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A Softcomputing Model for Depression Prediction

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Abstract

Depression is a psychological disorder that can cause serious health challenges if it remains undiagnosed, misdiagnosed and untreated. It is the most prevalent psychological disorder identified by the World Health Organization (WHO) to be affecting majority of the productive adult population worldwide. Physicians utilize psychometric tools based on guidelines given in diagnostic and statistical manual for mental disorder (DSM) to screen depression. Examining the DSM processing methods, it was discovered that classification of the disease is based on patients' subjective description of symptoms and doctor's perception. The statistical method is cumbersome, rigorous and time consuming because of the manual screening process. The study identified the qualitative and quantitative decision variables used for determining the severity of depression and adopted physiological factors as additional variables supported in literature and by expert physicians for improving the accuracy in the diagnosis of the disease. This study proposed a Neuro-fuzzy cased based expert system for depression prediction (NFCBxSdp) driven by Neural Network(NN), Fuzzy Logic(FL) and Case based reasoning (CBR) to provide a decision support platform that will assist medical practitioners in the efficient prediction of depression severity. An experimental study of the system was conducted using eighty (80) anonymous medical dataset of depression patients' cases as training set obtained from two university teaching hospitals in Nigeria through medical experts. The training set was used in the testing of twenty (20) cases. The performance efficiency computed for a DSM and the NFCBxSdp was 86.8% and 92.4% respectively. The systems' results were found to be consistent when examined by medical experts, thus making the model effective in providing accurate medical decision in depression severity prediction.

Keywords: *ANN, BMI, Case based Reasoning, Depression, DSM, Fuzzy logic, Neuro-fuzzy, PHQ9.*

1. Introduction

Depression is a disease whose symptoms in primary care are controversial, vague, imprecise and ambiguous. Depression symptoms range from everyday feelings of sadness, loss of interest or pleasure to suicidal ideations normally lasting a cycle of at least two weeks [1]. Although many other symptoms occur in varying proportions, the disease is a comorbid factor in many chronic health conditions such as diabetes, cardiovascular diseases (CVD), human immune deficiency (HIV), cancer, renal dysfunctions, alcohol abuse and drug addiction [2, 3, 4] . The disease has a relapsing course that adds to the morbidity resulting in higher costs to healthcare systems [5, 6]. The World Health Organization (WHO) estimates that the disease has affected over 120 million people worldwide and it will become the leading killer of individuals after heart disease by the year 2020 at the current growth rate [7]. Indeed, depression is a worldwide phenomenon and rivals cardiovascular disease (CVD) in terms of disability and mortality rates, as well as the significant personal and public health costs coupled with the associated co-morbidities [8, 9]. Several studies have also shown that the disease is a major public health problem with high prevalence amongst the adult population [10, 11]. Chattopadhyay et al. in [11] observed that the onset and course of the disease is capricious, highly fluctuating and often shows resistance to treatment. The debilitating effect of the disease reduces the quality of life of individuals hence there is much emphasis on early and correct diagnosis of the disease.

The acceptable standard for defining mental disorders is the WHO International Statistical Classification of Diseases and Related Health Problems (ICD) and the American Psychiatric Association (APA) Diagnostic and Statistical Manual of Mental Disorders (DSM) [7, 12]. The current versions are the ICD-10 and DSM-IV. Many primary care physicians use the depression screening tools which are usually questionnaires [13] that follow the guidelines given in DSM-IV [12]. Currently, they are no laboratory test, blood test, or X-ray that can diagnose a psychological disorder. Computed tomography (CT), magnetic resonance imaging (MRI), electro encephalogram (EEG), single-photon emission computed tomography (SPECT) and position emission tomography (PET) scans, which can help diagnose other neurological disorders such as stroke, or brain tumors cannot detect the subtle and complex brain changes in psychiatric illness [14,15]. In the treatment, management or follow up of depression disorder, there are currently two commonly used strategies: medication or psychotherapy (cognitive behaviour therapy (CBT)). However, despite these guidelines and tests it is often 'under' or 'over' diagnosed. Studies have shown that the perceptions of the disease by physicians do vary from person to person and the symptoms are extremely subjective in nature [11]. Diagnosis is therefore important because it will provide a guide on the type and intensity of medication to be administered on patients.

In the study of depression, the response to treatment, recurrence or disease-free is subjective. Statistical methods are commonly used in the analysis of depression data following DSM guidelines. Recent research efforts have considered soft computing (SC) techniques as alternative methods [16, 11]. Early SC models in medicine emerged to model expert behaviour by utilizing their knowledge and representing it in a symbolic form. This approach has been accepted by clinicians for its ability to produce high-quality results and demonstrate improvements upon previous techniques used [17, 18]. Bergman and Fors in [19] implemented a standardized interview for comparing computer-based and manual based approaches. In [20] and [21], a computer-aided CBT (CCBT) was proposed. CCBT systems are a form of self-help with the potential to increase the capacity of mental health services and overcome some of the barriers to accessing mental health services- stigma, travel time for rural patients, treatment delays and the low availability of skilled clinicians.

This research investigates the use of a hybrid soft computing framework to develop a model that can be utilized in problem solving to support medical experts in clinical decision making.

The remaining part of this paper is structured as follows: Section 2 presents review of related work; Section 3 presents the architecture of the proposed system; Section 4 presents an experimental study of the proposed system; Section 5 presents an evaluation of the proposed system, while Section 6 presents the conclusion drawn from the findings of the research.

2. Literature Review

2.1 Soft Computing

Soft computing (SC) is a computing methodology that encompasses methods that collectively provide a foundation for the conception, design and utilization of intelligent systems. The methodologies are; Artificial Neural Network (ANN), Fuzzy Logic (FL), Genetic Algorithm (GA), Case Based Reasoning (CBR), probabilistic reasoning, rough set theory and machine learning which deals with cognitive functions problems such as; perception, systematic thinking, reasoning, object recognition, data mining, episodic memory, control and knowledge management [22, 23]. The motivation in SC is that superior results can be achieved by employing the constituent methodologies in combination rather than in a stand-alone mode. Developments in intelligent medical systems research have exploited these methodologies in building programs intended to assist in the formulation of a diagnosis, prognosis and decision making.

2.2 Fuzzy Logic

Fuzzy logic (FL) provides the tool for representing uncertainty by permitting an input to have a value in a range of values between 0 (completely false) to 1 (completely true). It is useful in decision making problems where representative inputs are not clearly binary. A fuzzy inference system (FIS) is based on the concept of fuzzy set theory, fuzzy IF-THEN rules, and fuzzy reasoning [24]. FIS can then be defined as a process of mapping from a given input to an output, based on expert knowledge encoded as a set of explicit linguistic rules, which are easily understood. In [25], knowledge from an expert can be encoded as a set of rules, expertise captured and the human reasoning process provided at a cognitive level. So that one can express knowledge with subjective concepts such as ‘low’, ‘moderate’, ‘high’, ‘very high’, etc., which can be mapped into exact quantitative ranges. One of the main challenges of creating a FIS is the determination of the fuzzy sets and its fuzzy rules which require deep knowledge of human experts in a particular domain. The membership functions (MFs) of FIS are arbitrarily chosen, therefore fixed in nature. Generally, the shape of such MFs depends on certain parameters that can be adjusted. Fuzzy logic can be combined with ANN to form fuzzy-neural, neural-fuzzy or neuro- fuzzy systems that make the interpretation of decision variables more transparent. Rather than choosing the MF parameters arbitrarily, the neuro - adaptive (Neural Network) learning and tuning techniques provides a method for the fuzzy modeling procedure to learn information about a given dataset in order to automatically compute the MF parameters that allows the associated FIS to track the given input/output data relationship.

