academicJournals

Vol. 6(10), pp. 197-204, November, 2013
DOI: 10.5897/AJMCSR2013.0511
ISSN 2006-9731 ©2013 Academic Journals
http://www.academicjournals.org/AJMCSR

African Journal of Mathematics and Computer Science Research

Full Length Research Paper

A fuzzy inference system for predicting depression risk levels

EKONG, Victor E.[1]*, EKONG, Uyinomen O.[1], UWADIAE, Enobakhare E.[2], ABASIUBONG, Festus[3] and ONIBERE, Emmanuel A.[4]

[1]Department of Computer Science, Faculty of Science, University of Uyo, Uyo, Akwa Ibom State, Nigeria.
[2]Department of Mental Health, University of Benin Teaching Hospital, Benin City, Nigeria.
[3]Department of Mental Health, University of Uyo Teaching Hospital, Uyo, Akwa Ibom State, Nigeria.
[4]Department of Computer Science, Faculty of Physical Sciences University of Benin, Benin City, Nigeria.

Accepted 13 November, 2013

This paper reports the findings from the experimental study of an intelligent system driven by Fuzzy Logic (FL) for depression risk diagnosis. Depression is a common psychological disorder that can cause serious health challenges if it remains undiagnosed, misdiagnosed or untreated. It represents a major public health problem identified by the world health organization (WHO) to have affected a vast majority of the productive adult population. The confusing nature of the disease symptoms makes it difficult for physicians using psychometric assessment tools alone to determine the severity of the disease. With advances in artificial intelligence (AI), intelligent computing has accelerated new approaches that can enhance medical decision support services. This paper describes research results in the development of a fuzzy driven system to determine the depression risk levels of patients. The system is implemented and simulated using MATLAB fuzzy tool box. The result of the system is consistent with an expert specialist's opinion on evaluating the performance of the system.

Key words: Depression, depression risk, fuzzy logic, severity level, matlab, membership functions.

INTRODUCTION

Depression is a disease whose symptoms in primary care are controversial, vague, imprecise and ambiguous (Mila et al., 2009). Depression symptoms range from everyday feeling of sadness, loss of interest to suicidal ideations normally lasting a cycle of at least two weeks. Although many other symptoms occur in varying proportions, the disease is a comorbid factor in many chronic health conditions such as renal dysfunctions, diabetes, cancer, alcohol abuse, and cardiovascular diseases (Klinsman, 2003; Cohen et al., 2007). The disease has a relapsing course that adds to the morbidity, mortality and economic loss (Maja et al., 2008; WHO, 2009; Kessler, 2002).

Several studies have shown that the disease is a major public health problem with a high prevalence amongst the adult population (Pauliks, 2013; Chattopadhyay et al., 2012).

Nunes et al. (2011) observed that affected persons may exhibit noticeable signs of incapacity for work and social relationships.. Unfortunately, the disease remains largely under diagnosed in primary care although more than one in ten cases seen in primary care suffers from this condition (Sengupta, 2005; Olawale et al., 2010). The exact cause of the disease has often been disputed amongst authors. While some argue that the chemical imbalances in the brain and hormonal deficiencies are the cause, others attribute the disease to genetic links

*Corresponding author. E-mail: victoreekong@uniuyo.edu.ng.

(Sheikh et al., 2004). It is however generally accepted that certain conditions such as obstructive sleep disorder (OSD), stressful environments, childhood precursors, deteriorating physical health, adverse life events or experiences such as loss of a loved one or job, and the use of antidepressants medications are possible causes (About Depression, 2011).

Classification of the disease has been based on subjective results obtained from patients using psychometric tools that meet the criteria of the diagnostic and statistical manual of mental disorders, fourth edition (DSM-IV) and International Classification of Diseases version 10 (ICD-10) (American Psychiatric Association (APA), 1994; Mondimore, 2006; WHO, 1992; Mila et al., 2009). Physicians utilize a number of the DSM-IV based tools such as Becks depression inventory version two (BDI-2) (Becks, 1996); Hamilton's depression rating scale (HDRS)(Hamilton, 1967); Primary care evaluation of mental disorder (PRIME-MD) (Spitzer et al., 1994); Zung's scale (Ellen et al., 2002); Geriatric depression scale (Ellen et al., 2002) and the 9-item physical health questionnaire (PHQ-9) (Kroenke et al., 2001) for establishing the severity levels for the different onsets of the disease. Severity levels are graded manually with measures as 'mild-to-moderate' and 'moderate-to-severe', thus lacking medical precision and clarity (Ariyanti et al., 2010).

