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A Fuzzy Interface System to Predict Depression Risk

Archit Aggarwal[1], Tanupriya Choudhury[2*] and Bhupesh Kumar Dewangan[3*]

[1] Amity University, Noida, India
archit.aggarwal1508@gmail.com

[2]Department of Informatics, School of Computer Science, University of Petroleum and Energy Studies, Dehradun, India,
tanupriya1986@gmail.com

[3]Department of Informatics, School of Computer Science, University of Petroleum and Energy Studies, Dehradun, India,
bhupesh.dewangan@gmail.com

***Abstract*: Depression has been classified as a psychological disorder which is capable of affecting patients both mentally and physically with unique presentation across patients. This unique presentation makes it difficult to predict the onset or the risk of onset of the disease. This paper presents the use of a fuzzy logic based interface system, which takes into account four primary predictors and then determines the risk of the onset of depression in three age groups. The approach shows promising results with high accuracy.**

Keywords: Psychological disorder, Fuzzy Logic, Prediction Analysis.

I. Introduction

Depression today is one of the most common psychological disorders. It is a complex condition without any perfect medical definition or diagnosis, although it may be defined as a mental state of the human mind which causes severe symptoms that affect how an individual feels, adversely affects their thought process and hampers with their daily routine and regular activities like sleep, work and eating habits. Depression may be observed as a condition of low mood and apathy to activities that may have consequences on an individual's thoughts, behavior, feelings, and sense of well-being [1]. Several studies have shown depression to be a major global health problem increasingly prevalent in the teen and adult age categories numerically ranging from 16 till 22. This age group is considered to be the beginning of an individual's academic and financial career and are hence having depression at these stages can have extremely negative consequences which may be lifelong. High school students encountered with persistent bullying and other forms of harassment are more likely to report being seriously depressed and consider suicide. People diagnosed with depression are approximately three folds more likely than the remaining population to execute crimes violent in nature according to psychiatric experts [2]. Depression may or may not be a stand-alone disease. It can simultaneously occur with many other severe conditions like diabetes, cancer and heart disease. It is also known to amplify these conditions. Depression can also lead to several other diseases like improper sleep motor activity and chronic pains. One of the most common conditions associated with depression is anxiety. Depression and anxiety are commonly known to coexist.[3] Hence depression is an extremely complicated condition and it is necessary to diagnose it before it causes permanent damage to any part of an individual's life which may or may not be health related.

Depression symptoms are ambiguous in nature and have a tendency to vary for each individual case which is why the overall nature of the disease is ambiguous. The symptoms have a wide spectrum from something as simple as vague sadness to fatal suicidal tendencies [4, 5]. The number of symptoms and their individual presentation is distinct for each case, although some common symptoms are observed in majority of the cases. A symptom may be anything which causes a state of low mood in the individual and hence vary in each case which is majorly due to the difference in the response and handling of the symptom by the individual themselves. The exact cause of depression is a topic of ambiguity and debate. Many believe that the chemical imbalances and reactions in the human mind along with hormonal deficiencies could be the cause [6]. Some conditions such as sleep disorders, stressful environment, frustration, adverse life events and addiction to alcohol and/or drugs are generally accepted causes of depression.

The diagnosis of depression is ambiguous, and much like the symptoms, comprises of vagueness and uncertainty in facts and conclusions. Various methods of both objective and subjective nature are used to arrive at a conclusion. Some of the most commonly used questionnaires such as the Seasonal Pattern Assessment Questionnaire can be used to screen for seasonal affective disorder. Questionnaires like the Beck depression inventory can be used to assess the risk of depression or the severity of depression.[7] The diagnosis of the disease can prove to be tricky even for highly trained and experienced physicians due to the complex nature of the disease [8, 9]. Even with the use of tools like questionnaires and other psychological tests, the conclusive diagnosis is still based on the subjective description of symptoms and the physician's judgement.

Medical science has seen rapid development in the field of technology, diagnostic tools, statistics and mathematics. Along with these advancements, recent growth in Artificial Intelligence and machine learning have boosted the discovery of new approaches while reducing vagueness and ambiguity seen in traditional and subjective methods used for diagnosis.

Mathematical models like fuzzy logic provide an opportunity to arrive at definite conclusions more effectively due to its ability to handle non-linear and varying data. This paper develops a model for diagnosing the risk of depression and reports the analysis for three different age groups namely 16-18, 19-20 and 21-24 based on fuzzy logic while comparing the percentage of people at risk using patient cases from all three age groups. The system is implemented in MATLAB Fuzzy logic toolbox.

II. Background & Related Work

Depression is the result of any combination of environmental, psychological, physiological and socio-economic factors which slowly push an individual towards and endless feeling of sadness or hopelessness. For the purpose of this paper various symptoms were considered but some unique symptoms which presented to be inter-related were decided to be used. These symptoms are observed at early or developmental stages of the condition and hence pose as suitable predictors for the risk of depression. The symptoms are correlated as one symptom could lead to the development or amplification of the rest. The same symptoms are used as predictors for all age groups under consideration. Insomnia was considered to be the first predictor. Fatigue was considered to be the second. Frustration was considered to be the third indicator and Beck's Depression Inventory was considered to be the final indicator. These symptoms can be further explained as –

A. Insomnia

When an individual loses their ability to fall asleep and enter the REM cycle, the condition in known as insomnia. The individual is not able to get enough duration of sleep necessary to function actively and lead a healthy life.

B. Fatigue

The feeling of being tired perpetually. When an individual finds themselves lacking energy, will or motivation to do daily tasks or feeling more tired than usual while performing any such tasks is known as fatigue.

C. Frustration

It may be defined as a point of saturation in an individual's mental condition where a feeling of anger, sadness or denial may take over and the individual loses motivation to perform daily tasks. The individual has a feeling where they feel claustrophobic or suffocated. Reactions to fatigue is often anger which worsens the condition.