2.3 Artificial Neural Network (ANN)

An ANN is a computer program or hardwired machine that is designed to learn in a manner similar to the human brain. ANN is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It can be likened to the brain in three respects [23]: (i) Knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights, which can be used to store the knowledge, (ii) Ability to work parallel with input variables and consequently handle large sets of data swiftly, (iii) Ability to approximate any continuous function. ANN can automatically adjust their weights to optimize their behaviour as pattern recognizers, decision makers, system controllers, predictors, and so on. According to [22], adaptivity allows ANN to perform well even when the environment or system being modeled varies over time. While ANN has the ability to approximate any continuous function and to learn as they encounter new input-output pairs, some decision problems have inputs that are imprecise, ambiguous or incomplete. A hybridization of ANN and FL provides a solution that is capable of integrating the strength of both techniques and eliminating their weaknesses. It allows the NN modeling procedure to learn certain information about a given dataset in order to automatically compute the MF parameters that best drives the associated FIS. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) constructs a FIS whose MF parameters are tuned through NN by using either Back Propagation algorithm alone or in combination with Least Squares Estimation method. Studies in the field of mental health identified some early stage clinical decision support systems (CDSS) projects for classifying and predicting psychiatric problems. Florio in [26] investigated the application of a multi-layer perceptron (MLP) neural network for solving clinical decision making problems in psychiatry. Empirical and theoretical evidence supported the application of the MLP-NN compared to statistical logistic regression as classifiers for the clinical datasets in the diagnosis and prediction of psychiatric problems. Suhasini et al., in [27] implemented a neural network algorithm for identifying psychiatric problems by using a hybrid of radial basis function (RBF) and back propagation neural network (BPNN).

2.3 Case Base Reasoning (CBR)

Case based reasoning (CBR) is another SC approach that has reasoning ability of reusing past problem solving instances to find solutions for future problems [28]. CBR has been formalized for purposes of computer and human reasoning as a four step process, fondly referred to as the dynamic model of CBR cycle: Retrieve, Reuse, Revise and Retain. The CBR approach provides a paradigm for storing solved problems as cases, then searches the appropriate cases to determine their usefulness in solving new cases as presented to the expert – a typical model of how physicians solve medical cases. The retrieval process is performed on the basis of case similarity measurements to determine case classification. The combination of CBR and other SC techniques have been explored in [29]. The combined frameworks showed improvements in classification, scheduling, data mining, prediction, optimization and decision support for complex systems that might have non-linear, time-variant, and/or ill- defined problems. In [30, 31], a case based CDSS is developed for individual stress diagnosis using fuzzy similarity matching to support clinicians in analyzing and classifying finger temperature measurements. The approach enabled the reuse of experience from previous cases with analyzed temperatures and stress profiles. In the evaluation the fuzzy similarity matching method yielded the best performance concerning the ranking of retrieved cases, thereby producing a rank that is most consistent with the domain expert opinions. In [32], a CBR framework is proposed for the assessment and diagnosis of depression amongst cancer patients. The framework captured the properties intended to assess palliative patients through an informative graphical user interface.

3. Materials and Methods

The attributes considered for the diagnosis of depression after a series of consultation with medical experts and standard literatures in the field of mental health and psychiatry are presented in Table 1. Basically these decision variables are classified into physiological and psychological factors.

Table 1: Decision variables for depression diagnosis

SN	Category	Patient attributes	Code
1	Psychological factors (PSY)	Sadness	SAD
2		Irritability	IRR
3		Loss of interest in sex	LOI
4		Concentration difficulty	CON
5		Past failure	FAL
6		Loss of energy	LOE
7		Suicidal ideation	SUI
8		Changes in sleep	CSL
9		Changes in appetite	CAP
10	Physiological factors (PHY)	Age	AGE
11		Body mass index	BMI
12		Systolic blood pressure	SBP
13		Diabetes	DBT
14		Cancer	CNC
15		Alcoholic	ALC
16		Hypertension	HYP

From Table 1, sixteen (16) key variables were considered for the diagnosis of depression. The architecture of the proposed soft computing model nick named "Neuro Fuzzy Case Based expert System for depression prediction (NFCBxSdp)" is presented in Figure 1.

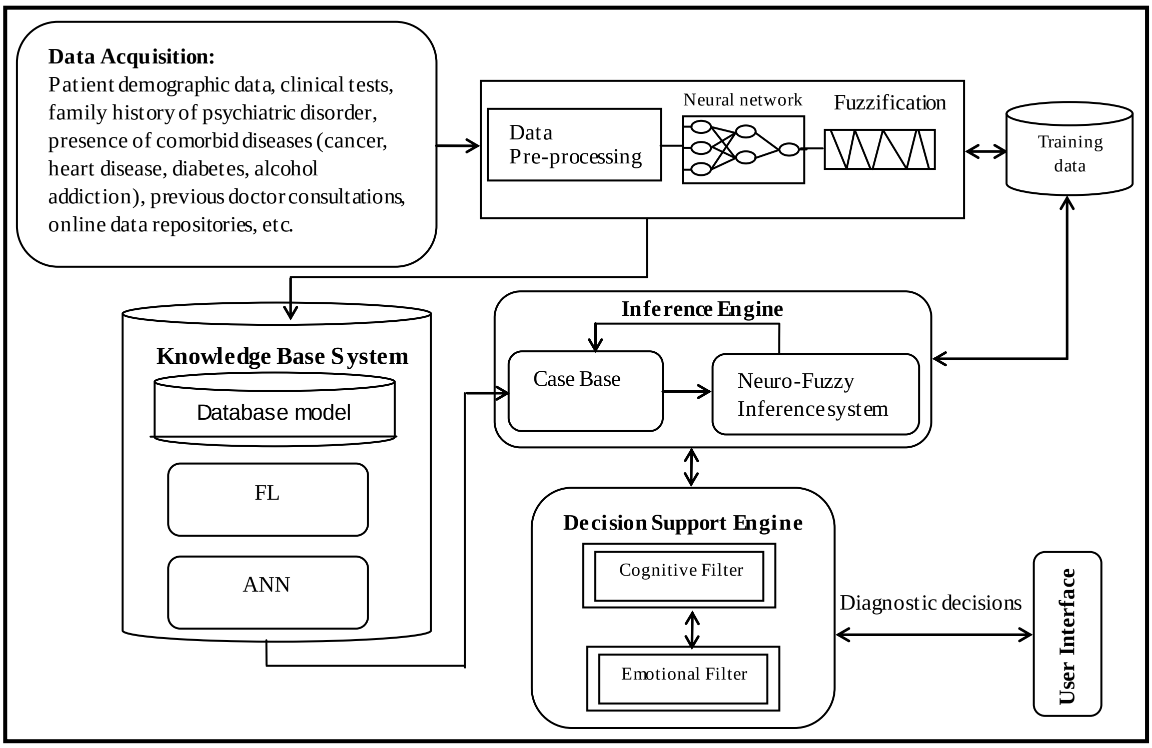


Figure 1: Architecture of the proposed Neuro-Fuzzy Case based expert System for depression prediction

The architecture consists of a Data Acquisition Module (DAM), a Knowledge Base System (KBS), an Inference Engine (IE) consisting of the neuro-fuzzy inference engine and a Case Base; a Decision Support Engine (DSE) consisting of Cognitive and Emotional filters that respectively handle the physician's objective and subjective feelings regarding a patients, and a User Interface (UI) which serves as an input/output module for the entry of decision variables and display of diagnostic decisions as results. The KBS stores structured (pre-processed) and unstructured knowledge about the problem domain and serves as a repository for operational data that are to be processed. The Database component of the KBS stores patient's demographic data, clinical tests, family history of psychiatric disorder, presence of comorbid diseases (cancer, heart disease, diabetes, alcohol addiction), previous doctor consultations and other relevant data attributes.