The task of medical diagnosis, unlike other diagnostic processes is complex because lots of vagueness, linguistic uncertainty, measurement imprecision, natural diversity is prominently evident (Emuoyibofarhe and Taiwo, 2012). Recent developments in AI and intelligent computing has accelerated new approaches that can enhance medical decision support services thereby reducing morbidity, mortality and economic loss to the health care systems (Chattopadhyay et al., 2012).

This paper reports a research result of the development of a fuzzy system that allows determining the level of severity of depression using patient cases. The system is implemented in MATLAB 7.6.0.324 (R2008) Fuzzy logic toolbox.

MATERIALS AND METHODS

A review of existing literature on depression and its management, and fuzzy logic was carried out. Depression disorder results from a combined effect of various physiological, environmental, psychological and socioeconomic factors. Recent studies show that biological predictors of blood pressure levels, heart rate and body mass index (BMI) are associated with depressive symptoms (Hamer et al., 2012; Hildrum et al., 2011; Carney and Freedland , 2007; Kim et al., 2005).

A group of psychiatrist and psychologist from two university teaching hospitals in Nigeria were consulted in order to arrive at selecting three physiological and one psychological predictor of the disease (Age, BMI, systolic blood pressure (SBP), 9-item patient health questionnaire (PHQ-9)). With their help, anonymous depression data were collected after following appropriate ethical approval measures. A total of 125 adult depression cases were obtained for the study, and the data were validated and checked for reliability prior to utilizing it in the experiment.

FL logic is an AI technique that provides the methodology for obtaining approximate solutions for real world problems which may contain various kinds of imprecision and uncertainties (Zadeh, 1994). It has the potential of combining human heuristics into computer assisted decision-making, which is applicable to individual patients as it takes into account all the factors and complexities of the individuals (Godil et al., 2011). FL has been applied in all disciplines of medicine (Sikchi et al., 2013; Innocent et al., 2005). In the domain of depression, a fuzzy set *a* in A (universe of discourse) of depression attributes denoted by x is given as Equation (1).

$$a=\{(x,\mu_a(x))\mid x\in A,\mu_a(x)\in[0,1]\} \tag{1}$$

where $\mu_a(x)$ is the membership function (MF) of x in *a*, and μ_a is the degree of membership of x in *a* in the interval [0, 1]. Commonly used MFs are Gaussian, Triangular and Trapezoidal (Vijaya et al., 2010). Triangular MFs have been used extensively in the medical domain because of their computational efficiency in modeling the human reasoning process. It provides a mathematical tool capable of dealing with all kinds of human cognitive processes and has been used in assisting medical practitioners in making decisions. In this work, the fuzzy system is used in the triangular function in Equation (2).

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

where *a*, *b* and *c* are the parameters of the MF. Each of these attributes are described using fuzzy linguistic label of 'near absent', 'mild', 'moderate', 'severe' and 'very severe' as shown by the MF for the output variable depression risk in Equation (3).

$$\mu_a(x)=\begin{cases}Near\ absent, & if\ \ x<0.25\\ Mild, & if\ 0.25\le x<0.45\\ Moderate, & if\ 0.45\le x<0.65\\ Severe, & if\ 0.65\le x<0.85\\ very\,Severe & if\ 0.85\le x\le 1.0\end{cases} \tag{3}$$

The architecture of the fuzzy system is presented in Figure 1. The major components are: Patient/Physician interface, fuzzification interface, knowledge base, inference engine and decision making module.