D. Beck's Depression Inventory

It is a set of questions used to evaluate the degree of depression or the risk of depression present in an individual. The total number of questions involved in the questionnaire is 21. Each question presents the individual with four options in order to rate the severity of each symptom. The total of the scored based is then added up. The sum total is then compared to ranges which define the level of depression where the lowest score being 0 means no depression and the highest score means severe depression. There are many iterations of the questionnaire available as the questionnaire has been revised over time.

In [10] a fuzzy interface system was suggested which makes use of symptoms like age, BMI (body mass index), Blood pressure and PHQ-9 scores as inputs for the fuzzy system. It has been determined that age is not an appropriate factor to be used for predicting the risk of depression. The body mass index of a person has little relevance to the mental state of an individual and no suitable explanation has been provided for the use of this as input. Blood pressure again is highly subjective to the conditions in which it was measured. Thus the inputs used in the system were not appropriate although the paper has in depth information about fuzzy logic and the system as a whole.

Chatopadhyay [11], fuzzy logic with the combination of neural networks is used to propose a system for the diagnosis of depression. The paper takes into account 14 symptoms and thousands of rules which are used to train a neural net which determines if a person has depression or not. The number of test cases used could have been larger. The paper takes into account a very wide spectrum of symptoms. The paper also presents great depth into the background of data finding techniques, fuzzy logic and neural nets. The paper proposes a unique solution with great results. The main difference between this manuscript is that we are trying to predict depression while the paper tries to diagnose it.

In [12] a system is proposed to automate the diagnosis of depression and it uses the concept of neuro-fuzzy which is a hybrid of fuzzy logic and neural networks. Fuzzy logic has been integrated within the five layers of the system. The paper uses real time depression data for training the system. Back propagation has been used to make the system more accurate. The system presents with good results and an add on tool for diagnosis of depression but not the prediction of it.

In [13] the proposed system uses fuzzy logic to handle non-crisp value symptoms. The paper provides great a mathematical analysis for neural networks and fuzzy logic. There are 25 symptoms used in combinations of five groups. Although a very strong system is proposed, implementation and results are not depicted in that particular manuscript. The paper focuses on the mathematical background of the system and does not provide any results or model simulations.

Fuzzy Logic

In theory assumptions exist to simplify things in order to arrive at a conclusion. In general, the world is infinitely complex in nature, and the source of the complexity is entropy or uncertainty. Thus it is required to use certain methodologies to solve these problems with all their complexity to arrive at an accurate solution. Fuzzy logic is a multi-valued logic to deal with reasoning that is approximate rather than precise [14]. It has the ability to combine human heuristics into machine assisted decision-making processes, which are applicable to individual patients as it takes into consideration all the unique factors and complexities of each unique individual [15].

The approach of fuzzy set theory has been used as follows - A fuzzy set 'a' in the universal set 'A' of depression predictors denoted by 'x' is given by Equation (1).

$$a = \{ (x , \mu(x)) \mid x \in A , \mu(x) \in [0,1] \} \quad \text{......... (1)}$$

Where μ(x) represents the membership functions of 'x' in 'a' and μ is the degree of membership of 'x' in 'a' in the interval

[0,1]. Triangular membership functions have shown computational efficiency in analyzing human reasoning and hence have seen extensive use in the field of medical science. For the purposes of this paper triangular function in Equation (2) has been used. Equation (2) expresses the triangular membership function in its general form.

$$\mu(x) = \begin{cases} 0, x \leq a \\ \frac{x-a}{m-a}, a < x \leq m \\ \frac{b-x}{b-m}, m < x < b \\ 0, x \leq b \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where ‘a’, ‘b’, ‘m’ are the parameter of the membership function. On the basis of the calculated membership function, each of the indicators is categorized as absent, low, moderate, high, severe as shown by Equation(3). Equation (2) and Equation (3) are an expression of the fuzzy logic system in the form of an equation. The actual values mentioned in the functions are derived using existing methodologies best suited for the problem at hand [16, 17]. The values obtained belonging to the range of zero to one which are used to determine the risk of depression are shown in Equation (3). Once the calculated value for each symptom is obtained, it is used as an input for the fuzzy system. The output value falls in at least one category of Equation (3) which is the resultant risk we want to calculate.

$$\mu(x) = \begin{cases} absent, x < 0.100 \\ low, 0.11 \leq x < 0.325 \\ moderate, 0.325 \leq x < 0.550 \\ high, 0.550 \leq x < 0.775 \\ severe, 0.775 \leq x \leq 1.000 \end{cases} \ldots\ldots\ldots\ldots (3)$$

Current methodologies rely on the analysis of the physician accompanied by one or more of the proposed predictors. This paper aims to use a unique combination of these predictors which hope to inculcate some of the drawbacks seen in usual approaches by covering a wide range of symptoms which provide a complete overview of the mental and physical attributes of the individual under consideration, thus providing a supplementary tool to professionals help predict the risk of depression at an early stage and provide better treatment.

III. Methodology & Implementation

The proposed research is based on six module as discussed:

A. The Fuzzy System

The fuzzy system comprises of six components namely User-Interface interactions, the fuzzy inputs and fuzzification, knowledge base, interface engine, deffuzification and depression risk as represented by Figure(1). The fuzzy system can be visualized in the form of these components. These components are a step by step explanation for the entire process of using fuzzy login to compute the solution of a problem. The system presents with highly dynamic nature. It can be used as seen fit by the individual creating the system. In this paper we present our particular implementation. Each of the components has been elaborated on individually to explain their purpose and implementation for the problem at hand.

