International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Revue d'Intelligence Artificielle
Vol. 37, No. 3, June, 2023, pp. 531-537
Journal homepage: http://iieta.org/journals/ria

A Patient-Centered Text-Derived Neural Network Paradigm for Diagnosis of Schizophrenia

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https://doi.org/10.18280/ria.370301

Received: 20 April 2022
Accepted: 25 March 2023

Keywords:
schizophrenia, medical data, neural prediction, digital healthcare, DSM-V

ABSTRACT

A text-derived neural network for diagnosing Schizophrenia is illustrated in this paper. Schizophrenia is a continuous mental condition that affects the job performance, social relationship, and livelihood of individuals. Using DSM-V criterion for schizophrenia diagnosis, we collected data from medical records of 1205 patients in psychiatric hospitals (57% Schizophrenia and 43% Related Illnesses) and developed a neural network model. In order for the developed model to categorize the test data into classes, significant features from the acquired dataset were fed into it to identify indicators in the training data. The model diagnosed schizophrenia with 90% accuracy, 92% specificity, 84% precision and Area under the Receiver Operating Characteristic (ROC) curve of 0.97. These results are promising for schizophrenia diagnosis in the near future. The text-derived ANN developed is more accurate and faster computationally and can be used to generalize in the case of new data when compared to image-based classification.

1. INTRODUCTION

Schizophrenia is an intense mental illness characterized by delusions, hallucinations and other cognitive impairments that affects 20 million people worldwide. Despite the fact that schizophrenia is a rare disorder, it is one of the top twenty primary causes of years spent disabled around the world [1, 2]. Given that Nigeria is Africa's most populous country, with a population of 186 million and a prevalence rate of 0.4 percent, the anticipated number of Nigerians living with schizophrenia is 1.86 million [3]. COVID-19 has resulted in self and social isolation, quarantine, and movement restrictions, leading to more persons suffering feelings of powerlessness, isolation, grief, worry, and depression, all of which may exacerbate the disease.

The financial costs of this condition are beyond the usage of health and self-welfare care to include its connected disease and fatality as well [4, 5]. The condition has been found to be a considerable financial burden on the health-care system and society as a whole [6]. In Nigeria, Schizophrenia is a costly disease, schemes to make treatment more bearable for patients and their families could drastically lower the cost of hospitalization.

Diagnosing schizophrenia is difficult, and it necessitates a variety of techniques in order to get an accurate diagnosis. Psychiatrists must prove that the symptoms have been present for at least a month, as specified in the DSM-V diagnostic specifications, and that the symptoms are not the result of other disorders, behavioral activities (e.g., alcohol intake), or a medicinal response. Due to these constraints, the diagnosis of schizophrenia has become a lengthy and complicated process. In order to facilitate early detection, timely treatment, and management of schizophrenia, psychiatrists need an effective method of diagnosing the disease [7]. During diagnosis, the psychiatrist has to interact with patients, and their relatives. Collating information is often challenging because some patients may have no recollection of some details of their previous episodes. Hallucinations and delusions in their various forms, unconscious behavior, haphazard speech, mood, and affect are some of the criteria used to diagnose schizophrenia, according to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V), two or more of which must be present during a one-month period [8].

In this study, we present a proof of concept for a text-derived neural network model suitable in extracting data from the medical record of patients suffering from schizophrenia and related illnesses in psychiatric hospitals. A robust approach to developing the model and assessment of model performance cum suitability accept and process the acquired data, training the model, and interpreting the results in the view of deciphering the appropriate medical intervention. The text-derived ANN is expected to reduce computational load and also overcome the bottlenecks associated with image-based classification.

2. RELATED WORKS

Although research indicates that magnetic resonance imaging may be a decisive biomarker for Schizophrenia, there is no traditional and recognized biomarker for the disorder [9, 10]. Due to the overlap in structural change caused by variables comparable to schizophrenia, such as alcohol addiction and anti-psychosis therapy, using MRI and imaging data to diagnose schizophrenia on the basis of structural alterations might be difficult [11].

The authors in the study [12] constructed a neural network model that predicted the likelihood of developing psychiatric problems such as anxiety, behavioral disorders, depression, and post-traumatic stress disorder with an accuracy of 82.35 percent.