Patient-physician interface

A patient consults a physician who obtains his or her medical history of the prevailing condition and other relevant information. The physician performs detailed medical examinations with specific attention on the presented symptoms. Physiological attributes (e.g. SBP, BMI, Age, etc.) are recorded and where psychological symptoms are suspected, a DSM-IV criteria PHQ-9 depression test is applied to generate a depression rating score. These are subjective reports, and when the physician carries out further

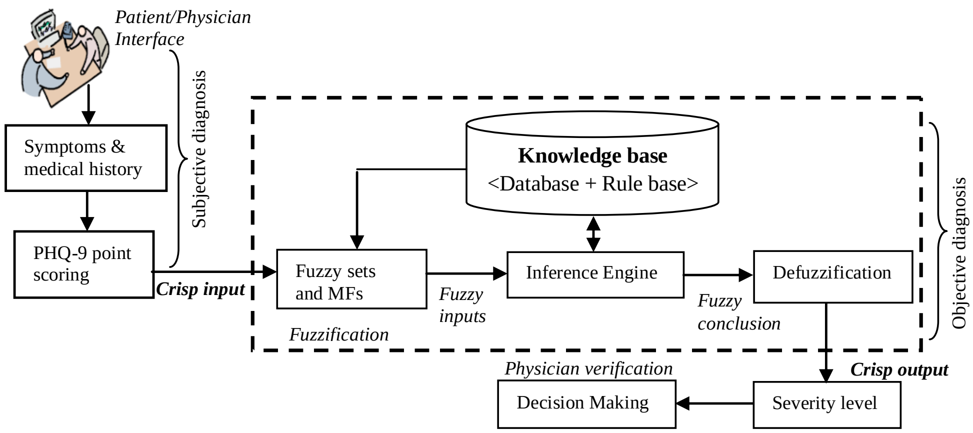

Figure 1. Architecture of the fuzzy system.

medical tests to identify signs related to the illness or the presenting symptoms, such findings are objective.

Fuzzification interface

Fuzzification is the process of converting the crisp input values into fuzzy values. The following attributes of depression are fuzzified: Age, BMI, SBP, PHQ-9 score and depression risk. We followed the guidelines in Vijaya et al. (2010) in choosing the trapezoidal MF for the input variables and triangular MF for the output variable. At the fuzzification interface, the input variable Age ranges from 20 to 100 years is fuzzified into three linguistic variables: 'young', 'middle-age' and 'old'. BMI ranges from 15 to 40kgm^{-2} are fuzzified into three linguistic variables: 'low', 'normal' and 'high'. SBP ranges from 90 to 280mmHg are fuzzified into four linguistic variables: 'low', 'normal', 'high' and 'very high'. PHQ-9 score ranges from 0 to 27, is fuzzified into three linguistic variables: 'mild', 'moderate', and 'severe'. The output linguistic variables are defined in Equation (3).

Knowledge base

The knowledge base is a component where knowledge is developed, stored, organized, processed and disseminated. It consists of a database and a rule base. The database provides the necessary elements for defining the linguistic variables and rules using IF - THEN control constructs. The database includes a set of facts used to match against the IF (condition) parts of rules stored in the knowledge base. It represents the set of facts known about the domain, for example, the details about a particular patient being diagnosed. The IF (condition) represents the 'antecedents' while the THEN part is the 'consequent'. In this work the antecedents are '*Age*', '*SBP*', '*BMI*', '*PHQ-9Score*' and the consequent is '*DepRisk*'.

Inference engine

The domain knowledge is represented by a set of facts about the current state of a patient. The inference engine compares each rule stored in the knowledge base with facts contained in the database. When the IF (condition) part of the rule matches a fact, the rule is fired and its THEN (action) part is executed (Negnevitsky, 2005).

The inference engine uses a system of rules to make decisions through the fuzzy 'AND' operator and generates a single truth value that determines the outcome of the rules. This way, they emulate human cognitive process and decision making ability and finally they represent knowledge in a structured homogenous and modular way (Aly and Vrana, 2006).

Defuzzification

Defuzzification is the process of converting the final output of a fuzzy system to a crisp value. For decision making purposes, the output fuzzy sets must be defuzzified to crisp value in the real life domain. The most commonly used defuzzification methods are the centroid method which returns the centre of area (COA) under the curve (Negnevitsky, 2005). COA defuzzification method finds a point representing the centre of area of the fuzzy set and is given in Equation (4).