B. User-Interface Interactions

The general process for the determination of the mental health of an individual involves verbal description and some physical tests to arrive at a conclusion. This method often sees the use of various questionnaires and data finding techniques to arrive at a numerical value for the gravity of the symptoms to get a better understanding of the case in the form of useful mathematical data which can be used further to monitor changes in the condition. Input values for each of the symptoms was required by the fuzzy system. It is proposed that one compiled questionnaire with the most relevant questions from all the individual questionnaires be used for scoring and input to the fuzzy system. The questionnaires were scored individually and the scores were determined for all four predictors, which are to be used as inputs for the fuzzy system. For the purposes of this study, synthesized data has been used.

C. Fuzzification

In general, we use methodologies like tests and questionnaires to arrive at a result in the form of a numerical integer which is compared to another predefined integer. Fuzzification refers to the process of converting these definite values into fuzzy values in order to further classify the results and enable their use as fuzzy values. The trapezoidal membership functions have been used as input and triangular membership function for the output.

The first predictor (Insomnia) was determined by the Insomnia severity index [18]. The score was ranged from 8-28. The output was divided into three variables after fuzzification namely ‘low’, ‘moderate’ and ‘severe’.

The second predictor (Fatigue) was assessed by the Multidimensional Fatigue Inventory [19]. A questionnaire with a score ranging from 4 - 20 was used. The output was fuzzified into three variables ‘low’,’moderate’ and ’severe’.

The third predictor (Frustration) was assessed by the Frustration Discomfort Scale. A questionnaire with a score ranging from 1 - 5. The output score was fuzzified into three variables ‘Not-frustrated’, ‘mildly frustrated’ and ‘highly frustrated’.

The fourth predictor used was the score of the Beck’s Depression Inventory [20]. The score ranged from 0 - 40 and was fuzzified [21] into four membership functions namely ‘low’, ’borderline’, ‘moderate’ and ’severe’.

After the User Interactions have been completed and the relevant crisp data has been obtained, fuzzification [22, 23] of the data is performed. This data is then stored in the knowledge base described in the next section.

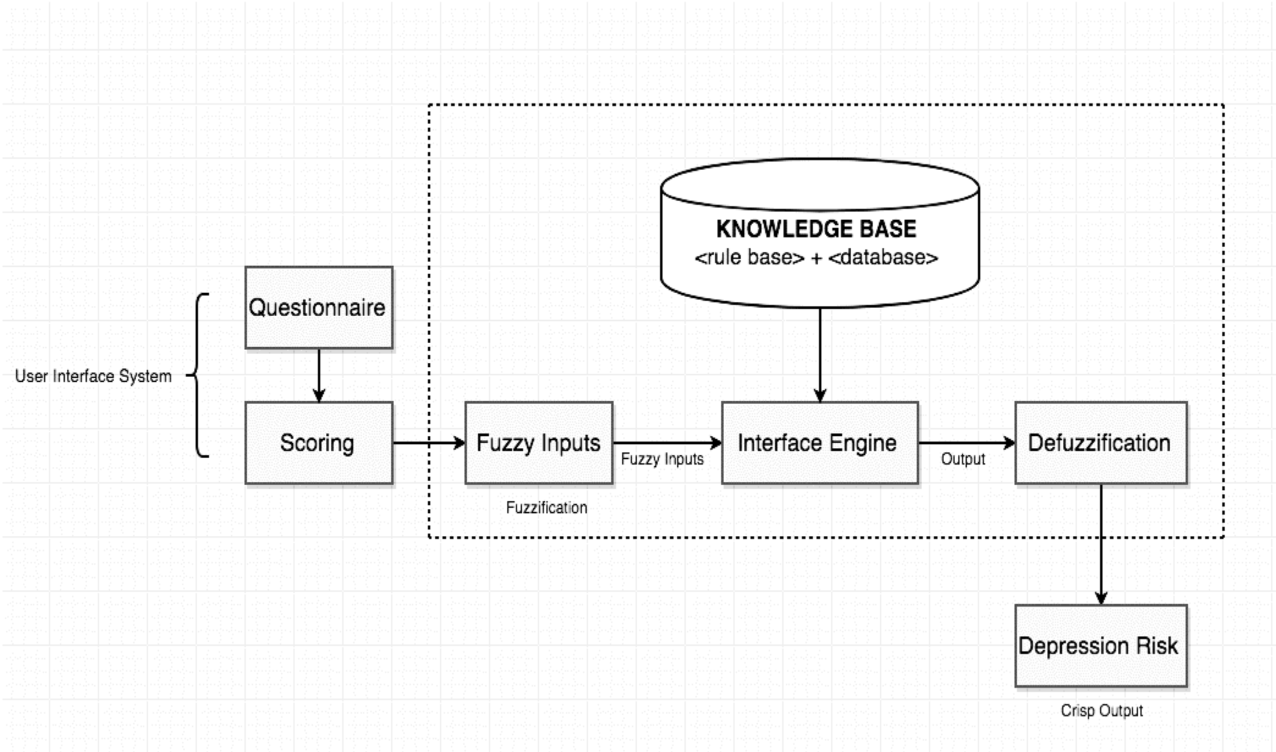

Figure 1. User interface interactions

D. Knowledge Base

The knowledge base is a structure or system where the data and facts are collected and stored for use by the interface engine. It is made up of two elements that are the rule base and the database. The database is responsible for supplying the elements for defining rules which are the IF - THEN constructs. The relevant data required to match these rules is also provided by the database. The rule base comprises of all the IF –ELSE - THEN rules which determine the desired output. The knowledge base here stores the dataset of the inputs and the 108 rules of the fuzzy system. The knowledge base is responsible for communication with the Interface Engine

For the purposes of this study a dataset has been synthesized using randomized values for a total of 420 cases based on the proposed parameters. This dataset has been used for the testing and evaluation of the model.

