The average accuracy is 0.9916101172115978 for Nigerian Data in case of Kernel SVM.

V.T. Van Hees et.al.[8] extracted each wavelet levels of Theta (4–8 Hz), delta (1-2 Hz), delta (2-4) Hz, alpha (8–16 Hz), beta (16–32 Hz), and gamma (32–64 Hz) using the Random Forest Classification approach. They were only able to categorize Nigerian data with an accuracy of 0.78% (0.02 standard errors), but our method produced accuracy results of 99.16%, 98.49%, and 98.28% using Kernel SVM, Random Forest, and Decision tree, respectively.



(a)



(b)

Fig -1: (a) The EEG signal, (b) Power Spectral Density of one epileptic subject

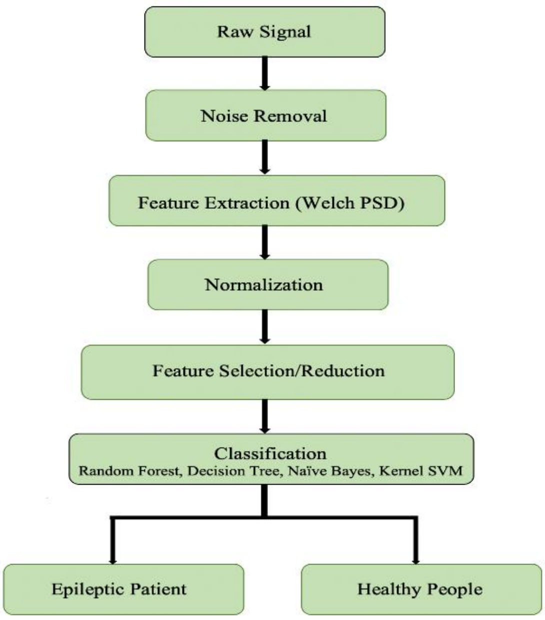


Fig -2: Flow chart of the Approach I (Power spectral density method)

Table -1: Performance Parameters for Nigerian data

Classifier	Accuracy (%)	Sensitivity (%)	F-1 Score (%)	Precision (%)
Random Forest	98.48	99.15	99.24	99.32
Decision Tree	98.37	99.04	99.18	99.32
Naive Bayes	72.23	**99.76**	83.75	72.17
Kernel SVM	**99.16**	99.16	**99.58**	**1.00**

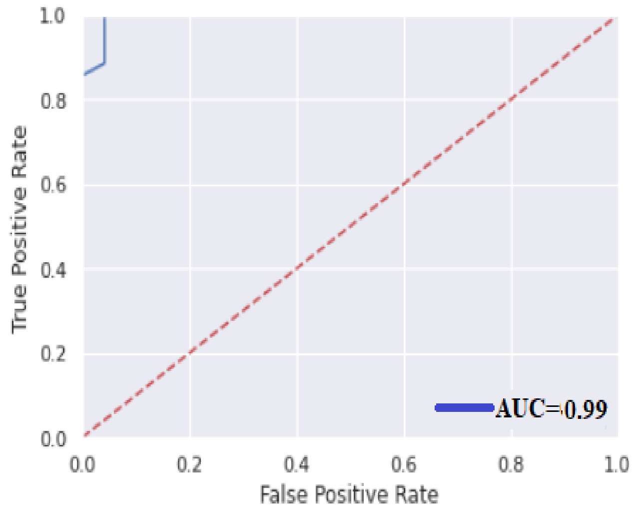


Fig -3: ROC curve with AUC value for Kernel SVM

2.2 Method II: Configuration of Proposed ChronoNet

The TUH EEG Corpus contains 23257 EEG recordings from 13551 patients [16]. In the overall dataset, 73% of the EEG data points could be assigned to abnormal sessions. A demographically balanced subset of the TUH EEG Corpus was hand-selected to establish the TUH EEG Abnormal Corpus. This subgroup consisted of 1529 normal EEG sessions and 1488 aberrant EEG sessions, the bulk of which were recorded at a sampling rate of 250 Hz. The training set contained 1190 abnormal and 1223 normal data, and the test set contained 298 abnormal and 306 normal data as a result of further splitting. Filtering the raw data and removing all non-eeg signal allowed for extremely accurate results.