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

where z is the crisp value that represents the severity level used for decision making, $\mu_{a_i}(x)$ is the degree of membership of the likelihood of the ith rule, y_i is the consequent of each rule.

Severity level (Output)

A multiple input single output (MISO) fuzzy system is used to obtain the severity level which is the only output variable of the system. The depression risk (DepRisk) determines the level of severity of depression risk given the input variables. The fuzzy system provides an objective process for obtaining the depression risk level.

MODEL SIMULATIONS

After determining the fuzzy membership functions, for the purpose of the study a standard rule base is developed to generate rules such that given M dimensions each of which is partitioned in N-

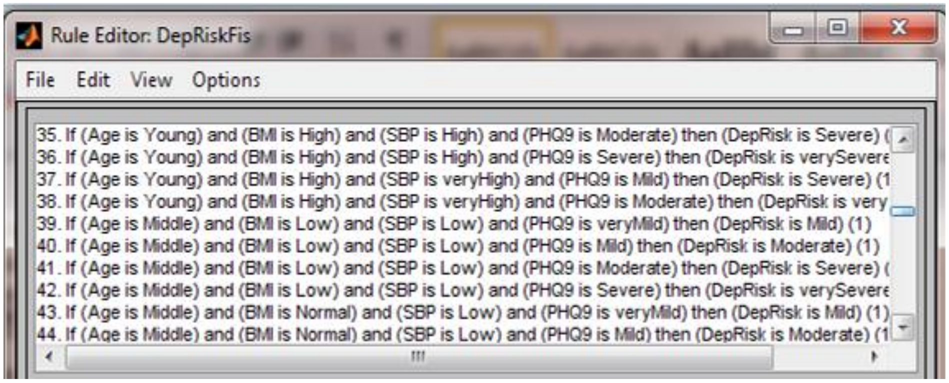

Figure 2. The Fuzzy Rule editor.

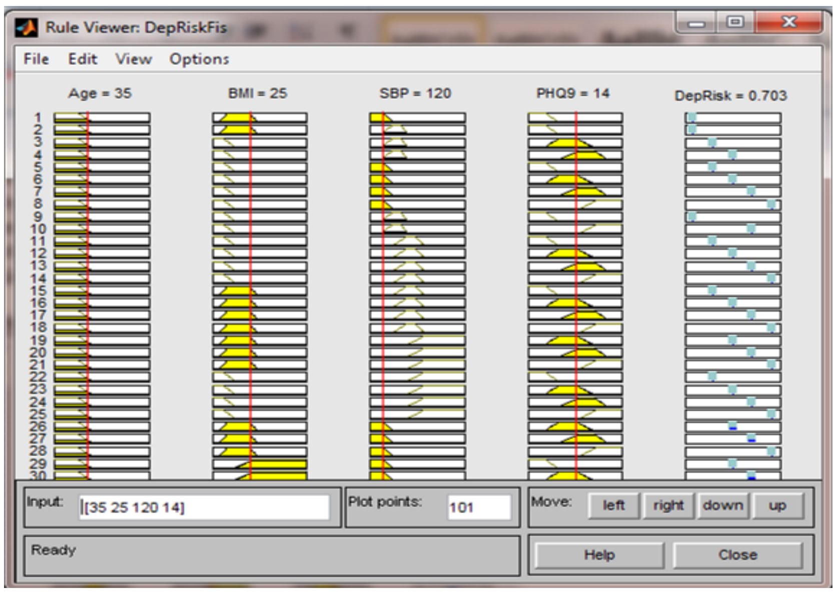

Figure 3. FIS rule viewer.

spaces, there exist N^M rules for the inference engine. For our fuzzy system we have four attributes representing four dimensions, with two divided into three subspaces and the other two split into four subspaces. A total of 144 (that is, 3^2x4^2) rules were generated representing four fuzzy linguistically designed input with *Age* and *BMI* having three membership functions and *SBP* and *PHQ9Score* having four membership functions each. The rules are based on the number of dimensions.

