Original Research Article

Early Depression Prediction Among Nigerian University Students Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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ABSTRACT

Depression is a mental disorder characterized by a sad mood, irritability, anger, agitations, loss of interest or pleasure, reduced energy, feelings of guilt, low self-esteem, troubled sleep, appetite loss, and poor attentiveness. The effects of late diagnosis of depression in Nigerian students have posed threats to the academic performance of the students, economic growth, and security threats. To address this challenge, an ANFIS model for early detection of depression among Nigerian Students is proposed. This aids in the reduction and possible elimination of prevalent cases of depression-related dangers among students in tertiary institutions. ANFIS is utilized because of its transparency and ability to classify and identify hidden symptoms of depression, and its tendency for reduced memorization errors for users. The database was developed to hold user data, symptoms, and prescriptions and linked to the ANFIS framework to enable the diagnosis of early-phase depression. Data was collected from the University of Uyo primary health care center, and the University of Uyo Teaching Hospital (UUTH). The ANFIS model implementation was implemented in MATLAB while the application forming the input interface was implemented with JAVA. The dataset for training was passed through ANFIS for 10 epochs and upon completion the system had a training error of 6.0138e-0.5 and an average testing error of 4.6648 on the test data, these results indicate that the system possessed 95% classification accuracy in the detection of early depression in Nigerian students.

Keywords: Depression, Adaptive Neuro-Fuzzy Inference System, Diagnosis

1. INTRODUCTION

University students in recent times have been found struggling with emotions such as hopelessness and despair that keep them unstable and downtrodden. A normal path of life includes feelings of sadness and grief but when these feelings become continuous, it can result in depression [1] defined depression as a mental disorder that presents with sadness, irritability, anger, agitation, loss of interest or pleasure, reduced energy, feelings of guilt, low self-esteem, troubled sleep, appetite loss, and poor attentiveness. This disease is characterized by changes in mood status presenting as feelings of sadness which may fluctuate from slight hopelessness to severe feelings of disappointment [2] [1] also considered depression as a mental disorder that presents with sad mood, irritability, anger, agitations, loss of interest or pleasure, reduced energy, feelings of guilt, low self-esteem, troubled sleep, appetite loss, and poor attentiveness. Some other core depressive symptoms are anhedonia (lessened interest or pleasure in all or almost all activities), significant unpremeditated weight loss or gain, insomnia or hypersomnia, psychomotor agitation or retardation, feeling of fatigue or loss of energy, feelings of worthlessness, excessive or inappropriate guilt, persistent suicidal ideation without a specific plan, a suicide attempt or a premeditated plan for committing suicide. These depressive symptoms may persist for weeks, months, or even years if it is not diagnosed early, misdiagnosed, or mistreated.

The work of [3] investigated the transitional phase of students on university campuses. It was noted that students in the university learn to leave traditional lifestyle practice into another lifestyle which may induce emotional instability in them. Depression is a common health problem ranked third, after cardiac and respiratory diseases, as a major cause of disability in persons [4]. It is a disease whose symptoms in primary care are debated, imprecise, inexact, and unclear [5]

The notable features of depression in students in the initial phase are isolation, skipping classes, loss of appetite, and low academic performance among others [6]. Depression is a common health problem, ranked third as a major cause of disability after cardiac and respiratory diseases [4]. This disease is characterized by changes in mood status presenting as feelings of sadness which may fluctuate from slight hopelessness to severe feelings of disappointment [2]. Some other core depressive symptoms are anhedonia (lessened interest or pleasure in all or almost all activities), significant unpremeditated weight loss or gain, insomnia or hypersomnia, psychomotor agitation or retardation, feeling of fatigue or loss of energy. Depression exists in phases that are used as a rationale for recommendation. Depressive disorder can be characterized into four phases mild, moderate, moderately severe, and severe depression [7]. The University of Michigan Medical School (UMHS) Depression Guideline update in 2011, established that each phase of depression has types of depressive disorder which include major depressive disorder, dysthymia, seasonal depressive disorder, persistent depression, manic depression, or bipolar disorder, depressive psychosis, perinatal depression, premenstrual dysphoric disorder, seasonal depression, situational depression, and atypical depression.