E. Interface Engine

The interface engine is the part of the system where all the processing and calculations take place. It is the central part of the entire system. The data from the knowledge base is fed to the interface engine for computation. The interface engine is the bit where all the previous elements of the fuzzy system come together to generate a result. The interface engine is the part which simulates the decision making ability of humans. Each individual patient data is compared with each rule and when all conditions inside a particular IF-EACH-THEN construct is met then the 'THEN' bit is executed. Each 'if' condition is for one symptom representing the severity level of that particular symptom, for example – If (Insomnia is low) and (Fatigue is low) and (Frustration is low) and (input4 is low) then (DepR is absent). A unique combination of all the different levels of each symptom are present as rules. The 'THEN' bit contains the output data which in this case is the depression risk level which belongs to the fuzzy output set as per Equation (3).

F. Defuzzification

Deffuzification is the process of obtaining a crisp (quantifiable) result from fuzzy sets and rules as input. The output of the computation of a fuzzy set needs to be converted to a crisp value in order to obtain the final output in the real life domain. The final defuzzified output will be the depression risk. The method used for deffuzification is the centroid method which outputs center of area under the curve. The method is represented by Equation(4). Where 'z' is the level of depression risk.

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

The process of the interface engine and the deffuzification produce the final output.

G. Depression Risk (output)

The system may be summarized as follows-

1. After the predictors have been selected, their membership values are obtained. Once the membership functions have been determined a standard rule base is developed. Four predictors(P) with three having membership functions (M) and one having four membership functions were used. Hence, a rule base of 108 rules from P^M (4^1x 3^3) combinations was created.

2. Raw data was obtained and then converted into fuzzy data.
3. This fuzzy data was then fed to the fuzzy system as input.

4. A fuzzy output is generated which is then converted into a crisp value. The final output is the risk classification of the system.

The depression risk is the only output variable. A multi-input single output system is obtained.

S.No	Rule
1	If Insomnia is low& Fatigue is low& Frustration is low& input4 is low then (DepR is absent
2	If Insomnia is low & Fatigue is low & Frustration is low& input4 is borderline then DepR is low
3	If Insomnia is low &Fatigue is low&Frustration is low&input4 is moderate then DepR is low
4	If Insomnia is low&Fatigue is low&Frustration is moderate&input4 is low then DepR is low
5	If Insomnia is low&Fatigue is low&Frustration is moderate&input4 is borderline then DepR is low
6	If Insomnia is low&Fatigue is low&Frustration is moderate&input4 is moderate then DepR is moderate
7	If Insomnia is low&Fatigue is low&Frustration is severe&input4 is low then DepR is low
8	If Insomnia is low&Fatigue is low&Frustration is severe&input4 is borderline then DepR is moderate
9	If Insomnia is low&Fatigue is low&Frustration is severe&input4 is moderate then DepR is high
10	If Insomnia is low&Fatigue is moderate&Frustration is low&input4 is low then DepR is moderate
11	If Insomnia is low&Fatigue is moderate&Frustration is low&input4 is borderline then DepR is moderate
12	If Insomnia is low&Fatigue is moderate&Frustration is low&input4 is moderate then DepR is moderate
13	If Insomnia is low&Fatigue is moderate&Frustration is moderate&input4 is low then DepR is low
14	If Insomnia is low&Fatigue is moderate&Frustration is moderate&input4 is borderline then DepR is moderate
15	If Insomnia is low&Fatigue is moderate&Frustration is moderate&input4 is moderate then DepR is moderate
16	If Insomnia is low&Fatigue is moderate&Frustration is severe&input4 is low then DepR is low
17	If Insomnia is low&Fatigue is moderate&Frustration is severe&input4 is borderline then DepR is moderate
18	If Insomnia is low&Fatigue is moderate&Frustration is severe&input4 is moderate then DepR is high
19	If Insomnia is low&Fatigue is severe&Frustration is low&input4 is low then DepR is low
20	If Insomnia is low&Fatigue is severe&Frustration is low&input4 is borderline then DepR is low
21	If Insomnia is low&Fatigue is severe&Frustration is low&input4 is moderate then DepR is moderate
22	If Insomnia is low&Fatigue is severe&Frustration is moderate&input4 is low then DepR is low
23	If Insomnia is low&Fatigue is severe&Frustration is moderate&input4 is borderline then DepR is moderate
24	If Insomnia is low&Fatigue is severe&Frustration is moderate&input4 is moderate then DepR is high
25	If Insomnia is low&Fatigue is severe&Frustration is severe&input4 is low then DepR is moderate
26	If Insomnia is low&Fatigue is severe&Frustration is severe&input4 is borderline then DepR is high
27	If Insomnia is low&Fatigue is severe&Frustration is severe&input4 is moderate then DepR is high
28	If Insomnia is moderate&Fatigue is low&Frustration is low&input4 is low then DepR is low
29	If Insomnia is moderate&Fatigue is low&Frustration is low&input4 is borderline then DepR is moderate
30	If Insomnia is moderate&Fatigue is low&Frustration is low&input4 is moderate then DepR is moderate
31	If Insomnia is moderate&Fatigue is low&Frustration is moderate&input4 is low then DepR is low
32	If Insomnia is moderate&Fatigue is low&Frustration is moderate&input4 is borderline then DepR is low
33	If Insomnia is moderate&Fatigue is low&Frustration is moderate&input4 is moderate then DepR is moderate
34	If Insomnia is moderate&Fatigue is low&Frustration is severe&input4 is low then DepR is low
35	If Insomnia is moderate&Fatigue is low&Frustration is severe&input4 is borderline then DepR is moderate
36	If Insomnia is moderate&Fatigue is low&Frustration is severe&input4 is moderate then DepR is moderate
37	If Insomnia is moderate&Fatigue is moderate&Frustration is low&input4 is low then DepR is low
38	If Insomnia is moderate&Fatigue is moderate&Frustration is low&input4 is borderline then DepR is low
39	If Insomnia is moderate&Fatigue is moderate&Frustration is low&input4 is moderate then DepR is moderate
40	If Insomnia is moderate&Fatigue is moderate&Frustration is moderate&input4 is low then DepR is low
41	If Insomnia is moderate&Fatigue is moderate&Frustration is moderate&input4 is borderline then DepR is moderate
42	If Insomnia is moderate&Fatigue is moderate&Frustration is moderate&input4 is moderate then DepR is high

