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A Genetic Neuro-Fuzzy System for Diagnosing Clinical Depression

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Abstract: Depression is a serious illness that affects millions each year and if left untreated, it may lead to the deaths of many. It comes in many flavors that can be very different among people and this makes diagnosing it very difficult. A lot of artificial intelligence systems have been designed to diagnosing depression but they failed to perform feature selection and extraction on the dataset used in training the systems and this has a huge implication on the classification accuracy of the system. The objective of this research work is to develop a depression diagnosis system, that takes into consideration feature selection and extraction of dataset using Genetic-Neuro-Fuzzy techniques. Feature selection and extraction, will enable identification of key symptoms and hidden traits which are vital in diagnosis of depression. In this work, a Genetic Neuro-Fuzzy Model which is capable of handling feature selection and extraction on depression dataset was proposed and designed for diagnosing clinical depression. The GA component optimizes the clinical dataset which consist of series of diagnosed depression cases by performing feature selection and extraction, while ANFIS is used in training the optimized dataset obtained from the GA. The system had 92.5% prediction accuracy. This is a significant improvement over the best related model in literature that achieved a prediction accuracy of 92.4%. The system is recommended for psychiatrist hospital to aid in depression diagnosis. The research is limited to the diagnosis of clinical depression; future work should focus on the other forms of depression and treatments. The model has incorporated feature selection and feature extraction for the prediction of clinical depression with significant results established with performance indicators.

Keywords: Depression, Genetic Algorithm, Neural Networks

1. Introduction

Depression is a psychological ailment that is characterized by sadness, loss of interest or pleasure, feelings of guilt or low self-worth, disturbed sleep or appetite, feelings of tiredness, and poor concentration [1]. It can have adverse effects on the quality of life of an individual and has drastically reduced the productive power of nations [2, 3]. It is also known to be a major contributor to the global burden of diseases [4], and affects humans irrespective of sex, race, and age [2, 5, 6]. In 2014, the World Health Organisation ranked depression as the second leading cause of suicide among 15 to 29-year-olds [7]. Statistics have shown that the total estimated number of people living with depression increased by 18.4% between 2005 and 2015 [8], and the proportion of the global population with depression as of 2015 was estimated to be 4.4%, with a higher percentage occurring in females (5.1%) than in males (3.6%) [8]. Prevalence of depression rates vary by age, peaking in older adulthood between aged 55-74 and it is estimated that above 7.5% occurs among females and above 5.5%, occurring among males [8]. Today the total number of people living with depression in the world is approximately 322 million [9]. Symptoms of depression can range from depressed mood, nearly every day feeling of sadness, persistent loss of interest in almost all activities of the day, significant weight loss/gain, insomnia, unnecessary agitation, everyday fatigue, feeling of worthlessness, recurrent thought of death, suicidal tendencies e.t.c [2, 10]. Depending on the number and severity of symptoms a depressive episode can be characterized as mild, moderate, or severe [8]. The major cause of depression is still

unknown but some factors can increase the chance of depression [1, 3] some of these factors include; abuse (physical, sexual, or emotional), abuse of drugs, conflict, sadness or grief from the death or loss of a loved one, serious illnesses, and genetics [1, 10]. While certain risk factors are associated with an increased risk of depression, an individual with a family history of depression may have an increased risk of developing depression [11-14].

There are two categories of psychometric instruments for diagnosing depression. They are

1) Self-administered tool.

2) Interviewer-Administered tool.

There are four types of self-administered psychometric instrument for diagnosing depression, They are; Beck Depression Inventory, Center for Epidemiological Studies Depression Scale (CES-D), Geriatric Depression Scale (GDS) and Zung Self-Rating Depression Scale (Zung SDS) while only one Interviewer-Administered tool exist for diagnosing depression which is the Cornell Scale for Depression in Dementia (CSDD) [15-20]. The diagnosis of clinical depression has been sponsored, supported, enhanced by various intelligent and autonomous models. These models have been built on the premises of the Artificial Intelligence (AI) concept. Machine learning techniques have been applied to diagnosing depression but most of the systems designed failed to perform feature selection and extraction on symptoms that consist of the dataset used for a depression diagnosis. This has reduced the classification accuracy of the machine learning algorithm [14, 21]. Although researchers have observed that the diagnosis of clinical depression has ignored optimal training, feature selection, and feature extraction [14, 21]. Therefore, it is imperative to design a model for diagnosing clinical depression, which performs feature selection and extraction on the dataset to be used for training the learning algorithm of the design system. In this paper, we used employed a genetic algorithm, neural network, and fuzzy logic in designing a system for diagnosing clinical depression.

