A MODEL OF DEPRESSION DIAGNOSIS USING A NEURO-FUZZY APPROACH

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ABSTRACT: Depression is a common psychological disorder that is often mis-diagnosed by primary care physicians due to the confusing nature of its symptoms. Advances in computer assisted Clinical Diagnosis Support Systems (CDSS) has accelerated the discoveries of new approaches for diagnosis, prognosis and treatments that can be helpful for primary care physicians in detecting and diagnosing of potential patients. This paper proposes a hybrid soft-computing neuro-fuzzy driven model for the diagnosis of depression. The system captures, analyzes and predicts the risk levels of patients in primary care settings. The system is implemented using data validated by medical experts from two University Teaching Hospitals in Nigeria. Out of the 54 instances obtained, 40 were trained using a feed-forward back-propagation neural network algorithm and 14 were used for testing purpose. An Adaptive Neuro-Fuzzy Inference System (ANFIS) handled fuzzy rules used in the diagnostic decision making. The proposed neuro-fuzzy model approach identified and classified cases appropriately, achieving a high accuracy of 97.13% in diagnosis prediction. This clearly shows that the proposed model can improve the inference procedures comparable to that of the domain experts.

INTRODUCTION

One of the most common forms of medical errors globally is an error in diagnosis. An improper diagnosis occurs when a doctor fails to identify or report a disease when the patient is actually unhealthy. Depression is a disease whose symptom in primary care is controversial. Depressive symptoms range from every day sadness to loss of interest to suicidal ideations. It represents a major public health problem with a high prevalence amongst the productive adult population. It is ranked by World Health Organization (WHO) as the fourth most burdensome diseases in terms of disability costs (WHO, 2009). The illness is also a comorbid factor in many chronic conditions such as Diabetes, Cancer, Cardiovascular diseases, Alcohol abuse, HIV/AIDS resulting in higher costs to the healthcare system (Maja *et al.*, 2008; WHO, 2009; Kessler, 2002). Based on psychiatric morbidity surveys, one in six persons in Nigeria would be diagnosed as having depression or chronic anxiety disorder, which means that one family in twenty-five, is likely to be affected (Ewhrujakpor, 2009 and Olawale *et al.*, 2010). Many authors have disputed the exact cause of depression disorder, some argue that genetic links to the disorder is closely related, while others attribute the disease with an imbalance of chemicals in the brain and hormonal deficiencies. It is however generally accepted that in some cases it can be set off by certain conditions, such as sleep deprivation, environmental factors, childhood precursors, adverse life event or experiences such as loss of a loved one or job, hypothyroidism, and the use of antidepressant medications (About Depression, 2011; Nunes *et al.*, 2011. Studies also show that persons with the disorder may not seek care because of the following reasons:

i. Stigma associated with mental health problems,
ii. Unavailability of treatment resources,
iii. High cost of psychological treatment,
iv. Symptoms simulated in an attempt to circumvent a situation to their advantage
v. Lack of access to specialist services
vi. Fear of losing their jobs

This contributes to the prevalence of the disease worldwide. Diagnosis of the disorder by primary care physicians is sometimes difficult (Iliffe *et al.*, 2002) due to:

i. Symptoms of depression can be vague or associated with other medical conditions
ii. The large array of information to be considered before they can make the right diagnosis
iii. The complexity and confusing nature of the disease as a psycho-social-biological disorder lacking certain aetiology and pathophysiology
iv. High variability in symptoms and signs
v. Absence of certainty factors like validated diagnostic tests or monitoring measures equivalent to blood pressure, glycosylated haemoglobin or peak flows.

However, in a recent study by Hamer *et al.*, (2012) and Hildrum *et al.*, (2011) blood pressures (systolic and diastolic) and Body Mass Index (BMI) ratio have been suspected to be somatic factors associated with major depressive symptoms.

Classification of the disease has been based on subjective results obtained from patients using psychometric instruments that meet the criteria of the diagnostic and statistical manual of mental disorders, version 4 (DSM-IV) (American Psychiatric Association (APA), 1994) and International Classification of Diseases version 10 (ICD-10) (WHO, 1992; Mondimore, 2006; Mila *et al*, 2009). For diagnosis, physicians utilize a number of the assessment tools such as Primary care evaluation of Mental Disorder (PRIME-MD), Becks Depression Inventory, version 2 (BDI-2), Hamilton's Depression Rating Scale (HRSD), Physical Health Questionnaire (PHQ-9), Geriatric depression scale or Montgomery-Asberg Depression Rating Scale (MADRS) to establish severity levels for different onsets of the disease (Ellen *et al.*, 2002; Ariyanti *et al*., 2010).