43 If Insomnia is moderate&Fatigue is moderate&Frustration is severe&input4 is low then DepR is moderate

44 If Insomnia is moderate&Fatigue is moderate&Frustration is severe&input4 is borderline then DepR is moderate

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47 If Insomnia is moderate&Fatigue is severe&Frustration is low&input4 is borderline then DepR is moderate

48 If Insomnia is moderate&Fatigue is severe&Frustration is low&input4 is moderate then DepR is moderate

49 If Insomnia is moderate&Fatigue is severe&Frustration is moderate&input4 is low then DepR is low

50 If Insomnia is moderate&Fatigue is severe&Frustration is moderate&input4 is borderline then DepR is low

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55 If Insomnia is severe&Fatigue is low&Frustration is low&input4 is low then DepR is low

56 If Insomnia is severe&Fatigue is low&Frustration is low&input4 is borderline then DepR is moderate

57 If Insomnia is severe&Fatigue is low&Frustration is low&input4 is moderate then DepR is moderate

58 If Insomnia is severe&Fatigue is low&Frustration is moderate&input4 is low then DepR is moderate

59 If Insomnia is severe&Fatigue is low&Frustration is moderate&input4 is borderline then DepR is high

60 If Insomnia is severe&Fatigue is low&Frustration is moderate&input4 is moderate then DepR is high

61 If Insomnia is severe&Fatigue is low&Frustration is severe&input4 is low then DepR is moderate

62 If Insomnia is severe&Fatigue is low&Frustration is severe&input4 is borderline then DepR is moderate

63 If Insomnia is severe&Fatigue is low&Frustration is severe&input4 is moderate then DepR is high

64 If Insomnia is severe&Fatigue is moderate&Frustration is low&input4 is low then DepR is moderate

65 If Insomnia is severe&Fatigue is moderate&Frustration is low&input4 is borderline then DepR is high

66 If Insomnia is severe&Fatigue is moderate&Frustration is low&input4 is moderate then DepR is severe

67 If Insomnia is severe&Fatigue is moderate&Frustration is moderate&input4 is low then DepR is moderate

68 If Insomnia is severe&Fatigue is moderate&Frustration is moderate&input4 is borderline then DepR is high

69 If Insomnia is severe&Fatigue is moderate&Frustration is moderate&input4 is moderate then DepR is high

70 If Insomnia is severe&Fatigue is moderate&Frustration is severe&input4 is low then DepR is moderate

71 If Insomnia is severe&Fatigue is moderate&Frustration is severe&input4 is borderline then DepR is high

72 If Insomnia is severe&Fatigue is moderate&Frustration is severe&input4 is moderate then DepR is severe

73 If Insomnia is severe&Fatigue is severe&Frustration is low&input4 is low then DepR is moderate

74 If Insomnia is severe&Fatigue is severe&Frustration is low&input4 is borderline then DepR is high

75 If Insomnia is severe&Fatigue is severe&Frustration is low&input4 is moderate then DepR is severe

76 If Insomnia is severe&Fatigue is severe&Frustration is moderate&input4 is low then DepR is moderate

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80 If Insomnia is severe&Fatigue is severe&Frustration is severe&input4 is borderline then DepR is high

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82 If Insomnia is low&Fatigue is low&Frustration is low&input4 is severe then DepR is high

83 If Insomnia is moderate&Fatigue is low&Frustration is low&input4 is severe then DepR is severe

84 If Insomnia is severe&Fatigue is low&Frustration is low&input4 is severe then DepR is severe

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88	If Insomnia is low&Fatigue is severe&Frustration is low&input4 is severe then DepR is severe
89	If Insomnia is moderate&Fatigue is severe&Frustration is low&input4 is severe then DepR is severe
90	If Insomnia is severe&Fatigue is severe&Frustration is low&input4 is severe then DepR is severe
91	If Insomnia is low&Fatigue is low&Frustration is moderate&input4 is severe then DepR is high
92	If Insomnia is moderate&Fatigue is low&Frustration is moderate&input4 is severe then DepR is high
93	If Insomnia is severe&Fatigue is low&Frustration is moderate&input4 is severe then DepR is severe
94	If Insomnia is low&Fatigue is moderate&Frustration is moderate&input4 is severe then DepR is high
95	If Insomnia is moderate&Fatigue is moderate&Frustration is moderate&input4 is severe then DepR is high
96	If Insomnia is severe&Fatigue is moderate&Frustration is moderate&input4 is severe then DepR is severe
97	If Insomnia is low&Fatigue is severe&Frustration is moderate&input4 is severe then DepR is severe
98	If Insomnia is moderate&Fatigue is severe&Frustration is moderate&input4 is severe then DepR is severe
99	If Insomnia is severe&Fatigue is severe&Frustration is moderate&input4 is severe then DepR is severe
100	If Insomnia is low&Fatigue is low&Frustration is severe&input4 is severe then DepR is severe
101	If Insomnia is moderate&Fatigue is low&Frustration is severe&input4 is severe then DepR is severe
102	If Insomnia is severe&Fatigue is low&Frustration is severe&input4 is severe then DepR is severe
103	If Insomnia is low&Fatigue is moderate&Frustration is severe&input4 is severe then DepR is severe
104	If Insomnia is moderate&Fatigue is moderate&Frustration is severe&input4 is severe then DepR is severe
105	If Insomnia is severe&Fatigue is moderate&Frustration is severe&input4 is severe then DepR is severe
106	If Insomnia is low&Fatigue is severe&Frustration is severe&input4 is severe then DepR is severe
107	If Insomnia is moderate&Fatigue is severe&Frustration is severe&input4 is severe then DepR is severe
108	If Insomnia is severe&Fatigue is severe&Frustration is severe&input4 is severe then DepR is severe