The simulation of the fuzzy system was carried out with MATLAB 7.6.0 in an environment characterized by Windows 7 operating system. The constructed fuzzy rule base is of the form shown by the rule editor in Figure 2. For each antecedent, the consequent value is determined based on domain expert's opinion. The fuzzy inference system (FIS) rule viewer shown in Figure 3, a depression risk of 0.703 representing a 'severe' severity level is obtained as output response for the input values (Age = 35, BMI = 25, SBP = 120 and PHQ-9 = 14). New input values generate new depression risk output responses. Also the inputs can be set explicitly using the edit field and this will again produce a corresponding output that is consistent with the fuzzy rule base. The input variables 'BMI' versus 'PHQ-9 Score' was plotted against the depression risk to observe the relationship between both attributes in the determination of depression risk levels. The relationship is shown in Figure 4. Another factor considered in the course of the research is the effect of the PHQ-9 scores and body mass index (BMI) on the level of severity of depression risk as shown in Figures 5 and 6.

RESULTS AND DISCUSSION

When the parameter 'PHQ-9 score' and 'BMI' were plotted against the 'DepRisk', it is observed that the higher the body mass index (BMI) of the patient, the higher the severity level of depression and vice versa. High severity levels occur when both the PHQ-9 scores and BMI are severe and high respectively as shown in

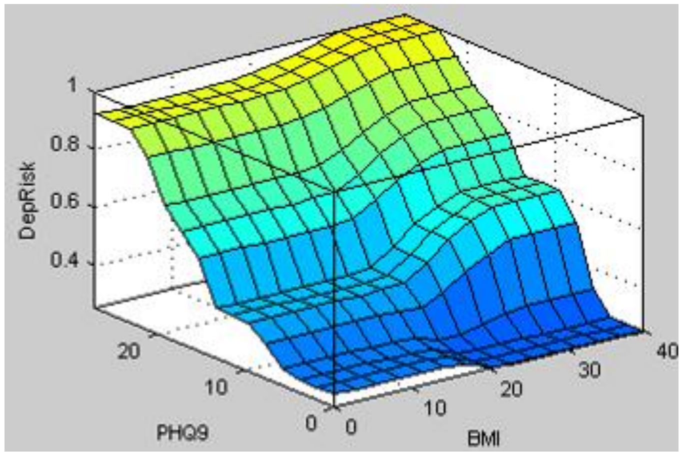

Figure 4. Plot of surface view for PHQ-9 score versus BMI against depression risk.

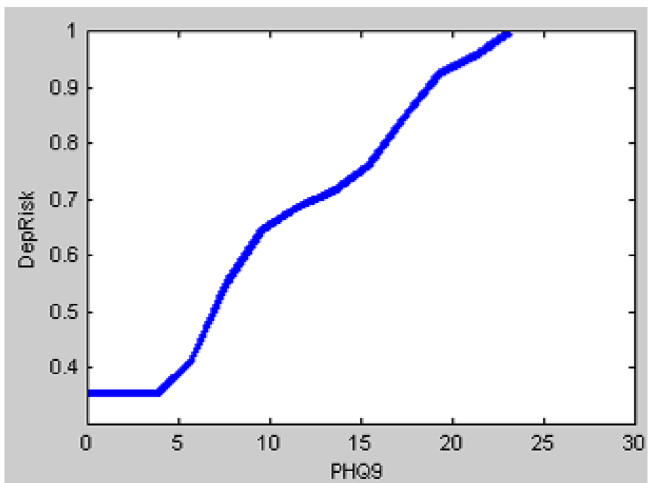

Figure 5. Plot of PHQ-9 Scores against depression risk.

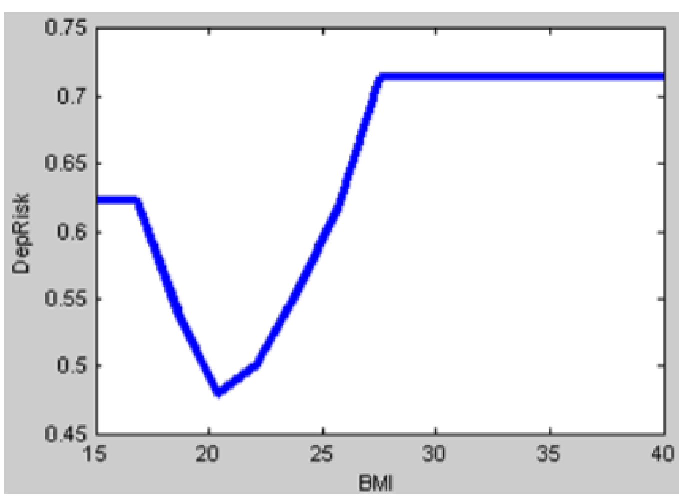

Figure 6. Plot of BMI against depression risk.

