MEDDOCS Open Access Publisher

Depression and Anxiety: Open Access

Open Access | Research Article

A Multi-Layer Fuzzy Inference System for the Prediction of Depression and Anxiety Levels

Momina Imran; Mouz Ramzan*

Department of Computer Science University National College of Businees Administration and Economics House No 995, Street 12, Badami Bagh, Lahore.

***Corresponding Author(s): Mouz Ramzan**

Department of Computer Science University National College of Businees Administration and Economics House No 995, Street 12, Badami Bagh, Lahore.

Email: mouzramzan@gmail.com

Received: Nov 22, 2023

Accepted: Dec 18, 2023

Published Online: Dec 25, 2023

Journal: Depression and Anxiety: Open Access

Publisher: MedDocs Publishers LLC

Online edition: http://meddocsonline.org/

Copyright: © Ramzan M (2023). *This Article is distributed under the terms of Creative Commons Attribution 4.0 International License*

Keywords: Multi-Layer fuzzy system; Psychological disorders; Anxiety; Depression; Fuzzy inference system; Anxiety and depression prediction.

Abstract

Talking about the most important thing in human life, it is the person's health. The healthier a person, the most efficiently he will work and think. And if we talk about the most important human organ, it is the brain. The health of the brain can be affected by many reasons. Sometimes the reasons may have a small effect on the person's health and sometimes they can cause a major disease or disorder. Major disorders such as Anxiety and Depression can lead to chronic diseases if left untreated. It is the carelessness that makes it even riskier. Most of the time, patients ignore the signs and symptoms that lead to the disease getting worse. The symptoms of anxiety and depression are related to one another, as are their connections. As we know that the use of technology is growing in the medical field and we are using technology to predict diseases and we are also using technology for finding the cure. So, we came up with a method that can tell whether a patient is depressed or anxious. Our suggested approach uses a multilayer fuzzy inference algorithm to determine the disease from the input symptoms. In addition, different places and individuals will experience different symptoms. For this reason, we have concentrated on the Asian Continent to best anticipate anxiety. We specifically selected symptoms that are prevalent in people from the Asian continent. To forecast both illnesses simultaneously and provide the most accurate findings, a multilayer fuzzy inference system is being built. Our system achieved accuracy of 87%.

Introduction

Anxiety, depression, extraversion, and motivation are only a few of the psychological factors that influence human behavior. Human behavior can also conduct in unique patterns, such as psychological thoughts and emotions that define each person's response to the circumstance of his life. Being extroverted is what it means to be lively, chatty, and filled of optimism and require outside stimuli [1]. Today, one of the most prevalent psychiatric diseases is anxiety and depression. It is a complex condition without an exact medical definition or diagnosis, but it can be described as a mental state of the human mind that produces severe symptoms that negatively impact how an individual feel, their ability to think clearly, and their ability to go about their daily lives as usual activities like sleeping, working, and eating. Low mood and apathy toward activities that could affect a person's thoughts, behavior, feelings, and sense of wellness are symptoms of depression and having panic attacks, increased heartbeat, sweating and nervousness are the symptoms of anxiety [2]. The World Health Organization (WHO) estimates that 30 percent of the world's population has detectable depression and anxiety. Of course, this is just the tip of

Cite this article: Ramzan M, Imran M. A Multi-layer Fuzzy Inference System for the Prediction of Depression and Anxiety Levels. Depress Anxiety Open Access. 2023; 2(2): 1011.

the iceberg, and the actual number may be far higher than this [3]. Due to the processing of higher dimensional, unprocessed, and evaluative clinical data, medical decision making as a whole is a complicated procedure. A clinical choice must be a coordinated effort of their high-level observations and intuitions about the disease process. The accuracy of the diagnosis is based on how frequently the symptoms match those of the reference disorders (also known as "classical cases") both manual diagnosis and the way an illness presents itself are frequently unique. As a result, in clinical medicine, the appropriateness of the term "classical"changes. Due to their operational similarity, higher data mining techniques and computational intelligence concepts have enormous research potential in simulating the clinical diagnosis process. Additionally, it presents a chance for interdisciplinary study [4]. The diagnosis of psychological disorders (depression and anxiety) is a highly difficult and tough undertaking. Consequently, one must take care to accurately diagnose them. The history of the patient can be examined to diagnose the issue and machine learning and data mining techniques can be used to mimic human thought processes or come to logical conclusions. Utilizing concepts from pattern recognition, probability, and other domains, some techniques can even operate with ambiguous or incomplete data [5].

So, after understanding the problem, there were two questions that arouse and those questions were:

- How better accuracy can be obtained by taking large number of inputs from the patient as symptoms?
- How well these inputs can help in differentiating between anxiety and depression?

These problems usually arise in all cases when the patient might be having different symptoms that are not taken as inputs in the system. This issue can lead to a false prediction and patient health can be more affected by that. Previously we have proposed two systems for the prediction of anxiety and depression and we found it important that there is a need to create a system that will predict both the disorders at the same time. To handle such kind of problem, we proposed a Multi-layer Fuzzy interface system that will take all the major symptoms from the user as input and with the help of all the inputs the system will predict the disorder with more accuracy.

The related work will be explained in section-2 which is the overall literature review of the paper that shows the work of other people in the same field, whereas the methodology is explained in section-3 which shows the overall performance of the proposed system and the methods used to achieve the desired results, section-4 shows the conclusion of the proposed system.

