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A Tandem Model To Categorise Patients Requiring Clinical Corrections From EEG Signals

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Abstract

Electroencephalograms (EEGs), which measure brain activity, are now the method most commonly used by doctors to diagnose epilepsy due to its inexpensive cost, ease of generation, and superior temporal resolution. The Electroencephalogram (EEG), which records brain electrical activity, is now the method that doctors use the most frequently to diagnose neurological illnesses. In this article, we provide an automated technique for detecting abnormal signals using recordings of raw EEG signals. A one-dimensional convolutional neural network (CNN) serves as the front end of the proposed system's preprocessing, and a support vector machine (SVM) serves as the back end. The method efficiently categorises unprocessed EEG signals without the extra work of feature extraction. The early detection of abnormal signals with the help of accurate predictive model with improved performance assisting psychiatrists in their diagnosis and so that the treatment could be started as soon as possible. An optimal combination of machine & deep learning models is designed to detect patients requiring clinical correction or not. HTER is the prime metric amongst other evaluated metrics as Accuracy, F1-score, Precision, Recall. The model runs over 10- fold cross validation for HTER for robust performance. This paper evaluates performance of Deep model with the proposed tandem model on various datasets on 5 performance metrics with 96.05% accuracy, 95.61%F1-score, 74% precision, 71% recall, 0.25±0.01 as HTER avg over 16 electrodes. The proposed framework's performance is validated using the public benchmark dataset Alzheimer's dataset, SNMC dataport. The experiment findings demonstrate that the developed framework outperforms established methods for EEG signal classification in terms of accuracy and F1-score, including numerous Machine Learning and Deep Learning algorithms.

Introduction

Over 90 million Indians of the country's population of 1.3 billion, suffer from some form of mental disorder, according to the WHO.A person's emotional, psychological, and social well-being are all reflected in their mental health. It determines how someone feels, thinks, and responds to situations. One can achieve their best potential and operate efficiently with good mental health. Every period of life, from childhood and adolescence to maturity, is vital for mental health. Stress, social anxiety, depression, obsessive com-pulsive disorder, substance addiction, and personality disorders are just a few of the many causes of mental health issues that result in mental disease. In order to preserve a healthy life balance, it is becoming more and more crucial to pinpoint the mental illnesses onset. The epileptic events can be accurately identified by EEG, which can distinguish between ictal (during a seizure), interictal (between seizures), and normal brain processes [1]. Neurologists must do an arduous and time-consuming visual review of EEG data in order to recognise epileptic patterns. It does not allow for precise interpretations, particularly given the necessity to physically check a massive number of EEG recordings accumulated over hours or even days. As a result, over the last two decades, scientists have developed a great interest in automating the seizure diagnosis process. Diagnostics are made easier, faster, and less prone to error, with the possibility of misjudgement reduced.

Automatic seizure detection is typically described as a two-stage method in the literature. The initial step involves taking distinctive features from the recorded EEG data. This features extraction procedure either uses the signals' spectral [2], temporal [3], or both [4] information. The retrieved features may then be subjected to statistical analysis techniques before being fed into a classifier in the subsequent stage. This two-stage technique is still difficult to learn while pre-processing and attempting to extract the most representative features from the raw signal, even though it achieves good results [5]. Finding a straightforward but effective methodology that can combine all seizure detection phases into a single automated system is therefore preferable. The Common Spatial Patterns (CSP) algorithm is a traditional and powerful method for extracting discriminative features from raw EEG signals. A number of CSP method versions have been developed and used in many MI BCI problems [6], [7]. For example, Aghaei et al. [7] created a separable common spatio-spectral patterns technique for MI BCI that required significantly less processing resources. Ashok et al. [8] presented and demonstrated better accurate MI task classification using two weighted CSP approaches. Ang et al. [9] introduced a filter bank CSP technique that improved MI signal categorization. Furthermore, several time frequency signal processing algorithms, such as the short time Fourier transform (STFT), empirical mode de-composition (EMD), and continuous wavelet transform (CWT) [10-12], are used throughout the feature extraction stage as well. Tabar and Halici [10] used STFT to simultaneously transform raw EEG data into pictures and extract time, frequency, and position information from the EEG signals. EEG signals were transformed to time-frequency spectrums using CWT by Lee and Choi [12]. To increase computational performance, a feature selection step is occasionally introduced to remove unnecessary data from the derived features. The feature classification phase typically makes use of linear discriminant analysis (LDA), artificial neural networks (ANN), support vector machines (SVM), and other machine learning classifiers [13]–[15].

