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Towards better intelligent implementation of Schizophrenia prediction using federated deep learning framework

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Abstract---Early detection of individuals susceptible to Schizophrenia (SZ) is critical for early intervention, which can reduce the risk of psychosis. This research proposes a deep learning method for classifying EEG data by picking important discriminative EEG features. While existing systems employ an R-CNN methodology, we propose a hybrid CNN-Bi-LSTM automated system that analyses EEG statistical data and performs the prediction. It uses a CNN for an optimised feature selection process to select the most important and informative features, with Bi-LSTM for prediction of susceptibility to develop SZ. The model when run on EEG data of schizophrenic paradigms gives output as "Schizophrenic" or "Non-schizophrenic". This method has a high level of classification accuracy when compared to most existing machine learning models. While it displays a lower accuracy than some complex deep learning systems, it is much more stable and easy to interpret and thus is more practical for clinical settings.

Keywords---deep learning, schizophrenia, Bi-LSTM, EEG.

Introduction

Schizophrenia (SZ) is a mental disorder that distorts a person's perception of reality, their thinking capability, their expression of emotions and their social interactions. Though less common than other mental illnesses, yet it is the most chronic and incapacitating. It's a severe and complicated mental illness with a wide range of risk factors, comorbidities, clinical presentations, course, therapeutic response, and functional result. It has no cure, but medication and therapy can help manage the severity. The electroencephalogram (EEG) is a common tool for diagnosing SZ. The electroencephalogram (EEG) detects irregularities in brainwaves and provides quantitative data. The main focus of this study is to predict if children and adolescents are predisposed to developing SZ. Identifying those susceptible can support early intervention strategies, thus reducing the risk of severe psychosis. Several deep learning models have been implemented to solve the prediction problem. So, from an initial set of EEG statistical data, a DL method is used. It is a CNN-Bi-LSTM approach, where a convolutional method extracts features and a Bi-LSTM makes the predictions.

Ahmedt-Aristizabal et al., [1] involves a deep learning approach that makes use of R-CNNs. The performance of this technique is compared with machine learning techniques such as KNNs and Decision trees on a dataset of EEG recordings, collected from patients during a passive auditory oddball paradigm. The R-CNNs outperform all the other approaches, being able to extract features automatically and showing 70% accuracy as compared to the machine learning approaches with 45% accuracy. The accuracy of this model may be further improved with comparison to other techniques in the survey and modifications to the units of the networks.

A machine learning technique is discussed in Min B et al., [2]. This paper proposes a way to predict a schizophrenic individual's response to ECT by analysing their resting-state EEG data using machine learning techniques in combination with Random Subset Feature Selection. While this technique has a good accuracy, it could be greatly improved with the incorporation of deep learning, as deep learning is often more accurate than machine learning and also doesn't require a manual feature extraction technique. A review Barros C et al., [3] analyses the benefits and disadvantages in using current techniques to distinguish between healthy versus high risk schizophrenia. It compares machine learning techniques like SVMs with deep learning techniques like RNNs and CNNs. It was found that SVM is the most commonly used classifier, however, it does not promise the accuracy that may come with networks like LSTMs and is susceptible to overfitting.

Su C et al., [4] is a review of the use of deep learning in mental health research. It examines deep learning models like LSTMs, RNNs, Autoencoders and CNNs. The deep learning techniques overall perform

better than existing machine learning methods on MRI data. However, they did not have as high of a performance as when performed on EEG data, which is unfortunate because EEG data is a much better biomarker. LuoYu, et al., [5] explores the possibilities of using EEG data as a biomarker for the prediction of schizophrenia. The technique introduced here is the use of SVM with Random Forests. The system achieves a high accuracy when compared to other machine learning techniques, but is prone to overfitting. But the paper reached the conclusion that EEG data is a very suitable biomarker for schizophrenia, hence, we shall be using EEG data in our system for prediction.

H. Wang et al., [6] proposes a system that will be able to predict intravenous immunoglobulin resistance in clinical settings. The system uses a multistage method that uses the explainable boosting machine with co clustering as a way to combine intelligible models with pattern mining for missing data. This creates a scalable system that has a low generalisation error. However the method proves to be impractical due to the large complexity that the technique presents when it comes to real time application, leading to an unstable network. Q. Chang et al., [7] proposes a system that uses EEG recordings to find out if a patient has first-episode schizophrenia, chronic schizophrenia or doesn't have schizophrenia (healthy control). A comparison is made between SVM and graph neural network. It is found that the deep learning technique classifies significantly more accurately than SVM. However deep learning requires more memory and processing power than SVM. Moreover, there are other deep learning techniques that can be more easily implemented, like LSTMs.