Literature review

Victor Ekong et al [6]. proposed a system that handles symptoms of non-crisp value using fuzzy logic. The paper gives excellent mathematical analysis for fuzzy logic and neural networks. There are 25 symptoms that are used in five different groupings. Although a fairly robust system is suggested, the book does not provide implementation or results. There are no outcomes or model simulations in the paper; instead, it concentrates on the mathematical foundation of the system. In the same domain, Chattopadhyay et al [4]. proposed a system for the diagnosis of depression using fuzzy logic and neural networks together. In order to train a neural network that identifies whether a person has depression or not, the article considers 14 symptoms and thousands of rules. The number of test cases used may have been increased. The paper considers a fairly broad spectrum of symptoms. The study also goes into great detail about the history of data-finding methods, fuzzy logic, and neural networks. The paper suggests a novel solution that yields excellent outcomes. The primary distinction between our manuscript and the publication is that we are attempting to predict depression whereas the paper is attempting to diagnose it. Furthermore, Anish Dasari et al [3]. Highlighted the idea of neuro-fuzzy, a combination of fuzzy logic and neural networks, is used in the system that is suggested to automate the diagnosis of depression. The five layers of the system have been integrated with fuzzy logic. The system is trained using real-time depression data in the article. The system has been improved with back propagation. The approach offers accurate data and a supplemental tool for diagnosing depression, but not for predicting it. In addition, Satvanti Devi et al. [1] proposed Neuro-Fuzzy technique, in which Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were idealized to establish a fuzzy logic with neural network and hybrid learning algorithms. It used only two inputs to predict anxiety, but with only two inputs there was a higher chance of having a less accuracy. The patient might get the wrong results which may result in complication of the disorder. Due to less number of inputs, the user might not have that symptoms so it would be difficult to predict. Besides, Victor Ekong et al. [7] highlighted an intelligent system using fuzzy logic. It was used to diagnose the depression risk. It was implemented and maintained through MATLAB fuzzy tool. A specialist opinion was also conducted on the outcomes of the system. Also Archit Aggarwal et al. [2] proposed a fuzzy interface system which is used to detect depression risk. In this system, four symptoms were taken as input with three different age groups to predict depression. A questionnaire of 21 questions was also included in the input process. Additionally, Akshi Kumar et al. [8] highlighted mixed anxiety-depression disorder using tweets. Over more than 100 tweets were collected through which the anxious depression disorder was diagnosed on the basis of words, timing, frequency, sentiment and contrast. The model was trained using three classifiers (naïve bayes, gradient boosting, and random forest). But in this case, only the social media (tweets) were used to predict the anxious depression disorder whereas the number of people suffering from it could be larger than this and cannot only be predicted through social media. Likewise, Pratyaksh Jain et al. [9] conducted analysis of depression and suicidal thoughts using Machine Learning algorithms and NLP. It was divided into help groups as depression and suicidal watch. The model was trained using four classifiers (naïve bayes, SVM, random forest and logistic regression). The precision and accuracy of these four models slightly vary from each other. Furthermore, the usage of neural networks were to be used for training the models in the upcoming time. Further, Usman Ahmed et al. [10] proposed a fuzzy system in the covid pandemic era. It used attention network to predict weighted words and then categorize patients on the basis of nine different symptoms. The text taken from it was first converted into lexicons and then fuzzy system uses those sets of lexicons to predict the mental health of the patients according to the list of the systems provided. Because of the weighted words the current model was facing the problems of overfitting. Moreover, Salih Tutun et al. [11] proposed a Decision Support System (DSS) that detects and diagnose various mental health related problems. It uses Network Pattern Recognition (NEPRA) algorithm to build assessment tools and then identify the questions that the participants had to answer. It showed that the proposed system can read up to 28 questions without human interaction (input) and had a relatively higher accuracy level. And the diagnostic tool of the mental health had even less questions. As well, Amna Amanat et al. [12] proposed a model which contains a Long-Short Term Memory (LSTM) model and recurrent neural networks by which the depression is detected from text. RNN was used to identify text depression and semantics from written content. The model was trained through LSTM in which two states were given (depressed and non-depressed) to predict the output of it. The results showed a higher accuracy. The next step for this will be implementing a hybrid neural network. In the same vein, Adegboyega Adegboye et al. [13] highlighted generic-neuro fuzzy techniques for the identification of key symptoms and characteristics of depression. The model performs selection and extractions on the provided dataset and on that basis it generates the output. But it is only limited for diagnosing and predicting clinical depression, other types of depression cannot be predicted through it. The output only shows negative or positive for the clinical depression. Even so, Elif Altintas et al. [14] identified 30 different machine learning techniques in which it was observed that the Random Forest algorithm works the best for the prediction of different types of anxiety at the early stages. Because the RFA uses categorical data instead of numerical data. The results indicated that the development of potential functional path ways will be guided by research on the pharmacogenetics of anxiety disorders using ML models. However, Juan Arturo et al. [15] proposed a system which is used to detect feelings expressed in written form on social networks. A large number of tweets were taken from twitter and those tweets which were not in Spanish were converted into it through translator. A SVM model is used to extraction and sentiment analysis. But in this case, the model only uses the text which was written in Spanish and not in any other language. Also, Hari Purnomo et al. [16] constructed a fuzzy system which is used to predict math anxiety in students. It included two variables (self-efficacy and positive attitude towards mathematics) as inputs. Three models were trained on the basis of these inputs, 2 fuzzy models and 1 regression model. It took inputs at 9 different levels and on that basis it predicted the output if the students suffer from anxiety or not. The results showed that fuzzy model can handle uncertainty better than the regression model. Similarly, Dilek Soysal et al. [17] presented a machine learning approach for the prediction of math anxiety in students with the help of variables as confidence and motivation. Classification and regression tree models were trained for this approach. It also showed that math anxiety has a relation with different variables also like gender and hours studied etc. But in this research, the data was self-reported and because of this there may be some issues in the accuracy of the result provided. Consequently, Deepak Chandra et al. [18] proposed mamdani fuzzy rule-based models for the prediction of psychological disorders. It used Maudsley Personality Inventory (MPI) and Siha's Comprehensive Anxiety Test (SCAT) for the collection of raw data. Using the scores of these questionnaires, neuroticism, extraversion and anxiety were predicted. The performance of the model was tested by the estimation of Mean Absolute Percentage Error (MAPE). Next, Farhad Lotfi et al. [19] highlighted a Machine learning system which is used for monitoring and managing anxiety in young people. It used State-Trait Anxiety Inventory (STAI) for getting raw data from people. This questionnaire consist of 40 questions each with 4 different levels that the person may prefer to answer with. The results showed that monitoring the anxiety levels helped in informing the people of the risks ahead and machine leaning algorithms play a vital role in predicting different types of disorders with higher accuracy. Lastly, Sabab Zulfiker et al. [20] investigated six machine learning algorithms to predict whether a person is suffering from depression or not. Also, three different selection methods were also used. A survey of questionnaire including 55 questions were conducted in which question from Burns Depression Checklist (BDC) were also included. The output was conducted on the basis of the score obtained from Burns Depression Checklist (BDC) questionnaire. But this research is only limited for predicting depression and not the severity of it.

The above literature specifies that the fuzzy systems which are already developed can only predict either depression or anxiety, a patient who is unknown to the disease may get a false prediction. Furthermore, the symptoms which were used as inputs does not include all the symptoms of depression and anxiety and even more, there are less categories which include gender and age in the systems which can lead to false results. Therefore the above literature indicates that there is a need to develop a fuzzy interface model that can predict both disorders (depression and anxiety) using a vast set of inputs taken from the patient or user. Moreover, the patients or the user need to be divided in categories both age and gender wise, so that the prediction can be more precise and accurate. For this purpose, we decided to use a multi-layer fuzzy system through which both the anxiety and depression can be predicted at the same time. But before learning about multi-layer, you need to understand what fuzzy logic is.

- **Fuzzy logic:**

Fuzzy logic is described as a many-valued logic form that allows variables' truth values to range from 0 to 1. Fuzzy logic provides extremely significant flexibility for thinking at that point.

- **Fuzzy logic architecture:**

A. Fuzzification module:

This module is used to change the system inputs. Given that it is a clear integer. It further assists in dividing the input signal into five separate phases.

B. Knowledge base:

We must keep it in the IF-THEN guidelines that were supplied by specialists in this.