Inception layers with exponentially rising kernel lengths are used with densely coupled recurrent layers to produce 1D convolution layers. In this study, GRUs are utilized in place of LSTMs since they require fewer parameters and enable faster generalization with the same amount of data. The inception module makes use of filters of various sizes as opposed to standard convolutional neural networks, which use a single, uniformly sized filter in a convolution layer to capture features [17]. The following conventions are used throughout the paper to define Conv1D and GRU layers: (layer name, filter length, number of filters, stride size) and (layer_name, number of filters).

The input/first layer of the method is (20000, 22), where 20000 is the length of the signal and 22 is the number of channels. Five convolution layers receive the Input Layer as input. Each layer has a different kernel size (2,4,8,32,64), and each layer has the same number of filters and strides (32,2). Each convolution layer's output is merged so that, when combined, each layer generates an output channel of 32 and receives 160 channels. Five concatenation layers are created after the first concatenation by repeating the structure. We have four GRU layers after this block. The fifth Concatenation Layer provides input to the first GRU layer, which then outputs to the second GRU layer. The outputs of the first and second GRU levels are then combined. The output of the third GRU layer is (625,32). When the activation function was ultimately built, the output of the third GRU layer was concatenated with the outputs of the first and second GRU layers.

Table 2 displays the suggested ChronoNet Model's description. A band pass filter with a bandwidth of 1–30 Hz and a sampling frequency of 128 Hz was used to filter the EEG data. For the five-convolution layer, the "relu" activation function was used. Because the GRU layer is binary, we used the "sigmoid" activation function. The model was then trained using the parameters optimizer = "adam," loss = "binary cross entropy," and metrics = "accuracy" using the keras Framework. The Splitting of training and testing is 80:20 for this approach. The accuracy after fitting the model is 97.20%, whereas Roy S. et. et al. [17] used linearly varying filter lengths of 3, 5, and 7 in a 1D convolution layer to produce an approximate 89.15% accuracy during training. Five-fold Cross Validation is utilized to validate the proposed ChronoNet Model. Table 3 shows the values of the performance parameters for the ChronoNet configuration. Fig. 4 shows the ROC curve with AUC value for the proposed ChronoNet Model. Table 4 shows the Comparison of the Accuracy for Different Configuration of ChronoNet Method.

Table -2: Parameter details of each layer of the proposed ChronoNet model

Name of Layers	**Output Shape**	**Kernel Size**	**Stride**
Input Layer	20000×22	-	-
Convolution layer (conv1d_1 - conv1d_5)	10000×32	2,4,8,32,64	2
Concatenation Layer 1 (Concatenating five conv1d (1-5) layer)	10000×160	-	2
Convolution Layer (conv1d_6-conv1d_10)	5000×32	2,4,8,32,64	2
Concatenation Layer 2 (Concatenating five conv1d (6-10) layer)	5000×160	-	2
Convolution Layer (conv1d_11-conv1d_15)	2500×32	2,4,8,32,64	2
Concatenation Layer 3 (Concatenating five conv1d (11-15) layer)	2500×160	-	2
Convolution Layer (conv1d_16-conv1d_20)	1250×32	2,4,8,32,64	
Concatenation Layer 4 (Concatenating five conv1d (16-20) layer)	1250×160	-	2
Convolution Layer (conv1d_21-conv1d_25)	625×32	2,4,8,32,64	2
Concatenation Layer 5 (Concatenating five conv1d (21-25) layer)	625×160	-	2
GRU_1	625×32	-	-
GRU_2	625×32	-	-
Concatenation Layer 6 (Concatenating GRU_1 and GRU_2 layer)	625×64	-	-
GRU_3	625×32	-	-
Concatenation Layer 7 (Concatenating GRU_1, GRU_2 and GRU_3 layer)	625×96	-	-
GRU_4	32	-	-
Dense	1	-	-

Table-3: Performance parameters for the ChronoNet Method

Method name	**Accuracy (%)**	**Sensitivity (%)**	**PPV (%)**	**F1 Score (%)**
ChronoNet Model	97.2	97.78	95.65	96.70

Fig -4: ROC curve with AUC value for the proposed ChronoNet Model

Table-4: Comparison of the Accuracy for Different Configuration of ChronoNet Method

No. of Convolutional Layer (conv 1d)	No. of Blocks	No. of Epochs	Batch Size	Accuracy (%)
5	5	120	12	97.2(±0.02 standard errors)
8	8	120	12	33.33(±0.03 standard errors)
6	6	100	10	95.56(±0.04 standard errors)
6	6	50	8	93.33(±0.03 standard errors)
6	6	80	5	94.44(±0.01 standard errors)