Steardo, Luca Jr et al., [8] uses SVM on fMRI data as a means to distinguish between schizophrenia patients and healthy patients. SVM gives a high accuracy, however it suffers from the pitfalls of every machine learning technique when compared to deep learning. This includes less accuracy and the need for manual feature extraction which makes it less effective for large amounts of data usually required in a clinical setting. CraikAlexander et al., [9] is a review of deep learning techniques such as CNNs, RNNs, CNN, DBN, RNN, SAE, Multi-layer perceptron neural network and Hybrid architectures on classifying EEG data. The networks have a high accuracy in these classification tasks when compared to older machine learning techniques. However, they are outperformed by LSTM systems, proposed by other papers.

Oh, ShuLih, et al., [10] proposes a 11 layered CNN to diagnose schizophrenia. It is robust, works well with a small dataset and has a high accuracy of about 99.12% when compared to traditional machine learning techniques. CNNs are however much more costly to compute when compared to traditional ML techniques and are outperformed by LSTMs in terms of accuracy. Matsubara, Takashi et al., [11] proposes a deep neural generative model, which, using fMRI images, can diagnose

the illness and document the progression of the illness. It achieves high accuracy in terms of diagnosis, mainly because of the use of the Bayes rule. It also is free of risk of extracting unrelated features, thus saving a lot of processing time. However, Its compatibility with EEG data is not good and it is much more complex to implement than other deep learning techniques. Sun, Jie, et al., [12] proposes a hybrid CNN and LSTM network that classifies patients as healthy or schizophrenic based on EEG data. It also compares the FuzzyEn and FFT feature extractors. While the technique in combination with FuzzyEn has about 99.2% accuracy, there is a need to optimise the training time of the system.

R. Buettner et al., [13] proposes the use of random forests on EEG data to exclude schizophrenic individuals from a dataset. It has an accuracy outperforming other machine learning methods. However, random forests, while suffering from the pitfalls of other machine learning methods such as manual feature extraction and lesser accuracy, are also prone to overfitting. N. V. Swati et al., [14] illustrates the utility of ML for detection and makes comparisons to newer deep learning techniques. As expected, deep learning techniques are the most recent innovation and provide far greater accuracy. However, techniques like Ensemble learning have been proven to give difficult to interpret results. Alves Caroline L et al., [17] proposes an automatic technique that diagnoses both Alzheimers and schizophrenia. This is done using CNNs on an EEG time series. This gives an accuracy of above 90% and can be adapted for any mental health disorder. However, this system may be more accurate if LSTMs were used, as LSTMs generally have better accuracy when compared to CNNs.

Chu, Lei, et al., [18] proposes schemes that use resting state EEG streams. These schemes involve RNNs and CNNs in combination with SVM and RF classifiers. The CNN and RF combination performs the best. However, it works on a small dataset and has a lower accuracy and robustness on larger dataset. In conclusion, from studying previous work, the first observation is that our proposed work should use EEG data, as it is an effective yet underused biomarker for schizophrenia. Deep learning [19, 20, 21] is favourable over machine learning techniques as they show better accuracies, are much more scalable due to automatic feature extraction and are the state-of-the-art at present. Moreover, hybrid systems are very rarely found in this line of deep learning research. Thus, we shall be exploring the possibility of using a hybrid model. We propose a CNN and Bi-LSTM hybrid network, capable of working with EEG data for the prediction of schizophrenia. The reason we are using this hybrid is its purported high accuracy in other applications like sentiment analysis. This is discussed in W. Yue et al., [15], which shows that such a system is capable of achieving accuracy levels of about 91.48%, while also being more stable. The contribution of the proposed work can be summarised as follows:

- A deep learning technique has been developed for the purpose

ofschizophrenia prediction from EEG data

- The technique is a hybrid CNN and Bi-LSTM adapted for this application
- CNN and Bi-LSTM is a stable hybrid network, which provides a fairly high accuracy when compared to existing systems
- An EEG database from research at Moscow State University is used.