C. Inference engine:

In general, it aids in the simulation of human thought. To do this, IF-THEN rules and fuzzy inference on the inputs are used.

D. Defuzzification module:

We must convert the fuzzy set into a crisp value in this module. A reasoning engine discovered that set. The membership functions, however, always operate on the same idea, namely fuzzy sets of variables.

- **Type-1 fuzzy systems:**

Type-1 fuzzy inference systems are the ones which uses 2-dimensional membership functions.

- **Type-2 Fuzzy Systems:**

Type-2 fuzzy inference systems are the ones which uses 3-dimensional membership functions.

- **Multi-layer Fuzzy Systems:**

Multi-layer fuzzy inference systems use different layers to process the data and the output of one layer is correspondingly used as input in the next layer. So, the overall system in interlinked with respect to the inputs and the outputs.

Methodology

We have used Design Science Research Methodology for our proposed system. It has three phases and each phase consist of three activities. The first phase explains the overall introduction and literature review and we identified the research questions and the objective. The second phase of the methodology defines a knowledge-based system through which we developed a multi-layer fuzzy system. The third phase is based on the evaluation of the proposed system with answers to the research questions. It shows the interface design of the system as well.

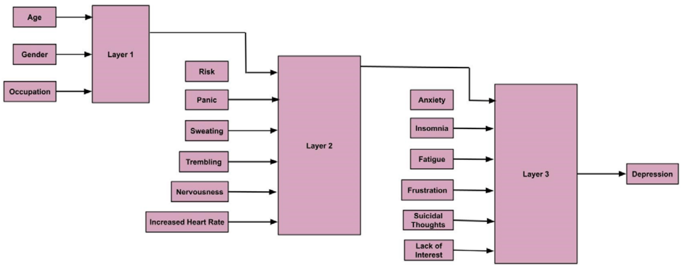

Figure 1: Shows the architecture of Multi-layer Fuzzy System.

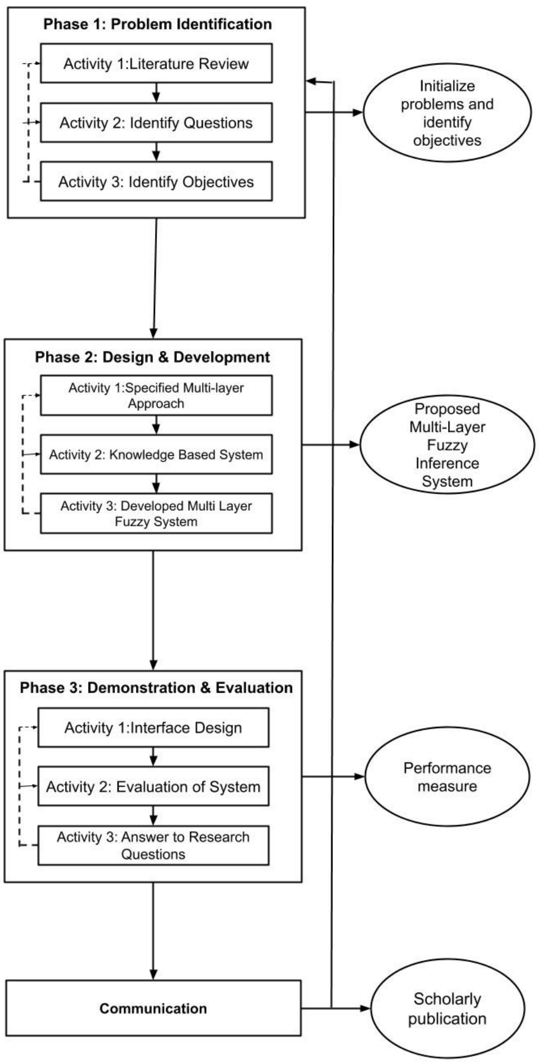

Figure 2: DSRM representation of the proposed system.

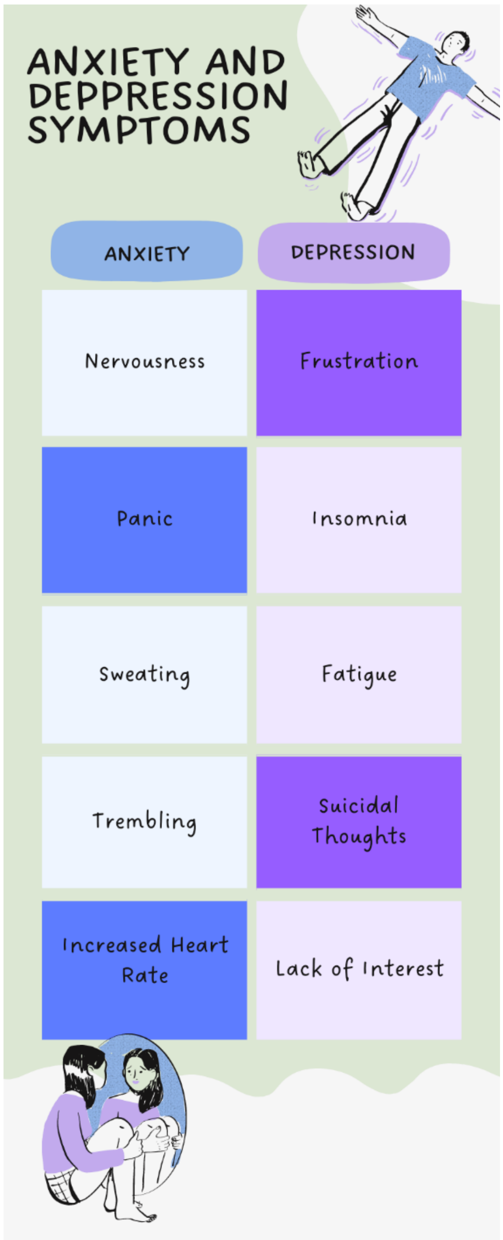

Figure 3: Symptoms of Depression and Anxiety.

Fuzzy system

In this multi-layer fuzzy system, we have used 3-layer system in which the output of the first layer is used as input in the second layer and the output of the second layer is used as input in the third layer and then the overall output is generated. If the system shows no sign of Anxiety in a person then the process would terminate on Layer 2 of the Fuzzy Systems. And if the system depicts some sign of Anxiety then the system would further predict if the patient is suffering from Depression or not, that is, moving onto the Layer 3. The process would be terminated on layer 2 because if the person is not showing any signs of anxiety there is a higher chance he will not be suffering from depression as anxiety and depression are interlinked and depression sometimes is prolonged form of anxiety.

Figure 4 shows the Input Output of the Fuzzy system of layer 1. For the first layer we have taken general details of the patient and categorized the output in three groups on the basis of age gender and occupation. From the study we found that the risk of disorder can be more in females because of the hormonal change while it is different in males. In the case of occupation, an unemployed person.

Group 1: This group contains the patients with low risk of the disorder.

Group 2: This group contains the patients with mild risk of the disorder.