Authors in the study [13] proposed a classification method for schizophrenia using a neural network (NN) approach and functional brain 'modes' estimated from resting state data using independent component analysis. The authors achieved a classification accuracy of 76%. In the study [14], the authors collected data of kinematic features of pen movements in handwritings of a group affected with Schizophrenia and another group of healthy persons, an artificial neural network (ANN) was used to precisely classify the two cases. Promising results were obtained from the use of ANN for extraction and classification of handwriting kinematic features. Data pertaining case files of the patients with schizophrenia were collected at the Medical Records Department of the Neuro-Psychiatric Hospital in Port-Harcourt, Nigeria which was used to generate the needed data in the study [15]. The study results indicate that 58.19% of patients admitted had schizophrenia.

Experimental analysis was performed in the study [16] using fMRI data and results such as receiver operation characteristic curves for the three-way classifier with area under curve values around 0.82, 0.89, and 0.90 for healthy control versus non-healthy, bipolar disorder versus non-bipolar, and schizophrenia patients versus non-schizophrenia binary problems were achieved respectively. A classification rate ranging from 70-72% for the testing data was achieved, while 80%, and was achieved using the one nearest-neighbor classifier.

In the study [17], the authors collected EEG data of 70 normal persons with no history of psychiatric disease, 80 schizophrenic and 80 bipolar patients. Feature vectors were extracted from obtained EEG rhythms using FFT segmentation. The authors proposed two algorithms for classification (MLNN and RBF), the proposed algorithms gave excellent outcomes when tested on the three classes of EEG rhythms. The MLNN model (98.67%) achieved a better classification rate compared to the RBF model (87.33%). The authors in the research [18] proposed a system that utilizes Principal component analysis for the classification of heart disease, the proposed system also apply feature extraction. They suggested that minimizing data dimensionality would aid in decreasing the cost for computation in performing prediction in the classifiers utilized. The authors [19] proposed an approach to predict various diseases by making use of data mining algorithms. The proposed methodology recommended that the amount of medical tests can be decreased by using the data mining methods for the illnesses like diabetes, breast cancer, heart disease etc. In the research [20], the authors applied natural language processing (NLP) algorithms on stories written by schizophrenic and non-schizophrenic subjects. Grammatical traits extracted in the narrative texts were used for classification of the test subjects. The achieved result indicates that a novel strategy to detect texts written by schizophrenic subjects was developed.

A dataset of 86 records was used to classify schizophrenia using Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Nave Bayesian (NB) algorithms [21]. SVM, RF and NB had the highest accuracy (90.7%) while performing slightly better than ANN (88.4%).

In the research [22], the authors developed a Convolutional Neural Network (CNN) with 11 layers to analyze EEG signals of 14 healthy subjects and 14 schizophrenic subjects. Important attributes were extracted from the acquired EEG signals to perform classification at the fully connected layer. For non-subject base testing and subject base testing, the suggested model attained classification accuracies of 98.1 percent and 81.3 percent, respectively.

One study, Shahriman et al. [23] proposed a CNN model for the classification of brain functional connectivity in healthy subjects and schizophrenic subjects. The proposed model uses Vector auto-regression (VAR) to extract connectivity features from EEG signals. The developed model produced accuracy 86.9%. In a recent study [24], a support vector machine (SVM) model was developed to classify Alzheimer' disease patients and normal controls, the proposed model attained an area under the curve (AUC) of over 88.82%. The authors [25] chose certain discriminative features and also Fisher's criterion was used in training the proposed SVM model. Consequently, the SVM model developed for distinguishing bipolar illness patients from normal people had a classification accuracy of 76.25 percent. A model for detecting first episode psychosis was proposed, while employing deep neural networks to create the classification model, PCA was utilized to reduce the amount of irrelevant features in cortical thickness and gray matter volume. The authors [26] were able to attain 70.5% classification accuracy.

3. METHODOLOGY

3.1 Data collection

Data used for this research were collected from the psychiatric clinics of the Lagos University Teaching Hospital and the Federal Neuropsychiatric Hospital, Lagos both in Nigeria with approval from the ethical committee of both hospitals. Features obtained from the patient case files were organized and saved into an excel file. In this study, a total of 1205 health records were collected. The data contains the medical history of persons recorded between the years 2013 and 2019 and includes patients diagnosed with schizophrenia (57%) and also patients diagnosed with other related illnesses (43%). The related conditions include schizoaffective disorder, bipolar disorder, depression and behavioural disorder etc. The record that was obtained comprises 38 features, including the CLASS column, as shown in Figure 1.