System architecture and methodology used

As seen in the survey, deep learning techniques are far more effective than machine learning techniques. Thus we shall be going with a hybrid CNN and Bi LSTM system, which is usually only used in image processing applications, adapted for the goal of this project. The convolutional network obtain features. The Bi LSTM, because it provides a better performance than the LSTMs due to being a combination of two LSTM units that track backward and forward dependencies, is used for prediction. So given an EEG reading, the system should be able to tell us if the patient is displaying signs of schizophrenia or not. This is detailed in the system architecture (figure 2.1).

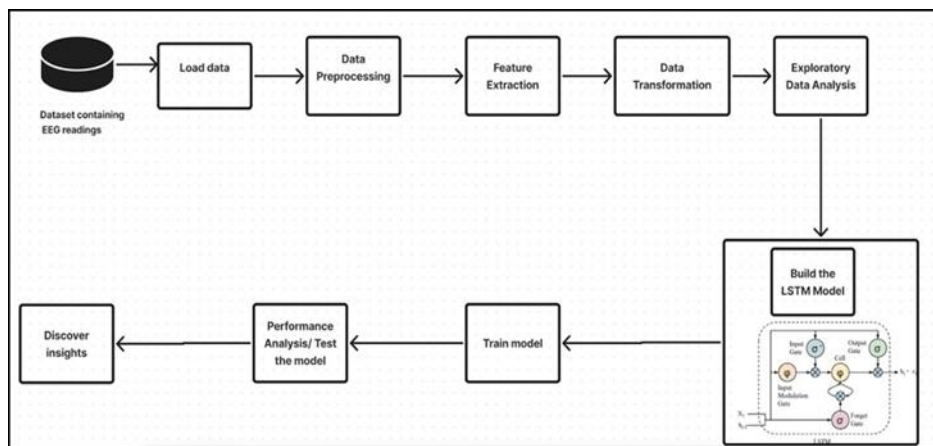


Fig 2.1 Architecture

CNNs were developed to process multidimensional data like images and time series. CNNs are extremely popular because of their ability to extract features automatically in their training phase, unlike manual extraction for conventional machine learning approaches. Two crucial parts of a CNN are extraction and classification of features. Several convolution layers are followed by max-pooling and an activation function in the feature extraction process. Typically, the classifier is made up of fully connected layers. Consider a time series with a length of n and a breadth of k . With respect to a multivariate time series, the length refers to the number of timesteps, and the width equals the number of variables- these refer to the number of channels (nodes on the head of a person) in EEG. The length of the convolution kernels can be adjusted, but their breadth is always the

same as the time series. Convolution is performed by shifting the kernel from the beginning to the end of a time series in one direction. It does not migrate to the left or right like it does when images are convolved in two dimensions.

After that, the results of the multiplication are merged, and the value is subjected to a nonlinear activation function. The kernel then moves forward in time to create the next value, which becomes an element of a new univariate time series that has been "filtered". The number of convolution kernels is the same as the number of new "filtered" time series. Different traits, properties, and "features" of the initial time series are captured in each of the subsequent filtered series, depending on the length of the kernel. The next step is to use global maxpooling to extract the highest value from each of the filtered time series vectors. These values are added together to form a new vector, and this vector of maximum values is the resulting feature vector that may be input into a fully connected layer. While the convolutional layers are responsible for feature extraction, output of a convolutional layer is calculated in the following manner.

$$n_{out} = ([n_{in} + 2p - k] / s) + 1$$

where:

n_{in} = number of input features

n_{out} = number of output features

k = convolutional kernel size

p = convolutional padding size

s = convolutional stride size.

Feature map is the output obtained after the extraction happens through convolution. The equation for the feature map is mentioned below.

$$s[t] = (x * w)t[a] \sum_{a=-\infty}^{+\infty} x[a]w[a + t]$$

where:

x = 2D matrix of input features

w = feature detector or kernel

Bi-LSTMs are made up of LSTM units. Each LSTM unit has four operations, all of them control information flow in one direction. These gates are namely: forget, store, update, output. Forget helps discard unnecessary information, store helps store the portion of the input to be retained, update creates the new cell state and output gives the output of the cell based on state and input. This type of unit is depicted by figure 2.2.

