International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Fuzzy Based System for Classification of Psychological Disorder

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Abstract
The classification of psychological disorders is vital role for accurate diagnosis, effective treatment. The proposed system utilizes linguistic variables and membership functions to evaluate patient-reported symptoms. By using fuzzy rule-based inference, the system processes imprecise and subjective input data, generating clear and interpretable classifications for disorders like Alcohol Dependency Disorder, Schizophrenia, Bipolar_Disorder, Obsession_Compulsive Disorder, Anxiety and Depression. The Fuzzy based system is designed to follow the decision-making processes of mental health professionals by including expert knowledge and established diagnostic criteria. The system is implemented as a user-friendly, web-based application to enhance accessibility for clinicians and researchers. The proposed system achieved an overall classification accuracy of 91.25%.This research paper highlights the potential of fuzzy logic as a robust computational tool for improving psychological disorder classification.

Keywords: Psychological Disorders, Fuzzy System, Mental Health , Rule-Based Fuzzy System, Symptoms

1. Introduction

One of the most common diseases in the world is a psychological disorder. In the past thirty years, a multitude of epidemiological investigations carried out globally have highlighted the notable public health issue presented by the widespread occurrence and long-lasting presence of mental illnesses [5]. In today's high-speed and challenging environment in every field, the well-being of individuals' psychological state has become more prominent. Psychological disorders are crucial as they disrupt emotional stability and security for individuals and their surrounding environment. Psychology problems are complicate. The problems are regarding feelings, thinking situations and behaviors. It makes very difficult to exactly explain. Understanding and classifying psychological disorders is offering critical insights for accurate diagnosis, effective treatment, and the progression of mental health studies. The classification of psychological disorders establishes a structured framework for identifying and organizing the countless ways in which mental health issues manifest. The process of classification primarily depends on the systematic evaluation of an individual's symptoms. These symptoms are assessed in relation to established diagnostic criteria, often characterized by recognized classifications such as the International Classification of Diseases (ICD 11) and Diagnostic and Statistical Manual of Mental Disorders (DSM 5)[1]. These frameworks describes symptoms and distinguishing one disorder from another by outlining characteristic symptoms, duration, severity, and the effect on day-to-day activities. A comprehensive classification method must account for the complexity of psychological disorders, which often involve overlapping symptoms. The importance of classification extends beyond clinical situations

Fuzzy logic, [2] introduced by Lotfi A. Zadeh in the 1960s, offers a departure from conventional binary logic by allowing for the representation of uncertainty and ambiguity through degrees of truth. Unlike traditional categorical distinctions, where phenomena are classified as either true or false, fuzzy logic accommodates the gradual transition between different states, reflecting the inherent vagueness often encountered in real-world scenarios [7]. This inherent flexibility makes fuzzy systems well-suited for tasks such as pattern recognition, decision-making, and classification, particularly in domains where boundaries between categories are inherently fuzzy [14]. The integration of fuzzy systems into psychological disorder classification holds promise across multiple dimensions. Firstly, it offers a more refined understanding of individual differences, accounting for the diverse manifestations of symptoms and the unique trajectories of illness progression. By capturing the inherent uncertainty in diagnostic decision-making, fuzzy systems can also mitigate the risk of misclassification and facilitate more accurate treatment planning. Moreover, the adaptability of fuzzy systems allows for the incorporation of diverse sources of information, including clinical assessments, neurobiological markers, and even subjective patient experiences, fostering a holistic and multi-dimensional understanding of mental health.

2. Related Work

This section discusses a few important studies related to our research.