Major Depressive Disorder (MDD) is the most severe form of depression that usually goes along with significant functional impairment and increased health services use. MDD is otherwise called classic depression or unipolar depression. Dysthymic depressive disorder is a long-lasting depression with less severe chronic depressive symptoms. Dysthymic Symptoms (qualifying symptoms for Dysthymic Disorder) may include poor appetite without weight change, low self-esteem, and feelings of hopelessness. Dysthymic depression is a clinical condition, characterized by low-grade depression which lasts at least two years (UMHS 2011). Seasonal Affective Disorder (SAD) is a seasonal form of major depression that has features similar to MDD but the occurrence of SAD is on a cyclical basis that relates to ambient light deprivation during very cold or winter months. Mood disorder is another form of depression with features similar to MDD but is part of the physiological sequel of major medical conditions such as cancer, stroke, myocardial infarction, major trauma, or neurodegenerative disorders such as Alzheimer’s disease. In adolescence, MDD can include substance abuse, antisocial behavior, social withdrawal, and academic failure, with suicide attempts and ideation.

Depression is a disorder that can be diagnosed and treated in primary care. According to [7] economic analysis; treating depression in primary care is achievable, inexpensive, and cost-effective. Preferable treatment options include basic psychosocial support with antidepressant medications or psychotherapy. Antidepressant medications and structured forms of short-term psychotherapy are very effective for cases of mild depression. Furthermore, these treatments have been identified to be very efficient for both moderate and severe depression. Studies have shown that self-help books or internet-based self-help programs are supportive in reducing and treating depression in a lot of Western countries [8]. Several prevention programs are active for adolescents through the depression lifespan.

And these prevention programs keep providing data that shows a decrease in elevated levels of depressive disorder symptoms. The non-ubiquitous nature of these programs limits availability and denies some intending persons accessibility, thereby making effective community approaches to prevent depression focus on several actions surrounding the strengthening of protective factors and the reduction of risk factors. [9] investigated the major risk factors of depression in students. The author pointed out that mental disorders, specific personality characteristics, genetic loading, and family processes in combination with triggering psychosocial stressors, exposure to inspiring models, and availability of means of committing suicide can result in late diagnosis of depression in students in the university communities.

It is at this instance that this work proposes a system that can diagnose mild or early-phase depression among Nigerian students using the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a prominent model that produces robust results compared to other fuzzy inference systems because of its flexibility, ability to adapt and work efficiently, and to learn rapidly on highly non-linear complex problems. This model provides a better estimate for early-phase depression diagnoses because it approximates medical plants with a high degree of accuracy. The model can be trained without depending solely on expert knowledge sufficient for a fuzzy logic model. The proposed depression ANFIS model is more transparent to the user and will contain less memorization of errors compared to ANN. After training the system with real data, ANFIS can respond to the new data set that was not used during the training phase.

2.0 RELATED WORKS

In [10], students' life at Addis Ababa University was investigated. It was observed that university life is a transitional phase because many students move away from their homes to prepare themselves educationally and otherwise for the future. During this period, traditional social support is sometimes lost, making the young students learn how to deal with financial difficulties as they have to cater for themselves for the first time in their lives without close supervision. [11] also agrees that the fleeting period from adolescence to adulthood is a very stressful time in a person's life. Stating that the transitory period brings anxiety with it. This anxiety may arise in a lot of students as they struggle to fit into the university system, maintain good grades, and plan to secure a stable future. And as they react to the stress and occurrences around them, depression may set in. [12] carried out a study on the Neuro-fuzzy approach for diagnosing depression. Fourteen symptoms of adult depression were considered, according to the Diagnostic and Statistical Manual (DSM)-IV-TR. The domain experts (psychiatrists) measured the load of each symptom and the corresponding severity of depressive disorders. Seven symptoms were extracted out of fourteen symptoms (as features), as latent factors using the Principal Component Analysis (PCA). A hybrid system consisting of Mamdani's Fuzzy Logic Controller (FLC) on a Feed Forward Multilayer Neural Net (FFMNN) was developed with these features as inputs. The backpropagation Neural Net (BPNN) algorithm was used to tune the output of the hybrid system. The model was validated using three hundred and two real-world adult depression cases and fifty controls (that is normal population). This study accomplished that the hybrid controller can diagnose and grade depression with an average accuracy of 95.50%.