Group 3: This group contains the patients with high risk of the disorder.

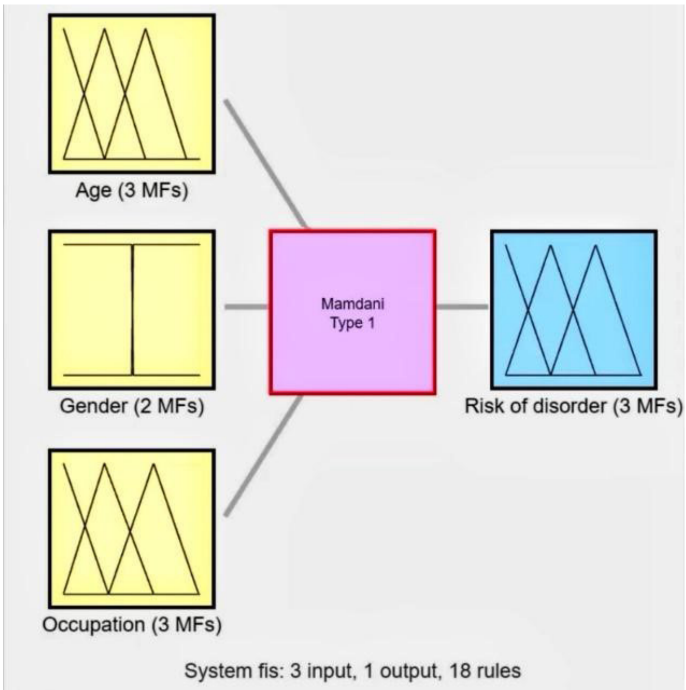

Figure 4: Input and Output of Layer 1.

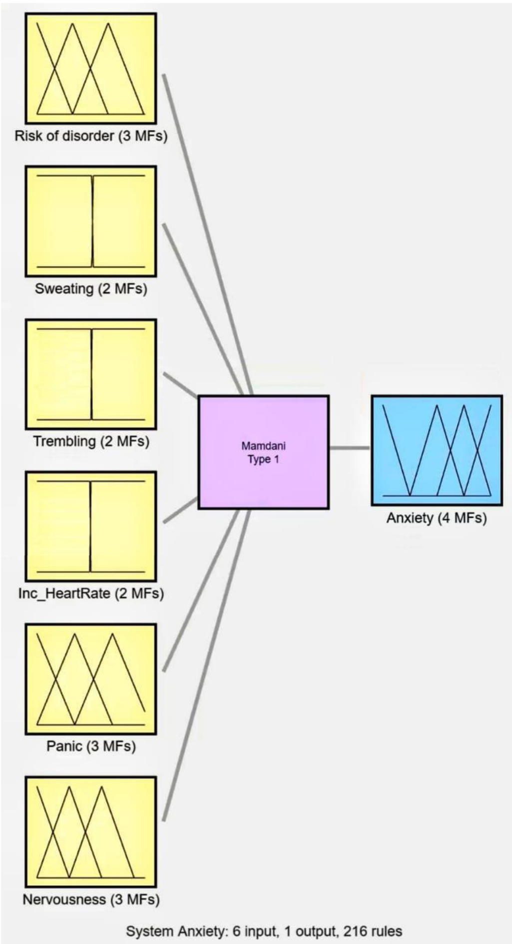

Figure 5: Input and Output of Layer 2.

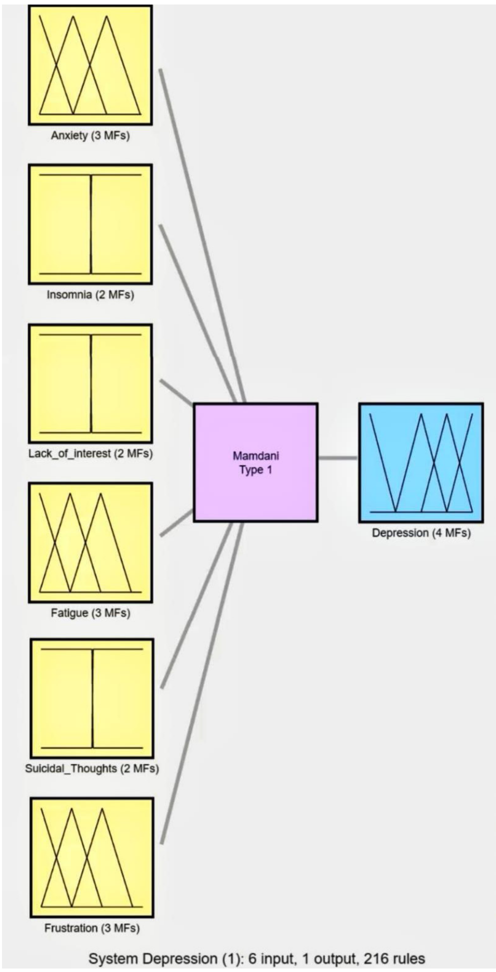

Figure 6: Input and Output of Layer 3

Knowledge based input output fuzzy system

This system was designed using three layers. In which the first layer has three input features, Age with three groups ranging from (18-40, 40-60 and 60-onwards), Gender including (Male and Female) and Occupation including (Doctor, Unemployed and Any other job). And the output is predicted as Risk of having the disorder in the form of groups (**Group1, Group2 and Group3**).

Table 1 shows the inputs and output of Layer 1 with respective parameters.

Second layer uses five initial inputs, Nervousness and Panic with three levels (low, mild and high), Sweating, Trembling and Increased Heart Rate with two parameters (yes and no) and one input from the output of previous layer1, Risk of disorder depending on three groups (**Group 1, Group 2 and Group 3**). And the output Anxiety is predicted on four levels (no, low, mild and high).

Table 2 shows the inputs and output of Layer 2 with respective parameters.

Third layer five initial inputs, Fatigue and Frustration with three levels (low, mild and high), Insomnia, Lack of Interest and Suicidal Thoughts with two parameters (yes and no) and one input from the output of previous layer1, Anxiety of disorder depending on three groups (low, mild and high) because the process would terminate at layer 2 if the patient doesn't show any signs of Anxiety. And the output Depression is predicted on four levels (no, low, mild and high).

Table 3 shows the inputs and output of Layer 3 with respective parameters.

Table 1: Ranges of Layer 1.

Input and Output variables	Linguistic term	Parameters of Fuzzy sets
Age	{18-40, 40-60, 60-onwards}	{[0 0 0.3], [0 0.3 0.6], [0.3 0.6 0.9]}
Gender	{"Male","Female"}	{[0 0 0.5 0.51], [0.5 0.51 1 1]}
Occupation	{"Doctor","Unemployed","Any other job"}	{[0 0 0.35], [0 0.35 0.70], [0.35 0.70 1.05]}
Risk of disorder	{"Group1","Group2","Group3"}	{[0 0 0.33], [0 0.33 0.66], [0.33 0.66 0.99]}

Table 2: Ranges of Layer 1.