2.3 Comparison Between the Methodology

In this study, two techniques were used to determine if a patient was seizure-prone or not. The suggested ChronoNet model was more stable for any type of data than the first method since it highlighted the most important aspects of the data. While different classifiers were suitable for different types of data, a proposed ChronoNet design that addresses the issue of training accuracy loss brought on by disappearing or expanding gradients incorporates several filters with exponentially variable lengths in the 1D convolution layers and dense connections in the GRU layers. The significant differences between the performance metrics of the two approaches are shown in Fig.5 (comparison between ChronoNet and PSD+Kernel SVM/Naïve bayes is shown to exhibit the novelty of the proposed ChronoNet model).

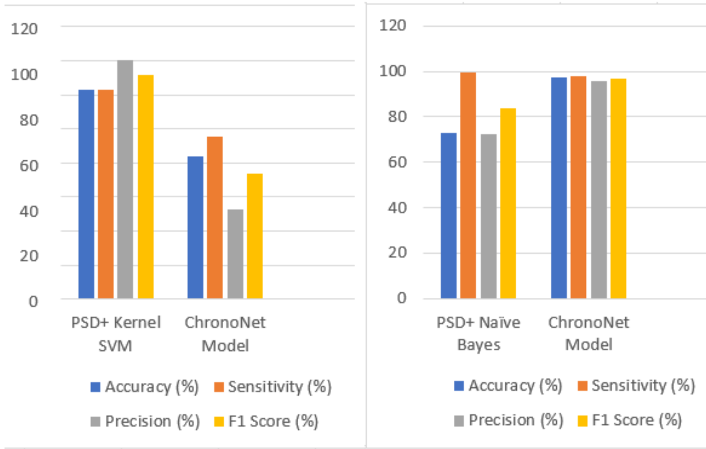


Fig -5: Significant differences between the performance metrics of the two approaches for detecting Epilepsy

3. APPROACH II: CLASSIFYING SCHIZOPHRENIA USING LOGISTIC LINEAR REGRESSION AND DEEP CNN

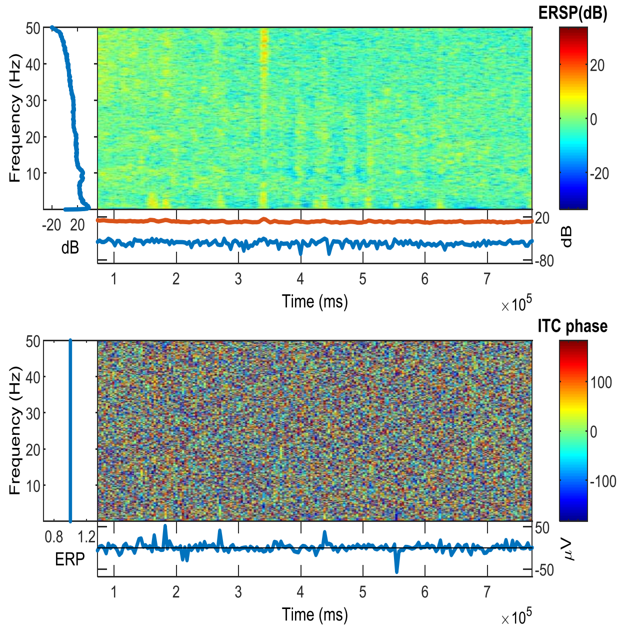
3.1 Method I: Logistic Linear Regression

14 paranoid schizophrenia patients and 14 healthy controls participated in the study. 19 EEG channels (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, T4, T5, P3, Pz, T4, T6, O1, O2) were used in the typical 10- 20 EEG montage to gather the data at a sampling rate of 250 Hz. The duration of the epochs was set to 25. The feature extractors (mean, standard deviation, kurtosis, root mean square, skewness, etc.) were utilized to extract the valuable data from the dataset. The features have then all been concatenated to create a list of feature sizes (1142, 228). 12 (228/19) features from the list were received. The Training and testing ratio is 70:30 for this approach.

A logistic regression model is applied to the data after it has been scaled for classification. Grid-SearchCV (CV=10) and 10-fold cross validation are combined to improve the performance of the model. After fitting the model, it gives an accuracy of 69.8% which is approximately 15% better than the related work [18] for the 10-fold cross validation. The event related spectral perturbation (ERSP) is shown in Fig. 6 for the clear understanding of the healthy people and schizophrenia patient. The Flow chart of the suggested method is shown in Fig.7.