3.1 Fuzzy Logic Subsystem

The FL component incorporates: a fuzzifier, a fuzzy rule base, a fuzzy inference engine and a defuzzifier.

3.1.1 Fuzzifier

The fuzzifier changes crisp input values into their corresponding fuzzy values. For instance, let D be the set of the disease attributes (universe of discourse), and its associated elements are denoted by x, then the set d in D is denoted by Equation 1 as:

$$\mathrm{d} = \{(x, \mu_{\mathrm{D}}(x)) \mid x \in \mathrm{D}, \mu_{\mathrm{D}}(x) \in [0,1]\} \tag{1}$$

where $\mu_{\mathrm{D}}(x)$ is the membership function of x in D and μ_{D} is the degree of membership of x in d in the interval of [0, 1]. The linguistic expressions for the output variable Depression risk (d) are evaluated from the triangular membership function in Equation (2):

$$\mu_d(d) = \begin{cases} Near\ absent, & if\ d < 0.25 \\ Mild, & if\ 0.25 \le d < 0.45 \\ Moderate, & if\ 0.45 \le d < 0.65 \\ Severe, & if\ 0.65 \le d < 0.85 \\ very\,Severe & if\ 0.85 \le d \le 1.0 \end{cases} \tag{2}$$

The MFs are derived using a triangular fuzzifier which is appropriate for the domain under investigation. In Figure 2, the disease risk probabilities are shown to be in the range of [0, 1], such that the linguistic values 'near absent' is in the range [0.0, 0.1, 0.25], 'mild' has a range of [0.25, 0.3, 0.45]. 'Moderate' has a range of [0.45, 0.5, 0.65] while 'severe' and 'very severe' have ranges [0.65, 0.7, 0.85] and [0.85, 0.9, 1.0] respectively.

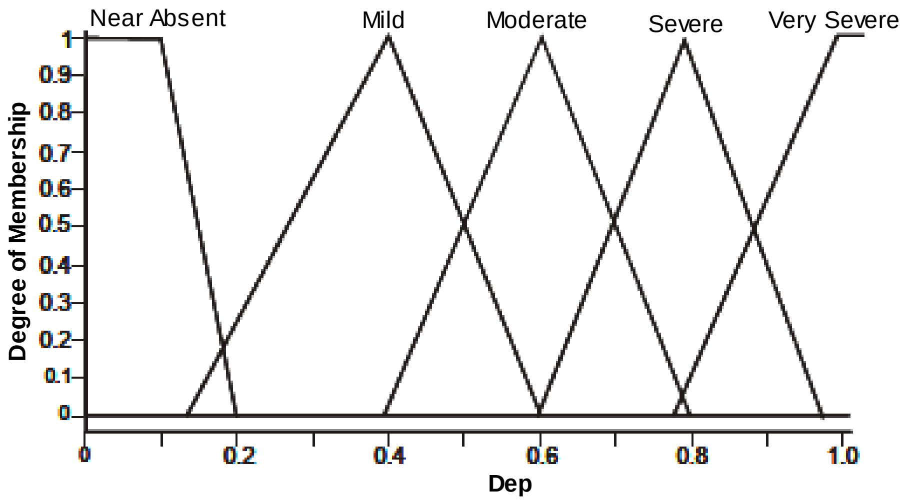


Figure 2: The MF graph for the depression risk variable

The fuzzy sets of the decision attributes for the diagnosis of depression are presented in Table 2. Each attribute in Table 2 is represented by a linguistic term that belongs to the defined fuzzy set, while each linguistic term has its associated numerical value. The input variables: Age, BMI, systolic blood pressure (SBP), PHQ-9 assessment and the output parameter, Depression diagnosis (Dep), are fuzzified into vectors that represent their degrees of membership with corresponding fuzzy sets partitioned according to the domain experts opinion and literature.

Table 2: Linguistic variables for depression and their fuzzy sets

Parameter	Variables	Domain	Linguistic variables
A	Age	Input	{Young, Middle Age, Old}
Bm	BMI	Input	{Low, Normal, High}
Bp	SBP	Input	{Low, Normal, High, very High}
p	PHQ9	Input	{very Mild, Mild, Moderate, Severe}
d	Dep	Output	{Near Absent, Mild, Moderate, Severe, very Severe}

3.1.2 Rule Base

The rule base for depression diagnosis is characterized by a set of IF-THEN rules in which the antecedent (IF part) and the consequents (THEN part) involve linguistic variables. The rules that constitute the rule base were carefully formulated with the assistance of medical experts in the field of mental health. A total of 144 (i.e. 3^2x4^2) rules were generated representing four fuzzy linguistically designed inputs with *Age* and *BMI* having three MFs, *SBP* and *PHQ9*, having four MFs each.

A rule fires if any of its precedence parameters such as “Near Absent”, “Mild”, “Moderate”, “Severe” and “very Severe” evaluates to true or 1, otherwise it does not fire. For instance:

Rule 6: IF AGE is Young AND BMI is Normal AND SBP is Low AND PHQ9 is Mild THEN Dep is Moderate

3.1.3 Fuzzy Inference Engine

The fuzzy inference engine receives its inputs from the rule base and the fuzzification interface, and then it applies a predefined procedure to a set of inputs in order to produce the desired output. The guidelines in [32] were followed in choosing the Root Sum Square (RSS) inference technique as presented in Equation (3):

$$\mathrm{RSS} = \sum_{j=1}^{m} \mathrm{R}_j^2 \tag{3}$$

where R_j represents a fired rule and j = 1, 2…m represents the number of fired rules for a particular diagnosis.

3.1.4 Defuzzification

Defuzzification is the process of converting the final output of a fuzzy system to a crisp value. The defuzzifier translates the output of the inference engine into a crisp value which is mostly required by the medical expert for proper analysis and interpretation, for it aids in efficient determination of the severity level of the disease. The centre of area (COA) centroid method is choosing for the defuzzification process. COA finds a point representing the centre of areas of the fuzzy set. This interface receives as input the output of the fuzzy inference engine and applies Equation (4) to determine the defuzzified (crisp) output Z.

$$Z = \frac{\sum_{i=1}^{n} \mu_{a_i}(x) x_i}{\sum_{i=1}^{n} \mu_{a_i}(x)} = \sum_{i=1}^{n} x_i \tag{4}$$

where $\mu_{a_i}(x)$ is the membership value of x_i as given by the MF in Figure 2 and x_i is the center of the MF.