[13] in their study developed a genetic-neuro-fuzzy system for grading depression. This study aimed to help general physicians with first-hand applications. In the work, the key symptoms of depression are identified. Data from patients through physicians were collected. Two approaches were utilized and optimized in the performance of the mode. The back-propagation algorithm with the Genetic Algorithm was considered and used in this model. The model was trained with seventy-eight data and validated with ten. In terms of diagnostic accuracy, the genetic algorithm superseded the back-propagation algorithm. It was therefore concluded that the soft computing-based diagnostic models can assist doctors in making informed decisions.

The study by [14] was designed to predict depression risk levels using Fuzzy Logic (FL). The work described research results in the development of a system driven by fuzzy logic to determine the risk levels of depressed patients. Their model was implemented and simulated using MATLAB fuzzy toolbox. The result of the system was found consistent with an expert specialist's opinion on evaluating the performance of the system. The system predicted depression risk severity levels accurately based on expert knowledge embedded as fuzzy rules and supplied patients' physiological and psychological parameters.[15] Designed an intelligent decision support system for depression diagnosis based on a Neuro-Fuzzy-Case Base Reasoning (CBR) hybrid. In this work, the need was to retain cases in a case base and reuse effective previous solutions for current cases, due to the conflicting, overlapping, and confusing nature of the multitude of symptoms of depression. Neuro-fuzzy-Case Base Reasoning (CBR) was proposed to drive the decision support system that utilizes solutions to previous cases in assisting physicians in the diagnosis of depression disorder. Twenty-five symptoms were grouped into five categories to represent depression disorder. Imprecise symptoms were handled by fuzzy logic and local similarity between the input cases and retrieved cases was achieved using the absolute deviation as the distance metric. Five best-matched cases were subjected to the emotional filter of the system for diagnostic decision-making. This approach derives strengths from the hybridization since the tools are complementary to one another.

In the study of [16] a hybrid of two techniques for estimating attendance at sports games was introduced. Being one of the foremost submissions that attempted to use an ANFIS model for that purpose, the author developed a soccer game attendance forecasting system using a hybrid of neural network (NN) and adaptive neuro-fuzzy inference system (ANFIS). The model was designed based on the characteristic problem; using previous games attendance data for training and testing model performance. Based on their results, the proposed hybrid model is very effective in forecasting attendance at soccer games. [17] carried out a study on postpartum depression utilizing an Adaptive neuro-fuzzy approach for diagnosis. Postpartum depression is a growing public health problem amongst nursing mothers, which is not given much attention in primary healthcare settings. It is a type of depression experienced after childbirth that affects an estimated 13–19% of nursing mothers. Postpartum depression is very difficult to diagnose and by concentrating on somatic illnesses, most medical practitioners frequently fail to recognize it. In utilizing ANFIS for Postpartum depression prediction; thirty-six data instances were used in training the model. The system had a training error of 7.0706e−005 at epoch 1 and an average testing error of 3.0185. The results suggest that the technique will facilitate the prompt and accurate diagnosis of postpartum depression disorder.

2.1 Causes of Depression in Students

Poor Academic Performance can be caused by several factors including institution-based factors, parental-based factors, environmental-based factors, and student-based factors, home environment, study habits, learning skills, gender, parent's occupation, class attendance, parent's income, the influence of lecturers, social economic status, boredom, motivation, attitude, self-esteem, stress, workload, active learning, time spent on task, extra-curriculum activities, peer influence, help-seeking effective time management tools, self-efficacy, class size, and marital status [18]. Also, the removal of fuel subsidies resulting in a high cost of living, tuition hikes, and transport hikes affect the mental well-being of the students resulting in depression.