Table 1. Fuzzy rule base with 108 rules

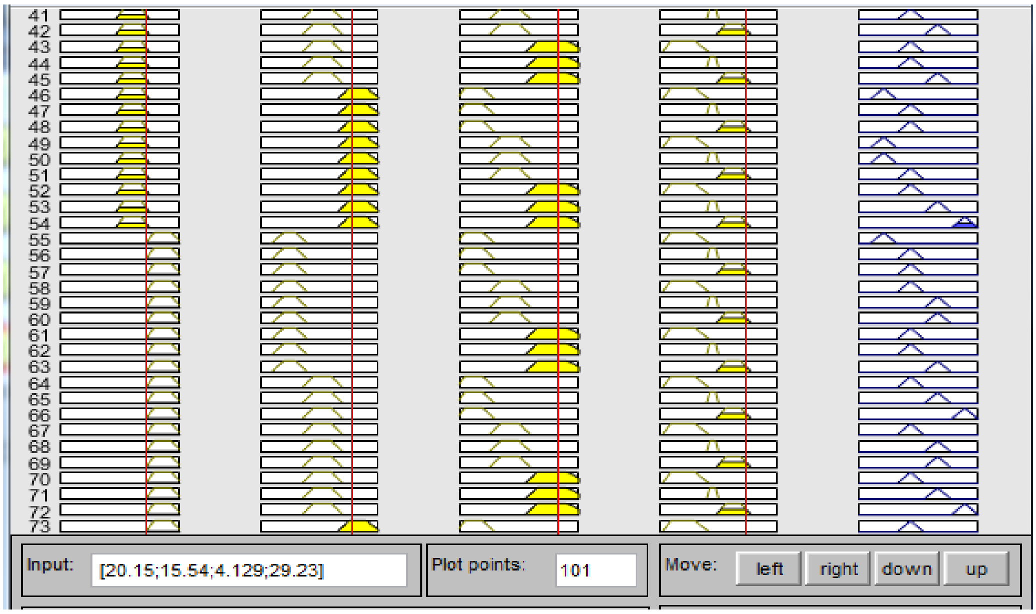

Figure 2. Model Simulation

IV. Results & Analysis

The system produces varying output with different inputs according to the rule base.

The simulations were carried out in MATLAB in the Windows 7 operating system. The output is determined with the help an expert's opinion. A selection of 10 rules has been shown in Table 1. The rules have the same weight age, thus the order is irrelevant. The fuzzy toolbox rule simulation is shown in Figure 2 depicts a depression risk of 0.887 representing a severe depression risk.

In the model simulation represented by Figure 2, we see that the system was presented with the data with the following levels in each symptom as per the questionnaire scores –

A. Insomnia – 20.15

B. *Fatigue – 15.54*
C. *Frustration – 4.129*
D. *Becks Depression Inventory – 29.93*

The system outputs a value of 0.887 which falls under the severe risk of depression category as per our classifications. The result matches with the real time evaluation of the depression risk. Any individual with these symptom values, has a severe risk of being depressed. The result of each case was evaluated by the system and manually with expert help in order to measure the accuracy of the system.

The combination of the three predictors were plotted against the output risk to study the relation between the predictors. The graphs obtained for the combination of various predictors were found to have a degree of similarity, thereby suggesting a relation between the symptoms and how one symptom can lead to the development or amplification of the other symptoms.

These graphs were generated by the MATLAB fuzzy system based on the values of each predictor submitted. The plot between frustration, fatigue and depression risk is shown in Figure 3.

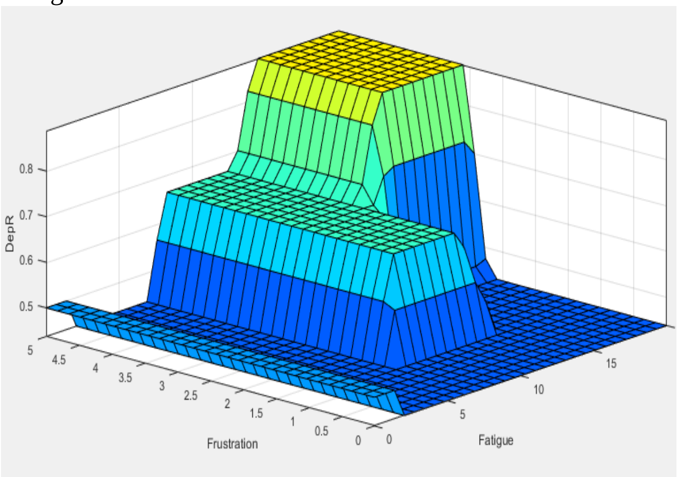

Figure 3. Frustration, fatigue and depression risk

The plot between insomnia, frustration and depression risk is shown in Figure 4.

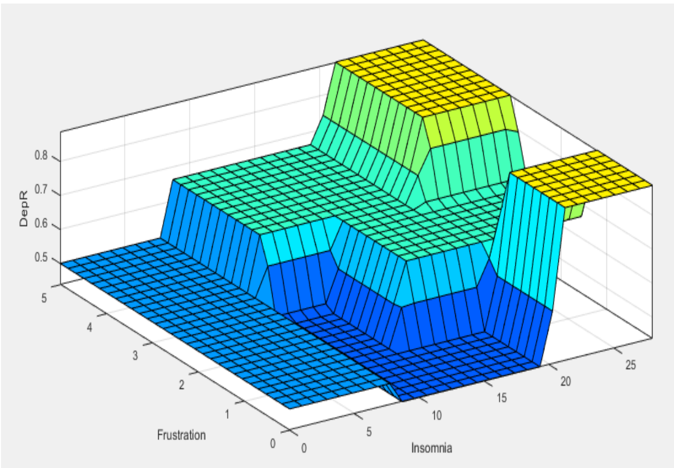

Figure 4. Insomnia, frustration and depression risk

The plot between insomnia, fatigue and depression risk is shown in Figure 5.