3.2 The ANN Subsystem

The ANN component is made up of attributes categorized as: Psychological (PSY) and Physiological (PHY) as shown in Table 1. Inputs for the network are Age, nine PHQ9 parameters, body mass index (BMI), systolic blood pressure (SBP) and co-existing medical problems (diabetes (DBT), cancer (CNC), alcoholic (ALC), hypertension (HYP)). These attributes together form the input neurons for the NN. The output is encoded as depression severity rated (0, 1, 2, 3, 4) for 'Near absent', 'Mild', 'Moderate', 'Severe' and 'very Severe' respectively. The ANN model is a feedforward multi-layer perceptron (MLP) presented in Figure 3. The algorithm used to train the networks is the back-propagation algorithm with sigmoid function for hidden and output layer neurons' transformation. Nodes PHY and PSY in the hidden layer compute the intermediate diagnosis using the physiological (PHY) and psychological (PSY) input signals. Every node in the hidden or output layer first acts as a summing junction which combines and modifies the inputs from the previous layer. The output of the ANN model is then given as Equations (5).

$$DepR = \sum_{i=1}^{16} (w_i x_i) \qquad (5)$$

where x_i represents the decision variable of the i^{th} input attribute and w_i represents its corresponding weights.

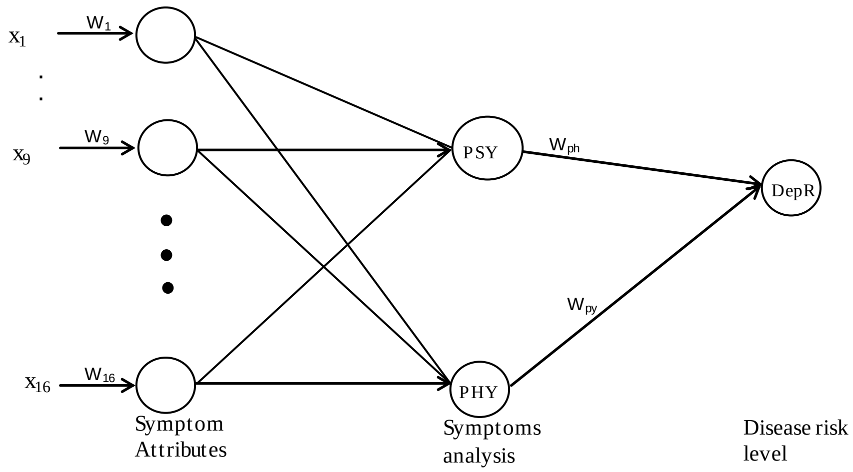


Figure 3: The ANN Subsystem for depression diagnosis

3.3 Neuro-Fuzzy Subsystem

The Neuro-Fuzzy inference engine is represented as a multilayered feedforward ANN. Its architecture is presented in Figure 4. The system is a fuzzy system that is trained with a backpropagation learning algorithm with gradient descent. The learning algorithm operates on local information and causes local modifications in the underlying fuzzy system. The ANN trained by the system consists of 4 nodes in the input layer; each node represents a linguistic value in the fuzzy set of depression symptoms. The hidden layer has 16 nodes and each node corresponds to a category of depression attributes considered. The output layer consists of 5 nodes, each representing the class of depression risk. The system extracts and evaluates rules from the fuzzy rule base and produces fuzzy outputs based on the input depression symptom attributes to the Neuro-Fuzzy inference system. These inputs represent the decision attributes that influences the eventual depression risk level. The learning process is data-driven, so a training data set of m-dimension is approximated by the system. The fuzzy rules encoded within the system represent the training data. The description of the data interaction had been presented in [33].

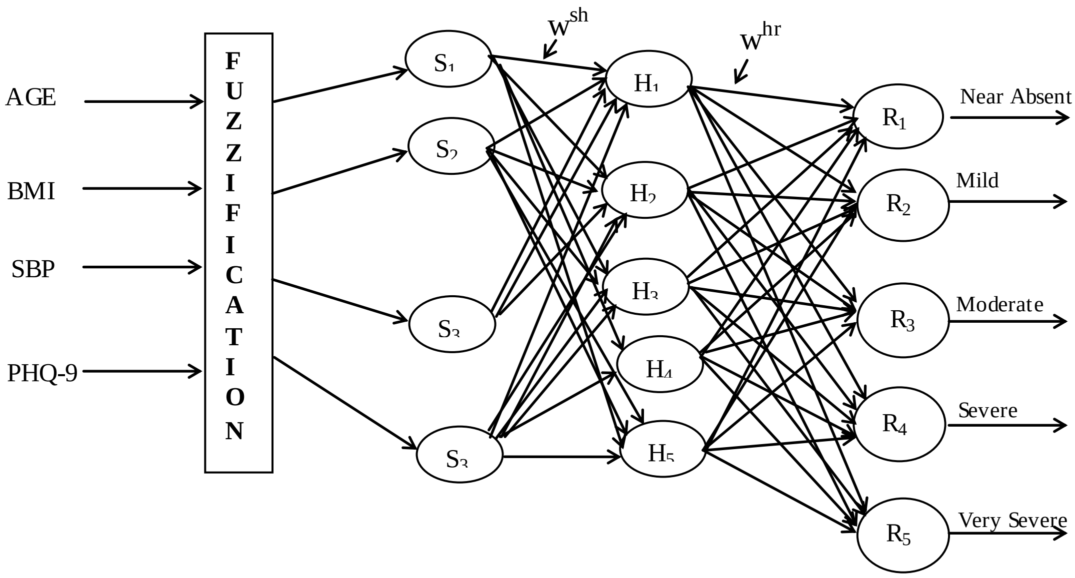


Figure 4: The Neuro-fuzzy subsystem for depression diagnosis [33]

3.5 Decision Support Engine Subsystem

The output of the Neuro-Fuzzy inference passes through the decision support engine (DSE) where further computation are performed before the final result from the NFCBxSdp model is presented. The DSE module is made up of the cognitive filter (CF) and emotional filter (EF). The system utilize input of factors such as; patient family history of mental disorder, child bearing, coexisting disease, losses, drug addiction and affective weather conditions. Each of the factors was provided through responses of 'yes' or 'no' to questions. A 'yes' is weighted 0.01 and a 'no' is weighted 0 in the DSE module. The cognitive rank (CR) is computed by adding the CF average value to the Neuro-Fuzzy result, while the DSE result is obtained by adding the EF average (EFA) to the CR. The EFA is obtained from the experts' emotional evaluation of the patient on an ICD-10 scale of (0.0 – 0.05) based on intensity of physical symptoms (fever, headaches, etc.).

The ANFIS rule viewer was used to extract the ANFIS outputs after training and the MFs adjusted to correspond with the FIS input MFs. The CFA for each case consists of the average from summing values computed for coexisting medical conditions in the system. The cognitive rank (CR) is computed as: CR = ANFIS + CFA and the system computes the DSE as EFA+CR.

4. Experimental Design

4.1 ANN Modeling

MATLAB version 7.6 was employed in the ANN modeling. It is a Windows® based package which supports several types of NN training algorithms. It operates via a graphical user interface (GUI) that enables the user to load the training and test data sets, design the network architecture, select the training algorithms and generate the individual models for each output variable in a single operation.

Data sets: The eighty (80) experimental data for the study were obtained from University of Benin and University of Uyo Teaching Hospitals in Nigeria. At the teaching hospitals, the medical data were gathered through doctors who have had interactions with the depressed patients for a period of 12 months using a modified Patient Mental Health Questionnaire, validated by the medical expert. During the period patients' past complaint details were recorded and interpreted by the medical doctor in-charge for proper documentation in the data collection instrument. Based on the data, the diagnoses prescribed by the doctors were also indicated. The data collected were analyzed and preprocessed to the required format. The experimental datasets were randomly divided into two sets in the ratio 60:40 for training and testing data.

