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A Generic Approach for Classification of Psychological Disorders Diagnosis using EEG

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Abstract— **Electroencephalogram (EEG) is a widely used technique to diagnose psychological disorders. Until now, most of the studies focused on the diagnosis of a particular psychological disorder using EEG. We propose a generic approach to diagnose the different type of psychological disorders with high accuracy. The proposed approach is tested on five different datasets and three psychological disorders. Electrodes having higher signal to noise ratio are selected from the raw EEG signals. Multiple linear and non-linear features are then extracted from the selected electrodes. After feature selection, machine learning is used to diagnose the psychological disorders. We kept the same generic approach for all the datasets and diseases and achieved 93%, 85% and 80% F1 score on Schizophrenia, Epilepsy and Parkinson disease, respectively.**

I. Introduction

One in five U.S. individual suffers from mental illness each year. Epilepsy, Schizophrenia and Parkinson have the highest prevalence among the psychological disorders. A person suffering from one psychological disease is at a higher risk of comorbidity. A recent study showed that individuals with epilepsy are at eight times more risk to suffer from schizophrenia as compared to an individual with no epilepsy. Similarly, people with schizophrenia are six times more likely to develop epilepsy. The same study showed found that approximately 63.8 million, 19.8 million, 8.5 million individuals suffered from Epilepsy, Schizophrenia and Parkinson, respectively [1]. Clinicians diagnose these disorders by observing patient response to generic questions. This manual way of diagnosis sometime leads to false positives [2], [3].

Different researchers had tried to overcome this misdiagnosis by using electroencephalogram (EEG) technology which captures the brain signals. Multiple statistical and artificial intelligence base studies ranging from event related potential (ERP), time frequency analysis to deep convolution neural networks (CNN) have been carried out to study the patterns in EEG signals for identifying the disease. V.T. van Hees et al. acquired signal for 5 minutes to identify epilepsy from two difficult-to-reach areas in rural Guinea-Bissau and Nigeria. The diagnosis accuracy in Guinea-Bissau and Nigeria area was 83% and 70% respectively [4]. Zhang diagnosed schizophrenia by combining EEG and Non-EEG features such as age, education etc and achieved an accuracy of 81% [5]. Jahmunah et al. used 157 non-linears features and SVM classifier to classify schizophrenia. They obtained an accuracy of 93% and their study is based on trial wise classification [6]. Li OH et al. used the same dataset and achieved an accuracy of 81% with subject wise classification using CNN [7]. Cavanagh et al. obtained 82% accuracy by carrying out ERP analysis to identify Parkinson disease from EEG signals using SVM.

All these techniques work for a particular dataset and disease and the methodology used for one data when implemented on other data resulted in poor performance as compared to the methodology made specifically for that data.

Some techniques are not applicable on other datasets such as ERP technique cannot be used to study non ERP data. We implemented these methodologies on different datasets. We obtained the same performance as in the original study but the results were poor when the technique is implemented on another related dataset. In this study, we proposed a generic technique that can work on multiple datasets and diseases. Using this technique, we achieved an F1 score of 93%, 85% and 80% on Schizophrenia, Epilepsy and Parkinson disease, respectively.

II. Methodology

A. Dataset

There are five datasets used in this study to ensure the validity of the proposed approach. Two of them are schizophrenia datasets, two are epilepsy datasets, and one is related to Parkinson disease. The proposed methodology takes each dataset and classifies the control and patient group of that dataset. The number of subjects (normal and abnormal), number of electrodes and sampling frequency of all five datasets are given in table I.

Schizophrenia dataset I (SzI) [8] was collected with three different audio stimuli. In each stimulus, 100 trials each of 3 seconds were collected. The three stimuli were as follow.

- Stimulus I (SzI SI): Subject pressed the button to generate an audio tone
- Stimulus II (SzI SII): Subject listened to previously generated tone without pressing the button
- Stimulus III (SzI SIII): Subject pressed the button, but no tone is generated.

Schizophrenia dataset II (SzII) [9] was comprised of 28 subjects. There is no stimulus involved in collecting data.