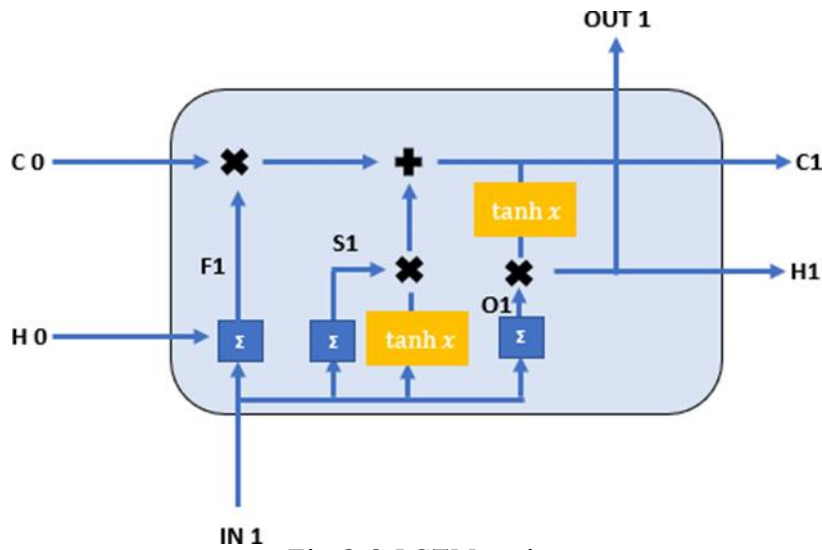


Fig 2.2 LSTM unit

The equations are as follows:

$$F1 = \Sigma(W_f.[H0, IN1] + bf)$$

$$S1 = \Sigma(W_s.[H0, IN1] + bs)$$

$$C1 = F1 * C0 + S1 * \tanh(IN1)$$

$$O1 = \Sigma(W_o.[H0, IN1] + bo)$$

$$H1 = O1 * \tanh(C1)$$

where Σ (sigmoid) and $\tanh$ are activations. W_f , W_s and W_o are forget layer, store layer and output layer weight matrices. They decide how much information is discarded, stored and shown as output. Meanwhile bf , bs and bo are the biases of the selayers.

Bi-LSTMs are a combination of two such LSTMs, each guiding information in opposite directions, thus being able to track the dependencies of the sequence forward and backward. Thus, by putting more information into the system regarding the dependencies of each data point, a Bi-LSTM improves the contextual information a network has, thus leading to more effective learning and a higher accuracy. In essence, it trains more data than LSTMs and thus can take on much larger datasets, such as a stream of information in real-time applications or research data that is constantly being updated. This makes it an appropriate choice for diagnosis systems, as clinical data is constantly updating and expanding as more studies are conducted. A Bi-LSTM is thus used to classify patients in our proposed model, given that the extraction of discriminative features and ranking of the features are done by the CNN layer.

The Bi-LST Minour proposed model consist soft layers of LST Munits. One layer analyses the values of the features that lead to the larger like lihood of a particular prediction, this is called the forward tracking layer. The other layer, given the prediction, analyses the likelihood of particular values for each feature.

Combining both these predictions gives us the most likely prediction of a label for the data.

Thus, given as equence of readings as shown in figure 2.3, the Bi-LSTM returns the categorization of the reading. If the sequence of EEG readings indicate the patient is schizophrenic, then the last output in the sequence is schizophrenic. Else,it is non-schizophrenic.