3.2 Method II: Deep CNN Model

The pre-processing part for the method II is same as the method I for determining schizophrenia as we have used the same dataset. The parameters for the proposed 15-layer Deep CNN model is shown in Table 5. Next, we used optimizer = "adam," loss = "binary cross entropy, "and metrics = "accuracy" to train the model. We have used the "sigmoid" activation function. Splitting of training and testing is selected as 80:20 for this approach. After training the model, we set the batch size =10 and Epochs =10. To validate the proposed Deep CNN model, Five-fold cross validation is used here. We achieved a maximum accuracy of 85.11%, which is better than the work that was done previously [7,18].



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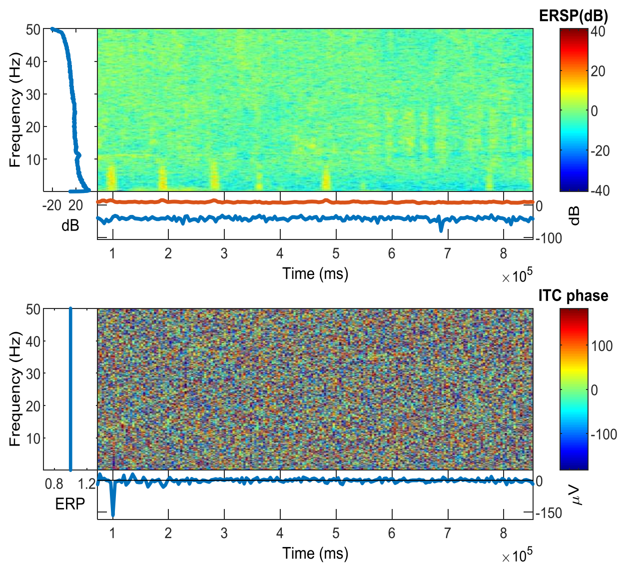

(b)

Fig -6: The event related spectral perturbation (ERSP) of the (a)schizophrenia patient and (b) healthy people

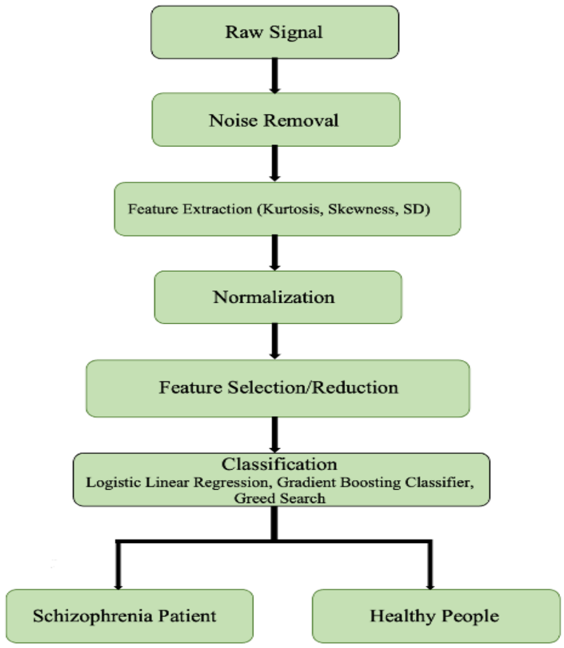

Fig -7: Flow chart of the Approach I (Logistic Linear Regression method)

Table-5: Parameter details of each layer of the proposed CNN model

Layers	**Name of Layers**	**Output Shape**	**Kernel/Pool Size**	**Stride**
1	Convolution	6248×5	3	1
2	Max Pooling	3124×5	2	2
3	Convolution	3122×5	3	1
4	Max Pooling	1561×5	2	2
5	Convolution	1559×5	3	1
6	Max Pooling	779×5	2	2
7	Convolution	777×5	3	1
8	Average Pooling	388×5	2	2
9	Convolution	386×5	3	1
10	Average Pooling	193×5	2	2
11	Convolution	191×5	3	1
12	Average Pooling	95×5	2	2
13	Convolution	93×5	3	1
14	Global Average Pooling	5	-	-
15	Dense	1	-	-

3.3 Comparative Analysis between the two methodologies

Two methods were illustrated for determining schizophrenia. Among the two methods, Deep CNN performed better than the method using logistic linear regression. If we increase the number of convolutional layers, the proposed Deep CNN Method provides better accuracy along with a trade-off between filter size and kernel size. The significant differences between the performance metrics of the two approaches for the detection of schizophrenia is shown in Fig.8.