3.0 MATERIAL AND METHODS

Data was gathered from the University of Uyo Teaching Hospital (UUTH) and primary care centers. These data were processed and classified into 21 cases based on peculiarity in symptoms. The adopted method for data training and testing was the Adaptive Neuro-Fuzzy Inference System (ANFIS). This is because ANFIS combines Artificial Neural Network and Fuzzy

Inference System thereby conquering the drawbacks of neural networks and weakness of learning in Fuzzy Inference System. The approach is flexible with the ability to adapt and work efficiently and learn rapidly on highly nonlinear complex problems hence it is suitable for application in the early phase diagnosis of depression. Table 1 shows sample cases of the depression dataset from the total cases. Where FS represents symptom 1 (feeling sad), LP represents symptom 2 (loss of pleasure), PA represents symptom 3 (psychomotor agitation), WL represents symptom 4 (weight loss), I represent symptom 5 (insomnia), HI represents symptom 6 (hypersomnia), LA represents symptom 7 (loss of appetite) were the inputs fed into the model. The Depression Level (DL) was the output fed out of the model.

Table 1: Sample Cases of Depression Dataset

SC	**FS**	**LP**	**PA**	**WL**	**I**	**HI**	**LA**
Case 1	9.34	5.54	5.04	4.47	3.23	9.22	5.35
Case 2	2.57	3.69	5.5	3.23	7.42	9.976	0.97
Case 3	5.59	1.1	2.94	4.63	4.74	8.67	2.44
Case 4	6.93	1.8	7.41	5.35	8.87	7.25	4.99
Case 5	2.53	7.98	0.97	4.46	7.88	5.01	5.51
Case 6	8.15	3.09	2.44	7.81	9.97	2.21	9.17
Case 21	8.7	1.2	3.3	5.5	1.5	4.74	6.192

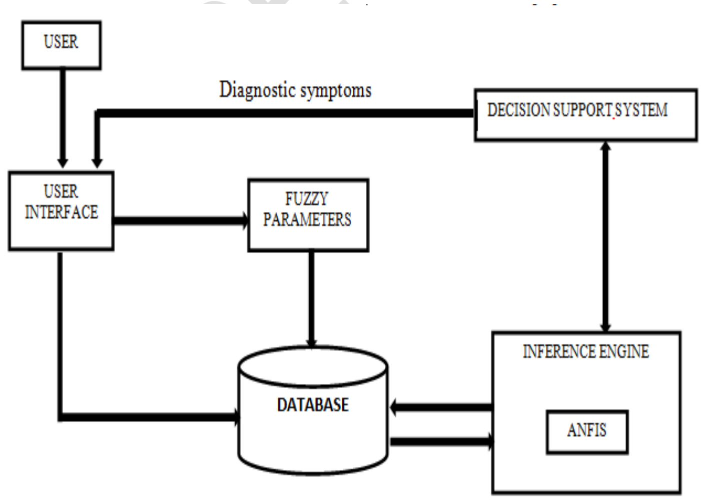

Fig 1: Proposed System Architecture

3.1 Proposed System

The effects of late diagnosis of depression have posed threats to society at large. The disease at its late phase is normally diagnosed in patients who present symptoms like irritable bowel syndrome, long-lasting fatigue syndrome, fibromyalgia, or chronic pain such as headache, low back pain, and pelvic pain. When these symptoms remain undiagnosed, untreated, or mistreated, the patient's health deteriorates into Major Depressive Disorder (MDD) which is the most severe form of depression. The late or severe phase of depression (Major Depressive Disorder) is characterized by symptoms such as self-harm or suicide. MDD is one of the major leading causes of suicide in society. Methods that existed for the diagnosis of depression from the depressed patients to the clinician or physician had limitations such as the inability to detect depression at its early or mild phase before deterioration, and the unavailability of known treatment to the majority of the affected persons. Also, portable and handy platforms for monitoring depression are scarce. The difficulty of providing easily accessible diagnostics platforms to depressed patients has been a major constraint. Hence, this work proposes an Adaptive Neuro-Fuzzy Inference System approach for diagnosing early-phase depression as depicted in Fig 1.