This article is divided into the following sections, Section II contains review of related works in literature, Section III contains the research methodology, Section IV contains the results obtained, discussion and finding while Section V contains the conclusion.

2. Review of Related Works

In the previous study [14], a soft-computing model for depression prediction was presented. The objective of the research work is to diagnose depression. The methodology consists of Neural Network (NN), Fuzzy Logic (FL), and Case-based reasoning (CBR). The system has a high level of result accuracy and reduced system error rate but it failed to incorporate feature extraction and selection of data in its design. In the existing work [22] An Artificial Neural Network (ANN) Model to Predict Depression among Geriatric Population at a Slum in Kolkata, India was presented. The research objective is to predict depression among the geriatric population from socio-demographic and morbidity attributes. It used Artificial Neural Network as a research methodology. This research work finding shows that the system has an accuracy of result prediction, learning ability through unsupervised learning, and reduced system error rate. However, the system design did not incorporate feature extraction and selection on the dataset used for predicting depression.

In the earlier study [21], a neuro-fuzzy approach for the diagnosis of postpartum depression disorder was presented. The objective of this research work is to diagnose postpartum depression. The methodology used for this research work is the Adaptive Neuro-Fuzzy Inference System. The system has a high level of result accuracy and a reduced system error rate. However, it failed to implement feature extraction and selection on the dataset used for the diagnosis of postpartum depression disorder.

S. Yoshihiko et al [23], proposed Forecasting Depressed Mood Based on Self-Reported Histories via Recurrent Neural Networks. The objective of the research is to predict depression. Recurrent Neural Networks were used as methodology. The work demonstrates the accuracy of result prediction, learning ability through unsupervised learning, reduced system error rate, and highlights the usefulness of Artificial Neural Networks (ANN) rate but it failed to incorporate feature extraction and selection of data in its design. In [11], a Neuro-Fuzzy System for Modeling the Depression was presented. The research objective is to predict depression. The research work used the Adaptive Neuro-Fuzzy Inference System as its methodology. The research finding shows the accuracy of result prediction, learning ability through unsupervised learning, and reduced system error rate. But the research work does not apply feature extraction and selection to the dataset.

3. Methodology

A study of the conventional system for diagnosing depression was carried out at Federal Medical Center, Owo, Ondo State to establish the process of diagnosing depression. Relevant data, medical information, expert knowledge regarding depression were used in obtaining relevant information in modeling the proposed Soft computing system. The proposed Soft computing model for diagnosing clinical depression employs the use of a Genetic Algorithm (GA) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The GA module was used for feature selection and extraction because it combines both feature selection and feature extraction while ANFIS was used in training the optimized dataset obtained from the GA. The proposed Hybrid Soft-Computing Model for diagnosing depression has three basic components; Dataset, a Genetic Algorithm, and Adaptive Neuro-Fuzzy System. The system utilizes a supervised hybrid learning algorithm combining the least square estimator and backpropagation gradient descent. The model was simulated and tested, using Matrix Laboratory, and results were analyzed and an informed conclusion drawn from analyzed

data was used to design the system using Java.