- In [9] author proposed that he examined six machine learning algorithms for their efficacy in determining whether individuals were experiencing depression. Additionally, three distinct selection methods were employed. A survey comprising 55 questions, including items from the "Burns Depression Checklist (BDC)", was managed. The output prepared on the collected score from the BDC questionnaire. Though, it was important to note that research focused especially for prediction depression rather than assessing its severity.
- Author [10] has developed a "Decision Support System (DSS) "to identify a range of mental health issues. Utilizing the "Network Pattern Recognition (NEPRA) algorithm", it constructs assessment tools and determines the questions participants need to answer. The system demonstrated the capability to autonomously process up to 28 questions with a notably high accuracy rate, suggesting potential for reducing human intervention. Moreover, the diagnostic tool for mental health requires even fewer questions.
- Author [11] introduced a system designed to monitor and address anxiety in youth through machine learning techniques. The researchers described the architecture of smartphone applications that used machine leaning application to prediction and treatment for anxiety in youth.
- In research paper [12] described, the reserachers introduce an "FIS model" custom-made for medical identification within the psychiatry. The system effectively guesses the severity levels of depression risk by utilizing knowledgeable understanding and determined as fuzzy guidelines and incorporating patients' biological and mental condition. This research underscores the sensitivity and specificity of Fuzzy Logic (FL) as a valuable tool supporting medical judgment. Moreover, it suggests that the fuzzy methodology could be expanded to offer smart tools for assessing and predicting severity levels across various health disciplines.
- This paper presented [13] the findings of a research endeavor focused on crafting a fuzzy system

capable of assessing the depression severity level. The system is used “MATLAB R2008” and its fuzzy rules.

- The development of web-based fuzzy expert system to help manage diabetes and determine the risk factors for the disease is covered in the study article. People can assess their risk of diabetes with this online tool, increasing public awareness of the condition. Users can enter data into the system's HTML-based interface, and the fuzzy inference engine—which is backed by a knowledge base—produces the outcomes. The system's rule set aids in output prediction, and Python is used to manage the knowledge base and perform the inference method [17].
- Author utilized fuzzy rules for the acidifying and deacidifying. This study whereas develop a fuzzy coordination that exhibits outcomes. Research described fermentation process which is depends on amount of carbonate and tartaric acid. Web system used a developed framework for Python programming specifically axing on scikit-fuzzy and flask. Python is known for having diverse libraries across different domains, which is one of the reasons it is so widely used in research. This user interface is built on HTML5, CSS and Bootstrap framework. JavaScript is used as Client-side programming [14].

3. Methodology and Designing Fuzzy Based System for Classification of Psychological Disorder

This research study consists of various steps. All these described as follows.

A. Collection of data

Data collected from Medical College. This data was sourced from patient records, as well as input provided by medical students, senior psychiatrists, and medical staff members.

B. The process of selecting and distributing data

The suggested system used 20 symptoms of psychiatric illnesses as input variables. Disorder name was used as output variable. The following table includes disorder symptoms, output variables and codes.

Table1. Input and Output variables for Classification of Psychological Disorder

Sr.No	Category	Symptoms	Symbols
1	Input Variables	Depressed_Mood	SDM1
2		Loss_of_Interest	SLM2
3		Decreased_Energy	SDM3
4		Headache	SHM4
5		Sleep_problem	SSM5
6		Anger_outbrust	SAM6
7		Excessive_Worry	SEM7
8		Fear	SFM8
9		Sweaty_hands	SSM9
10		Dry_mouth	SDM10
11		Delusions	SDM11
12		Hallucinations	SHM12
13		Disorganized_Speech	SDM13
14		Obsessions	SOM14
15		Compulsions	SCM15

16		Racing_Thoughts	SRM16
17		Distractibility	SDM17
18		Compulsive_Alcohol_Use	SCM18
19		Loss_of_Control	SLM19
20		Continuing_to_Use_Alcohol	SCM20
21	Output Variables	Depression	DEPR
22		Anxiety	ANXI
23		Schizophrenia	SCHI
24		Bipolar	BIPO
25		OCD	OCD1
26		Alcohol dependency syndrome	ADS1

C. Methodology for Classification

a) Linguistic variable and Fuzzy parameters for classification

In this section described linguistic variables as well as fuzzy parameters for input and out variables.