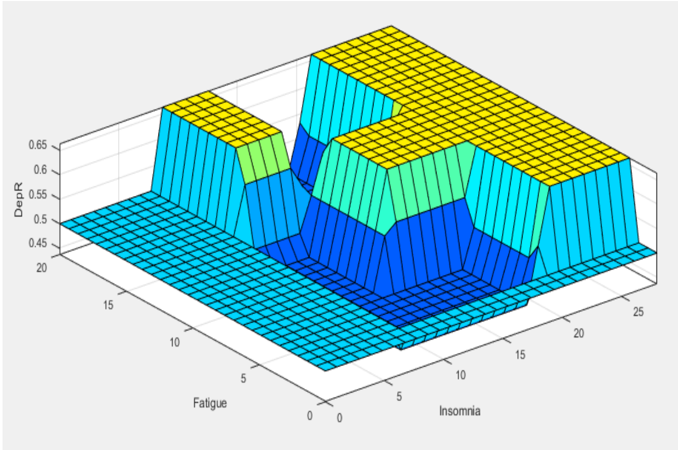

Figure 5. Insomnia, fatigue and depression risk

The plot between frustration, BDI and depression risk is shown in Figure 6.

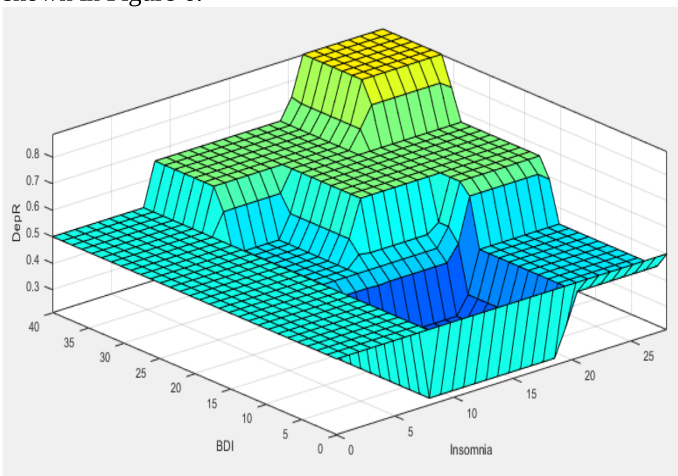

Figure 6. Frustration, BDI and depression risk

The plot between insomnia, BDI and depression risk is shown in Figure 7.

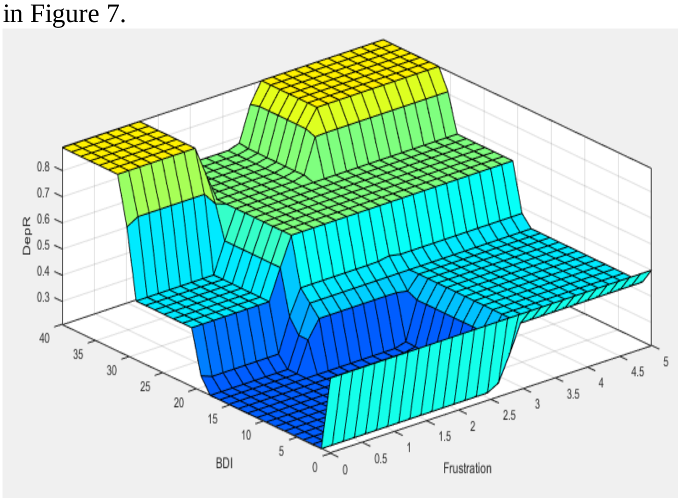

Figure 7. Insomnia, BDI and depression risk

The plot between BDI, fatigue and depression risk is shown in Figure 8. The plots may be used as a visual representation of the correlation between predictors, utilized two at a time and then help us evaluate the relation between their existences together and how relevant values affect the overall risk of depression.