3.1.1 User Interface

The user interface describes the medium through which user inputs are accepted into the system for processing. It incorporates user authentication via the login page and all other operations performable by the user on the system. In addition, the user interface is a graphical representation that allows users to communicate with the underlying software. It accepts the user's identification (ID) and symptoms as input and outputs diagnostic results and prescriptions in a form that can be understood by the user.

3.1.2 Fuzzy Sets

Fuzzy logic fuzzifies all input values into fuzzy membership functions. It executes all applicable rules in the rule base to compute the fuzzy output functions. It defuzzifies the fuzzy output functions to get crisp output values. Linguistic variables are non-numeric values often used to facilitate the expression of rules and facts. The linguistic variable for this system is symptoms of depression. Where FS represents symptom 1 (feeling sad), LP represents symptom 2 (loss of pleasure), PA represents symptom 3 (psychomotor agitation), WL represents symptom 4 (weight loss), I represent symptom 5 (insomnia), HI represents symptom 6 (hypersomnia), and LA represents symptom 7 (loss of appetite). The Depression Level (DL) is the output fed out of the model. Three linguistic terms such as low, moderate, and high are defined for the linguistic variables. Defuzzification operations can be used to map a fuzzy output membership function into a "crisp" output value that can be used for decision or control purposes.

3.1.3 Decision Support System

The Decision Support System (DSS) is integrated to support decision-making activities in the system. The DSS will be an interactive subsystem that helps patients and physicians use communications technologies, data, documents, knowledge, and/or models to complete decision process tasks of depression diagnosis.

3.1.4 Adaptive Neuro-Fuzzy Inference Engine

ANFIS handles fuzzy rules whose antecedents are mapped local similarities of each category symptoms for global similarity measurement, upon which the retrieved cases are ranked. ANFIS which is a branch of Artificial Intelligence (AI) can play a vital role in medical diagnosis to curb THOSE inaccuracies due to external human factors. The proposed system is designed to allow IF-THEN rules and membership functions (fuzzy logic) to be constructed based on historical data and also include the adaptive nature for automatic tuning of the membership functions. ANFIS refers to an inference system that integrates the best features of neural networks and fuzzy logic. In ANFIS, the fuzzy logic component is in the hidden layer of the neural network and the combination of these techniques makes ANFIS a hybrid model

Layer 1: This is also known as the input layer. This layer contains seven (7) neurons which are the clinical symptoms (feeling sad, loss of pleasure in activities previously enjoyed, psychomotor agitation, weight loss, insomnia, hypersomnia, fatigue, etc. The dataset is fed into the ANFIS model where each neuron is equivalent to a particular clinical symptom represented mathematically as shown in Eqn 1

$$O_i^l = X_i \tag{1}$$

Where O^1_i is the *i*th neuron output from layer 1, *x* is the symptom value for the *i*th symptom.

Layer 2: This is known as the membership function layer. In the ANFIS architecture, it is the first hidden layer. This layer contains the membership function which maps linguistic variables from the first layer (layer 1) to linguistic labels in a fuzzy set. Various membership functions exist, but in the proposed model, bell membership function was utilized in mapping these symptoms to a fuzzy set because it can approach a non-fuzzy set and has a non-zero value at all points. The bell membership function is represented in Eqn 2

$$\mu(x) = \frac{1}{1+\frac{x-c^2}{\alpha}} \qquad (2)$$

Where*a is* the mean of symptom values, b determines the bell curve of the symptoms, *c* is the center of the curve, *x* is the symptom value, and *μ*(*x*) is the membership function of *x*.

Layer 3*:* This is also known as the rule layer. It is the second hidden layer of the ANFIS architecture. Each neuron in this layer receives input from the preceding (membership function) layer and computes the truth value for each rule. This layer is subjected to the Takagi–Sugeno inference rule shown in Eqn 3

$$O_i^{3 =\mu(x)* \mu(y)} \qquad (3)$$

Where, $O_i^3$is the *i*th neuron output from layer 3 ,*μ*(*x*) and *μ*(*y*) are the membership functions of *x* and *y*, respectively.