Data collection: This dataset used in this study was collected from Federal Medical Center Owo, Ondo State. Observational data were collected manually from patients' medical diagnosis card and some retrospective diagnostic tools were obtained from some experienced psychiatrists at the federal medical center Owo. The data was verified and validated by qualified and experienced psychiatrist at the federal medical center Owo. the data obtained were formatted in the format required for this study. the dataset consist of 22 columns; the first 21 columns consist of the 21 criteria (Mood, Pessimism, Sense of failure, Self-dissatisfaction, Guilt, Punishment, Self-dislike, Self-accusation, Suicidal ideas, Crying, Irritability, Social withdrawal, Indecisiveness, Body image change, Work difficulty, Insomnia, Fatigability, Loss of appetite, Weight loss, Somatic preoccupation and Loss of libido for diagnosing clinical depression while the last column represents the diagnostic outcome. A total of 134 dataset obtained were examined by us and some experienced psychiatrists at the Medical center in arriving at the diagnostic prediction. At Federal Medical Center Owo, they employed the Becks Depression Inventory in diagnosing depressive episodes. The beck inventory scale was model into a mathematical equation. The modeled mathematical equation served as the objective function in the Genetic Algorithm. The Genetic Algorithm component and the ANFIS component was designed using Matlab. The datasets were optimized using the GA component and passed into the ANFIS for training. The model was trained for was trained for 60 epochs and it had an MSE saturated value of 0. 00000142. The figures below shows the output from the simulation. Figure 6 shows the testing layer of the Anfis simulation. The simulated result indicated that the ANFIS model has 96.9% accuracy in predicting depression.