Methods

An optimal combination of machine learning & deep learning technique has been designed. As indicated in Figure 3, five convolutional layers are used, followed by max-pooling layers. For the loss function, the Adam optimizer is utilised. The classifier runs for a total of 50 epochs. To avoid over-fitting, a 0.5 maintain rate dropout is implemented into the classifier's flattening layer. When compiling, the loss parameter is sparse categorical entropy. The results of features at output layer of gelu activation of CNN is given to Support Vector Machine classifier to classify the signals into normal or abnormal EEG wave pattern. Four things are referred to by the Proposed model: 1) employ a 5-layer CNN instead of the 2-, 3-, or 4-layer CNNs previously used in the literature for clinical correction of EEG signals; and 2) use the gelu activation function at the output in conjunction with the relu activation function at the previous layers. 3) The first convolution layer utilises a big 1x64 kernel to reduce the dimension of the many retrieved features, whereas the second through fifth convolution layers use tiny 1x3 kernels. 4) Since our data is not image data, 1D CNN is used (MRI, CT scans). In most cases, 2D CNN OR 3D CNN employs image data. The suggested system's pre-processing is handled by a one-dimensional convolutional neural network (CNN) shown in Fig 1, and the back end is handled by a support vector machine (SVM) with rbf kernel in Fig 2. Fig 1 classifies normal & abnormal EEG signals. In order to improve performance in terms of accuracy, F1-score, HTER a range of machine learning algorithms are tried and tested as shown in Fig 4 and 5.

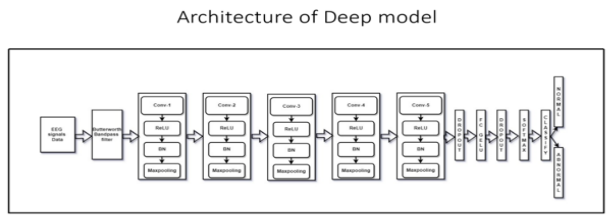

Figure 1 Architecture for deep model for abnormal patient detection

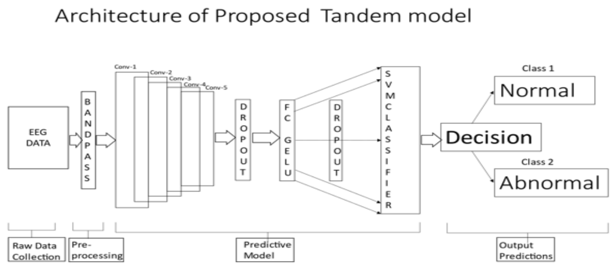

Figure 2 Architecture of Tandem model

Results

The proposed model is tested and validated on the following four datasets

1) Real time Data:

In the database for this pilot study, there were 20 patients with a likely clinical correction who can be categorised as abnormal patients (14 men; 6 women; age: 26.910.25 years, mean SD) and 24 patients without a likely clinical correction termed as normal patients (17 men; 7 women; age: 3211.17 years, mean SD).

According to the worldwide ten-twenty system, ethical approval was obtained for the recording of EEG signals. 16 Electrodes viz FP2 - F4, F4 - C4, C4 - P4, P4 - O2, FP2 - F8, F8 - T4, T4 - T6, T6 - O2, FP1 - F3, F3 - C3, C3 - P3, P3 - O1, FP1 - F7, F7 - T3, T3 - T5, T5 - O1 were used. The subjects were instructed to close their eyes while lying on a bed. Hyper ventilation and photovoltaic technology were employed to examine the patient's condition. With the use of the Brain Tech Traveller Acquisition system from Mohali - Chandigarh, India, the EEG data for each user was captured for more than 9 minutes. A hardware low-pass filter with a trimmed frequency of 100 Hz was utilised before the signals were sampled at 256 Hz. Bipolar longitudinal data were converted to digital form using a 12-bit A-to-D converter. Each EEG sample, which lasts one second, has a 256-point window, and 512 (i.e for 2 seconds). One patient has 143360 samples total. The EEG readings were given to a psychiatrist for offline processing.