Soft Computing (SC) is a methodology used to find approximate solutions for real world problems which contain various kinds of inaccuracies and uncertainties (Zadeh, 1994). The underlying paradigms of SC are Artificial Neural Networks (ANNs), Fuzzy logic (FL), and Genetic Algorithms (GA). Each of these paradigms has advantages and limitations. For example, the main advantage of fuzzy systems is their simplicity and transparency as they can express knowledge in the form of linguistic IF-THEN fuzzy rules but lacks the learning capabilities of ANNs. The latter method, however, suffers from the lack of the transparency as the knowledge extracted by ANNs from the data during the learning process is not understandable. Through the hybrid neuro-fuzzy system, the learning limitation of fuzzy system and non-transparency problem of neural networks can be overcome (Ajith, 2003). A hybrid system proposed uses the learning capabilities of ANNs to create a fuzzy system from data. SC also encourages the integration of these techniques and tools into both every day and advanced applications (Ainon *et al*., 2009).

Our motivation in this work is first, the need for intelligent diagnostic systems and secondly, the worldwide impact of depression disorder. Although there has been research using intelligent techniques in medical fields, there has not been a significant use in a hospital or clinic routinely. The reason is that people do not think of machines to be much reliable when it comes to diagnosis of a disease. SC tools like ANNs, FL and GA can do well to ease and complement the work of medical experts (Ganesan *et al*., 2010; Hongmei *et al.*, 2006). They can help to filter out the real patients, which will reduce the costs and time required for diagnosis. The doctors can then provide all their attention to the actual patients. By properly using these techniques, a trust can be established between them and the patients.

METHODOLOGY

The methodology is shown in Figure 1. Artificial Neural Networks (ANN) and fuzzy logic system are the two methods used. The main contribution of ANN is that, in its gross imitation of the biological neural network, it allows for very low level programming to allow solving complex problems, especially those that are non-analytical, nonlinear, non-stationary and/or stochastic, and to do so in a self-organizing manner that applies to a wide range of problems with no reprogramming or other interference in the program itself (Suhasni *et al*., 2010). The ANN algorithm used is Back Propagation (BP), which uses a gradient descent approach to minimize output error in a feed-forward network and hence uses supervised learning to train the network. FL provides a means for representing and manipulating data that are not precise, but rather fuzzy. FL presents an inference mechanism that enables the human reasoning process to be applied to knowledge-based systems. The theory of fuzzy logic utilizes a strong mathematical principle to represent uncertainties found in human cognitive processes (Akinyokun *et al*., 2009). A fuzzy set is represented by expressing it as a function and then map the elements of the set to their degree of membership (Zadeh, 1965). Some of the membership functions that exist are Gaussian, Triangular, Trapezoidal, S-function and L-function (Vijaya, *et al*., 2010). Triangular and Trapezoidal membership functions (MF) have been used extensively due to their computational efficiency (Jang *et al.*, 1997). A graph of their MF is shown in Figure 2.

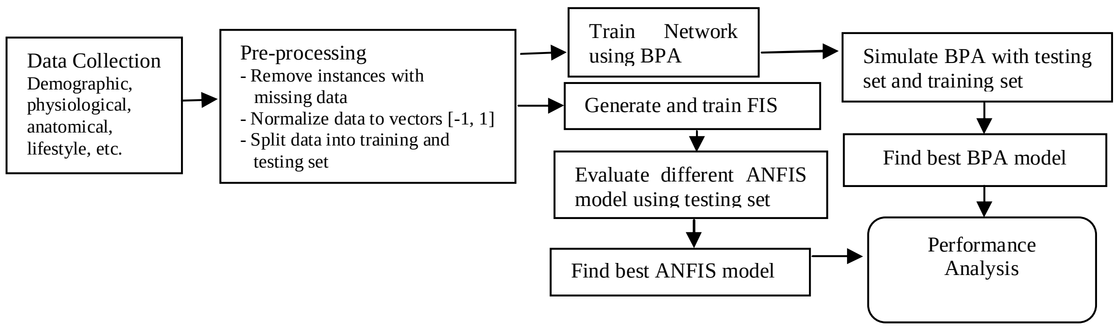


Figure 1: Block diagram of methodology

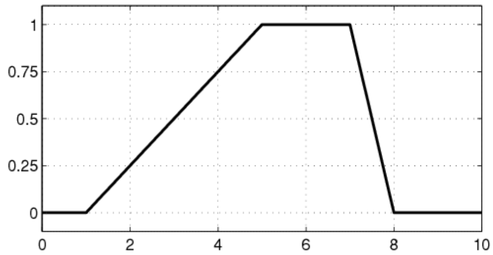
Neuro-fuzzy computing is a framework for solving complex problems and is an integrated system combining the concepts of FIS (Fuzzy Inference System) and ANNs. Adaptive neuro fuzzy inference system (ANFIS) is a fuzzy inference system implemented in the framework of adaptive networks, and hence has the advantages of both FIS and NN (Inyang and Inyang, 2011; Jang *et al*., 1997). In this study both networks have been simulated using the software package MATLAB (Beale *et al.*, 2013).