1	YEAR	AGE	SEX	OCCUP	MAR_STA	DUR_EPI	P_PSY_HX	P_MED_	FAM_P_	P_SOC_H	P_SEX_HX	FOR_HX
539	2019	30	M	STUDENT	SINGLE	55	YES	NO	NO	NO	NORMAL	YES
540	2019	71	F	RETIRED	MARRIED	36	YES	NO	NO	YES	NORMAL	NO
541	2019	53	M	UNEMPLOY	MARRIED	103	YES	YES	YES	YES	NORMAL	YES
542	2019	28	M	STUDENT	SINGLE	206	NO	NO	NO	YES	NORMAL	NO
543	2019	20	F	STUDENT	SINGLE	309	NO	YES	NO	NO	NORMAL	NO
544	2019	50	F	UNEMPLOY	MARRIED	24	YES	YES	YES	NO	NORMAL	NO
545	2019	31	F	UNEMPLOY	MARRIED	348	YES	YES	NO	YES	NORMAL	NO
546	2019	21	F	STUDENT	SINGLE	24	YES	NO	NO	NO	NORMAL	NO
547	2019	17	F	STUDENT	SINGLE	348	NO	YES	YES	YES	NORMAL	NO
548	2019	32	F	UNEMPLOY	SINGLE	24	NO	YES	NO	NO	NORMAL	NO
549	2019	36	F	BUSINESS	MARRIED	3	YES	NO	NO	NO	NORMAL	NO
550	2019	45	F	BUSINESS	SINGLE	6	NO	YES	NO	YES	NORMAL	NO
551	2019	43	F	SALES	SINGLE	48	NO	YES	NO	NO	NORMAL	NO
552	2019	33	M	SALES	SINGLE	1	NO	YES	YES	YES	NORMAL	NO
553	2019	27	M	STUDENT	SINGLE	2	YES	NO	YES	YES	NORMAL	NO
554	2019	48	M	UNEMPLOY	MARRIED	6	YES	YES	YES	YES	NORMAL	YES
555	2019	25	F	STUDENT	SINGLE	12	YES	NO	NO	NO	NORMAL	NO
556	2019	22	M	STUDENT	SINGLE	42	YES	NO	NO	NO	NORMAL	NO
557	2019	32	M	UNEMPLOY	MARRIED	4	YES	YES	NO	YES	NORMAL	NO

Figure 1. Window showing some section of the acquired dataset

3.2 Data pre-processing

The data acquired for this study was unstructured and required preprocessing. In essence, empty entries within the dataset were sorted out by replacing the missing entries with values that have the highest frequency. Furthermore, the text attributes in the dataset was converted to numeric format for the model to process it; Label Encoding was utilized to perform said function. The encoded columns are fitted into the original dataset using the *fit_transform* class. Prior to training the model, it is important to scale features in the dataset. The Sci-Kit Learn library's *Standard Scaler* class transforms each data point. In this manner, the attribute variances are all within the same range. In a case where some features have higher variances than others in the dataset; it can result in misclassification thereby compromising the model's reliability.

3.3 Feature selection

Features relevant towards the diagnostic case should be employed for training and testing in classification models. Feature selection helps to optimize the accuracy of the classification model by discarding trivial and redundant features within the dataset. For our model, features were sort out based on the diagnostic criteria of schizophrenia (DSM-V) and also the correlation coefficient between said features.

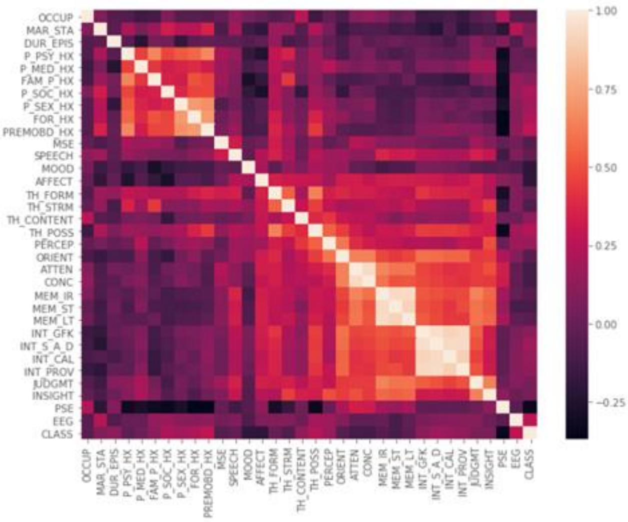

Figure 2. Heat map of the pearson's correlation values between each pair of features

Figure 2 shows that maximum correlation exists between the following group of features ([ATTEN and CONC], [MEM_IR, MEM_ST, MEM_LT and INT_S_A_D], [INT_GFK, INT_CAL and INT_PROV]). Subsequently, CONC, MEM_IR, MEM_LT, INT_GFK, INT_CAL and INT_PROV were withdrawn from the dataset to improve the accuracy of the model. We also consulted clinical psychiatrists and based our feature selection for the model on DSM-V.