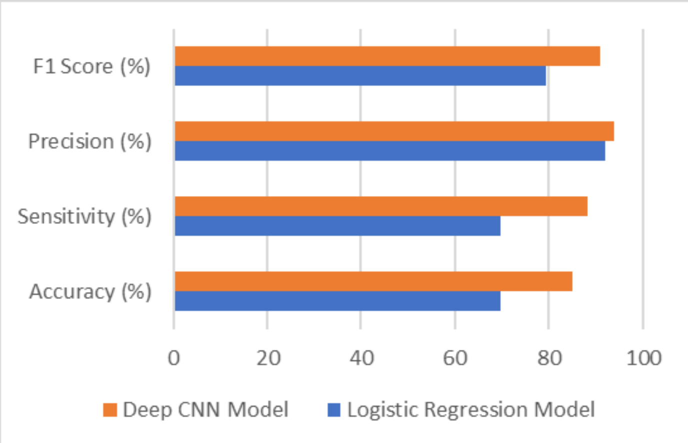

Fig -8: The significant differences between the performance metrics of the two approaches for the detection of schizophrenia patient

4. COMPARISON OF THE PERFORMANCE PARAMETERS WITH THE EXISTING WORKS

Two Comparison tables (Table 6 and 7) are shown in this section to exhibit the novelty of the work with the existing works. To make it clear, a fair comparison is made with the existing works for detecting Epilepsy (Approach I) using Proposed ChronoNet Method in Table 6, while Table 7 is drawn to show the comparison of the proposed Deep CNN network for detection of Schizophrenia patient with the relevant works.

Table -6: Comparison chart of the related works with the proposed model (ChronoNet Model for Detecting Epileptic Patient)

Network	Layer	Classifier	Dataset and validation	Accuracy (%)
Deep Gated RNN network [17]	14	SoftMax	TUH EEG 5-fold cross validation (CV)	89.15
1D-CNN [19]	23	SoftMax	TUH EEG 10-fold CV	79.34
1D-CNN [20]	15	SoftMax	CHB-MIT Train, Test validation	84
1D CNN-LSTM [21]	7	Sigmoid	TUH EEG 30-fold CV	89.73
Deep CNN and bidirectional LSTM [22]	-	SoftMax	SEED and DEAP dataset 10-fold CV	SEED:81.54 DEAP:72.38
CNN inspired by FBCSP [23]	15	SoftMax	CHB-MIT dataset 5-fold stratified CV	90.9
Proposed Work ChronoNet	18	Sigmoid	TUH EEG dataset and 5-fold CV	97.20

Table -7: Comparison chart of the related works with the proposed model (Proposed CNN Model for Detecting Schizophrenic Patient)

Networks	Classifier	Dataset and validation	Accuracy (%)
Analysis of EEG signal in Schizophrenia Detection [7]	SoftMax	RepOD for EEG in Schizophrenia 5-fold cross validation (CV)	81.5
Discriminant Deep Learning with Functional Connectivity MRI [24]	SoftMax	Multi-site fcMRI raw dataset 1-fold CV	81 (leave-site-out transfer classification)
Deep neural network layer-wise relevance Propagation [25]	SoftMax	Resting-state fMRI dataset 10-fold CV	82
Multimodal Multivariate Pattern Recognition Analysis [26]	-	Mind Research Network COBRE 20-fold CV	Maximum accuracy= 75
Deep Learning Using fMRI [27]	SoftMax	Mind Research Network COBRE 10-fold CV	84.3
Convolutional neural network [28]	Sigmoid	National Institute of Standards and Technology (NIST) 5-fold stratified CV	Maximum accuracy = 70
Proposed Work: Deep CNN Network (For Detecting Schizophrenia)	Sigmoid	RepOD for EEG in Schizophrenia 5-fold CV	85.11

5. CONCLUSION

An EEG's ability to detect abnormal brain activity is often the first step in diagnosing a neurological disorder. Since manual EEG interpretation is a costly and time-consuming activity, any classifier that automates this first distinction will have the ability to shorten treatment periods This study employed two methods for identifying epileptic patients and schizophrenia from healthy ones. Although the first method (welch spectral density) gives a very high accuracy than ChronoNet for Epilepsy classification, The latter one provides stable result for all type of data. The Deep CNN Model outperforms the method involving logistic Linear Regression for detecting schizophrenia patient.

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