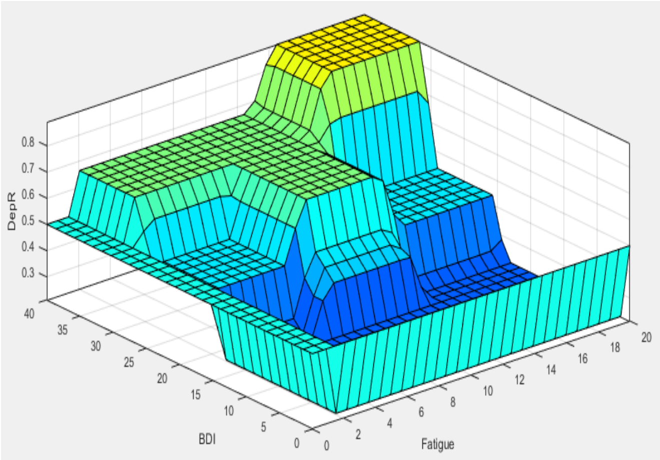

Figure 8. BDI, fatigue and depression risk

For instance, the plot in figure 3 shows the fatigue input value may be low but the risk of depression is still in the middle region because of the high frustration value. This shows depression risk may be more persistent with higher values of frustration rather than fatigue on their own, also when the two are increased or decreased slightly, there is a large impact on the overall risk factor. This also helps us arrive at a conclusion for aiding those affected. Lowering just one value may result in greatly reducing the depression risk. These plots assist in the evaluation of these inputs based on their presentation with other predictors and allow targeted treatment to help reduce the risk of depression. Consider figure 5,when the value of frustration is 3 insomnia is 10, the graph seems to start peeking suddenly. If we target frustration, which is at a lower and more treatable level, the risk goes down drastically. Plots between different combinations of different predictors shows the consequence of one predictor on the other. For instance, Insomnia causes increase in fatigue thereby increasing the risk of depression. In adults, constant frustration in any domain of life results in fatigue thereby generating a feeling of helplessness and failure which drastically increases the individual's risk of depression. These links between various predictors can be assessed using the plots. It is noticed in all plots that high levels of one symptom correspond to both high and low levels of the other, thereby suggesting that one symptom can cause the others or amplify them or they may be completely unrelated. This thus depicts the complex nature of the symptoms. The ability of the system to combine the effect of all the factors is unique and provides a new dimension to the analysis of the diagnosis of subjective diseases. The fuzzy system was able to predict the 'absent' cases with 100% accuracy and 'low', 'moderate', 'high' and 'severe' cases with 96%, 87%, 91% and 93% accuracy respectively. The accuracy results have been combined for all three age groups. The high levels of accuracy prove that the tool may be used to confirm the risk of depression. The tool hence the potential to explore further symptoms and traits tailored to each individual case hence enabling diagnosticians to deal with increasing complexity pertaining to each case.

The percentage of people at depression risk from moderate to severe in the first age group were 9%. This is the age group ranging from 16 to 18.

Similarly, the people at depression risk from moderate to severe for the second (19-20) and the third (21-24) age group were 13% and 11% respectively. All the calculations have been performed on the self-synthesized dataset as the system is unique. Any other standard dataset cannot be used for calculation since the particular values required are unique for each patient and need to be obtained uniquely.

V. Conclusion

Depression has become a global health problem. The risk of depression among young ages is rising at a worrying rate. The symptoms have gained complexity over time and the combination of various systems has made it more difficult to arrive at a conclusive diagnosis. In this paper, a fuzzy system for the prediction of depression risk based on suitable predictors was presented. The system accurately predicts depression risk for different age groups based on expert knowledge instilled in the fuzzy system. The fuzzy system can be extended further with more symptoms and other various complexities, making the prediction of depression more concrete and easier in order to implement preventive measures. The number of people at the risk of depression has seen an increase in the results of this paper in comparison to recent studies thereby depicting the constantly degrading minds of people at all age groups. These age groups represent early adult life and main academic and professional ladders. Increasing number of people are seen to be at a depression risk at early stages promoting irreparable damage to their lives in all domains. Depression in these stages can have long term consequences on the individual and those around them. The system proposed also shows great scope for customizations in order to cater to different symptoms. This will enable a much better capacity for handling complexity in cases therefore resulting in quicker and accurate diagnosis of a subjective disease. Diagnosis at early stages may result in complete prevention. Hence we may conclude that there is a requirement for mathematical and computational systems to help prevent and diagnose serious diseases like depression. Fuzzy logic has proven to be a successful candidate to promote better systems as seen in this manuscript.

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Authors Biography

Archit Aggarwal is a Student at Amity University Uttar Pradesh. He has worked as a part of more than 10 research projects. He has also completed training in business and entrepreneurship from the National University of Singapore in 2018 as part of the NUS Enterprise Summer Programme. He has worked with multiple companies including MereEdu Services LTD, Nation IT Association and the Indian Engineering Teachers Association in the field of Web Development and Machine Learning. He is also a Amazon Web Services certified Cloud Computing Practitioner. His areas of interests include Machine Learning, Image Processing, and Cloud computing and psychological disorders. He has been associated with many conferences in India and abroad with more than 10 publications overall publishes across various journals and conferences

Dr. Tanupriya Choudhury received his bachelor’s degree in CSE from West Bengal University of Technology, Kolkata, India, and master’s Degree in CSE from Dr. M.G.R University, Chennai, India.He has received his PhD degree in the year 2016. He has Ten years experience in teaching as well as in Research. Currently he is working as an Associate Professor in dept. of CSE at UPES Dehradun. Recently he has received Global Outreach Education Award for Excellence in best Young researcher Award in GOECA 2018 His areas of interests include Human computing,Soft computing,Cloud computing,Data Mining etc.He has filed 14 patents till date and received 16 copyrights from MHRD for his own softwares.He has been associated with many conferences in India and abroad.He has authored more than 85 research papers till date.He has delivered invited talk and guest lecture in Jamia Millia Islamia University , Maharaja Agersen college of Delhi University , Duy Tan University Vietnam etc. He has been associated with many conferences throughout India as TPC member and session chair etc. He is a lifetime member of IETA, member of IEEE, and member of IET(UK) and other renowned technical societies. He is associated with Corporate and he is Technical Adviser of DeetyaSoft Pvt. Ltd. Noida , IVRGURU ,and Mydigital360 etc.He is holding the post of Secretary in IETA (Indian Engineering Teacher’s Association-India), He is also holding the Advisor Position in INDO-UK Confederation of Science, Technology and Research Ltd.,London, UK and International Association of Professional and Fellow Engineers-Delaware-USA.

Prof. Bhupesh Kumar Dewangan pursued Bachelor of Technology form Pt Ravi Shankar Shukla University (STATE UNIVERSITY), Raipur and Master of Technology from Chhattisgarh Swami Vivekananda Technical University (STATE TECHNICAL UNIVERSITY), Bhilai in computer science and engineering. Currently he is pursuing PhD in computer science and engineering and Assistant Professor, Department of Informatics, at University of Petroleum and Energy Studies. He has more than 40 research publications in various international journals and conferences with SCI/SCOPUS/UGC indexing. His research interests in Autonomic Cloud Computing, Resource Scheduling, Software Engineering, and Testing. He is a member of various organizations like ISTE, IAPFE, etc.