Figure 3 shows the number and percentage of the two classes present in the dataset. There are 682 recorded schizophrenia cases and 523 recorded cases of other related illnesses in the dataset.

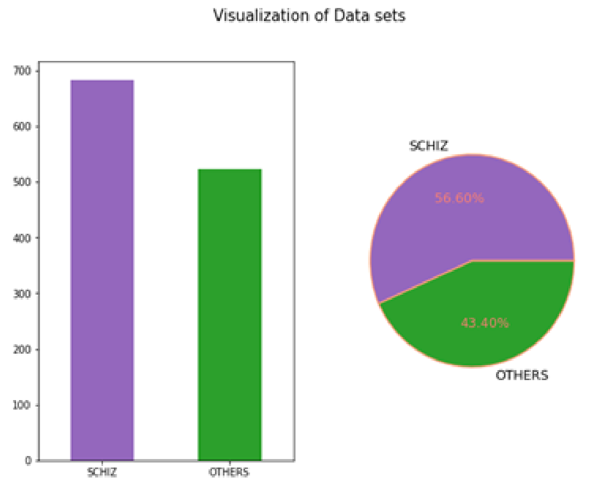

Figure 3. Bar chart and pie chart of recorded schizophrenia cases and other related illnesses

3.4 Neural network model

A neural network is a model that is provided with input and output values and is required to discover a pattern from the training data. The goal of the system is to generate an accurate mapping function, so that when the test data is introduced into the system, the algorithm can predict the output. The error between the actual value and the predicted value is continuously feedback into the system until an acceptable level of accuracy is attained. The design of our proposed neural network is indicated in Figure 4 and Figure 5.

LAYER	SUMMARY
Input layer	This layer's nodes have 16 input features that are fed into the network.
Hidden Layer No. 1	There are 8 RELU activation nodes in this layer. The layer is assigned a dropout probability of 0.3.
Hidden Layer No. 2	There are 4 RELU activation nodes in this layer. The layer is also assigned a dropout probability of 0.3.
Output layer	For classification, the output layer uses a sigmoid activation function.

Figure 4. Design of the neural network model

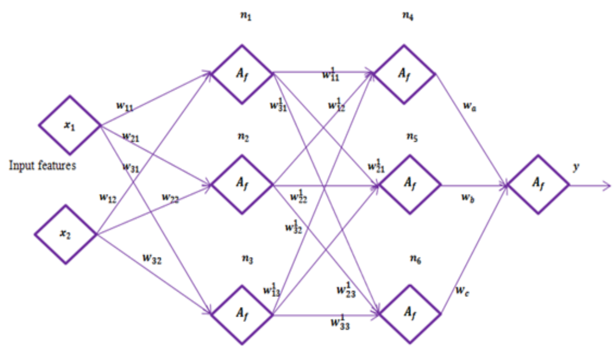

Figure 5. Representation of the neural network model design

$$y = A_f.(\sum_{j=0}^{n} w_{kj}x_j + b) \quad (1)$$

where,

A_f represents the activation function;

x_j represents the input features (e.g., past psychiatric history, thought content, perception etc.);

w_{kj} represents weights, and b represents the bias.

3.4.1 Matrix representation of the model

In the matrix representation of the model, the bias and activation function are not considered.

For the output at the first hidden layer:

$$H_i = W_{ij}.I_i \quad (2)$$

where,

H_i represents the first hidden layer which is a 3×1 matrix;

W_{ij} represents the weights between the input layer and the first hidden layer;

I_i represents the input features of the model.

Therefore, the output at the first hidden layer is given by:

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} . \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} w_{11}x_1 + w_{12}x_2 \\ w_{21}x_1 + w_{22}x_2 \\ w_{31}x_1 + w_{32}x_2 \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} \quad (3)$$

For the output at the second hidden layer:

$$H_j = W_{ij}^1.H_i \quad (4)$$

where,

H_j Represents the second hidden layer which is a 3×1 matrix;

W_{ij}^1 Represents the weight between the first hidden layer and the second hidden layer.