The training was used to compute the network parameters. The testing data was used to ensure robustness of the network parameters. Various topologies were examined and the network with 16 input neurons, 2 hidden layer neurons and 1 output provided the best performance as presented in Table 3. The mean square error (MSE) of prediction by the ANN model and the regression correlation coefficient (R) were obtained to ascertain the goodness of the model.

Table 3: ANN model performance summary

Network Model	MSE	Correlation coefficient (R)
16:1:1	0.10893	0.95118
16:2:1	0.10605	0.96456
16:3:1	0.26159	0.88919
16:4:1	0.15608	0.93062

Figure 5 shows a high correlation in training, test and validation cases for the chosen network model. For the training set, the correlation coefficient R is 0.9943, while for the test and validation, it is 0.91345 and 0.90243 respectively. The overall correlation coefficient is 0.96456, which is substantial to validate the performance of the developed ANN model.

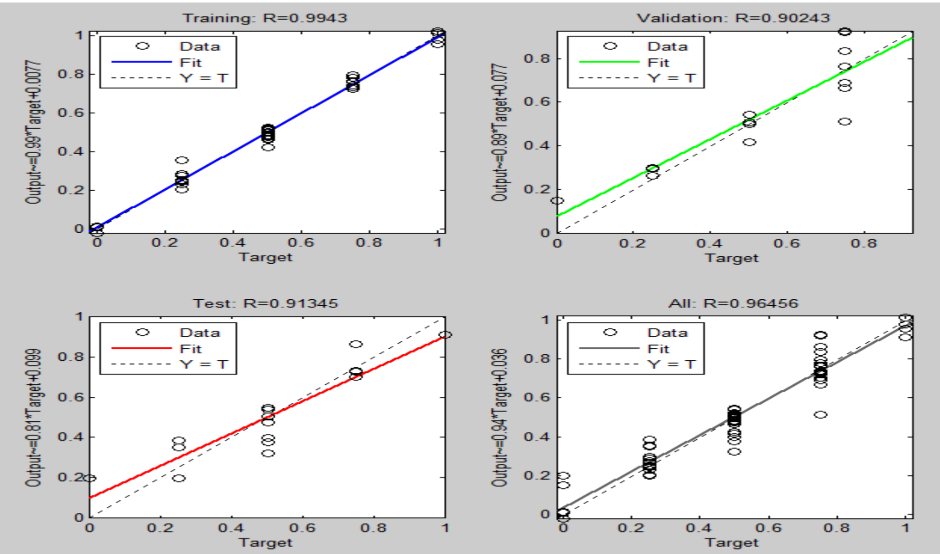


Figure 6: The outcome of the training and testing sessions of the FIS

The predictive ability of the generated ANN model was estimated and used to build the ANFIS. The outcome of the training and testing sessions of the FIS by the network is presented in Figure 7 with the training dataset appearing in circles and the testing data appearing in the plot as pluses superimposed on the training data. The developed FIS modules in MATLAB and the intermediate results are presented in [34].

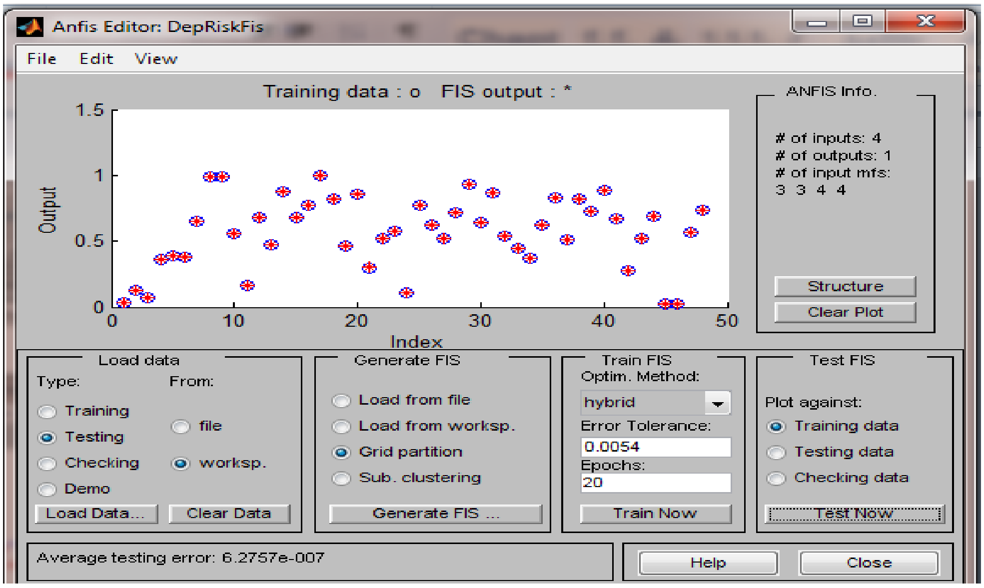


Figure 7: The outcome of the training and testing sessions of the FIS

4.2 Model Implementation

The NFCBxSdp model is implemented as a desktop application with Net Beans 7.2.1 Java API, MATLAB® 7.6.324 (2008a) and MS Excel as the frontend engine, while MS SQL DBMS provided the back-end. The interaction between the development tools is shown in Figure 8.

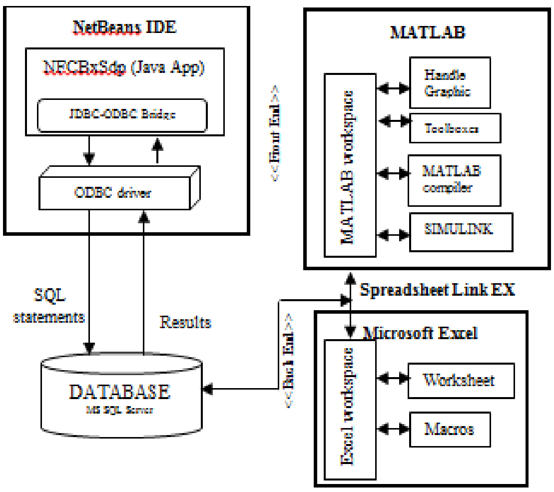


Figure 8: The interaction between NetBeans IDE, the Database, MATLAB and MS Excel.

The NFCBxSdp application window in Figure 9 consists of three main menu items namely; File, Operation and Help. The desktop input new case form enables the user to enter the demographic data, clinical details, PHQ9 depression screening and coexisting medical conditions of a patient. On saving a record or committing a transaction, a unique case identification number (generated automatically) is mapped to a particular patient.