Analysis of existing models in the literature were applied on this dataset.

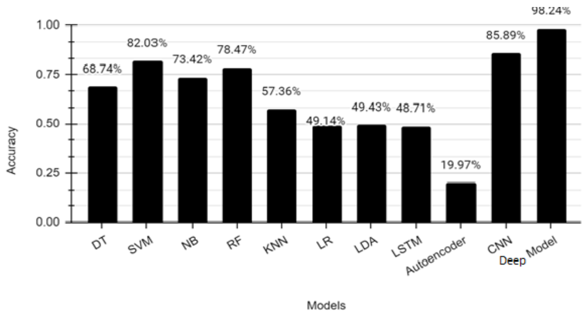

Figure 3. Accuracy Comparison of existing model performances on real time signal data

Figure 3 shows that deep model performs well over all the machine learning & deep learning algorithms [16]. Deep model comprises of 5 layers of CNN called as improved CNN.

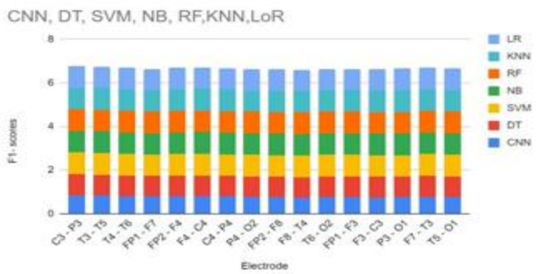

Figure 4 Enhanced scores of ML algorithms using improved CNN model

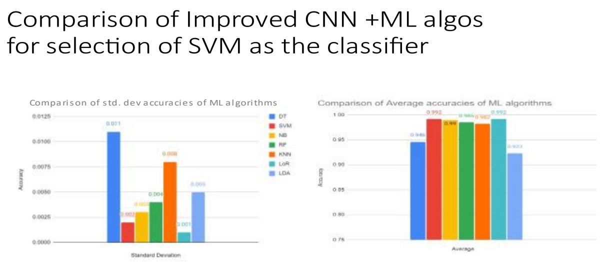

Figure 5 Selection of SVM in tandem model

Figure 5 shows that standard deviation of accuracies of all ML algorithms is calculated in order to find best performing algorithm. Logistic Regression has least std compared to all algorithms. Average of accuracies of all ML algorithms is assessed. SVM & Logistic Regression have same average accuracies. Standard deviation & average of accuracies is found out for all ML algorithms. But Logistic Regression is good for linear data whereas SVM is good for non-linear data. Hence SVM is chosen in association with CNN called as tandem model.

Table 1 Pseudocode for Proposed Tandem model

Pseudocode for Proposed Tandem model

```
Algorithm
Inputs:
Feature Vector and Label
Output:
Class prediction
Begin
    Build feature vector model from previous improved CNN model
    Function:train_svm(X,y,number_of_runs)
    Initialize: learning rate, gamma, rbf using grid search method
    For learning_rate in number_of_runs
      Error=0;
      For i in X
        If(y[i]*(X[i]*w)) <1 then
           Update: w=w+learning_rate((X[i]*y[i]) *(-2*(1/number_of_runs)*w)
        Else
           Update: w=w+learning_rate *(-2*(1/number_of_runs)*w)
        End If
      End For
    End For
End
```

Proposed tandem model performance is shown in following table. Performance of tandem model is higher compared to deep model for all the electrodes [16].