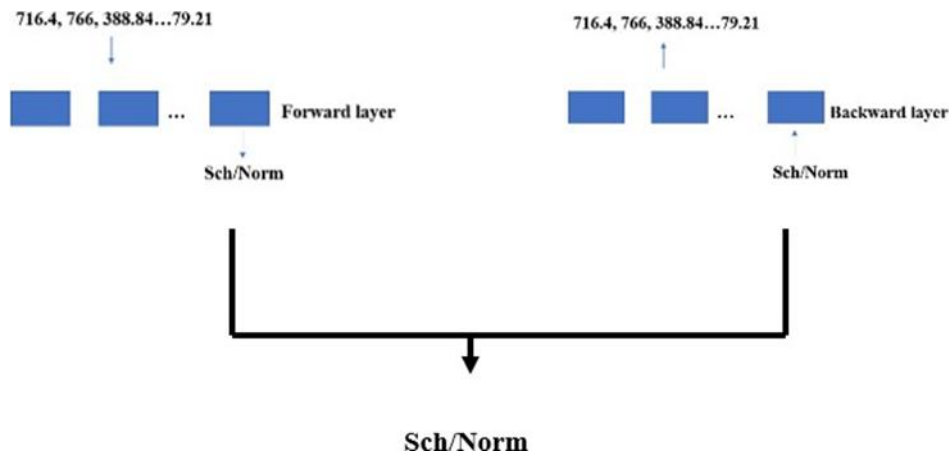


Fig 2.3 Working of the Bi-LSTM Module

Experimental Results

For this work we shall be using two databases of EEG data collected by Moscow State University from [22]. The data has been Each database has data is from 16 EEG channels, each TXT file in a database containing 7680 samples from each channel. Each channel represents one position of an electrode from 16 electrodes placed on the patients head. Each sample is the EEG amplitude at that electrode position. The data is collected at a rate of 128 Hz, therefore, each patient's EEG signals have been recorded for about a minute. One database is collected in the manner described above from 45 schizophrenic patients. This is shown in figure 3.1.

122877	122878	122879	Diag
716.48	388.84	79.21	sch
-22.66	-196.37	-226.58	sch
-481.25	-30.72	139.51	sch
-93.56	-450.26	-532.13	sch
-50.90	-211.25	-290.15	sch
778.29	778.29	679.98	sch

Fig 3.1 Sample of schizophrenic EEG recordings

The other database has data collected from 39 healthy control individuals in the same manner as the previous database. This is shown in figure 3.2.

122877	122878	122879	Diag
-571.35	-632.07	-521.67	norm
279.41	439.46	399.67	norm
-570.87	-30.23	219.75	norm
388.62	258.38	-21.01	norm
-410.72	-370.35	-270.10	norm
-90.62	-321.45	-400.10	norm

Fig 3.2. Sample of healthy control EEG recordings

The “Diag” column in both databases has two labels, either “norm” for healthy control or “sch” for schizophrenic. For the purpose of our proposed work, we will need to merge these databases into a single database by interpolating the data. The final result is as shown in figure 3.3.

subject	condition	Fz	FCz	Cz	FC3	FC4	C3	C4	CP3
1	1	5.533701	5.726507	5.469535	5.386723	4.588875	6.560092	4.542811	5.397492
1	1	5.651489	5.837326	5.773131	5.627975	4.822217	6.739976	4.811770	5.541357
1	1	5.717580	5.932924	5.948466	5.826460	4.979647	7.026199	5.053779	5.634972
1	1	5.703267	5.968103	5.851512	5.812192	4.992899	6.940671	5.106650	5.543577
1	1	5.571578	5.917541	5.812808	5.744715	4.963338	6.726491	5.158073	5.454069

Fig 3.3. Sample of final database

As shown indicated in the plot Figure 9, the data distribution is even, that is, there are an equal amount of records for schizophrenic individuals and the healthy controls.

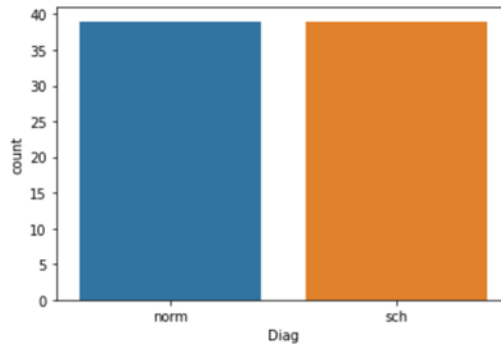


Fig 3.4. Distribution of final database

To evaluate the performance of the model, we can use F1 scores, precision (Pr) and accuracy (Acc) measures as given below:

$$F1 = (2 * Pr * Re) / (Pr + Re)$$

[1]

$$\text{Acc} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

[2]

Where,

$$\text{Pr} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Re} = \text{TP} / (\text{TP} + \text{FN})$$

Accuracy is the percentage of samples classified correctly as schizophrenic or non-schizophrenic from the total number of samples. It is a good measure of performance, however, it does not give us the full picture as it does not evaluate the misclassification of samples. Thus, an added evaluation metric that can present a more holistic picture of system performance is the F1 score. It involves two metrics to be measured, namely, precision and recall. Precision is the fraction of samples classified correctly as schizophrenic from the total number of samples that are supposed to be classified as schizophrenic. Recall is the fraction of samples classified correctly as schizophrenic from all the samples classified as schizophrenic, both correctly and incorrectly. These measures are combined to produce the F1 score, as per the formula illustrated. We begin with the cleaning of the data and the normalisation, followed by transformation. Once the data is cleaned, the features of the data are extracted. Here, we can use a CNN. The model we use here is one with 4 kernels and uses ReLU as an activation function. This is depicted in figure 3.5.