Therefore, the output at the second hidden layer is given by:

$$\begin{bmatrix} w_{11}^1 & w_{12}^1 & w_{13}^1 \\ w_{21}^1 & w_{22}^1 & w_{23}^1 \\ w_{31}^1 & w_{32}^1 & w_{33}^1 \end{bmatrix} . \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} = \begin{bmatrix} h_1w_{11}^1 + h_2w_{12}^1 + h_3w_{13}^1 \\ h_1w_{21}^1 + h_2w_{22}^1 + h_3w_{23}^1 \\ h_1w_{31}^1 + h_2w_{32}^1 + h_3w_{33}^1 \end{bmatrix} = \begin{bmatrix} h_4 \\ h_5 \\ h_6 \end{bmatrix} \quad (5)$$

The total output of the model after forward propagation process is given by:

$$O_k = W_{ij}^2.H_j \quad (6)$$

$$[w_a \quad w_b \quad w_c] \cdot \begin{bmatrix} h_4 \\ h_5 \\ h_6 \end{bmatrix} = [h_4w_a + h_5w_b + h_6w_c] = [O_k] \quad (7)$$

W_{ij}^2 represents the weight between the second hidden layer and the output layer;

O_k represents the total output of the model as indicated in Eq. (7).

3.5 Setup of computational experiment

To determine the use of neural networks for the task of schizophrenia diagnosis, we trained and tested our model on data with 1205 data points using 17 features. Initially, 100 and 250 epochs were employed in training the network; however, for appropriate training, a batch size of 16 and 500 epochs was used later in the experiment. We trained our models on several train/test ratios (40/60, 35/65, 50/50, 65/35 and 60/40) initially in order to obtain the best configuration of the model, the 60/40 configuration produced the best accuracy with the least degree of over-fitting and was therefore presented in this work as the optimal model. In training the model, the default learning rate for Adam optimizer was used, and also network hyper-parameters were tuned. The dropout technique [27] was implemented in the model to eliminate over-fitting and boost the accuracy of the model. The proposed model was built using python on Anaconda IDE with inbuilt libraries such as Scikitlearn, Keras, Tensorflow, Numpy, Matplotlib etc. All experimentation was carried out on an Acer Aspire E1-531 Laptop computer with 6GB RAM, 500GB HDD and a 2.2GHz Intel Pentium processor. Our model's predictive performance was evaluated using the test dataset while also validating with 20% of the test dataset.

4. EXPERIMENTAL RESULTS

In this section, the model's loss and accuracy plots are presented; a confusion matrix was utilized to assess the model's performance indicators, and a plot of the Receiving Operating Characteristic is also presented.

		Actual Class	
		Schizophrenics	Non-Schizophrenics
Predicted Class	Schizophrenics	107	21
	Non-Schizophrenics	21	253

Figure 6. Confusion matrix of the developed model

The result in Figure 6 indicates that the model is able to predict 107 schizophrenia cases correctly, while the number of patients diagnosed erroneously as schizophrenics is 21. Also, the model predicted 253 non-schizophrenia cases correctly and diagnosed 21 patients as non-schizophrenics incorrectly. The developed model produced an accuracy of 89.6% and ROC area of 0.97. From the confusion matrix of the test dataset in Figure 6, the following performance metrics are calculated in Eqs. (8)-(11). The parameters used in calculating said metrics (TP, TN, FP, and FN) are briefly described below.

True Positive (TP): The model predicted the condition as positive and it's true.

True Negative (TN): The model predicted the condition as negative and it's true.

False Positive (FP): The model predicted the condition as positive and it's false.

False Negative (FN): The model predicted the condition as negative and it's false.

$$Specificity = \frac{TN}{TN + FP} = 92.3\% \quad (8)$$

The model had a specificity of 92% based on Eq. (8).

$$Recall = \frac{TP}{TP + FN} = 83.6\% \quad (9)$$

The model had a recall of 84% based on Eq. (9).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = 89.6\% \quad (10)$$

The model had an accuracy of 90% based on Eq. (10).

$$Precision = \frac{TP}{TP + FP} = 83.6\% \quad (11)$$

The model had a precision of 84% based on Eq. (11).

The accuracy plot of the text-derived model is depicted in Figure 7. The train accuracy increased from 0.85 to 0.95 between 100 and 500 epochs. The validation accuracy was recorded as 0.92 at 300 epochs and increased afterwards. The average training accuracy was reported to be 91%. From the plot, it is observed that there is no over-fitting in the text-derived model and it indicates that the model can be used to accurately predict the condition in the case of new data.