Table 2 Performance metric for Deep model Vs Tandem model on real-time data

Real Time Data	Deep model						Tandem model					
Electrode	Accuracy	F1-score	Precision	Recall	HTER mean	HTER std	Accuracy	F1-score	Precision	Recall	HTER mean	std
FP2 - F4	0.9616	0.78	0.78	0.78	0.296	0.007	0.991	0.991	0.789	0.7702	0.213	0.028
F4 - C4	0.9657	0.79	0.79	0.79	0.227	0.028	0.996	0.996	0.806	0.769	0.204	0.026
C4 - P4	0.9729	0.77	0.77	0.77	0.224	0.031	0.997	0.997	0.767	0.77	0.212	0.029
P4 - O2	0.9653	0.78	0.78	0.78	0.231	0.027	0.994	0.994	0.793	0.749	0.211	0.027
FP2 - F8	0.9595	0.74	0.74	0.74	0.288	0.035	0.992	0.992	0.754	0.746	0.246	0.028
F8 - T4	0.959	0.75	0.75	0.75	0.304	0.029	0.993	0.993	0.742	0.75	0.240	0.031
T4 - T6	0.9699	0.79	0.80	0.79	0.233	0.027	0.993	0.993	0.793	0.788	0.202	0.027
T6 - O2	0.9571	0.77	0.77	0.77	0.256	0.031	0.992	0.992	0.771	0.747	0.221	0.030
FP1 - F3	0.9699	0.75	0.75	0.75	0.266	0.033	0.995	0.995	0.776	0.724	0.234	0.025
F3 - C3	0.9582	0.73	0.73	0.73	0.284	0.031	0.993	0.993	0.746	0.727	0.240	0.026
C3 - P3	0.9798	0.85	0.85	0.85	0.153	0.023	0.991	0.991	0.865	0.839	0.137	0.022
P3 - O1	0.9697	0.74	0.74	0.74	0.279	0.030	0.994	0.994	0.757	0.73	0.244	0.029
FP1 - F7	0.9712	0.77	0.78	0.77	0.248	0.029	0.993	0.994	0.808	0.733	0.204	0.0255
F7 - T3	0.9718	0.79	0.79	0.79	0.270	0.007	0.99	0.990	0.806	0.779	0.195	0.026
T3 - T5	0.9814	0.81	0.81	0.81	0.247	0.032	0.995	0.995	0.820	0.796	0.175	0.025
T5 - O1	0.9677	0.74	0.74	0.74	0.284	0.031	0.992	0.992	0.748	0.737	0.251	0.028

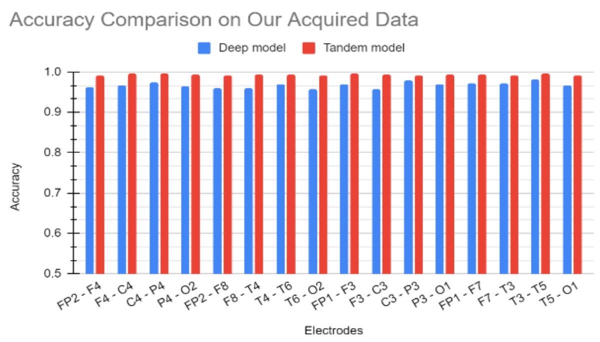

Figure 6. Accuracy Comparison on Acquired real-time Data

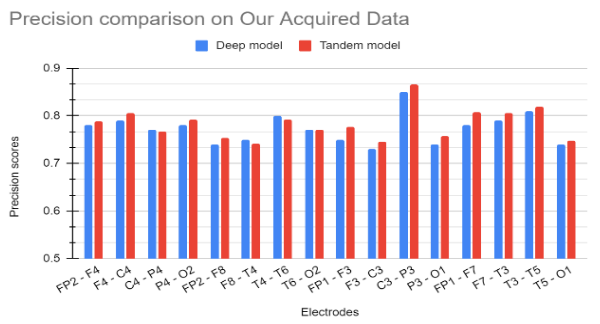

Figure 7 Precision comparison on Our Acquired real-time Data

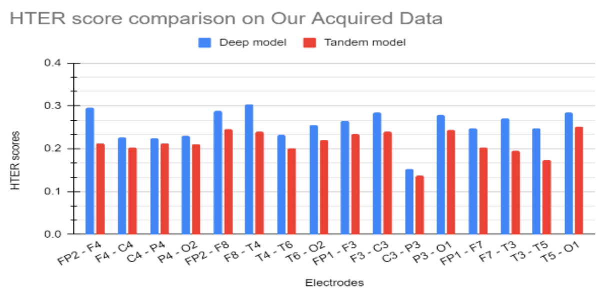

Figure 8 HTER score comparison on Acquired real-time Data

2) Alzheimer’s disease datatset:

the Alzheimer's Dataset from Hospital Clnico Universitario de Valladolid (Spain) having 16 electrodes [17] giving efficient performances compared to their model. dataset has 11 patients with plausible AD (5 men; 6 women; age: 72.5±8.3 years) and 11 individuals with no AD (7 men; 4 women; age: 72.8±6.1 years) using 16 electrodes [17]. Figure 8 shows comparison of the models used in the literature. Tandem model has least HTER value amongst all the models [16]. High accuracy is shown by T4, T6, O1 ; High F1-score for T4, T6, O1 ; Low HTER is for O1, O2, F4

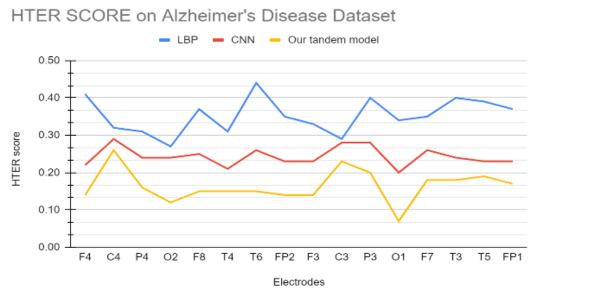

Figure 9 HTER score comparison of the proposed model with other existing models on Alzheimer’s dataset

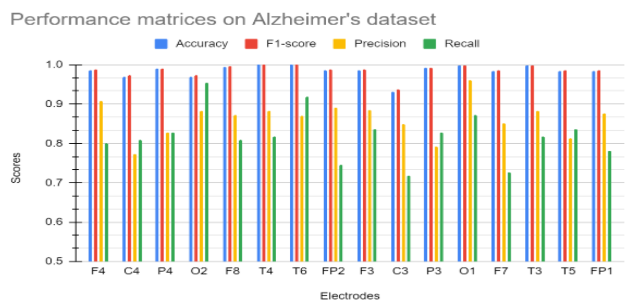

Figure 10 Accuracy, F1-score, Precision, Recall performances on Alzheimer’s dataset for all the electrodes

3) SNMC Seizure Dataport:

This dataset contains data from 11 patients of whom seizures are observed in EEG for 2 patients [18]. The total duration of seizures is 170 seconds. The number of channels is 16 and data is collected at 256Hz sampling rate. The final dataset files in .csv format contain 87040 rows x 17 columns, where 17 columns are 16 channels and one outcome column indicating seizure(1) and not seizure(0). Preprocessd EEG dataset with epileptic seizure from SNMC dataport Bagalkot, India. 87040 rows are obtained by 170 seconds x 256 seizure data and 170 seconds x 256 non seizure data. Epilepsy data: SNMC port data size 159.5 GB 11 patients having 16 electrodes (2 epileptic & 9 non-epileptic). High accuracy is shown by T3-T5, T4-T6, F4-C4; High F1-score for T3-T5, T4-T6, F4-C4; Low HTER is for T3-T5, F7-T3, F3-C3

Table 3 Various Performance matrices on Seizure dataset:

SNMC Data Port	Deep model				Tandem model			
Electrode	Accuracy	F1-score	Precision	Recall	Accuracy	F1-score	Precision	Recall
FP2 - F4	0.8057	0.78	0.78	0.78	0.847	0.809	0.78	0.659
F4 - C4	0.9284	0.9	0.9	0.9	0.958	0.95	0.898	0.857
C4 - P4	0.9225	0.9	0.91	0.9	0.953	0.943	0.9266	0.848
P4 - O2	0.837	0.82	0.84	0.82	0.871	0.837	0.876	0.726
FP2 - F8	0.8981	0.87	0.88	0.88	0.944	0.933	0.881	0.818
F8 - T4	0.9093	0.88	0.88	0.88	0.954	0.946	0.873	0.8508
T4 - T6	0.9299	0.92	0.92	0.92	0.963	0.957	0.918	0.897
T6 - O2	0.9044	0.89	0.89	0.89	0.950	0.941	0.885	0.855
FP1 - F3	0.8783	0.79	0.81	0.8	0.881	0.868	0.763	0.815
F3 - C3	0.9321	0.91	0.91	0.91	0.954	0.945	0.934	0.865
C3 - P3	0.9095	0.89	0.89	0.89	0.937	0.923	0.9109	0.825
P3 - O1	0.8793	0.86	0.86	0.86	0.903	0.88	0.880	0.788
FP1 - F7	0.8916	0.89	0.89	0.89	0.936	0.923	0.901	0.837
F7 - T3	0.9384	0.9	0.91	0.90	0.958	0.949	0.932	0.868
T3 - T5	0.9468	0.93	0.93	0.93	0.98	0.976	0.926	0.927
T5 - O1	0.9087	0.88	0.88	0.88	0.938	0.924	0.905	0.822