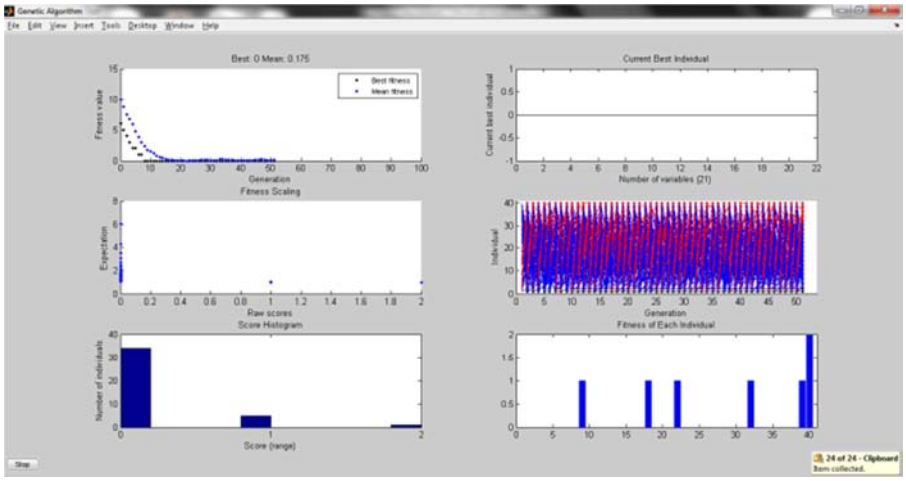

Figure 1. *Output from the GA Simulator at the 50th Generation.*

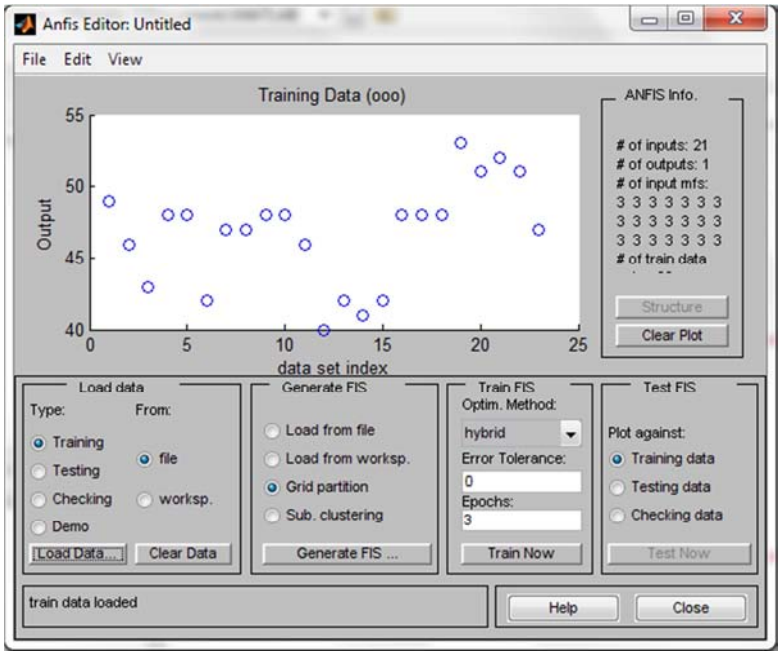

Figure 2. *ANFIS Training Interface.*

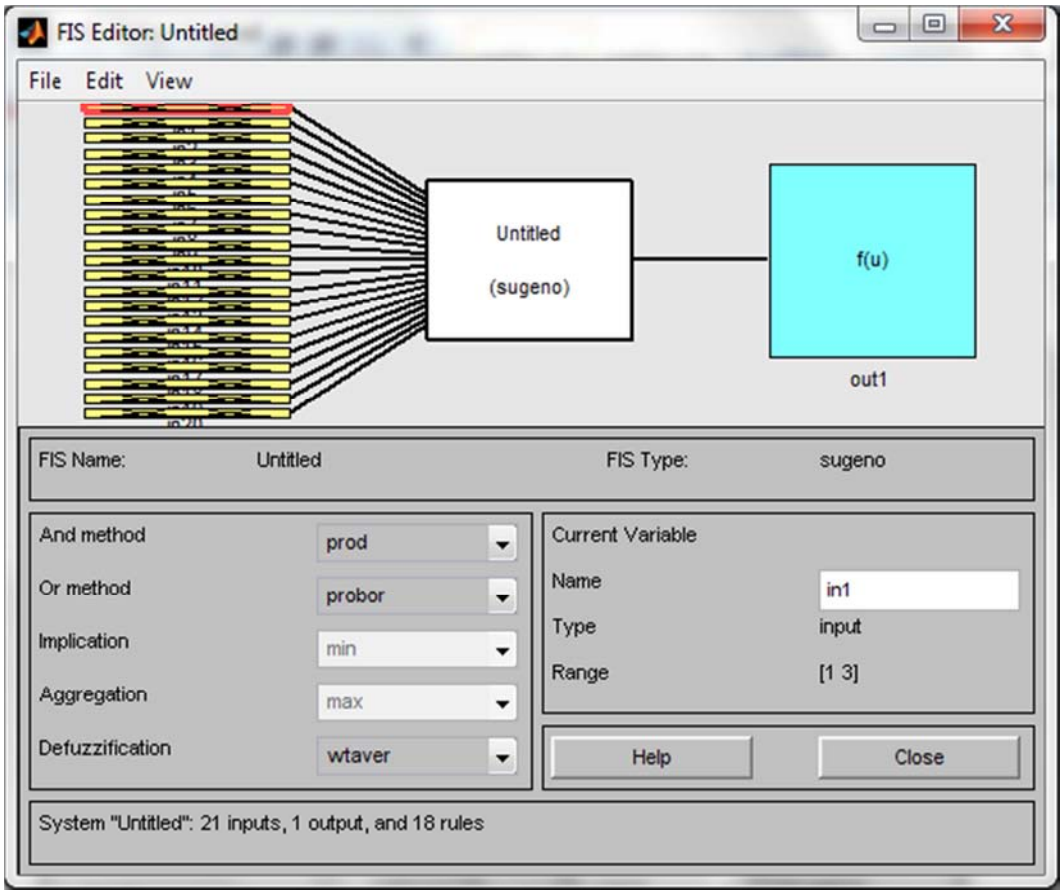