The model's training and validation losses are depicted in Figure 8. As indicated in the graph, the loss function was at its minimum after training (i.e. 500 epochs). For a text-derived model, the low loss function has significance to the accurate diagnosis of schizophrenia as corroborated in the literature.

From Figure 9, it is shown that the model has an area under the curve of 0.97 which indicates that the model was able to differentiate between the positive and negative classes correctly.

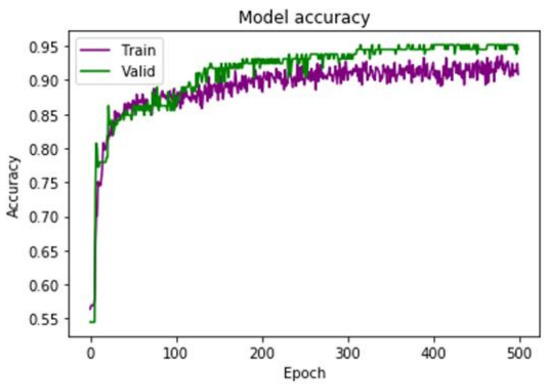

Figure 7. Training and validation accuracy of the text-derived neural network model

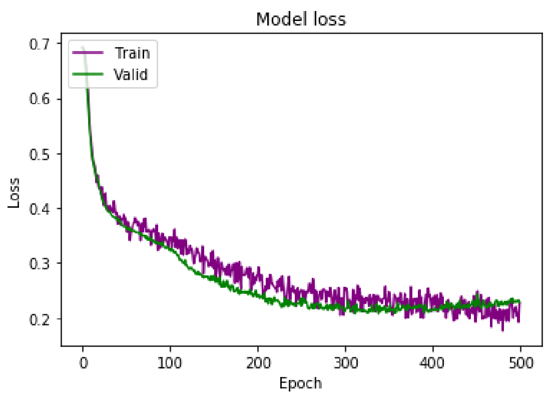

Figure 8. Training and validation loss of the text-derived neural network model

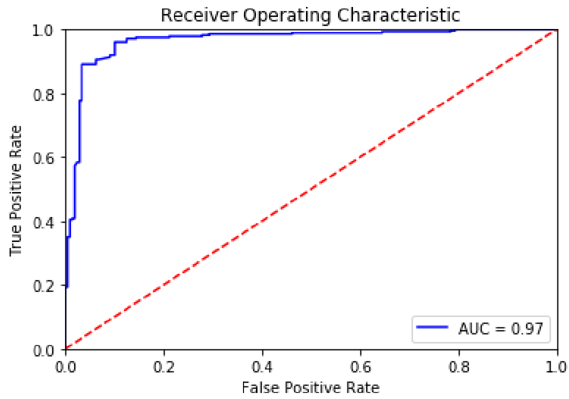

Figure 9. ROC curve of the model

In essence, the model's efficiency for various configurations demonstrates the model's ability to be used as a strategy for accurately diagnosing schizophrenia. The model's accuracy is promising at 90% and can be reliably used to determine whether a new case of similar attributes has Schizophrenia or not. The sensitivity of the model (84%) indicates the probability of the model to predict positive instances as positive. Also, the area under the ROC curve determines the discriminant efficiency of the model.

5. CONCLUSION

We present a novel text-derived neural network algorithm which is a simplification of the traditional EEG-MRI derived dataset popularly used in modeling schizophrenia. A text-derived neural network model was developed by collecting data from the medical record of patients suffering from schizophrenia and related illnesses from psychiatric hospitals, developing the model to suit the acquired data and training the model and also evaluating and interpreting the results from the tests data. The text-derived ANN developed is more accurate and faster computationally and can be used to generalize in the case of new data when compared to image-based classification. Our text-derived neural network achieved an accuracy of 90% and a specificity of 92% with an AUC of 0.97. These results are promising for schizophrenia diagnosis in the near future. In terms of medical application, the model can help psychiatrists detect schizophrenia quickly and accurately, as well as establish treatment plans and control the condition, because the extent of an episode is a determinant in the effectiveness of the drugs prescribed. Lastly, the accuracy of the text-derived neural network model can be considerably enhanced through collecting relevant data at different mental health facilities. For future work, an electronic medical record and a user interface could be developed to improve the model's accessibility.

ACKNOWLEDGEMENT

The authors graciously thank and acknowledge the Chancellor Research Initiative for funding this study.

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