Epilepsy dataset 1 & 2 [4] datasets were collected using EMOTIVE with the 128 Hz sampling frequency. Epilepsy I (EpI) dataset was collected in GuineaBissau (97 subjects). Epilepsy II (EpII) dataset was measured using the same protocol in Nigeria (112 subjects).

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TABLE I: Dataset description

Datasets	Subjects	Age	Elec	Fs
SzI	Normal 32 Patients 51	Normal:38.37 ±13.69, Patient: 40.00 ±13.48	64	1024
SzII	Normal 14, Patients 14	Normal:27.75, Patient: 28.10	19	256
EpI	Normal 46, Patients 51	Normal: 25±8, Patient :25±13	14	128
EpII	Normal 92, Patients 112	Normal: 21±12, Patient :20±8	14	128
PD	Normal 25, Patients 25	Normal:69.32±9.58, Patient 69.68±8.73	60	500

SZ I and II: Schizophrenia dataset I and II, Ep I II: epilepsy dataset I and II, PD: Parkinson dataset. Elec: Number of electrodes, Fs: sampling frequency in Hz

Parkinson dataset (PD) [10] was comprised of 50 subjects. Oddball paradigm approach was applied while collecting this data.

B. Filtering

Each dataset is filtered using a band-pass filter. The low-cut and high cut frequency is different for each dataset as the amount of noise, and frequency range for the disease varies in each dataset. For schizophrenia I dataset, low and high frequency are set to 0.1 Hz and 60 Hz respectively. For schizophrenia II dataset, filtering is performed within a range of 0.1 to 45 Hz. Both epilepsy datasets are filtered within a range of 0.3-30 Hz. Parkinson dataset is filtered with a frequency range of 0.1-60 Hz.

C. Electrode selection

Most diseases only affect a specific part (location) of the brain. Studies show that in case of schizophrenia prefrontal and medial temporal lobes regions are most commonly affected [11]. Changes in basal ganglia, cerebellum, thalamus and hypothalamus are observed in Parkinson disease in multiple studies [12]. Therefore, the selection of brain area for signal acquisition is very important for each disease. For this purpose, we proposed an approach for electrode selection for the disease datasets. Instead of choosing the best electrodes manually, electrodes are selected on the basis of a variance threshold. Low variance electrodes are dropped, and only high variance electrodes are kept. This method increases the performance while simultaneously decreasing the computation time.

First, principle component analysis is used to find the number N of electrodes that contained 95% of the variance. Once number N is obtained using PCA, the top N most variate electrodes are selected across all subjects of data. Resultantly, we retain original EEG data instead of principle components, as top N variate electrodes are picked instead of principle components. Retaining the original data is required to extract suitable EEG features which might not be the case when PCA components are used.

D. Feature extraction

Pre-processed data is segmented into epochs of 4 seconds in case of non ERP data and original trial length is kept in case of ERP data. Twenty-six linear and non linear features including statistical features, time and frequency domain features entropy features, Hjorth parameters etc are calculated. Some of the important features are shown in table IV.

E. Feature selection

Forward feature selection approach is used for feature selection. First, the features are sorted based on accuracy using linear SVM owing to its low time complexity. We start adding features until adding a feature does not help in the improvement of the performance.

F. Classification

Different machine learning classifiers are used for classification such as RBF kernel, support vector machine (SVM), logistic regression (L.R.), K nearest neighbor (KNN) and decision trees (DT). Grid search technique is used to tune the hyper-parameters of these classifiers. Five fold cross validation is applied to mitigate over-fitting issue. Four folds are used for feature selection and model training and the fifth fold is used for testing. This process is done five times in such a way that there is no data leakage. Grid search technique from python scikit-learn is used perform hyper-parameter tuning in four folds and tuned model is used to test the fifth fold of data.

G. Simulated noise

To check the robustness of our methodology, we added noise to the dataset before filtering the data. We experimented by adding 10% and 20% noise to the data. We assume that the noise distribution is same as signal distribution, so we take the mean and standard deviation of the data as the mean and standard deviation of the noise [14].