Figure 3. *Fuzzy Inference Engine of the ANFIS.*

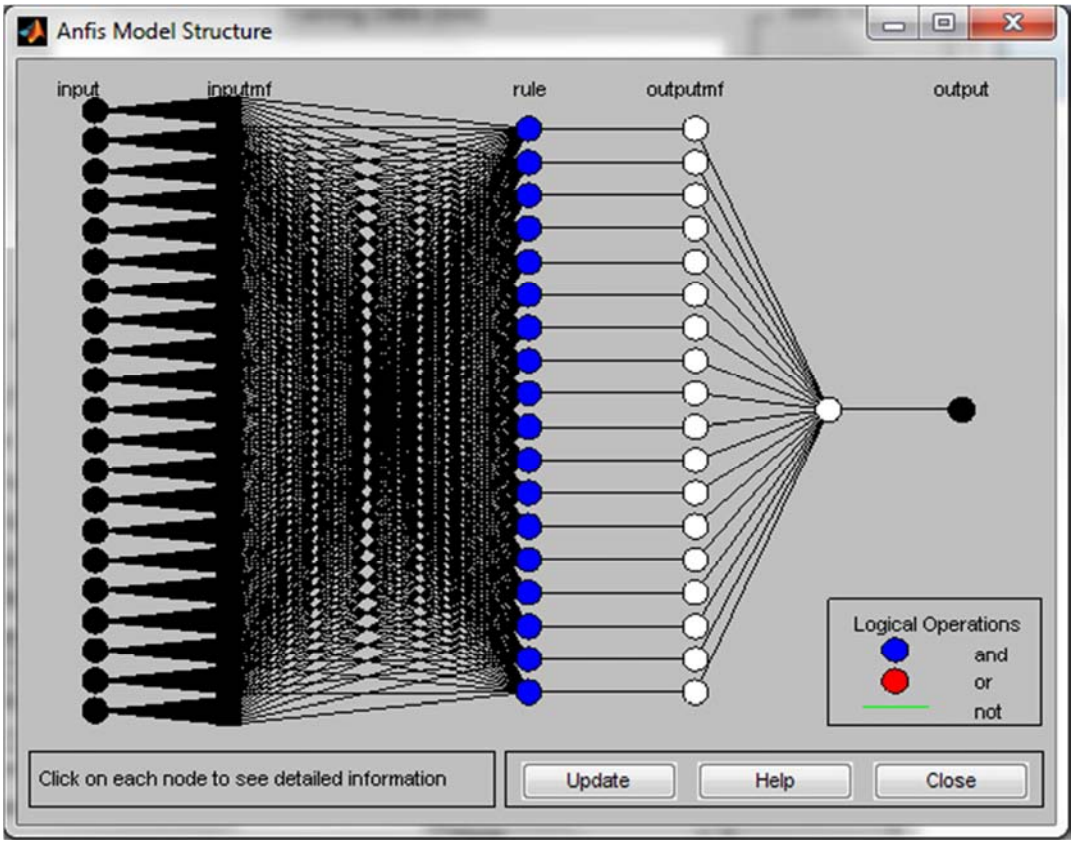

Figure 4. *ANFIS architecture of the model.*

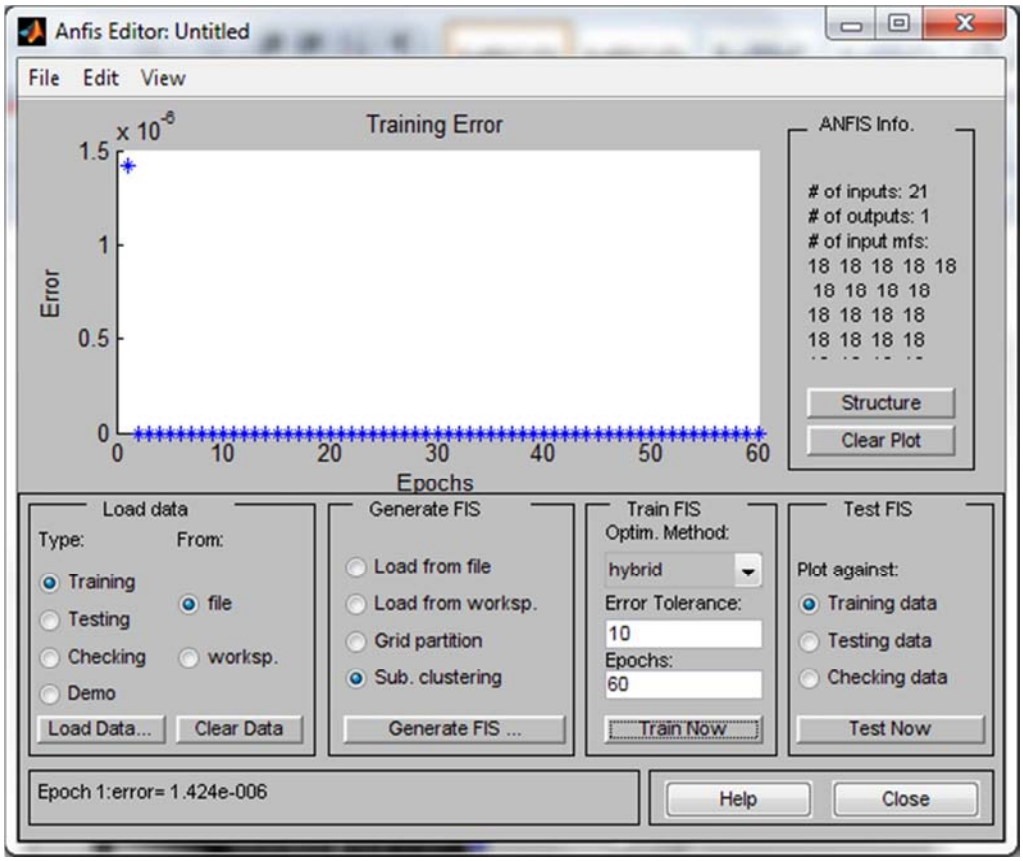

Figure 5. *Training Layer in the ANFIS for the model.*