Data Set

The patient case features are classified as demographic, anatomical, physiological, lifestyle factors and coexisting medical conditions (Table 1). Artificial cases of 54 patient records made up of 26 females (48%) and 28 male (52%) were given to four senior psychiatrists from two

University Teaching Hospitals in Nigeria with a mean experience of 12.6 years to assess. The physicians were asked to classify each case using the simulated symptoms as either depressed patient (Present) or not depressed (Absent). The resultant evaluation contained 16 absent (30%) and 38 present (70%) values each having 21 attributes. Four attributes (Age, BMI, SBP, PHQ9 score and depression risk) were extracted from the dataset based on the experts' opinion.

$$trap\,(x;a,b,c,d) = \begin{cases} 0, & if \quad x \le b \\ \dfrac{x-a}{b-a} & if\ a \le x \le b \\ 1, & if\ b \le x \le c \\ \dfrac{d-x}{d-c}, & if\ c \le x \le d \\ 0, & if\ d \le x \end{cases} \tag{1}$$



$$trian\,(x;a,b,c) = \begin{cases} 0, & if \quad x \le b \\ \dfrac{x-a}{b-a} & if\ a \le x \le b \\ \dfrac{c-x}{c-b} & if\ b \le x \le c \\ 0, & if\ c \le x \end{cases} \tag{2}$$

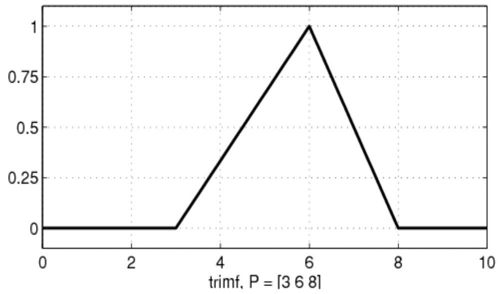


Figure 2: Trapezoidal and triangular membership functions with their graphical representation

Table 1: Features associated with depression disorder

Features	Attributes
Demographic	Age, Gender
Anatomical	Body mass index (BMI)kg/m^2
Physiological	Blood pressure mmHg
Psychological (PHQ-9)	Sadness, loss of interest, loss of energy, suicide thoughts, sleep disturbances, changes in appetite, psychomotor agitation, concentration difficulty
Life style	Alcohol abuse
Coexisting medical problem	Diabetes, Cancer, Cardiovascular diseases, HIV/AIDS

Model Simulations

A fuzzy set of each of the inputs and output variables are expressed as functions while the elements of the set are mapped to their degree of membership. The trapezoidal and triangular MFs are utilized for inputs and the output respectively. The actual MF of each element in the fuzzy set are derived by inserting the selected inputs into the horizontal axis and projecting vertically to the upper boundary of the MF to determine the degree of membership (Akinyokun *et al*., 2009). This is then used to map the output value specified in individual rules to fuzzy linguistic values. First, we partition using fuzzy linguistic labels because it seems most intuitive since it groups the values that are close together within the same interval. For Age, we have three partitions: {Young, Middle-aged and Old}. BMI is partitioned into: {Low, Normal and High}. For PHQ9 scores, we have it partitioned into: {Mild, Moderate, and Severe}. Blood pressure is partitioned into: {Low, Normal, High and Very High}. The output (Depression risk) is partitioned into: {Near Absent, Mild, Moderate, Severe, Very severe}. Examples of some derived MFs are shown in Figure 3a and 3b.

Secondly, all the data were normalized so that the value of every attribute is between -1 and +1. Out of the 54 instances, 40 instances were used for training the system and 14 were used for testing purposes. The output (Depression risk) was classified into five classes, assigned fuzzy linguistic labels of near absent, mild depression, moderate depression, severe depression and very severe depression.