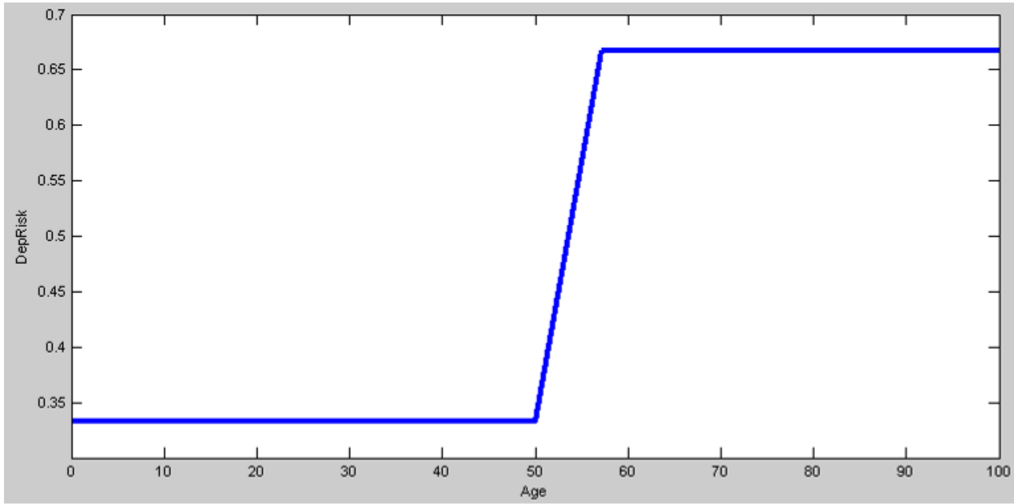

Figure 7. Plot of Age against depression risk.

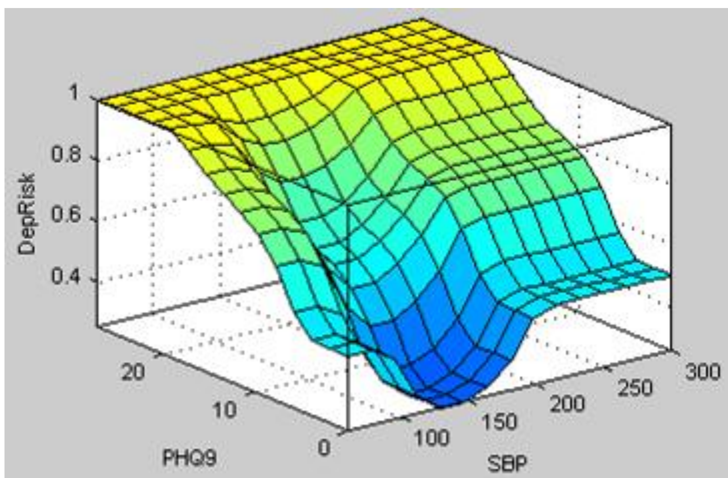

Figure 8. Surface plot of PHQ-9 score versus SBP against depression risk.

Figures 4, 5 and 6. The importance of fuzzy inference is the ability to combine the effect of multiple factors and come up with a holistic view of the prevalent scenario. In Figures 4,5,6,7and 8, it can be seen that the system combines adequately, factors like PHQ-9 Score, BMI, SBP and DepRisk amongst others and presents the fuzzified result as the level of severity.