Layer 4: This layer is also known as the normalization layer. It is the third hidden layer of the ANFIS architecture. Each neuron in layer 4 corresponds to exactly one neuron in the rule layer and it calculates the firing strength of each rule. This can be represented mathematically as in Eqn 4

$$O_i^4 = O_1^3 + O_2^3 + \cdots + O_n^3 \qquad (4)$$

Where O_i^4 is the ith neuron output from layer 4, is the ith neuron output from layer 3, and *n* is the total number of neurons in layer 3.

Layer 5: This is also known as the defuzzification layer; it is the fourth hidden layer of the ANFIS architecture. It consists of just a single neuron to which all the neurons from the normalization layer are connected. The output from this layer is derived by multiplying the firing strength of a rule by its consequent parameters. This is represented mathematically in Eqn 5

$$O_i^5 = O_i^4(p_i(x) + q_i(y) + r) \qquad (5)$$

Where $O_i^5$is the *i*th neuron output from layer 5, *pi*, and *qi* are the consequent parameters, and *r* represents bias.

Layer 6: This is also known as the output layer; it is the sixth layer of ANFIS. The neurons in this layer produce the final output of the ANFIS. The input into this layer is gotten from layer 5 and it produces its output by summing its inputs. Mathematically, this can be represented as in Eqn 6

$$O_i^6 = \sum_i^n O_i^5 \qquad (6)$$

Where$O_i^6$is the *i*th neuron output from layer 6, $O_i^5$is the *i*th neuron output from layer 5 and *n* is the total number of neurons in layer 3 as presented in Fig 2.

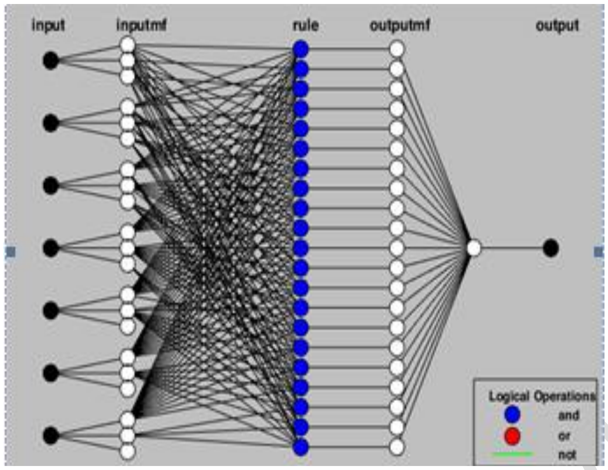

Fig 2: ANFIS Depression Structure

3.1.5 Membership Function

The membership function in this work defines a function that specifies the degree to which a given input belongs to the set. The generalized bell membership function based on the Sugeno mechanism is adapted. The generalized bell membership function is a function with three parameters: a responsible for its width, c- responsible for its center, and b- responsible for its slopes as demonstrated in Eqn 7

$$Gbellmf(x,b,c) = \frac{1}{1+\frac{x-c^{2b}}{b}} \qquad (7)$$

3.1.6 Procedures for Implementing ANFIS

i. First, the dataset that contains the desired input/output data pairs of the target system to be modeled was collected. The datasets are now divided into training and checking datasets.
ii. The training and checking datasets are saved in Excel files.
iii. The training and checking datasets are imported individually into the MATLAB workspace using the import command.
iv. The ANFIS editor is then invoked from the MATLAB command window using the command "anfis edit" command.
v. From the load data section of the ANFIS editor, training and checking data were loaded by selecting the appropriate commands and buttons. The loaded data is then plotted on the plot region.
vi. The FIS model was generated by clicking on the grid partition in the Generate FIS section of the ANFIS editor.
vii. FIS model structure was viewed once an initial FIS had been generated or loaded by clicking the Structure button.
viii. The FIS model parameter hybrid optimization method: which is a mixture of backpropagation and least squares method was chosen in the Train FIS