(a) (b)

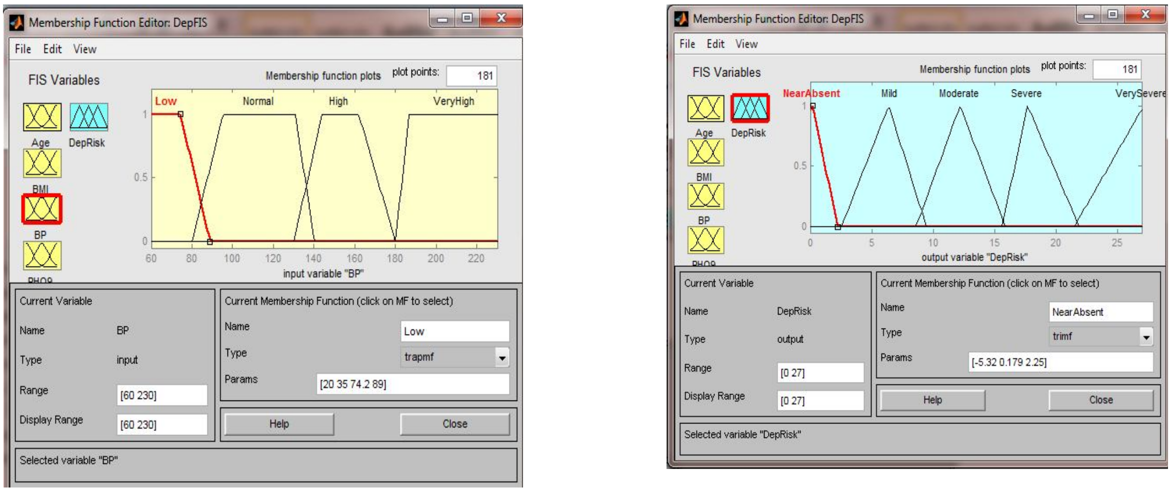


Figure 3: Membership functions for blood pressure and depression risk

A BP network with two hidden layers was used for neural network training as shown in Figure 4. The transfer function used in the first and second hidden layer neuron is *tansig* and the output layer neurons used *purelin* transfer function.

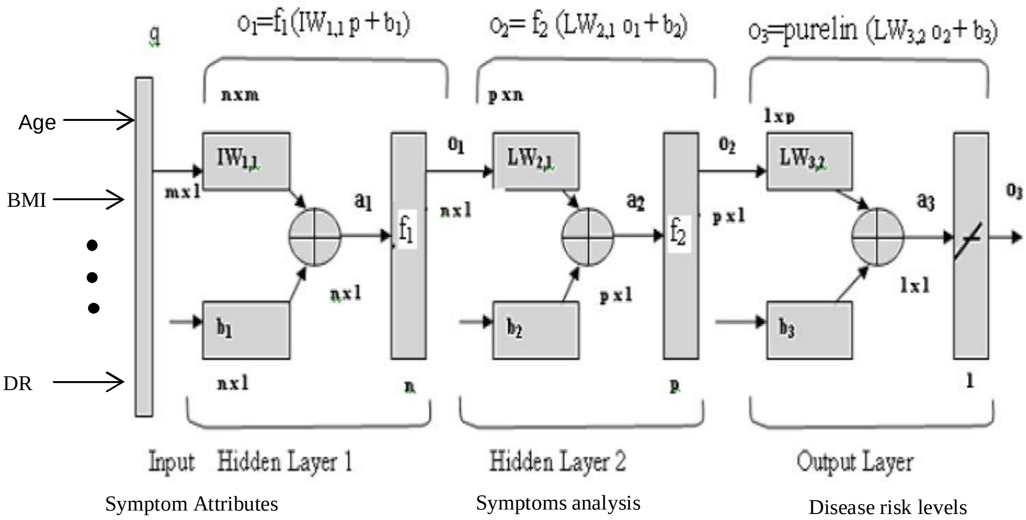


Figure 4: Two-layer feed forward BP network for depression analysis

The values of the momentum, learning rate and number of hidden neurons were changed to obtain different BP models and the best optimal one is chosen.

RESULTS AND DISCUSSIONS

Table 2 shows the experimental result of diagnosing using BP network. From the table, the BP network with 20 hidden neurons and having a percentage accuracy of diagnosis of 88.76% is the best BPN for the diagnosis of depression. It shows that the diagnosis is correct in 48 out of 54 cases.