Table2. Linguistic Variables Input and Output variable

Category	Symbols	Linguistic Variables	Fuzzy Parameters
Input Variables	SDM1	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SLM2	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SDM3	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SHM4	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SSM5	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SAM6	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SEM7	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SFM8	No	[0, 0, 1]

		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SSM9	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SDM10	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SDM11	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
Input Variables	SHM12	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SDM13	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SOM14	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SCM15	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SRM16	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SDM17	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[0, 1, 2]
	SCM18	No	[1, 2, 3]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SLM19	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
	SCM20	No	[0, 0, 1]
		Un_tell	[0, 1, 2]
		Yes	[1, 2, 3]
Output Variables	Disorder	DEPR	[0, 1, 2]
		ANXI	[1, 2, 3]

		SCHI	[2, 3, 4]
		BIPO	[3, 4, 5]
		OCD1	[4, 5, 6]
		ADS1	[5, 6, 7]

b) Fuzzy operator and fuzzy set determination

Fuzzy sets are defined in relation to the data set used for this study. Data is normalized and categorized such as SDM1 (No, Un_tell, Yes). Similarly, output fuzzy variables are defined as Disorder (DEPR, ANXI, SCHI, BIPO, OCD1, ADS1 etc.). This study uses a Fuzzy AND operator.

c) Determine fuzzification

In this process, the fuzzy triangular limits [a1,b1,c1] for the variables derived based on expert opinions and literature review.

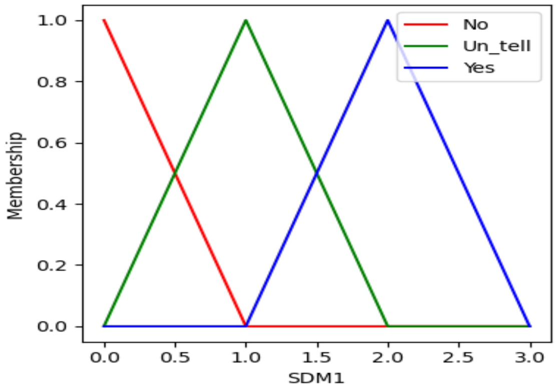
For instance, consider Symptom SDM1 with the corresponding linguistic variable values: SDM1(No) = [0, 0, 1],SDM1(Un_tell) = [0, 1, 2] and SDM1(Yes)=[1,2,3]. The triangular membership functions for these variables are defined by the equations below.

$$\mu\ No(x) = \begin{cases} 0 & \text{if } x < 0 \\ x/0 & \text{if } 0 \le x \le 0 \\ (1-x) & \text{if } 0 < x < 1 \\ 0 & \text{if } x > 1 \end{cases}$$

$$\mu\ Un\_tell(x) = \begin{cases} 0 & \text{if } x < 0 \\ (x-0) & \text{if } 0 \le x \le 1 \\ (1-x) & \text{if } 1 < x < 2 \\ 0 & \text{if } x > 2 \end{cases}$$

$$\mu\ Yes(x) = \begin{cases} 0 & \text{if } x < 1 \\ (x-0) & \text{if } 1 \le x \le 2 \\ (1-x)/2 & \text{if } 2 < x < 3 \\ 0 & \text{if } x > 3 \end{cases}$$

Figure 1: Member function for SDM1 Input Variable



d) Determining Fuzzy Rules

Fuzzy rules were developed based on data obtained from a hospital that included the 20 symptoms of psychological disorders, resulting in the creation of 17 fuzzy rules. The AND operator was used to link the inputs, while the IF-THEN structure worked as the mapping function between input variables and outputs variables . The defuzzification process determined the centroid by calculating the center of the fuzzy region area. Here are some rules derived as interpretations of Table III.