The presented simulated results are in three-dimensions. This is because presently it is difficult to represent higher dimensions without distorting the figure in MATLAB graphical user interface (GUI) tools. This has limited the number of variables to be considered, to two against the fixed variable (output). It has not in any way hindered the functionality of the system because each factor represented is depicted as an integral part of the whole system whose variables have been fuzzified. When 'Age' was plotted against depression risk, the peak of the curve appears only when the age is above 50 years as represented in Figure 7. This accounts for reasons why depression disease is prevalent among adults (Pauliks, 2013).

Other combinations of the input variables can be generated using a similar approach. The FIS was able to predict the depression risk severity class labels for 'Near absent' and 'Mild' cases with 100% accuracies, and 'Moderate', 'Severe' and 'Very Severe' cases with 84%, 92% and 94% accuracies respectively. While assessing the performance of the system, it is evident that the FIS can accurately predict near absent and mild depression with 100% certainty. The FIS has an accuracy of 94%. The correlation value between the FIS model and standard depression severity scale was 0.746, which signifies that it can be used to evaluate the severity of depression as well as to track the course of the illness. The FIS model successfully predicted 125 cases with a high correlation coefficient (r = 0.88, P value <0.001) observed between actual and predicted cases. When compared with studies in relevant literature that were conducted using different methods, it is seen that the FIS can be used as a supplemental tool that may effectively support the physician's decision-making process.

Conclusion

Depression is becoming a global health problem. The need to design intelligent systems that would support physicians in tele-medical diagnosis of the disease cannot be overemphasized. In this paper, the authors presented an FIS model for medical diagnosis in the area of psychology and psychiatry. The system accurately predicts depression risk severity levels based on expert knowledge embedded as fuzzy rules and supplied patients' physiological and psychological parameters. The study clearly highlights FL as a sensitive and specific tool that has the potential of supporting medical diagnosis and disease management. Finally, the fuzzy system approach can be extended to provide intelligent tools for evaluating quantitatively and predicting the severity levels of patient encounters in other medical specialties such as cardiology, neurology and epidemiology.

ACKNOWLEDGEMENT

Authors gratefully acknowledge the psychiatrist and psychologist colleagues who had helped in collecting and validating the depression data.

REFERENCES

About Depression (2011). Depression Highlights: Screening for depression, Available online at: http://.adam.about.net/report/depression.

Aly S, Vrana I (2006). Toward efficient modeling of fuzzy expert systems: a survey, *AGRIC. ECON.*- CZECH, 52(10):456-460.

American Psychiatric Association (1994). *Diagnostic and Statistical Manual for mental disorders, 4th ed.*, Washington DC.

Ariyanti RD, Kusumadewi S, Paputungan IV (2010). Beck Depression Inventory Test Assessment using fuzzy inference system, In *Proc. of* Int'l Conf. on Intelligent Systems Modeling and Simulation, IEEE Computer Society, pp. 6-9.

Becks AT (1996).Comparison of Beck Depression Inventories – IA and II in Psychiatric Outpatients, J. Personality Assess., 67(3):588-597.

Carney RM, Freedland KE (2007). Depression and heart rate variability in patients with coronary heart disease, Cleve Clin. J. Med. 76(2):513-517.

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

Cohen SD, Lorenzo N, Acquaviva K, Peterson RA, Kimmel PL (2007). Screening, Diagnoses, and Treatment of Depression in Patients with End-Stage Renal Disease. Clin. J. Am. Soc. Nephrol. 2:1332-1334. DOI:10.2215/CJN.03951106.

Ellen AJ, Erin EM, Raymond WM (2002). Depression in primary care: Tools for screening, diagnosis and measuring response to treatment, BMCJ, 44(8):415-419.

Emuoyibofarhe OJ, Taiwo KF (2012). Fuzzy-based system for determining the severity level of knee osteoarthritis, Int. J. Intell. Sys. Appl. 9:46-53.

Godil SS, Shamim MS, Enam SA, Qidwai U (2011). Fuzzy logic: A "simple" solution for complexities in neurosciences, Surg. Neurol. Int. 2:24.

Hamer M, Fraser-Smith N, Lesperance F (2012). Depressive Symptoms and 24-Hour Ambulatory Blood Pressure in Africans: The SABPA Study, Int. Journal of Hypertension, P. 6, DOI:10.1155/2012/426803.

Hamilton M (1967). A rating scale for depression, J. Neurosurg. Psychiatr. 23:56-62.