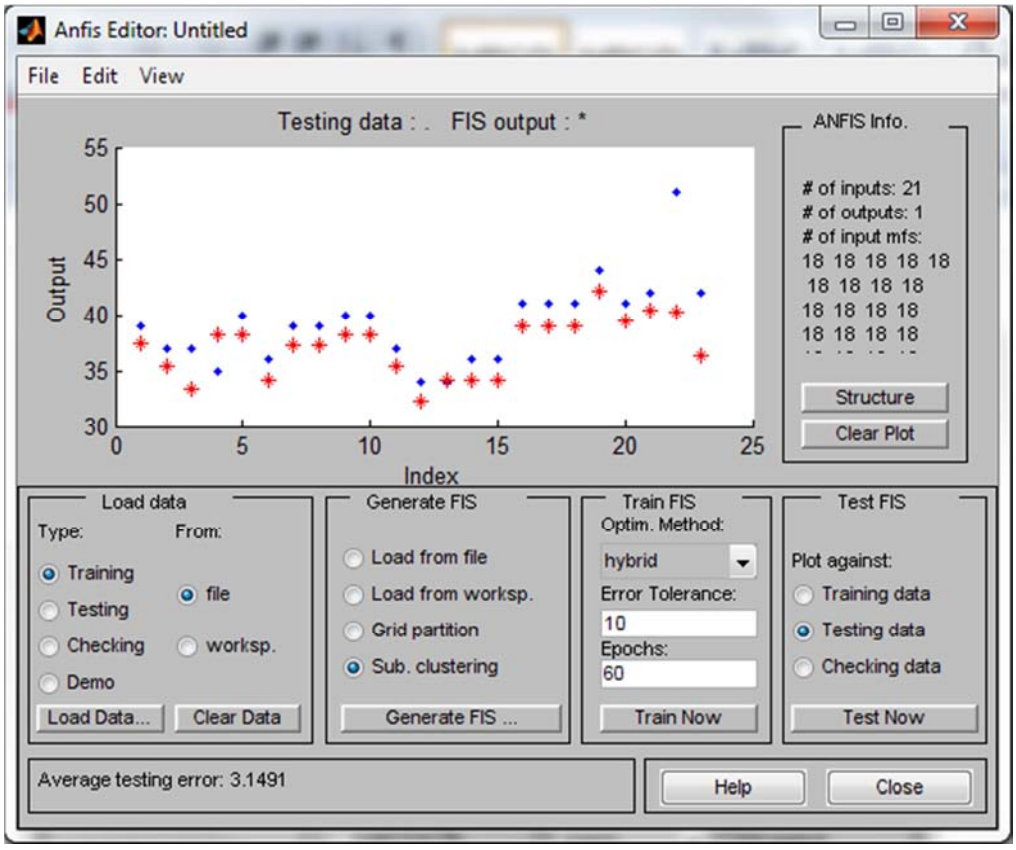

Figure 6. *Testing Interface of the ANFIS.*

Figure 6 shows the testing layer of the Anfis simulation. The simulated result indicated that the ANFIS model has 96.9% accuracy in predicting depression.