III. Results

First we implemented the papers discussed in introduction section on different dataset. Table II shows the results of replicated methodologies. Zhang [5] used demographic features so methodology used to classify schizophrenia I dataset cannot be used to classify disease when demographic dataset is not available. Similarly Parkinson data is ERP data and ERP technique cannot be implemented on non ERP data. Slight modifications is made in methodology to overcome the difference in number of channels. For example in SZII dataset, there are 19 channels, but in epilepsy dataset there are 14 channels, so number of channels in CNN is reduced from 19 to 14. We observed that the performance of technique used in epilepsy and schizophrenia II dataset deteriorate significantly on other datasets. To handle this issue, we proposed a simple generic approach to classify different psychological disorders. After filtering, the first step is to

TABLE II: Accuracy achieved in cross implementation

Data	Base	Our	SZ I	SZ II	Epilepsy	Parkinson
SZI	81.1%	81.5%	No demographic data			
SZII	81.6%	80 %	63%	Base	67%	62%
Ep	70%	71%	60%	72%	Base	70%
PD	82%	80%	ERP Study			

TABLE III: Electrodes selected based on the magnitude of variance

Data	Slct/tot	Electrodes
SzI SI	10/64	**AF3, AF4, AF7, AF8, AFz**, Fp1, **AFp2, Fpz**, Fz, and Pz.
SzI SII	12/64	**AF3, AF4, AF7, AF8, AFz**, Fp1, **AFp2, Fpz**, Fz, F3, F4, and F6.
SzI SIII	15/64	**AF3, AF4, AF7, AF8, AFz,Fp2, Fpz** CP1, CP3, CPz, C1, C3,Cz, FC1, FCz.
SzII	9/19	F8, Fz, F7, P4, Pz, Fp1, O2, Fp2 and T5
EpI	8/14	**AF3, O2, F4, FC6, T8, AF4, F8 and P8**
EpII	10/14	**AF3, O2, F4, FC6, T8, AF4, F8, P8,** F7, FC5
PD	30/64	F4, TP8, POz, CP1, C3, FC5, FC3, T8, PO3, CP5, PO7, T7 F3, F5, F8, FC1, C1, F2, P6, TP7, C2, P1, F6, AF4, AF8, Fp2, AFz, AF7, Fp1, AF3

Slct/tot: Selected electrodes/total number of electrodes. Bold electrodes shows that similar equipment and data collection procedure for a particular disease show similar position of important electrodes.

select the best electrodes from the data based upon variance of the electrodes. Table III shows the selected electrodes for each dataset. As there are different conditions/stimuli in schizophrenia I dataset, so for each stimuli electrodes are selected separately. The bold value in schizophrenia I dataset shows that with same device under different stimuli, most variant electrodes remain similar. Similarly in the epilepsy datasets, electrodes are common even when data is collected from two different countries. Therefore, using same equipment having same frequency for a particular disease, the best electrodes remain similar.

To check the importance of individual features we trained a linear SVM classifier using each feature alone. Table IV shows the accuracy of individual features for all datasets. Hjorth complexity, Hjorth mobility, kurtosis, permutation entropy, Katz and Petrosian fractal dimension, sample entropy, root mean square, standard deviation, variance and zero crossing are the features which show high accuracy in at least 3 datasets. We found that features more related to variance worked well such as standard deviation (root of variance), Hjorth mobility which is the variance of first derivative divided by the variance of signal. Similarly, Hjorth complexity which reflect changes in frequency; is the ratio of first derivative of mobility and mobility of signal also worked well. Entropy based features were also selected as final features for classification. Approximate entropy is the measure of complexity of signal. It showed good result in schizophrenia II and both epilepsy datasets. Sample entropy is the improved version of approximate entropy and its result resembled that of approximate entropy. The phase and frequency information from the signal captured by approximate and sample entropy is discarded in spectral entropy, this is reflected in our analysis as spectral entropy did not capture irregularity and complexity [13] and resulting in a lower accuracy. Among the fractal features, Katz fractal showed the best performance as it was selected in four datasets. Higuchi showed worst performance as it is selected in two datasets only. These results are also observed in other studies as Katz is insensitive to noise and Higuchi is more sensitive to noise [15], [16].