3. RESULTS AND DISCUSSION

Figs 3 to 6, show the relationship between FS (feeling sad) and LP (loss of pleasure) to the diagnosis of depression level, the relationship between LP (loss of pleasure) and PA (psychomotor agitation) to the diagnosis of depression level, the relationship between WL (weight loss) and I (insomnia) to the diagnosis of depression level, and the relationship between LA (loss of appetite) and WL (weight loss) to the diagnosis of depression level. This ANFIS model utilized a bell membership function and the hybrid optimization learning algorithm which had its error tolerance at 0. The dataset used for training was passed through the ANFIS for 10 epochs and upon completion the system had a training error of

6.0138e-0.5 and an average testing error of 4.6648 on the test dataset, which indicates that the system was able to classify approximately 95% of the test dataset accurately. The dataset used to train and test the ANFIS was passed through an artificial neural network for 20 epochs using a hybrid learning algorithm and it had a training error of 4.6648 and an average testing error of 5.0217, an indication that the artificial neural network could classify approximately 90% of the test dataset as depicted in Fig 3.

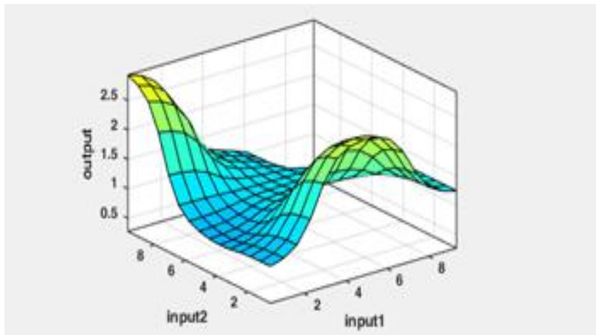

Fig 3: FS and LP input variable mapped against depression level.

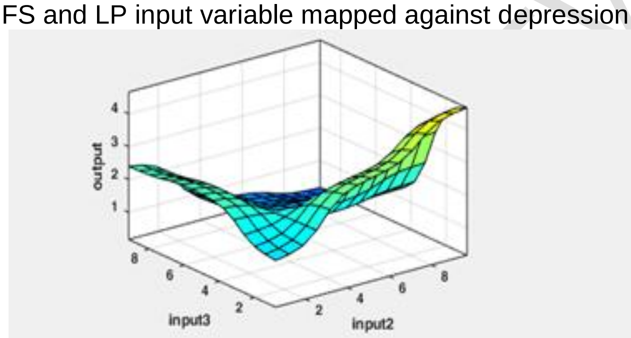

Fig 4: LP and PA mapped against Depression Level

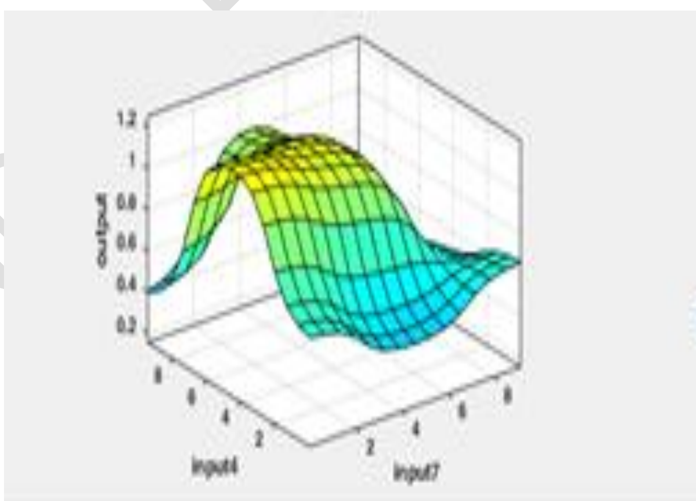

Fig 5: WL and I mapped against Depression Level

4. CONCLUSION

The proposed system investigates the early symptoms of depression among Nigerian students. This research has given a full description and a detailed review of early-phase depression diagnosis. The system developed in this work comprises the systems architecture, the conceptual design, and the database design. Data were collected and processed using MATLAB. The results obtained show that the dataset used for training was passed through the ANFIS for 10 epochs and upon completion, the system had a training error of 6.0138e-0.5 and an average testing error of 4.6648 on the test data, which indicates that the system was able to classify approximately 95% of the test data accurately. This work will help diagnose and identification of depression at its early stage before it deteriorates into Major Depressive Disorder (MDD) which leads to suicide. This system will help in reducing the rate of suicide in the university communities

REFERENCES

[1] Marcus, M., Yasamy, M. T., van Ommeren, M. V., Chisholm, D., & Saxena, S. (2012). Depression: A global public health concern.