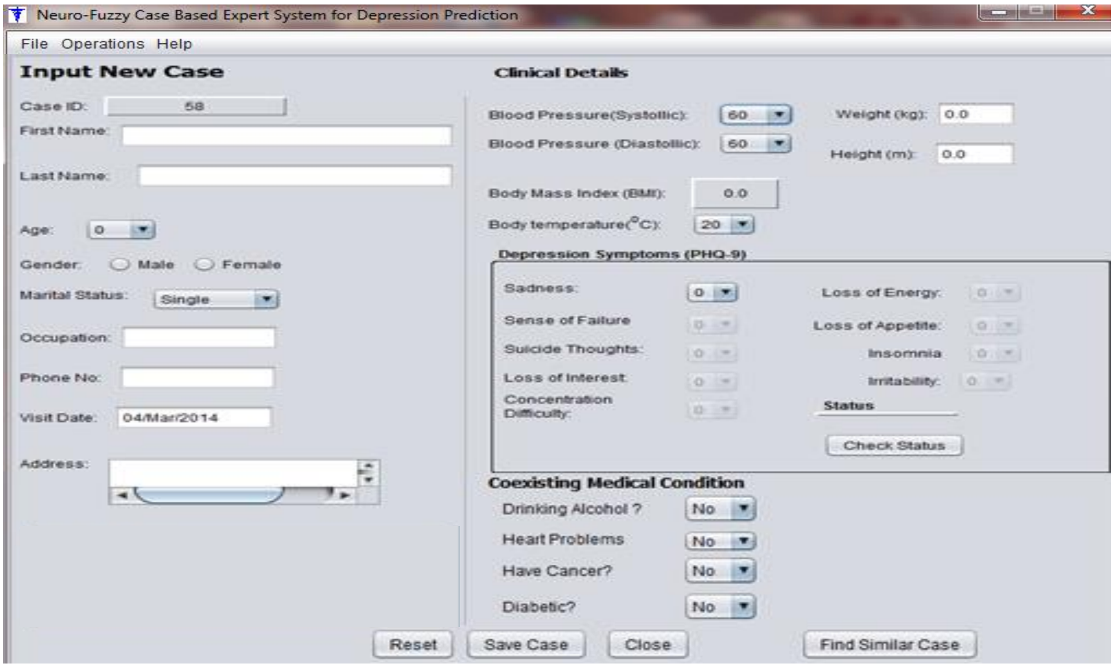


Figure 9: Input entry screen for a new consultation.

The selection of the operations menu will activate a menu with two options; Fuzzification and ANN Training. Selecting ANN Training will activate an Open file window for selecting Microsoft Excel and MATLAB program that performs the training and testing of the datasets shown in Figure10.

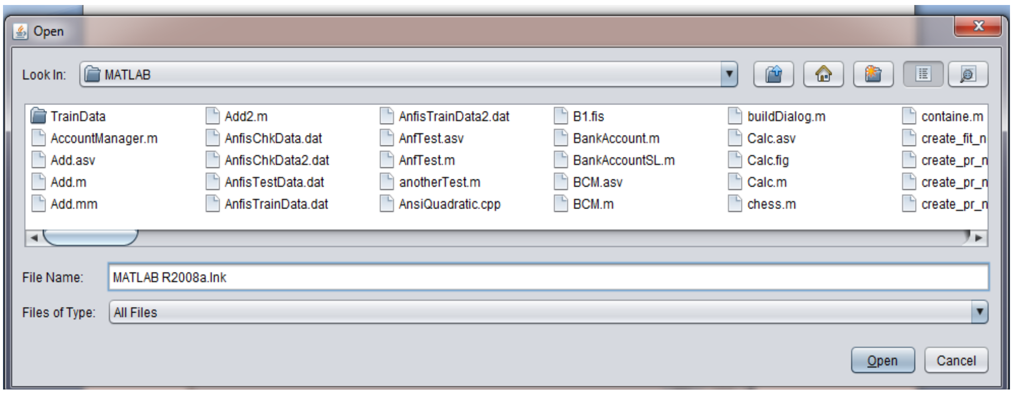


Figure 10: An Open window for selecting a dataset in MATLAB workspace for training

The selection of the option ‘Fuzzification’ from the operations menu invokes an SQL code segment in Java that transforms the datasets in the database table into their membership grades and assigns the linguistic labels; ‘youngAge’, ‘middleAge’, ‘oldAge’, …’very HighBP’ as shown in Figure 11.

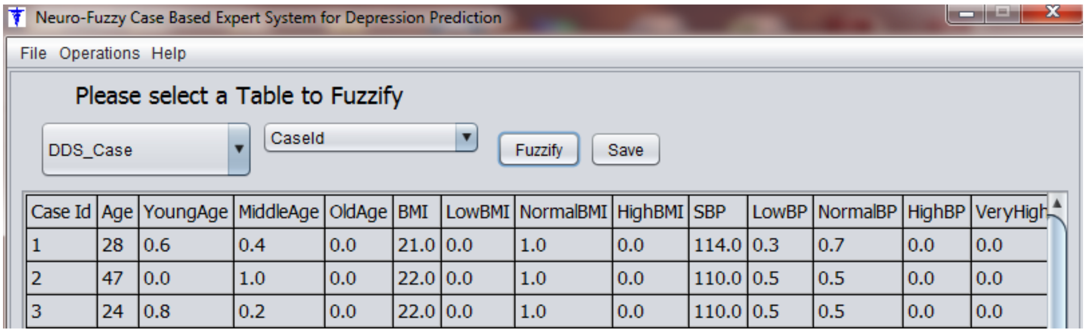


Figure 11: Fuzzification of decision variables for depression diagnosis

The CBR module relates with the fuzzy database where all the decision attributes in the main database are normalized to their fuzzy linguistic attributes. Since the attributes are represented by fuzzy linguistic labels with their corresponding membership grades, the similarity matching algorithm presented in [31, 32] were studied and utilized in the program for obtaining similar cases during a consultation query.

A new patient with Case_ID 85 is entered into the system having attributes as shown in Figure 12. On selecting the "Find Similar Case" button, the system uses the current case to compute the range of each attribute in the case base. The value of the new case (Case_ID 85) is compared with every value of the same attribute in the case base to find local similarity for that particular attribute. The same process is repeated with other attributes in the case base. Finally, the system calculates the global similarity for Case_ID 85 compared to each case in the case base.