4. System Testing and Result

The performance of the system is evaluated using four measures: Confusion Matrix, Sensitivity, Specificity and Classification Accuracy. The system performance was evaluated using Receiver Operating Characteristic (ROC). The designed system was tested and the results compared with the test data. The following values were obtained.

Table 1. *Confusion Matrix for the research work.*

Test Result	Positive	Negative	Total
Positive	20 (TP)	2 (FP)	22
Negative	1 (FN)	17 (TN)	18
Total	21	19	40

Sensitivity=TP/TP+FN=20/20+1=0.95

Specificity=TN/TN+FP=17/17+2=0.895

Positive Predictive Value (PPV)=TP/TP+FP=20/20+2=0.909

Negative Predictive Value (NPV)=TN/TN+FN=17/17+1=0.895

False Negative Rate=FN/TP+FN=1/20+1=0.048

False Positive Rate=FP/TN+FP=2/17+2=0.105

False Discovery Rate=1-PPV=1-0.909=0.091

False Omission Rate=1-NPV=1-0.895

Critical Success Index=TP/TP+FN+FP=20/20+1+2=0.87

Accuracy=TP+TN/TP+TN+FN+FP=20+17/20+1+2+17=0.925

From the above the system predictive accuracy is 92.5%.

Comparing our model with those in literature it was observed that symptoms based utilized in diagnosing depression are different. In comparing our model with that of Anish et al, (2012) it was observed that 7 symptoms (Feeling Sad, Loss of Pleasure, Weight Loss, Insomnia, Hypersomnia, Loss of appetite, and Psychomotor Agitatio) were used by them in diagnosing depression which is quite small compared to the 21 symptoms utilized in our study. Their model was trained for 30 epochs and it had an MSE saturated value of 0.0116043. The ANFIS model was trained for 60 epochs and it had an MSE saturated value of 0.00000142.

It was also observed that the system designed by [13] had a prediction accuracy of 92.4% while the model had an accuracy of 92.5%. Ekong et al, (2012) tested his model with only 20 cases, this could be the reason they had such a high prediction accuracy.

5. Findings

1) The efficiency of the system was significant when compared with the dataset obtained from Federal Medical Centre, Owo, Ondo State. Out of the forty (40) test cases used to test the system, thirty-seven (37) cases turned out to be accurately predicted.
2) The system had a sensitivity prediction score of 0.952. This score indicates that the system had a 95.2% in predicting clinical depressive cases in the dataset used in testing the model.
3) The system had a specificity prediction score of 0. 895. This score indicates that the system had 89.5% in predicting cases in the dataset used in testing the model.
4) The system had a prediction accuracy score of 0. 925. This score indicates the reliability of the system and it shows that the system had 92.5% in predicting both normal cases and depressive cases in the dataset used in testing the model.
5) The predictive power of ANFIS for diagnosing clinical depression was greatly enhanced by the inclusion of a genetic algorithm with a prediction accuracy value of 92.5%. This is a significant improvement over the model designed by Ekong et al, (2012) which had a prediction accuracy of 92.4%.

6. Conclusion

As can be seen, a large amount of work has already been done in the area of depression diagnosis; nevertheless, there is still significant room for improvement. In this paper, a Genetic Neuro-Fuzzy Model for diagnosing clinical depression was proposed and designed. The model employed a Genetic Algorithm (GA) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The GA component performs feature selection and extraction on the symptoms that consist of clinical dataset, while ANFIS uses the optimized dataset to train the model.

References

[1] DSM V, Diagnostic and Statistical Manual for Mental Disorder Fifth Edition (DSM-V) Psychiatric Association Washington, DC, 2010.

[2] S. Stanislava and D. Stoyanova, Depression Factors Symptoms, Prevention and the Role of open journal of depression Vol. 3, No. 1, 3-4., 2014.

[3] Q. Feng, G. Frances, P. Nick, and J. Gunn, An exploratory statistical approach to depression pattern identification. Physical A 392 Pp. 889–901. www.elsevier.com/locate/physa. (Accessed July 12, 2017), 2013.