[2] Lotfi, M. H., Aminian, A. H., Ghomizadea, A., & Zarea, S. (2010). Prevalence of depression amongst students of Shaheed Sadoughi University of Medical Sciences, Yazd, Iran. *Iranian Journal of Psychiatry and Behavioral Sciences*, *4*(2), 51-5.

[3] Gashaw, Y. (2015). *Depression among Addis Ababa University Students Sidist Kilo Campus: Prevalence, Gender Difference and Other Associated Factors* (Doctoral dissertation, Addis Ababa University).

[4] Ibrahim, A. K., Kelly, S. J., Adams, C. E., & Glazebrook, C. (2013). A systematic review of studies of depression prevalence in university students. *Journal of psychiatric research*, *47*(3), 391-400.

[5] Kwiatkowska, M., Kielan, K., & Michalik, K. (2009). A Fuzzy-Semiotic Framework for Modeling Imprecision in the Assessment of Depression. In *IFSA/EUSFLAT Conf.* (pp. 1717-1722).

[6] Şahin, M., & Erol, R. (2017). A comparative study of neural networks and ANFIS for forecasting attendance rate of soccer games. *Mathematical and computational applications*, *22*(4), 43.

[7] WHO." Depression, Mental Health: Depression, Available Online"2012 at, http://www.who.int/mediacentre/factsheets/fs369/en/.

[8] Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: a meta-analysis. *PloS one*, *5*(10), e13196.http://doi.org/10.1371/journal.pone.0013196

[9] Bilsen, J. (2018). Suicide and youth: risk factors. *Frontiers in psychiatry*, *9*, 540.doi: 10.3389/fpsyt.2018.00540

[10] Gashaw, Y. (2015). *Depression among Addis Ababa University Students Sidist Kilo Campus: Prevalence, Gender Difference and Other Associated Factors* (Doctoral dissertation, Addis Ababa University).

[11] Sarokhani, D., Delpisheh, A., Veisani, Y., Sarokhani, M. T., Manesh, R. E., &Sayehmiri, K. (2013). Prevalence of depression among university students: a systematic review and meta-analysis study. *Depression research and treatment*, *2013*.DOI:org/10.1155.

[12] Chattopadhyay, S. (2017). A neuro-fuzzy approach for the diagnosis of depression. *Applied computing and informatics*, *13*(1), 10-18.

[13] Ashish, K., Dasari, A., Chattopadhyay, S., & Hui, N. B. (2018). Genetic-neuro-fuzzy system for grading depression. *Applied computing and informatics*, *14*(1), 98-105.

[14] Ekong, V. E., Ekong, U. O., Uwadiae, E. E., Abasiubong, F., &Onibere, E. A. (2013). A fuzzy inference system for predicting depression risk levels. *African Journal of mathematics and computer Science Research*, *6*(10), 197-204.

[15] Ekong, Victor E., Udoinyang G. Inyang, and Emmanuel A. Onibere. "Intelligent decision support system for depression diagnosis based on neuro-fuzzy-CBR hybrid." *Modern Applied Science* 6, no. 7 (2012): 79.

[16] Şahin, M., & Erol, R. (2017). A comparative study of neural networks and ANFIS for forecasting attendance rate of soccer games. *Mathematical and computational applications*, *22*(4), 43.

[17] Osubor, V. I., &Egwali, A. O. (2018). A neuro fuzzy approach for the diagnosis of postpartum depression disorder. *Iran Journal of Computer Science*, *1*, 217-225.