Hildrum B, Romild U, Holman J (2011). Anxiety and depression lowers blood pressure: 22 year follow up of the population based HUNT study, Norway, BMC Journal of Public Health, 11:601, DOI: 10.1186/1471-2458-11-601.

Innocent PR, John RI, Garibaldi JM (2005). Fuzzy methods for medical diagnosis, J. Appl. Artificial Intelligence, 19:69-98. DOI:10.1080/08839510590887414.

Kessler RC (2002). Epidemiology of depression, [In] LH Gotlib and CL Hamman (Eds) Hand book of depression, NY Guilford Press.

Kim CK, McGorray SP, Bartholomew BA (2005). Depressive symptoms and heart rate variability in post-menopausal women. Archive of Intern. Medicine, 165:1239-1244.

Klinsman MS (2003). The role of algorithms in the detection and treatment of Depression in Primary care, J. Clinical Psychiatry, 64(2):19-24.

Kroenke K, Spitzer RL, Williams JB (2001). The PHQ-9: validity of a brief depression severity measure, J. General Internal Med. 16(9):606-613.

Maja H, Meifania C, Tharam SD (2008). Towards mental health ontology, Proc. of IEEE Int'l Conf. on Bioinformatics and Biomedicine, P. 284. ISBN: 978-7695-3452-7, DOI: 10.1109/BIBM.2008.59

Mila K, Kielan K, Michalak K (2009). A fuzzy semiotic framework for modeling imprecision in the assessment of depression, *IFSA_EUSFLAT2009.* ISBN: 978-989-950-79-6-8, pp. 1717-1722.

Mondimore F (2006). Depression, the mood disease, John Hopkins University Press, 2715 North Charles St. Baltimore, USA, pp. 3-37.

Negnevitsky M (2005). Artificial Intelligence, Pearson Education Ltd., USA.

Nunes LC, Pinheiro PR, Pepqueno TC, Pinheiro MC (2011). Support tool in the diagnosis of major depressive disorder, In *Springer's Advances in Experimental Medicine and Biology*, Arabnia HR and Tran QN (Eds.), 696:573-580, ISBN: 978-1-4419-7046-6.

Olawale OO, Francis AO, Abasiubong F, Adebayo RE (2010). Detection of mental disorders with the Patient Health Questionnaire in primary care settings in Nigeria, J. Mental Illness, 2(1), DOI:10.4081/mi.2010.e10.

Pauliks LB (2013). Depression in Adults with congenital heart disease-public health challenge in a rapidly expanding new patient population, World J. Cardiology, 5(6):186-195. DOI: 10.4330/wjc.v5.i6.186.

Sengupta S (2005). Diagnosis of depression in general practice, *Indian* J. Med. Sci., 59: 217-225. Available online at: http://www.indianjmedsci.org/text.asp?2005/59/5/217/16261.

Sheikh N, Farhadi N, Arahchian M, Kashani K (2004). The relationship of cholesterol and Triglyceride with depression, Acta Medica Iranica, 42(3):185-187.

Sikchi SS, Sikchi S, Ali MS (2013). Fuzzy expert systems for medical diagnosis, Int. J. Comp. Appl. 63(11):7-15.

Spitzer RL, Williams JB, Kroenke K (1994). Utility of a new procedure for diagnosing mental disorders in primary care, The PRIME-MD 1000 study. JAMA, 272:1749-1756.

Vijaya K, Nehemiah HK, Kannan A, Bhuvaneswari NG (2010). Fuzzy Neuro Genetic Approach for Predicting the Risk of Cardiovascular Diseases. Int. J. Data Min. Model. Manage. *2*(4):388-402. Available online at: http://dx.doi.org/10.1504/IJDMMM.2010.035565

World Health Organization (2009). Mental Health: Depression, Available Online at, http://www.who.int/mental_health/-management/depression/definition/en.

World Health Organization (1992). International classification of Mental and Behavioral Disorders - 10th Ed. (ICD-10), Geneva: World Health Organization.

Zadeh LA (1994). Fuzzy logic, neural networks, and soft Computing, Commun. ACM 37:77-84.