Input and Output variables	Linguistic term	Parameters of Fuzzy sets
Risk of Disorder	{"Group1", "Group2", "Group3"}	{[0 0 0.33], [0 0.33 0.66], [0.33 0.66 0.99]}
Sweating	{"No","Yes"}	{[0 0 0.51 0.52], [0.51 0.52 1 1]}
Trembling	{"No","Yes"}	{[0 0 0.5 0.51], [0.5 0.51 1 1]}
Increased Heart Rate	{"No","Yes"}	{[0 0 0.49 0.50], [0.49 0.50 1 1]}
Panic	{"Low", "Mild", "High"}	{[0 0 0.35], [0 0.35 0.70], [0.35 0.70 1.05]}
Nervousness	{"Low", "Mild", "High"}	{[0 0 0.3], [0 0.3 0.6], [0.3 0.6 0.9]}
Anxiety	{"No","Low", "Mild", "High"}	{[0 0 0.25], [0 0.25 0.50], [0.25 0.50 0.75], [0.50 0.75 1]}

Table 3: Ranges of Layer 3.

Input and Output variables	Linguistic term	Parameters of Fuzzy sets
Anxiety	{"Low", "Mild", "High"}	{[0 0 0.33], [0 0.33 0.66], [0.33 0.66 0.99]}
Lack of Interest	{"No","Yes"}	{[0 0 0.51 0.52], [0.51 0.52 1 1]}
Insomnia	{"No","Yes"}	{[0 0 0.5 0.51], [0.5 0.51 1 1]}
Suicidal Thoughts	{"No","Yes"}	{[0 0 0.49 0.50], [0.49 0.50 1 1]}
Fatigue	{"Low", "Mild", "High"}	{[0 0 0.35], [0 0.35 0.70], [0.35 0.70 1.05]}
Frustration	{"Low", "Mild", "High"}	{[0 0 0.3], [0 0.3 0.6], [0.3 0.6 0.9]}
Depression	{"Low", "Mild", "High"}	{[0 0 0.33], [0 0.33 0.66], [0.33 0.66 0.99]}

Table 4: Membership Functions of Layer 1.

Input	Membership Functions
Age	$\mu_{low}(age) = \left\{\frac{0.3-x}{0.3}\ 0 \le x \le 0.3\right\}$
	$\mu_{mild}(age) = \left\{\frac{x}{0.3}\ 0 \le x \le 0.3\ \frac{0.6-x}{0.3}\ 0.3 \le x \le 0.6\right\}$
	$\mu_{high}(age) = \left\{\frac{x}{0.6}\ 0 \le x \le 0.6\ \frac{0.9-x}{0.3}\ 0.6 \le x \le 0.9\right\}$
Gender	$\mu_{no}(gender) = \left\{\frac{y-0}{0}\ 0 \le y \le 0\ \frac{0.51-y}{0.01}\ 0.5 \le y \le 0.51\right\}$
	$\mu_{yes}(gender) = \left\{y-0.5\ 0 \le y \le 0\ \frac{1-y}{0}\ 0.5 \le y \le 0.51\right\}$
Occupation	$\mu_{low}(occupation) = \left\{\frac{0.35-x}{0.35}\ 0 \le x \le 0.35\right\}$
	$\mu_{mild}(occupation) = \left\{\frac{x}{0.35}\ 0 \le x \le 0.35\ \frac{0.70-x}{0.35}\ 0.35 \le x \le 0.70\right\}$
	$\mu_{high}(occupation) = \left\{\frac{x}{0.70}\ 0 \le x \le 0.70\ \frac{1.05-x}{0.35}\ 0.70 \le x \le 1.05\right\}$
Risk of Disorder	$\mu_{low}(risk) = \left\{\frac{0.33-x}{0.33}\ 0 \le x \le 0.33\right\}$
	$\mu_{mild}(risk) = \left\{\frac{x}{0.33}\ 0 \le x \le 0.33\ \frac{0.66-x}{0.33}\ 0.33 \le x \le 0.66\right\}$
	$\mu_{high}(risk) = \left\{\frac{x}{0.66}\ 0 \le x \le 0.66\ \frac{0.99-x}{0.33}\ 0.66 \le x \le 0.99\right\}$

Membership functions

Membership functions define the ranges or parameters of fuzzy logic sets. They are typically used to perform mathematical operations on the given data set by the system. They apply the same value across other platforms as well. The membership procedures of layer 1 for the mentioned system are described in **Table 4.**

The membership procedures of layer 2 for the mentioned system are described in **Table 5.**

The membership procedures of layer 3 for the mentioned system are described in **Table 6.**

Defuzzification

Defuzzification is the process of taking sets of fuzzy logic and associated membership degrees and converting them into a crisp logic output that can be calculated or quantified. The process is also referred to as a decision-making algorithm since it selects the ideal crisp input and output value based on a fuzzy set.

Experimental results

With the help of MATLAB tool, we calculated the experimental results of all three layers of the proposed system.

Table 5: Membership Functions of Layer 2.

Input	Membership Functions
Risk of Disorder	$\mu_{low}(risk) = \left\{\frac{0.33-x}{0.33} \; 0 \le x \le 0.33\right\}$ $\mu_{mild}(risk) = \left\{\frac{x}{0.33} \; 0 \le x \le 0.33 \, \frac{0.66-x}{0.33} \; 0.33 \le x \le 0.66\right\}$ $\mu_{high}(risk) = \left\{\frac{x}{0.66} \; 0 \le x \le 0.66 \, \frac{0.99-x}{0.33} \; 0.66 \le x \le 0.99\right\}$
Sweating	$\mu_{no}(sweating) = \left\{\frac{y-0}{0} \; 0 \le y \le 0 \, \frac{0.52-y}{0.01} \; 0.51 \le y \le 0.52\right\}$ $\mu_{no}(sweating) = \left\{\frac{y-0}{0} \; 0 \le y \le 0 \, \frac{0.52-y}{0.01} \; 0.51 \le y \le 0.52\right\}$
Trembling	$\mu_{no}(trembling) = \left\{\frac{t-0}{0} \; 0 \le t \le 0 \, \frac{0.51-t}{0.01} \; 0.5 \le t \le 0.51\right\}$ $\mu_{yes}(trembling) = \left\{t-0.5 \; 0 \le t \le 0 \, \frac{1-t}{0} \; 0.5 \le t \le 0.51\right\}$
Increased Heart Rate	$\mu_{no}(heartrate) = \left\{\frac{u-0}{0} \; 0 \le u \le 0 \, \frac{0.5-u}{0.01} \; 0.49 \le u \le 0.50\right\}$ $\mu_{yes}(heartrate) = \left\{u-0.49 \; 0 \le u \le 0 \, \frac{1-u}{0} \; 0.49 \le u \le 0.50\right\}$
Panic	$\mu_{low}(panic) = \left\{\frac{0.35-x}{0.35} \; 0 \le x \le 0.35\right\}$ $\mu_{mild}(panic) = \left\{\frac{x}{0.35} \; 0 \le x \le 0.35 \, \frac{0.70-x}{0.35} \; 0.35 \le x \le 0.70\right\}$ $\mu_{high}(panic) = \left\{\frac{x}{0.70} \; 0 \le x \le 0.70 \, \frac{1.05-x}{0.35} \; 0.70 \le x \le 1.05\right\}$
Nervousness	$\mu_{low}(nervous) = \left\{\frac{0.3-d}{0.3} \; 0 \le d \le 0.3\right\}$ $\mu_{mild}(nervous) = \left\{\frac{d}{0.3} \; 0 \le d \le 0.3 \, \frac{0.6-d}{0.3} \; 0.3 \le d \le 0.6\right\}$ $\mu_{high}(nervous) = \left\{\frac{d}{0.6} \; 0 \le d \le 0.6 \, \frac{0.9-d}{0.3} \; 0.6 \le d \le 0.9\right\}$
Anxiety	$\mu_{no}(anxiety) = \left\{\frac{0.25-z}{0.25} \; 0 \le z \le 0.25\right\}$ $\mu_{low}(anxiety) = \left\{\frac{z}{0.25} \; 0 \le z \le 0.25 \, \frac{0.5-z}{0.25} \; 0.25 \le z \le 0.5\right\}$ $\mu_{mild}(anxiety) = \left\{\frac{z}{0.5} \; 0 \le z \le 0.5 \, \frac{0.75-z}{0.25} \; 0.5 \le z \le 0.75\right\}$ $\mu_{high}(anxiety) = \left\{\frac{z}{1} \; 0 \le z \le 1 \, \frac{1-z}{0.25} \; 0.75 \le z \le 1\right\}$