Rule 1 = If (SDM1 ['yes'] and SLM2 ['yes'] and SDM3 ['yes'] and SHM4 ['yes'] and SSM5 ['yes'] and SAM6 ['yes'] then Disorder [DEPR])

Rule3 = If (SEM7 ['yes'] and SFM8 ['yes'] and SSM9 ['yes'] and SDM10 ['yes'] then Disorder [ANXI])

Rule 5 = If (SMD11 ['yes'] and SHM12 ['yes'] and SDM13 ['yes'] and SLM2 ['yes'] and SAM6 ['yes'] then Disorder [‘SCHI’])

Rule17 = If(SCM18['yes'] and SLM19 ['yes'] and SCM20['yes'] and SSM5['yes'] and SAM6['yes']and SFM8['yes'] and then Disorder[ADS1])

d) Defuzzification

Defuzzification is the final step in the process, where a crisp input value is converted into a crisp output value. In this study, Centroid of Area (COA) method used to transform fuzzy rules into crisp output values. The COA technique demonstrated superior diagnostic accuracy compared to BOA, MOM, and SOM methods.

f) Algorithm

Input: The crisp values for

Depressed_Mood(SDM1),Loss_of_Interest(SLM2) , Decreased_Energy(SDM3),Headache(SHM4), Sleep_problem (SSM5), Anger_outbrust (SAM6), Excessive_Worry (SEM7), Fear (SFM8), Sweaty_hands (SSM9), Dry_mouth(SDM10), Delusions(SDM11), Hallucinations(SHM12), Disorganized_Speech(SDM13), Obsessions(SOM14), Compulsions(SCM15), Racing_Thoughts(SRM16), Distractibility(SDM17), Compulsive_Alcohol_Use(SM18), Loss_of_Control(SM19), Continuing_to_Use_Alcohol(SM20)

Output: The crisp value for Disorder (DEP, ANX, BIP, SCH, OCD, ADS)

Begin

Step 1: Creating the fuzzy numbers for symptoms

Step 2: Creating the fuzzy numbers for Disorder (DEPR, ANXI, SCHI, BIPO, OCD1, ADS1).

Step 3: Create the crisp values for fuzzy variables

Step 4: Calculate the triangular membership role for each linguistic variable of fuzzy variables.

Step 5: The related triangular relationship function is calculated for each linguistic variable.
Step 6: Implementation of Mamdani's technique for Fuzzy inference mechanism.
Step 7: Defuzzification of crisp value by Centre of Area (COA) method.

$$\text{Classification} = \frac{\sum_{i=1}^{num} \mu X\,(ai).\,ai}{\sum_{i=1}^{num} \mu X\,(ai)}$$

Where num = number of output coding level,
X = fuzzy set.

Step 8: Demonstrating disorder fuzzy calculation in human language interpretation

End

D. Development for classification of psychological disorders

1) Sample design Code for input symptoms

SDM1 = ctrl.Antecedent(np.arange(0, 3, 1), 'SDM1')
SLM2 = ctrl.Antecedent(np.arange(0, 3, 1), 'SLM2')
Disorder = ctrl.Consequent (np.arange (0, 8, 1), 'Disorder')

2) Membership Function Code

SDM1['No'] = fuzz.trimf(SDM1.universe [0, 0, 1])
SDM1['Un_tell'] = fuzz.trimf(SDM1.universe [0, 1, 2])
SDM1[Yes'] = fuzz.trimf(SDM1.universe [1, 2, 3])
Disorder['DEPR'] = fuzz.trimf(Disorder.universe [0, 1, 2])
Disorder['ANXI'] = fuzz.trimf(Disorder.universe [1, 2, 3])

3)Rule base for classification of Psychological Disorders

Rule1= ctrl.Rule (SDM1 ['Yes'] and SLM2 ['Yes'] and SDM3 ['Yes'] and SHM4 ['Yes'] and SSM5 ['Yes'] and SAM6 ['Yes'], Disorder [DEPR])
Rule9= ctrl.Rule (SOM14 ['Yes'] and SCM15 ['Yes'] and SSM5['Yes'] and SLM2['Yes'] then Disorder[OCD1])
Rule 17 = ctrl.Rule (SDM11 ['yes'] and SHM12 ['yes'] and SDM13 ['yes'] and SLM2 ['yes'] and SAM6 ['yes'] then Disorder [SCHI])

4) Outcome and Result

For proposed system, python language , Flask , MySQL has been used for development of fuzzy based system. HTML , CSS and JavaScript used as Client side scripting.