For the stimulus I of schizophrenia dataset, the highest

TABLE IV: Some of the individual feature's accuracy.

	Schizophrenia I			**SZII**	**EpI**	**EpII**	**PD**
Features	SI	SII	SIII				
Approximate entropy	0.66	0.61	0.63	0.73	**0.78**	**0.72**	0.65
Hjorth complexity	**0.67**	0.64	**0.64**	**0.78**	0.7	0.67	**0.77**
Hjorth mobility	**0.68**	0.61	0.63	**0.87**	**0.79**	**0.70**	0.71
Katz fractal dimension	0.63	0.66	0.67	**0.87**	**0.78**	**0.69**	0.70
Higuchi fractal dimension	0.66	0.69	**0.68**	0.70	**0.81**	0.66	0.66
Kurtosis	**0.69**	0.65	**0.7**	0.77	0.61	0.60	**0.73**
Petrosian fractal dimension	0.63	0.69	0.63	**0.87**	**0.82**	**0.71**	0.56
Root mean square	0.65	**0.70**	0.61	**0.78**	0.67	0.64	**0.82**
Sample entropy	0.62	0.61	0.63	**0.77**	**0.78**	**0.72**	0.72
Spectral entropy	**0.67**	0.61	0.61	0.65	0.7	**0.7**	0.72
Standard deviation	**0.74**	**0.73**	0.61	**0.78**	0.67	0.64	**0.82**
Variance	**0.74**	**0.70**	0.62	0.58	0.60	0.60	**0.81**
Zero crossing	**0.68**	0.61	**0.67**	**0.77**	0.65	0.68	**0.76**

Bold shows that these features are selected as final features for the dataset.

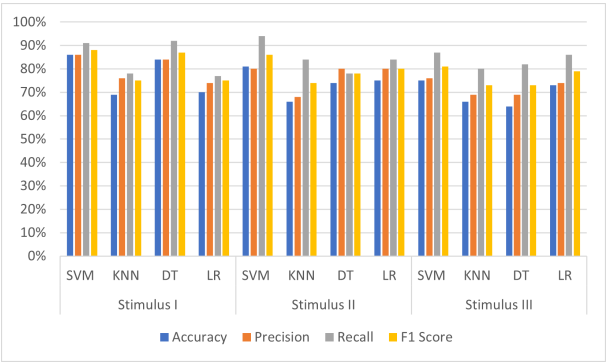

Fig. 1: Comparison of different classifiers for three different stimuli of schizophrenia I dataset with selected electrodes and features.

accuracy achieved without selecting the best features and electrodes is 72% which increased by 10% when feature selection technique is applied. The accuracy reaches up to 86% by extracting features from the selected electrodes according to proposed methodology as shown in fig 1. This accuracy achieved is 5% better than previous best model proposed by Zhang [5]. The accuracy, precision and recall of other two stimuli are also shown in fig 1.

The same methodology is used for another schizophrenia dataset to confirm the validity of model for diagnosis of schizophrenia disease. Fig 2 shows the model performance with the selected electrodes and features. 93% accuracy is achieved with subject wise classification using decision tree classifier which is 12% better than the results obtained by S.L. Oh [7].

In order to figure out whether our approach can be used for other disease datasets, two epilepsy datasets collected from two different region of Africa were used. As compared to previous best model [4], we got 2% and 12% increase

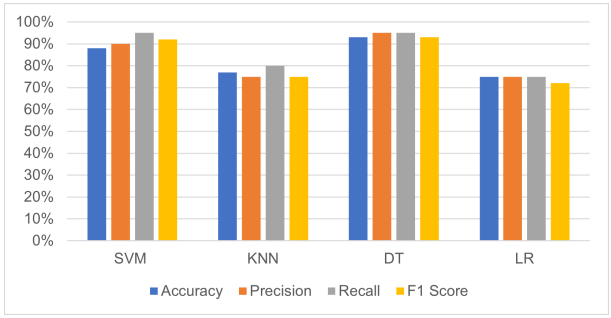

Fig. 2: Machine learning classifiers comparison of schizophrenia dataset II with selected electrodes and features.