Figure 7 defines the rules as (Age as 18-40) and (Gender as Male) and (Occupation as Doctor) then (Risk of disorder lies in **Group1**).

Figure 8 defines the rules as (Risk lies in Group3) and (Sweating is Yes) and (Trembling is Yes) and (Increased Heart Rate is Yes) and (Panic is High) and (Nervousness is High) then (Anxiety is High).

Figure 9 defines the rules as (Anxiety is High) and (Insomnia is Yes) and (Lack of interest is Yes) and (Fatigue is High) and (Suicidal Thoughts is Yes) and (Frustration is High) then (Depression is High).

Table 6: Membership Functions of Layer 3.

Input	Membership Functions
Anxiety	$\mu_{low}(anxiety) = \left\{\frac{0.33-x}{0.33} \; 0 \le x \le 0.33\right\}$ $\mu_{mild}(anxiety) = \left\{\frac{x}{0.33} \; 0 \le x \le 0.33 \, \frac{0.66-x}{0.33} \; 0.33 \le x \le 0.66\right\}$ $\mu_{high}(anxiety) = \left\{\frac{x}{0.66} \; 0 \le x \le 0.66 \, \frac{0.99-x}{0.33} \; 0.66 \le x \le 0.99\right\}$
Lack of Interest	$\mu_{no}(interest) = \left\{\frac{y-0}{0} \; 0 \le y \le 0 \, \frac{0.52-y}{0.01} \; 0.51 \le y \le 0.52\right\}$ $\mu_{yes}(interest) = \left\{y-0.51 \; 0 \le y \le 0 \, \frac{1-y}{0} \; 0.51 \le y \le 0.52\right\}$
Insomnia	$\mu_{no}(insomnia) = \left\{\frac{t-0}{0} \; 0 \le t \le 0 \, \frac{0.51-t}{0.01} \; 0.5 \le t \le 0.51\right\}$ $\mu_{yes}(insomnia) = \left\{t-0.5 \; 0 \le t \le 0 \, \frac{1-t}{0} \; 0.5 \le t \le 0.51\right\}$
Suicidal Thoughts	$\mu_{no}(suicide) = \left\{\frac{u-0}{0} \; 0 \le u \le 0 \, \frac{0.5-u}{0.01} \; 0.49 \le u \le 0.50\right\}$ $\mu_{yes}(suicide) = \left\{u-0.49 \; 0 \le u \le 0 \, \frac{1-u}{0} \; 0.49 \le u \le 0.50\right\}$
Fatigue	$\mu_{low}(fatigue) = \left\{\frac{0.35-x}{0.35} \; 0 \le x \le 0.35\right\}$ $\mu_{mild}(fatigue) = \left\{\frac{x}{0.35} \; 0 \le x \le 0.35 \, \frac{0.70-x}{0.35} \; 0.35 \le x \le 0.70\right\}$ $\mu_{high}(fatigue) = \left\{\frac{x}{0.70} \; 0 \le x \le 0.70 \, \frac{1.05-x}{0.35} \; 0.70 \le x \le 1.05\right\}$
Frustration	$\mu_{low}(frustration) = \left\{\frac{0.3-d}{0.3} \; 0 \le d \le 0.3\right\}$ $\mu_{mild}(frustration) = \left\{\frac{d}{0.3} \; 0 \le d \le 0.3 \, \frac{0.6-d}{0.3} \; 0.3 \le d \le 0.6\right\}$ $\mu_{high}(frustration) = \left\{\frac{d}{0.6} \; 0 \le d \le 0.6 \, \frac{0.9-d}{0.3} \; 0.6 \le d \le 0.9\right\}$
Depression	$\mu_{low}(depression) = \left\{\frac{0.33-x}{0.33} \; 0 \le x \le 0.33\right\}$ $\mu_{mild}(depression) = \left\{\frac{x}{0.33} \; 0 \le x \le 0.33 \, \frac{0.66-x}{0.33} \; 0.33 \le x \le 0.66\right\}$ $\mu_{high}(depression) = \left\{\frac{x}{0.66} \; 0 \le x \le 0.66 \, \frac{0.99-x}{0.33} \; 0.66 \le x \le 0.99\right\}$

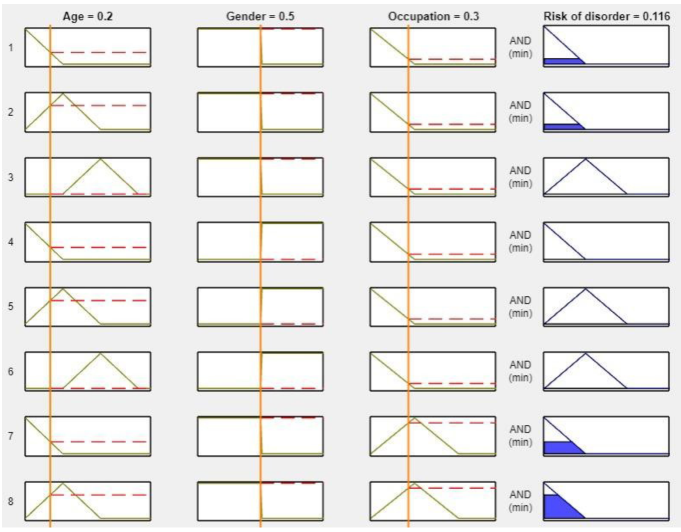

Figure 7: Lookup Diagram for Group 1.