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Figure 2: Input Screens1

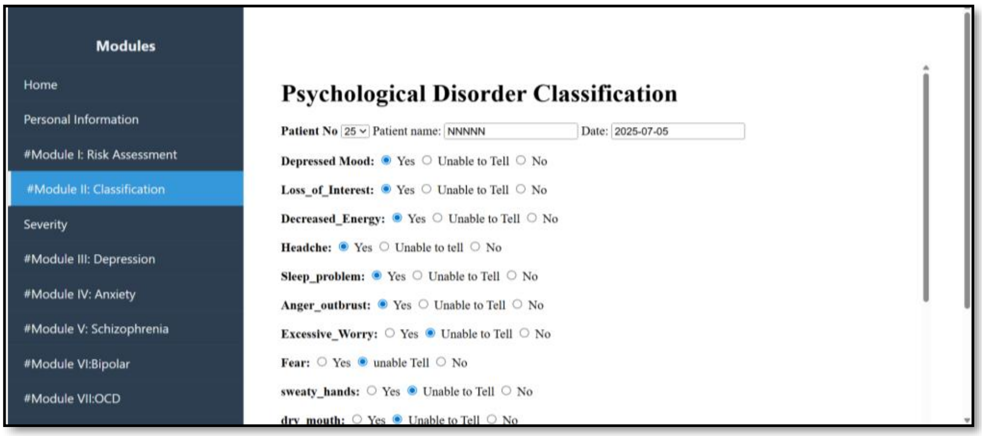


Figure 3: Input Screens2

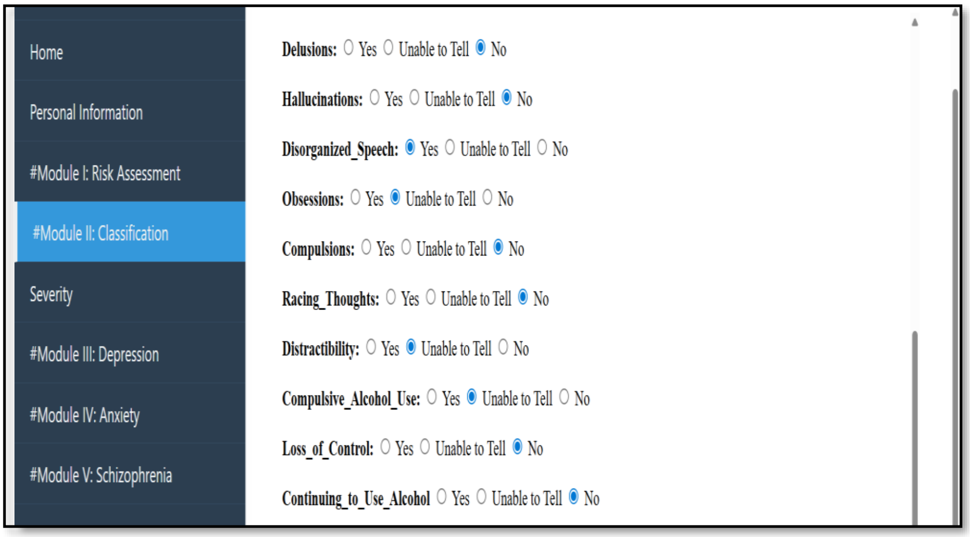


Figure 4: Result Screens

4. Conclusion

The proposed system effectively classified Psychological Disorders with 91.25% accuracy. Although minor variances were noted between the system's diagnoses and individual responses, the rules generated by the system closely reflected actual values and aligned with expert logic. Moreover, the system is designed to assess disorder symptoms, improving its flexibility as well as effectiveness in assisting diagnoses symptoms on a larger scale.

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