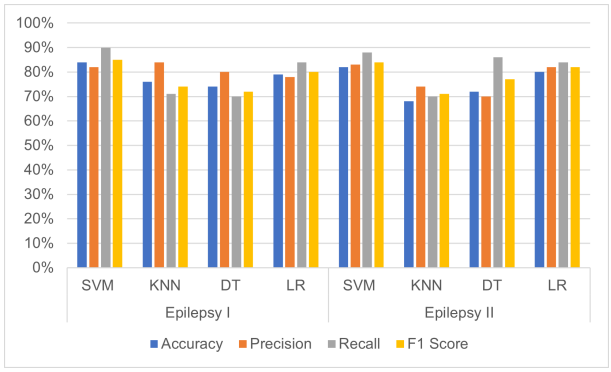

Fig. 3: Classifier comparison for Epilepsy data with most variate electrodes and selected features.

in accuracy in epilepsy I and II datasets, respectively. For epilepsy dataset I and II, 78% and 79% accuracy is achieved without selecting the best features, respectively. So, our feature selection technique increased the accuracy by 6% and 3% respectively for dataset I and II. The performance of classifiers on both epilepsy datasets are shown in Fig 3.

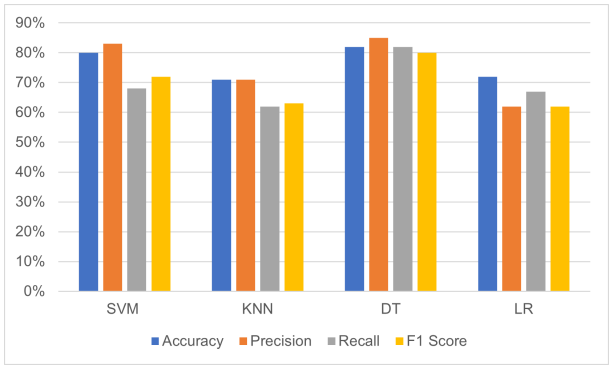

Fig. 4: Machine learning classifiers performance for Parkinson disease

In order to further validate our proposed methodology, the 5th dataset used is Parkinson disease dataset, where we achieved equivalent result as compared to the previous state-of-the-art technique [10]. However, the previous implementation is event related potential (ERP) specific and cannot be implemented on non-ERP data. But our proposed approach can be implemented on both ERP and non-ERP datasets. Fig 4 shows the performance of different classifiers.

A. Electrode Selection

In order to demonstrate the importance of electrode selection, we compared the accuracy of the models developed using most variate electrodes to the models developed using all electrodes. Table V shows the accuracy and F1 score when most variate electrodes and all electrodes are selected separately. In schizophrenia I dataset with stimulus I, using 10 most important electrodes, the accuracy is 86% and F1-score is 88%. Whereas using 64 electrodes, accuracy is 76% and F1-score is 82%. Precision is reduced by 10% from 86% to 76%, whereas there is not much difference in recall. Accuracy is decreased by 10% when number of electrodes increased from 10 to 64 as using all the electrodes is not an optimal solution. Using the nine top variate electrodes in schizophrenia II dataset accuracy is 93%, which is reduced to 90% when all electrodes are selected. The F1 score is 2% lower when using all electrodes as recall decreased by 5%. The decrement of recall shows the importance of electrode placement. In epilepsy dataset, total number of electrodes are 14, and using 8 and 10 most variate electrodes in dataset I and II resulted in F1-score of 85% and 84% respectively. When all electrodes are used, F1-score reduced by 1% and 4% in epilepsy I and II dataset, respectively. In the epilepsy dataset, the total number of electrodes is 14, still our proposed methodology managed to choose the optimal electrodes from a very few numbers of electrodes. Parkinson dataset has 60 electrodes and using 30 most variate electrodes accuracy and F1-score is 82% and 80%. There is a slight improvement in accuracy when all electrodes are selected as it increased by 2% but F1 score is decreased by 5%. The recall has also reduced significantly by 12% when all electrodes are used. This analysis shows that electrode selection minimizes the noise, reduces computation time and improves the algorithm's performance.