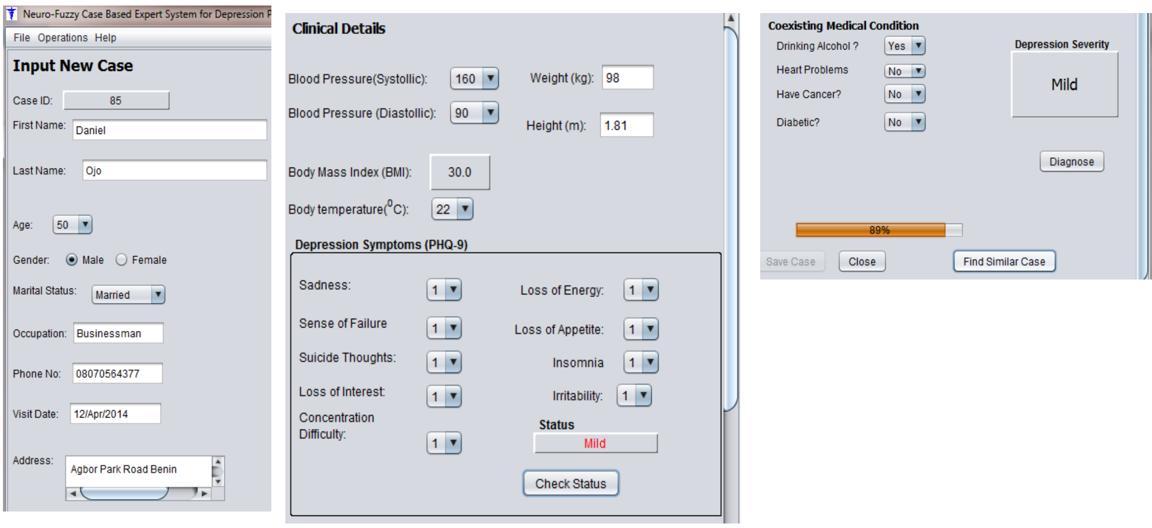
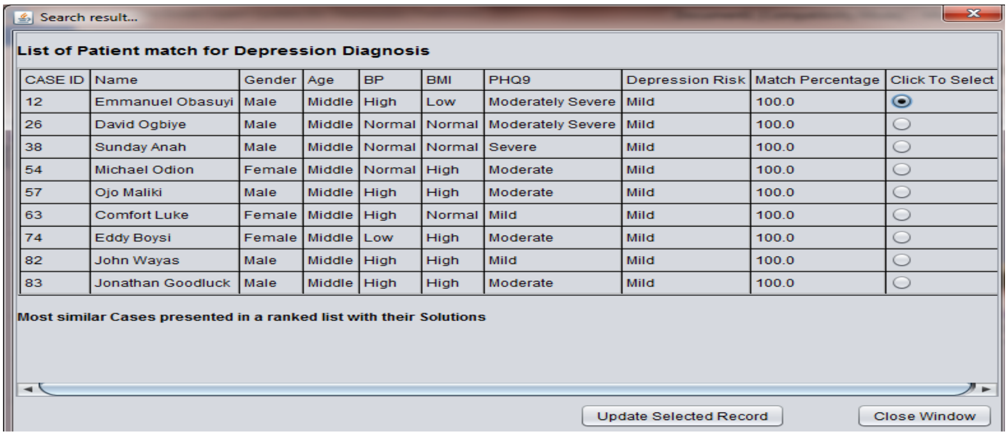


Figure 12: Input attributes and results for patient Case_ID 85

A list of the matched cases of patient diagnosis of depression from the case base similar to Case_ID 85 is displayed in Figure 13 with their match percentages.



Search result...

List of Patient match for Depression Diagnosis

CASE ID	Name	Gender	Age	BP	BMI	PHQ9	Depression Risk	Match Percentage	Click To Select
12	Emmanuel Obasuyi	Male	Middle	High	Low	Moderately Severe	Mild	100.0	◉
26	David Ogbiye	Male	Middle	Normal	Normal	Moderately Severe	Mild	100.0	○
38	Sunday Anah	Male	Middle	Normal	Normal	Severe	Mild	100.0	○
54	Michael Odion	Female	Middle	Normal	High	Moderate	Mild	100.0	○
57	Ojo Maliki	Male	Middle	High	High	Moderate	Mild	100.0	○
63	Comfort Luke	Female	Middle	High	Normal	Mild	Mild	100.0	○
74	Eddy Boysi	Female	Middle	Low	High	Moderate	Mild	100.0	○
82	John Wayas	Male	Middle	High	High	Mild	Mild	100.0	○
83	Jonathan Goodluck	Male	Middle	High	High	Moderate	Mild	100.0	○

Most similar Cases presented in a ranked list with their Solutions

Update Selected Record   Close Window

Figure 13: List of patient cases that match the current Case_ID 85

As shown in the list of patient match with Case_ID 85, the results show 100% match of Depression Risk ‘Mild’. This is suggested correct for the model as the best matched case can be selected by the physician as a diagnosis option for Case_ID 85. The selected case can be updated and retained as a new solution in the case base.

5. Model Evaluation

The degree of validity of the softcomputing model is based on its evaluation outcomes. We performed a comparative analysis of the diagnostic result for cases obtained from five medical experts and diagnosis obtained using a Takagi-Sugeno FIS and diagnosis obtained using NFCBxSdp. Takagi-Sugeno FIS is based on Beck’s depression Inventory (BDI) version 2 DSM proposed in [35]. Twenty (20) non-smoking adults with no medical history of cancer were used as test cases. The empirical result of the investigation for determining DSE and ANFIS result is presented in Table 4.

Table 4: ANFIS and DSE analysis results

Case No	ANFIS result	Cognitive Filter average(CFA)	Cognitive Rank(CR) CR=ANFIS+CFA	Emotional Filter average (EFA)	DSE result = EFA+CR	NFCBxSdp prediction
1	0.20	0.01	0.21	0.01	0.22	Near Absent
2	0.15	0.02	0.17	0.01	0.18	Near Absent
3	0.07	0.00	0.07	0.01	0.08	Near Absent
4	0.54	0.00	0.54	0.00	0.54	Moderate
5	0.14	0.02	0.16	0.00	0.16	Near Absent
6	0.54	0.02	0.56	0.01	0.57	Moderate
7	0.13	0.04	0.17	0.03	0.20	Near Absent
8	0.09	0.00	0.09	0.01	0.10	Near Absent

Follow Table 4: ANFIS and DSE analysis results

Case No	ANFIS result	Cognitive Filter average(CFA)	Cognitive Rank(CR) CR=ANFIS+CFA	Emotional Filter average (EFA)	DSE result = EFA+CR	NFCBxSdp prediction
9	0.81	0.02	0.83	0.00	0.83	Severe
10	0.50	0.02	0.52	0.01	0.53	Moderate
11	0.79	0.02	0.81	0.01	0.82	Severe
12	0.55	0.02	0.57	0.03	0.60	Moderate
13	0.34	0.05	0.39	0.05	0.44	Mild
14	0.47	0.02	0.49	0.01	0.50	Moderate
15	0.35	0.02	0.37	0.01	0.38	Mild
16	0.52	0.02	0.54	0.03	0.57	Moderate
17	0.49	0.04	0.53	0.01	0.54	Moderate
18	0.30	0.04	0.34	0.03	0.37	Mild
19	0.56	0.02	0.58	0.01	0.59	Moderate
20	0.75	0.00	0.75	0.01	0.76	Severe

The desired diagnosis results produced by the medical experts were assigned weights whose membership grade ranged from 0.0 to 1.0 depending on the intensity of the individual diagnosis. Table 5 shows the analysis of the 20 desired diagnosis result obtained by the domain expert, the Takagi-Sugeno FIS BDI-2 DSM evaluation and the NFCBxSdp system.

Table 5: Statistical analysis of depression diagnosis results

Cases	Doctor's result of Diagnosis (Desired)	Diagnostic result of T-S FIS DSM	Predicted result of NFCBxSdp	Error in diagnosis of T-S FIS DSM	Error in diagnosis of NFCBxSdp	Accuracy level in T-S FIS DSM (AcDSM)	Accuracy level in NFCBxSdp (AcNFCBxSdp)
1	0.19	0.04	0.22	0.15	0.09	0.85	0.91
2	0.15	0.07	0.18	0.08	0.03	0.92	0.97
3	0.11	0.19	0.08	0.08	0.03	0.92	0.97
4	0.37	0.22	0.54	0.15	0.17	0.85	0.83
5	0.11	0.26	0.16	0.15	0.05	0.85	0.95
6	0.52	0.37	0.57	0.15	0.05	0.85	0.95
7	0.19	0.04	0.20	0.15	0.01	0.85	0.99
8	0.15	0.0	0.10	0.15	0.05	0.85	0.95
9	0.41	0.48	0.53	0.07	0.12	0.93	0.88
10	0.33	0.16	0.45	0.17	0.12	0.83	0.88
11	0.63	0.52	0.82	0.11	0.19	0.89	0.81