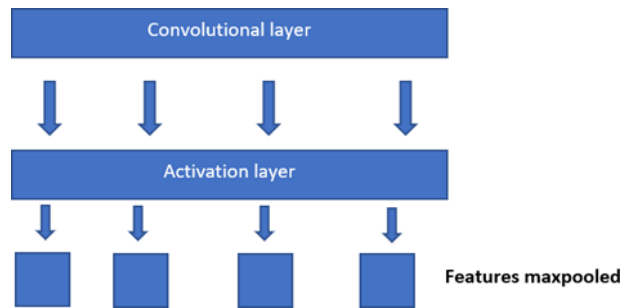


Fig 3.5. Feature extraction model

The CNN extracts the features by first filtering with the feature using the activation layer neurons. This gives us a list of important signals to consider in the diagnosis, the signals that contribute most to the diagnosis will be considered while the rest of the readings from any input will be ignored. CNNs are generally effective at extracting features from images, but for our proposed model, we use a version that works with natural language data to extract features, as our EEG data is alphanumeric. This version is similar to an existing version of CNNs used for sentimental analysis and emotion detection based on text. The features obtained from the CNN are then provided to the Bi-LSTM model.

The Bi-LSTM model uses these features to predict the label of the data, that is, to predict whether a patient is a healthy control or afflicted by

schizophrenia. The adam optimizer is used to add speed to this processing. This is done by sequence prediction. Given a sequence of important features, it is up to the Bi-LSTM to predict the data that will come under "Diag", this being "sch" for schizophrenic and "norm" for healthy control. This Bi-LSTM is thus trained for such prediction, by tracking dependencies forward and backward. Two LSTM layers work in tandem for this. One Bi-LSTM layer checks given the important feature readings, what the prediction of the network will be. The other checks, given a prediction, what the readings of the important features will be. Thus, combining both the predictions, we can arrive at the most likely prediction. This is the output of the system. This is depicted by figure 3.6.

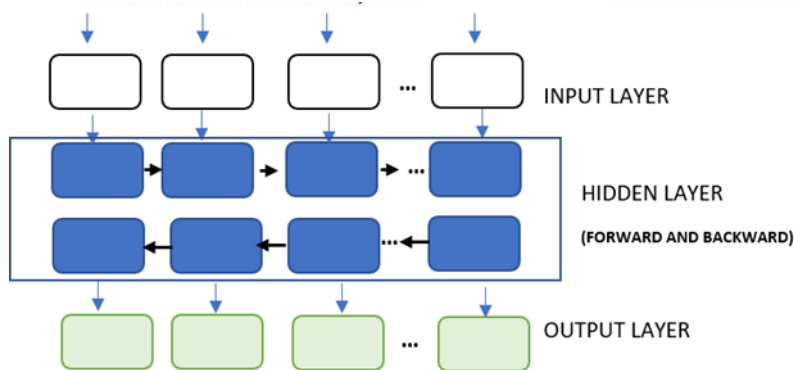


Fig 3.6. Bi-LSTM

The Bi-LSTM provides greater accuracy than LSTMs because it tracks both forward and backward dependencies. It is also better at tracking long-term dependencies than RNNs and CNNs, given that each unit takes into account the output of other units and the importance of the data to be preserved or forgotten. The input to the system is shown in figure 3.7.