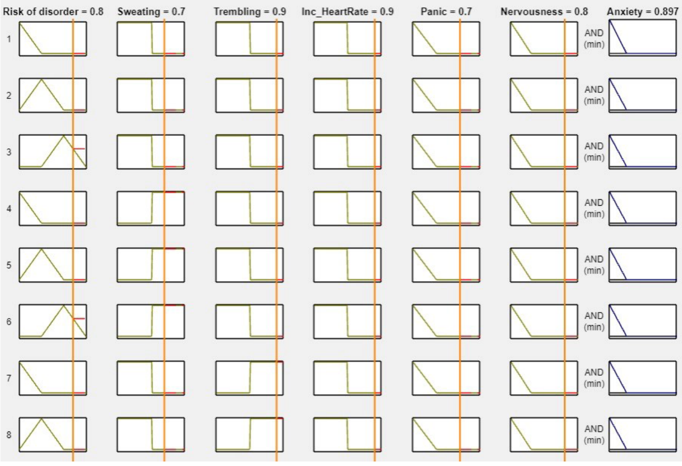

Figure 8: Lookup Diagram for High Anxiety.

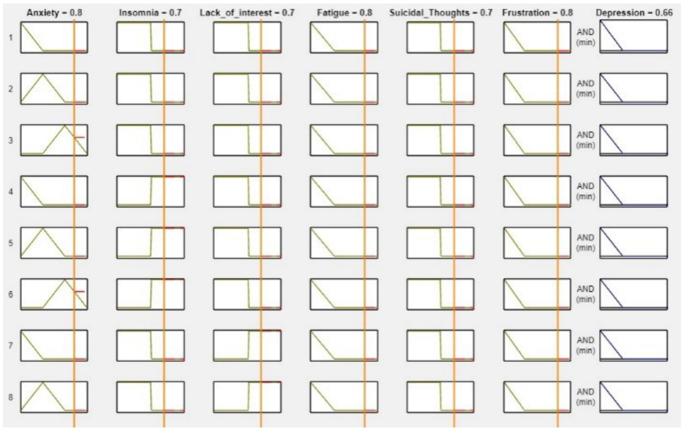

Figure 9: Lookup Diagram for High Depression.

Answer to research questions

The two key questions of this research are as follows:

"How better accuracy can be obtained by taking large number of inputs from the patients as inputs?" The response to this research question is that people show different symptoms as of their own condition. The psychological disorders have a huge impact on peoples mental as well as physical health, the symptoms are probably based on their self-esteem and coping mechanism that's why they differ. If we take less symptoms as input it is possible that the person suffering from the disorder doesn't show that particular symptom, this will lead to system's false prediction. If we take many symptoms as input it is possible that the disorder can be predicted with a higher accuracy because the system will then cover a large scope including the symptoms that vary from person to person.

"How well these inputs can help in differentiating between anxiety and depression?" The response to this question is that anxiety and depression are somewhat related. People who have prolonged anxiety are at a higher risk of suffering from depression. Although the two disorders are related yet they have different symptoms. Anxiety majorly has minor symptoms such as nervousness and increased heart rate etc. but the symptoms of depressions are rather severe which includes suicidal thoughts, frustration etc. and some cases also include prolonged anxiety. The early stages inputs help better in differentiating anxiety from depression and can also help to improve a person's health before it gets any worse.

Multi-layer fuzzy system

The system will first take the inputs of the first layer age, gender and occupation. And then move onto the next layer. In layer the 2 system will take the inputs nervousness, sweating, trembling, panic and increased heart rate and the output of the previous layer as risk of disorder and will predict anxiety on the basis of these symptoms. If the person shows no sign of anxiety, the process will terminate but if the person shows some level of anxiety such as low, mild or high, the system will then move onto layer 3. On this layer it will take inputs as frustration, fatigue, insomnia, suicidal thoughts and lack of interest as well as the level of anxiety from the previous layer output. On these bases it will then predict depression on three distinct levels (low, mild and high). **Figure 10** shows the Disorder prediction fuzzy system.

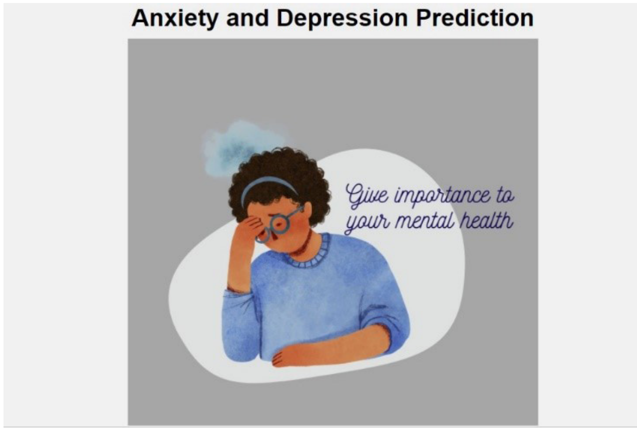

Figure 10.1: Interface Design.

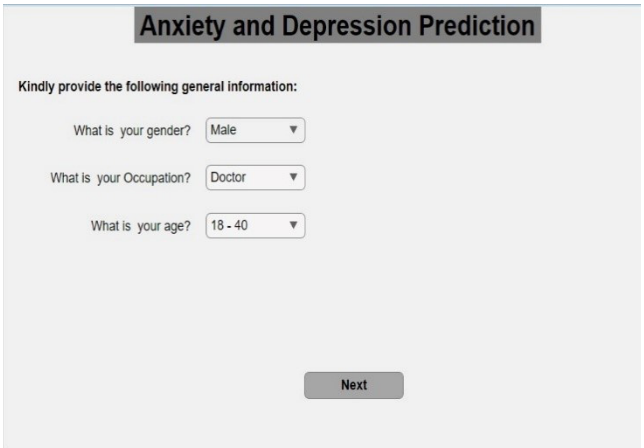

Figure 10.2: Interface Design of Layer 1.

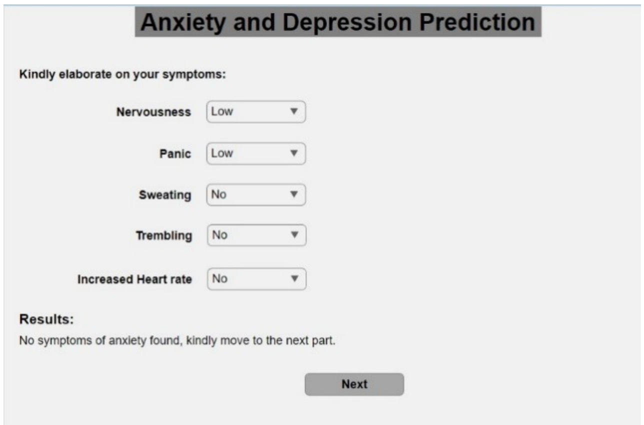

Figure 10.3: Interface Design of Layer 2.