Follow Table 5: Statistical analysis of depression diagnosis results

Cases	Doctor's result of Diagnosis (Desired)	Diagnostic result of T-S FIS DSM	Predicted result of NFCBxSdp	Error in diagnosis of T-S FIS DSM	Error in diagnosis of NFCBxSdp	Accuracy level in T-S FIS DSM (AcDSM)	Accuracy level in NFCBxSdp (AcNFCBxSdp)
12	0.44	0.37	0.60	0.07	0.16	0.93	0.84
13	0.37	0.52	0.44	0.15	0.07	0.85	0.93
14	0.44	0.59	0.50	0.15	0.06	0.85	0.94
15	0.33	0.22	0.38	0.11	0.05	0.89	0.95
16	0.56	0.44	0.57	0.12	0.01	0.88	0.99
17	0.44	0.52	0.54	0.08	0.10	0.92	0.9
18	0.37	0.13	0.37	0.24	0.0	0.76	1.00
19	0.59	0.48	0.59	0.11	0.0	0.89	1.00
20	0.60	0.40	0.76	0.20	0.16	0.80	0.84

To determine the degree of accuracy with the desired diagnosis, the error in the diagnosis outputs for the Takagi-Sugeno FIS based BDI-2 DSM and NFCBxSdp is obtained by computing their differences as shown in Table 5. The mean accuracy and efficiency of the Takagi-Sugeno FIS based BDI-2 DSM and NFCBxSdp approaches are computed as Equation (5) and (6).

Mean accuracy of T-SFISDSM (m_T-SFISDSM) = $$\frac{\sum_{i=1}^{20}(\mathrm{AcT\text{-}S\,FIS\,DSM}_i)}{20} \tag{5}$$

$= 0.868$

Efficiency is computed as Eff_T-SFIS DSM = (m_T-SFIS DSM) x100

= 0.868x100 = 86.8%

Mean accuracy of NFCBxSdp (m_NFCBxSdp) = $$\frac{\sum_{i=1}^{20}(\mathrm{AcNFCBxSdp}_i)}{20} \tag{6}$$

$= 0.924$

Efficiency is computed as Eff_FIS = (m_ NFCBxSdp) x100 = 0.924x 100 = 92.4%

The performance measure for the softcomputing model and the T-S FIS DSM are 92.4% and 86.8% respectively. From the outcome of the statistical computation, the softcomputing model provided a better diagnosis result than the T-S FIS DSM. A graph of the comparison is presented in Figure 14. The breakdown of the result based on each fuzzy linguistic label for the twenty (20) test cases is presented in Table 6 and summarized by the graph presented in Figure 15.

Table 6: Summary of the prediction accuracy of the model for 20 cases

Cases	**Grades of Depression**				
	Near Absent	Mild	Moderate	Severe	Very Severe
Correctly Predicted	5	3	8	3	-
Incorrectly Predicted	1	0	0	0	-
Accuracy (%)	83.33	100.0	100.0	100.0	-

From the 20 cases analyzed, Table 6 show that five (5) 'Near Absent' cases were accurately predicted as 'Near Absent' and one was predicted as 'Mild' giving a prediction accuracy of 83.33% for 'Near Absent' cases. Three (3) 'Mild' cases, 3 'Severe' cases and 8 'Moderate' cases were 100% accurately predicted. There were no cases diagnosed as 'Very Severe'. From the statistical outcomes we conclude that the proposed softcomputing model can predict the diagnosis of depression to an acceptable level of accuracy.

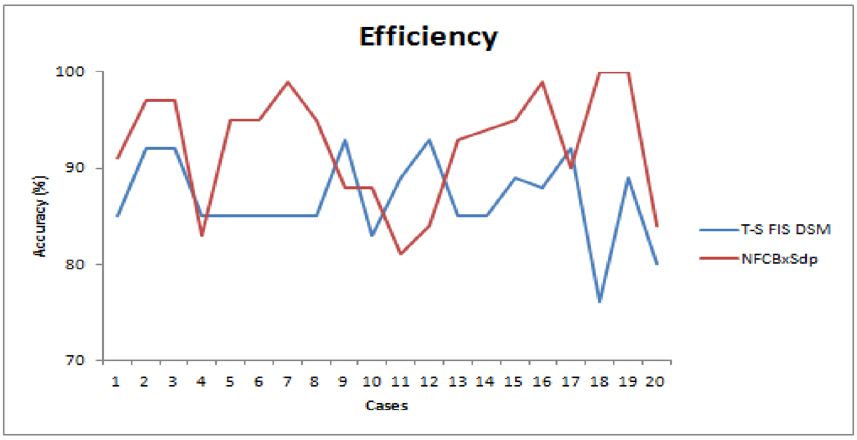


Figure 14: Performance Efficiency of NFCBxSdp Softcomputing model

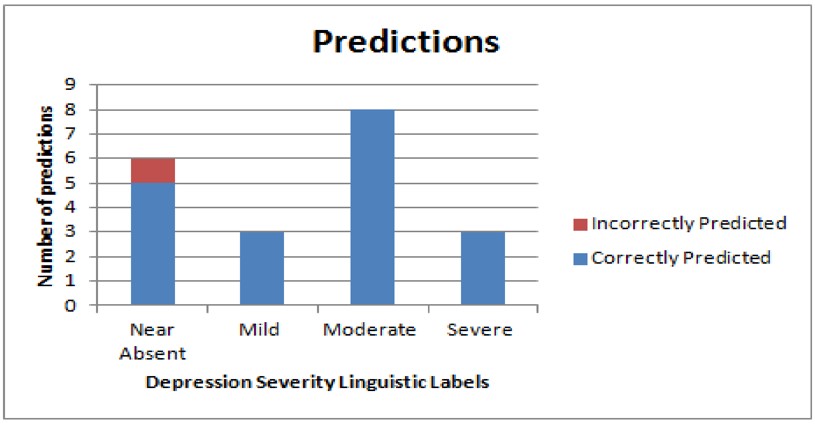


Figure 15: Prediction accuracies

6. Conclusion and Recommendation

This study proposed a Neuro-fuzzy cased based expert system for depression prediction (NFCBxSdp) driven by Neural Network, Fuzzy Logic and Case based reasoning to provide a decision support platform that will assist medical practitioners in the efficient diagnosis of depression. The significance of the NFCBxSdp model lies in the fact that management of depression depends fully on the severity of the disease and it requires the knowledge and experience of a specialist (psychiatrist or psychologist) to give correct diagnosis based on the severity of the symptoms. There is the need to look into the exploitation of softcomputing approaches because they offer a flexible, user friendly, and scalable design that can intelligently combine the key attributes of disease symptoms to provide diagnosis results that is accurate, timely and cost effective. NFCBxSdp can be extended to provide intelligent solution for evaluating and predicting severity levels of patients within the ICD-10 classification of mental health disorder in the domain of psychiatry. The system can serve as a self-learning tool for clinical students of psychiatry or mental health and information system researchers exploring issues of neural networks, fuzzy logic and case based reasoning. It can be embedded into the routine clinical consultations as a medical decision support tool, but cannot completely replace the medical expert. Finally, the adoption of the product of this study when deployed in mental healthcare centres offer a good contribution for developing countries to meet some of the millennium development goals which is centred on healthcare by providing an effective IT-based decision support for healthcare providers and policy makers.

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