48.77	8.75	28.76	108.80	128.81	128.81	88.79	...	8.75
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Fig 3.7. Input to system

It is a sequence of EEG readings from 16 electrodes on a patients head during an auditory oddball paradigm. The model passes it to the hybrid system for further processing. The hybrid system is already trained with the data from the aforementioned dataset, which is formed by combining datasets from schizophrenia afflicted patients and patients from the healthy control group. This dataset is extracted from several TXT files, that contain EEG data from 16 electrodes, 7680 readings per electrode. The data from this dataset has been cleaned, interpolated and fed to the system, which uses a CNN to extract and rank important discriminative features. The CNN has 4 kernel convolutional layer to extract the features and this gets sent to an activation layer, which fixes the importance of these features. This is then used as input to the Bi-LSTM. The Bi-LSTM, given the input EEG data, predicts the last column of the input, which is the diagnosis or "Diag" column using

sequence prediction. This gives us our final diagnosis. Thus, the system gives output as "Schizophrenic" or "Non-schizophrenic" as output, as shown in Figure 3.8.

Case 1: EEG data indicates schizophrenic symptoms

This patient may be schizophrenic

Case 2: EEG data does not indicate schizophrenic symptoms

This patient is not schizophrenic

Figure 3.8 Output of system

Due to using a Bi-LSTM network over R-CNNs and RNNs, the network is able to track long term dependencies more effectively and does not suffer from a vanishing gradient. The ability of this technique to automatically extract features gives it an evident advantage over other machine learning based approaches. It also provides interpretable results, that deep learning systems with higher accuracies, such as ensemble learning cannot provide. The system is stable throughout the processing, even with large amounts of data. The results of the output are easily understood by people working in clinical settings, who may have little to no experience with programming. Moreover, it is easy to modify and correct the system to improve the accuracy. The accuracy achieved by the system currently is above 72%. This is shown by figure 3.9 and Table 1.

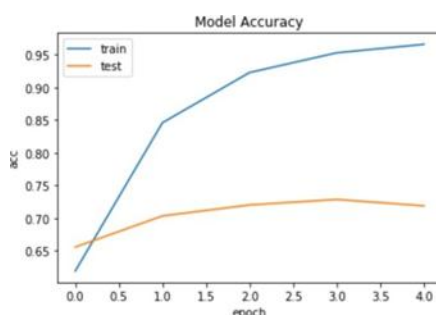


Fig 3.9 Accuracy of system over time

Table 1

Performance evaluation of system

Accuracy (%)	F1 score
72.8%	0.78

The model has an accuracy over most existing stable machine learning models, while also providing a higher accuracy over some stable deep learning systems, like R-CNNs and Deep Neural Generative networks. While some deep learning systems surpass it in terms of accuracy, they are not as stable with large datasets. This is summarised by Table 2.

Table 2
Accuracy comparison

Model	Accuracy	Stability
Proposed Hybrid	72.8%	Stable
Random Forests	70.8%	Stable
R-CNN	70%	Stable
Deep Neural Generative	76.6%	Unstable

Thus the proposed model compensates for its lower accuracy with higher practicality. It is also scalable, adaptable for large scale diagnosis in real time with large datasets as well as for small scale applications like diagnosis of an individual at a time, as long as the EEG data for a such a purpose is available. However, accuracy improvement is still a viable future direction. Thus, we propose a model that can also be easily interpreted and corrected to further improve its performance and be adapted to other applications. This can be done by experimenting with different optimizers, changing the number of units in the CNN and LSTM layers and perhaps even integrating with other systems that take into account patient history from transcriptions or MRI scans.

Conclusion and Future Enhancement

The proposed work presents a system, which given EEG data of an individual can classify them as showing symptoms of schizophrenia or not. This is done by using a combination of a CNN and an LSTM model known as a Bi-LSTM. The system proposed is stable when compared to similar deep learning systems, is scalable and produces interpretable results. It reaches an accuracy of 72.8% which is greater than the surveyed stable machine learning models for this application and is comparable to some deep learning models as well. Some future enhancements are possible for this work, one being the use of a live stream of medical data from a hospital. Another is taking more features into account other than EEG data, that is, MRI scans and patient background. For example, the sex of a patient may be taken into account for determining how likely and when susceptibility to symptoms may occur as shown in Iacono, W.G. et al., [16]. Moreover, one can proceed in the direction of trying to improve the accuracy of the proposed system further for instance by training it on larger datasets or adjusting hyperparameters, as it does not compare to the high accuracy of unstable deep learning systems. Some other enhancements are experimenting with the use of word embeddings, as suggested by W. Yue et al., [15] to further improve performance, as the data used is alphanumeric.

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