TABLE V: Performance comparison of all dataset with and without electrode selection technique

Dataset	Accuracy		F1-score		Precision		Recall	
	All	Most	All	Most	All	Most	All	Most
SzI SI	76%	86%	82%	88%	76%	86%	90%	91%
SzI SII	75%	81%	82%	86%	75%	80%	93%	94%
SzI SIII	69%	75%	74%	81%	67%	76%	87%	87%
SzII	90%	93%	92%	93%	95%	95%	90%	95%
EpI	83%	86%	84%	85%	85%	82%	84%	90%
EpII	78%	82%	80%	84%	84%	83%	88%	88%
PD	84%	82%	75%	80%	87%	85%	70%	82%

Most: Most variate electrodes selected. All: All electrodes are selected. Bold indicate the best performance between all electrodes and most variate electrodes used.

B. Noise Tolerance

In order to check the robustness of our methodology, we added noise to the electrodes. Table VI shows the result achieved when 10% and 20% noise is added to each electrode. The noise is added before electrode selection, but our proposed methodology automatically selected the best electrodes from the noisy data. We found that our algorithm selects slightly more electrodes with noisy data. For schizophrenia I stimulus I, number of electrodes selected

TABLE VI: Impact of adding 10% and 20% Gaussian noise.

Data	Accuracy		Precision		Recall		F1 Score	
	10%	20%	10%	20%	10%	20%	10%	20%
SzI SI	85%	72%	85%	75%	91%	84%	87%	78%
SzI SII	72%	75%	73%	80%	84%	82%	78%	79%
SzI SIII	72%	72%	76%	80%	81%	80%	77%	76%
SzII	87%	87%	87%	88%	95%	95%	88%	89%
EpI	82%	78%	79%	84%	90%	76%	84%	78%
EpII	80%	71%	81%	75%	86%	78%	83%	75%
PD	80%	80%	85%	83%	75%	80%	76%	78%

10% and 20% shows the percentage of added noise. Adding noise did not reduce the performance of model significantly, proving the tolerability of models.

is 10 without noise, 11 for 10% noise and 17 for 20% noise. Similar trend is observed in epilepsy dataset I where without noise 9 electrodes are selected as compared to 11 electrodes with noise. For schizophrenia dataset I stimulus I, accuracy decreased by 1% with 10% noise and 14% with 20% noise. In case of schizophrenia II, accuracy decreased by 5% with 10% and 20% noise. Accuracy decreases by 2% in both epilepsy datasets when 10% noise is added. There is not much difference in performance when 20% noise is added to the epilepsy dataset. Accuracy achieved in case of Parkinson is reduced from 82% to 80% when 10% and 20% noise is added. This analysis gave us the confidence that if data is not filtered properly or if electrodes are not placed properly and the resultant data is noisy, we can still achieve reliable results. In case of schizophrenia I and both epilepsy datasets, support vector machine outperformed the other classifiers, but in case of schizophrenia II dataset and Parkinson dataset decision tree work better than support vector machine. The difference between performance of SVM and D.T. is 1% only for schizophrenia II dataset, therefore we conclude that kernel SVM works better than decision tree classifier in our datasets. SVM often provides high accuracy with noisy sensors data as hyperparameter selection of SVM chooses optimal vectors to create hyperplane segregating each of the category. This causes the removal of minor noise for final model construction [17]. We also observed the same behaviour as support vector machine works well even with noisy data as compared to decision tree as shown in table 5 and 6, where we used all electrodes and noisy data, respectively.

IV. Conclusion

Our proposed approach is generic and independent of the dataset. We tested our methodology using five different EEG datasets and achieved better or equal performance as compared to the existing state of the art methods. The electrode selection method is simple yet robust and our feature selection method automatically chooses the best features, by simply sorting the feature based on individual feature accuracy. The advantage of generic model is that we do not need to manually input the best features for each dataset. It automatically selects the best features independent of the dataset. We prefer machine learning over deep learning, as deep learning is data hungry and requires a lot of data for training. To check the robustness of the model, we added 10% and 20% noise to the data and our model remained stable in most cases. To check the effect of electrode selection, we experimented with all electrodes and noticed significant decrement in performance.

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