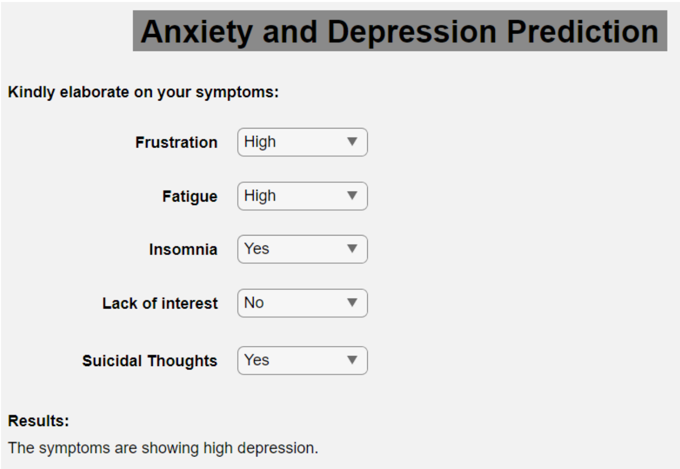

Figure 10.4: Interface Design of Layer 3.

Comparing the outcomes of expert opinion, our suggested system, and actual results is shown in **Table 7.** For this, we tested the system using patient data from Shalimar Hospital and compared it to the doctor's evaluation and the patients' real results to ensure the system's correctness.

The accuracy of our proposed system was 87%. We were able to assess the accuracy by comparing our findings to the patients' actual results. Of the 15 patients, 13 had their disorder accurately predicted using the suggested method.

Table 7: Comparative Analysis.

Patients	Expert opinion	Proposed system	Actual results
Patient 1	No Anxiety	No Anxiety	No Anxiety
Patient 2	High Anxiety	High Anxiety	High Anxiety
Patient 3	Low Depression	Low Depression	Low Depression
Patient 4	Low Anxiety	Mild Anxiety	Low Anxiety
Patient 5	No Anxiety	No Anxiety	No Anxiety
Patient 6	High Depression	High Depression	High Depression
Patient 7	Low Anxiety	Low Anxiety	Low Anxiety
Patient 8	Mild Depression	Mild Depression	Mild Depression
Patient 9	Low Depression	Low Depression	Low Depression
Patient 10	Mild Anxiety	Mild Anxiety	Mild Anxiety
Patient 11	High Depression	Mild Depression	High Depression
Patient 12	High Anxiety	High Anxiety	High Anxiety
Patient 13	Mild Depression	Mild Depression	Mild Depression
Patient 14	High Depression	High Depression	High Depression
Patient 15	Low Anxiety	Low Anxiety	Low Anxiety

Conclusion

The questions that were raised in our research paper were answered briefly and we got the accuracy as well for our system. The proposed system is a multi-layer fuzzy system which uses three layers to predict anxiety or depression in any patient. The multi-layer fuzzy system helped in the achievement of better accuracy of predicting the common psychological disorders, anxiety and depression. When predicting more than one disorder, it is better to use a multi-layer fuzzy system. For our future work we can use other symptoms the patients show as well. These symptoms are usually shown on early stages whereas other symptoms that shows the severity of the disorder and how likely a patient can recover from the disorder can also be taken into consideration.

References

1. Devi S, S Kumar, GS Kushwaha. An a daptive neuro fuzzy inference system for prediction of anxiety of students. In 2016 eighth International Conference on Advanced Computational Intelligence (ICACI). 2016. IEEE.

2. Aggarwal A, Choudhury T, Dewangan B. A Fuzzy Interface System to Predict Depression Risk. International Journal of Computer Information Systems and Industrial Management Applications. 2020; 12: 286-296.

3. Dasari A, NB Hui, Chattopadhyay S. A neuro-fuzzy system for modeling the depression data. International journal of computer applications. 2012; 54: 0975-8887.

4. Chattopadhyay S. A neuro-fuzzy approach for the diagnosis of depression. Applied computing and informatics. 2017; 13: 10-18.

5. Pintelas, EG, et al. A review of machine learning prediction methods for anxiety disorders. In Proceedings of the 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion. 2018.

6. Ekong VE, Inyang UG, Onibere EA. Intelligent decision support system for depression diagnosis based on neuro-fuzzy-CBR hybrid. Modern Applied Science. 2012; 6: 79.

7. Ekong VE, et al, A fuzzy inference system for predicting depression risk levels. African Journal of Mathematics and Computer Science Research. 2013. 6: 197-204.

8. Kumar A, Sharma A, Arora A. Anxious depression prediction in real-time social data. Arxiv preprint arXiv: 1903.10222, 2019.

9. Jain P, Srinivas KR, Vichare A. Depression and Suicide Analysis Using Machine Learning and NLP. In Journal of Physics: Conference Series. 2022. IOP Publishing.

10. Ahmed, U, JCW Lin, Srivastava G. Fuzzy Contrast Set Based Deep Attention Network for Lexical Analysis and Mental Health Treatment. Transactions on Asian and Low-Resource Language Information Processing. 2022: 21: 1-16.

11. Tutun S, et al. An AI-based Decision Support System for Predicting Mental Health Disorders. Information Systems Frontiers. 2022: 1-16.

12. Amanat A, et al. Deep learning for depression detection from textual data. Electronics. 2022; 11: 676.

13. Adegboye A, Agboizebeta IA. A Genetic Neuro-Fuzzy System for Diagnosing Clinical Depression. Machine Learning Research. 2021; 6: 17.

14. Altintaş E, Aksu ZU, Demir ZG. Machine Learning Techniques for Anxiety Disorder. Avrupa Bilimve Teknoloji Dergisi. 2021; 365-374.

15. Pérez-Cebreros JA, et al. SVM based Learning System for the Detection of Depression in Social Networks.Computación y Sistemas. 2022; 26.

16. Susanto HP, Purnamasari MI. Constructing a Fuzzy Model to Predict Math Anxiety. In5th International Conference on Current Issues in Education (ICCIE 2021). 2022. Atlantis Press.

17. Soysal D, Bani-Yaghoub M, Riggers-Piehl TA. A machine learning approach to evaluate variables of math anxiety in STEM students. Pedagogical Research. 2022; 7.

18. Pandey DC, GS Kushwaha, Kumar S. Mamdani fuzzy rule-based models for psychological research. SN Applied Sciences. 2020; 2: 1-10.

19. Lotfi F, B Rodić, Z Bogdanović. A System for Monitoring and Managing the Anxiety Among The Young People Using Machine Learning. In E-business technologies conference proceedings. 2022.

20. Zulfiker MS, et al. An in-depth analysis of machine learning approaches to predict depression. Current research in behavioral sciences. 2021; 2: 100044.