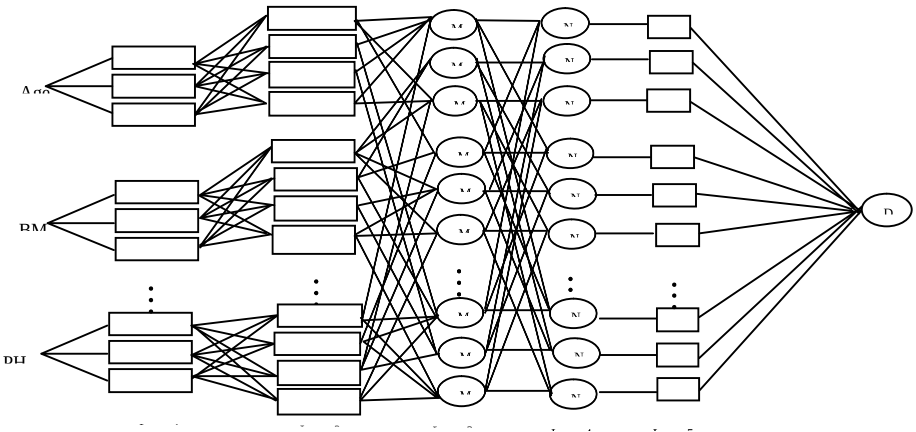


Figure 5: Architecture of ANFIS

For ANFIS we used a combination of the least squares method and the back-propagation gradient descent method for training FIS membership function parameters for a given training dataset. The ANFIS architecture is shown in Figure 5 and experimental results are shown in Table 3. The percentage accuracy of diagnosis in this case is 97.13%. Figure 6 shows the best correlation coefficient for ascertaining the goodness of the model fit. Figure 7 shows the graphical representation of accuracy of ANFIS for diagnosis of depression.

Table 2: Experimental results for BP network for diagnosis of depression

No. of hidden neurons	Momentum	Learning rate	No. of epochs	Training time (seconds)
20	0.7	0.05	4955	12.97
20	0.8	0.06	6566	10.33
30	0.7	0.05	7972	13.83
30	0.8	0.06	1796	23.78

Table 4 shows the performance comparison of BPA and ANFIS to find the best diagnostic system for depression. Both the networks trained with the specified data produce the same accuracy of diagnosis, but, ANFIS took much lesser time in training than BP network for producing the same result. Hence, ANFIS provided a better network for depression diagnosis.

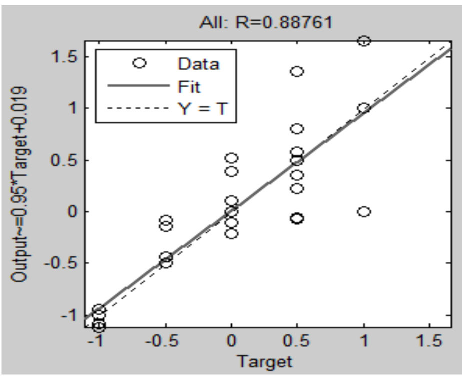


Figure 6: The best goodness fit for the BP network

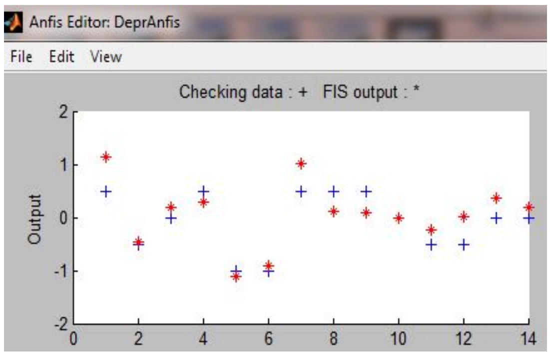


Figure 7: Comparison of checking data with ANFIS output

Table 3: Experimental results for ANFIS

No. of nodes	Training time	% accuracy of diagnosis	Error
302	8.34	97.13	0.00000245

Table 4: Performance comparison to find the best diagnostic system

Network	% of accuracy of diagnosis	Training Time (seconds)	MSE
BPA	88.76	10.33	0.01
ANFIS	97.13	8.34	2.45e-006

CONCLUSION

Depression is becoming is a global health problem. The need to design a model that would assist physician in tele-medical diagnosis of depression cannot be over- emphasized. This study which demonstrates the practical application of soft computing in the health sector, presents a hybridization of fuzzy logic and neural network to generate a neuro-fuzzy model that assist in diagnosis of depression utilizing a set of fuzzy sets. The neuro-fuzzy model exhibited more accuracy and precision than a traditional system. It should however be noted that the model was not designed to proffer prescription or treatment decisions on depression but can be expanded to do so in subsequent research. The study revealed that the best diagnostic system for depression is the neuro-fuzzy inference system with 97.13% test accuracy. The performance of the diagnostic system is application dependent and is based on the nature of datasets used. In this study we conducted the experiment with neural networks and neuro-fuzzy systems to find the best system for the diagnosis of depression. The neuro-fuzzy model provided the best model that will be able to support the decision making process of the medical expert. The model can be extended using other soft computing methods like genetic algorithm and also for other disease domains. It can form a subcomponent of a complete medical expert system.

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