[4] W. Jinghui, W. Xiaohang, L. Weiyi, L. Erping, Z. Xiayin, L. Wangting, Z. Yi, C. Chuan, Z. Xiaojian, L. Zhenzhen, W. Dongni, and L. Haotian, Prevalence of depression and depressive symptoms among outpatients: a systematic review and meta-analysis BMJ ; 7-8, 2017.

[5] D. Pilgrim, The survival of psychiatric diagnosis, Social Science & Medicine 65 Pp. 536 547, 2007.

[6] S. Chattopadhyay, P. Kaur, F. Rabhi, and R. Acharya, An automated system to diagnose the severity of adult depression, Proc. of 2nd IEEE Int. Conf. on Emerging Applications of Information technology. Pp. 121-124. DOI: 10.1109/EAIT.2011.17., 2012.

[7] WHO: World Health Organization, Depression Fact Sheet, 2014.

[8] WHO: World Health Organization, Depression Fact Sheet, 2016.

[9] WHO: World Health Organization, Depression Fact Sheet, 2017.

[10] N. Neil and R. Francisco, Nedley Depression Hit Hypothesis: Identify Depression and its causes. American Journal of Life Style Medicine Pp. 423-428, 2016.

[11] D. Anish, B. Nirman, and C. Subhagata, ANeuro-Fuzzy System for Modeling the Depression Data. International Journal of Computer Application. Volume 54, No 6. Pp. 1-6., 2012.

[12] V. E. Ekong, Ekong, UO, Uwadiae E, Abasiubong, F and Onibere, E. A., A Fuzzy Inference System for Predicting Depression Risk Levels, African Journal of Mathematics and Computer Research, Vol. 6, No. 10. Pp. 197-204., 2013.

[13] V. E. Ekong, U. G Inyang, and E. A. Onibere, Intelligent DSS for depression diagnosis based on NF-CBR Hybrid, International Journal of Modern Applied Sciences, Vol. 6, No. 7. Pp. 79-88., 2012.

[14] V. E. Ekong and E. A. Onibere, A Soft Computing Model for Depression Prediction. Egyptian Computer Science Journal Vol. 39 No. 4 Pp 1-21., 2015.

[15] G. S. Alexopoulos, R. C. Abrams, R. C Young, and C. A. Shamoian, Cornell Scale for Depression in Dementia. Biol Psychiatry 23, 271-284., 1988.

[16] L. S. Radloff, The CES-D scale: A self-report depression scale for research in the general population. Appl Psychological Measurement 1, 385-401., 1977.

[17] L. K. Sharp, and M. S. Lipsky, Screening for Depression across the lifespan: A review of measures for use in primary care settings. Am. Fam. Physician 66 -6: 1001-1008., 2002.

[18] J. I. Sheikh, and J. A. Yesavage, Geriatric depression scale (GDS): Recent evidence and development of a shorter version. Clinical gerontology: pp 165-173., 1986.

[19] J. A. Yesavage, T. L Brink, T. L. Rose, O. Lum, V. Huang, M. B. Adey, and V. O. Leirer, Development and validation of a geriatric depression screening scale: A preliminary report. J Psychiatr Res 17, 37-49., 1983.

[20] W. W. Zung, A self-rating depression scale. Arch Gen Psychiatry Vol. 12, pp 63-70, 1965.

[21] V. I. Osubor and A. O. Egwali A neuro fuzzy Approach for the diagnosis of postpartum depression disorder, Iranian Journal of Computer Science 5-6, 56: 61. Doi: 10.1007/s42044-018-0021-6, 2018.

[22] S. Arkaprabha and B. Ishita, Artificial Neural Network (ANN) Model to Predict Depression among Geriatric Population at a Slum in Kolkata, India. J Clin Diagn Res. 11-5: VC01–VC04., 2017.

[23] S. Yoshihiko, X. Yinzhan, and S. P. Alex, DeepMood: Forecasting Depressed Mood Based on Self Reported Histories via Recurrent Neural Networks ACM. 978-1-4503-4913 2017, 2017.