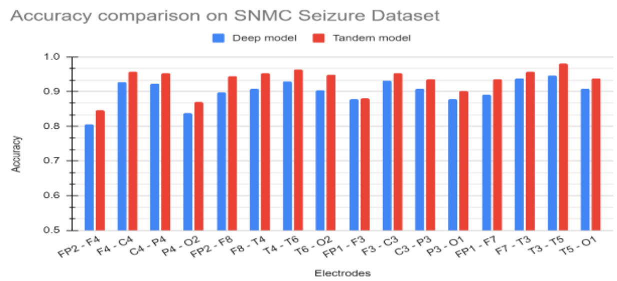

Figure 11. Accuracy comparison Deep Model Vs. Tandem model

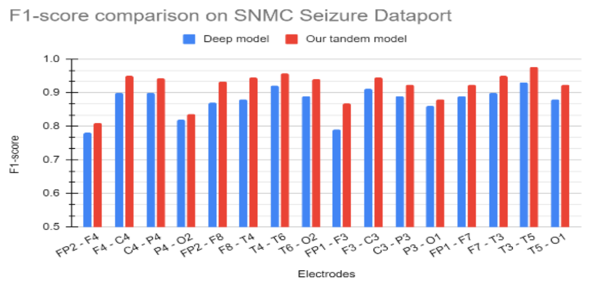

Figure 12. F1-score comparison Deep Model Vs. Tandem model

4) Epileptic Dataset IIT Kharagpur:

This dataset consists of EEG data of 200 epileptic seizure patients (both male and female) of age from 4 to 80 years [19]. The raw data was collected from VIRGO EEG machine at Hospitals, Kharagpur, India. The EEG electrodes were placed according to 10 – 20 International standard. The EEG data was recorded for one channel at 256 samples per second.

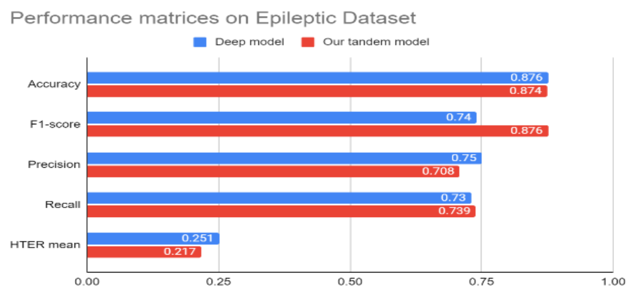

Figure 13. Model comparison with various performance matrices

Conclusion

On the basis of recordings of EEG signals, an unique method of automatic abnormal signal recognition was put forth. A tandem model is used by the system to accurately distinguish between normal and abnormal EEG signals. The suggested method does not require feature extraction because it operates directly on raw EEG signals. The system's classification accuracy was tested using 10-fold cross-validation to validate its robustness and stability with changing data. Tandem model performs well on the original real time dataset of normal & abnormal signal detection with 96.05% accuracy, 95.61%F1-score, 74% precision, 71% recall, 0.25±0.01 as HTER avg over 16 electrodes. There is increase in the accuracy, F1-score for tandem model and decrease in HTER score depicted in Figure. The proposed model is validated on different datasets. Tandem model shows least HTER score on Alzheimer's dataset compared to deep model. Higher scores for Accuracy, F1-score, Precision & Recall are shown for tandem model on SNMC dataport. Tandem model has good performance score for F1- measure, Recall and good score for HTER on Epileptic dataset. Results can be drawn according age and gender in the future work.

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