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Research Article

Comparative Analysis of Fuzzy Logic Models for Depression Prediction: Python and LabVIEW Approaches

Nurul Rismayanti [1], Gilberth Valentino Titaley [2], Anik Nur Handayani [3,*]

[1] Universitas Negeri Malang, Malang, Indonesia, nurul.rismayanti.2305348@students.um.ac.id
[2] Universitas Negeri Malang, Malang, Indonesia, gilberth.valentino.2405348@students.um.ac.id
[3] Universitas Negeri Malang, Malang, Indonesia, aniknur.ft@um.ac.id

Correspondence should be addressed to Anik Nur Handayani; aniknur.ft@um.ac.id

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Abstract:

Depression is one of the mental disorders with a significant impact on individuals' quality of life and productivity. The diagnostic process for depression, which typically relies on subjective assessment, often encounters challenges of uncertainty and variability in symptoms. This study aims to develop a fuzzy model for predicting depression levels based on five primary symptom variables: worthlessness, concentration, suicidal ideation, sleep disturbance, and hopelessness. The model is implemented on two platforms, Python and LabVIEW, to evaluate the accuracy and consistency of prediction results between these platforms. The analysis process begins with data pre-processing, input variable fuzzification, inference using 243 fuzzy rules, and defuzzification to generate a crisp output value classified into four depression levels: No Depression, Mild, Moderate, and Severe. The study results indicate a very small error margin between the two platforms, with error values below 0.01 in each trial. These findings suggest that both Python and LabVIEW can produce nearly identical and consistent predictions. This conclusion supports the effectiveness of fuzzy logic in addressing uncertainty in clinical data, especially for cases of depression with varying symptoms. Nonetheless, there are limitations related to the subjectivity in selecting membership functions and rules, as well as limitations in the number of variables used. Therefore, this study recommends expanding the developed fuzzy model with additional variables or integrating it with machine learning approaches to improve prediction accuracy. These findings are expected to serve as a foundation for the development of fuzzy-based systems in future mental health diagnostics.

Keywords: Depression; Fuzzy Logic; LabView; Mental Helth Prediction; Phyton

1. Introduction

Mental health is currently one of the most prominent global health issues, particularly with the significant rise in depression cases across various countries. Depression is a mental disorder that not only affects emotional well-being but also has a substantial impact on individual productivity, social relationships, and physical health. This condition positions depression as one of the illnesses with high economic and social burdens. Amid growing awareness of its profound impact, efforts are being made to enhance the quality of depression diagnosis and management through technology. One compelling approach is the utilization of fuzzy logic [1], [2], which enables predictive modelling by addressing uncertainty and variability in data, a common occurrence in patients with mental disorders. In this context, fuzzy logic can facilitate the creation of more adaptive depression assessment systems that account for the diverse symptoms of patients, making it a promising approach to improve the accuracy of early diagnosis.

Currently, traditional approaches to diagnosing depression rely heavily on interviews and subjective questionnaires conducted by professionals. While considered valid, these methods often result in inconsistencies due to subjective perceptions from both patients and assessors. Additionally, limited time and resources frequently pose challenges in providing timely and equitable assessments. Therefore, there is an urgent need to develop assessment systems that are not only effective but also widely implementable with consistent accuracy. A fuzzy logic-based system [3] allows assessments based on measurable symptom scales, reducing subjectivity and providing more objective diagnoses. The primary challenge lies in constructing a model that is practical to implement and delivers accurate results while comparing the effectiveness of different development platforms, such as Python and LabVIEW.

This study aims to develop and evaluate a fuzzy logic model for predicting depression levels in individuals based on several key symptoms, such as feelings of worthlessness, concentration issues, suicidal ideation, sleep disturbances, and hopelessness. The model will be implemented on two platforms, Python and LabVIEW, to determine whether there are significant differences in accuracy and suitability between the two approaches. Additionally, the study seeks to explore the extent to which fuzzy logic can reduce subjectivity in depression assessment and provide consistently reliable results [4], [5]. By examining the differences in outcomes between these platforms, this study hopes to offer new insights into the strengths and limitations of each in applying fuzzy logic models, along with practical recommendations for developing similar systems in the future [6]–[8] .

Previous research highlights the significant outcomes of fuzzy logic applications across various fields, ranging from healthcare to education and decision-making. For instance, [9] tested fuzzy methods for detecting stress levels through sleep analysis, where the Mamdani method achieved higher accuracy compared to the Tsukamoto method, underscoring the potential of sleep analysis in identifying psychological conditions. Additionally, [10] applied fuzzy logic to determine the best packaged milk based on nutrition and price, showcasing the role of fuzzification and defuzzification in assisting consumers in making more precise decisions. In another context, [11] found that the Mamdani method enhanced effectiveness and efficiency in employee recruitment by providing more accurate recommendations, especially in situations with numerous variables among applicants.

On the other hand, several studies using similar approaches on platforms like MATLAB or other specialized software have demonstrated good results but often require advanced technical knowledge, making them less suitable for practical implementation in clinics. Therefore, by selecting Python and LabVIEW for this study, we aim to create a system that is not only accurate but also user-friendly for practitioners with diverse technical backgrounds.

This research is expected to contribute to the development of a fuzzy logic-based system for early depression diagnosis that is both affordable and accessible, especially in healthcare facilities with limited resources. The study's findings are also anticipated to provide empirical evidence on the effectiveness of Python and LabVIEW as alternative platforms for developing fuzzy systems for depression prediction. Furthermore, the results are expected to pave the way for future studies aimed at enhancing model accuracy by considering more clinical variables or integrating other methods such as machine learning. Thus, this research not only contributes to the development of fuzzy-based diagnostic tools but also advances understanding of the most appropriate platforms for implementing such technologies.

2. Method:

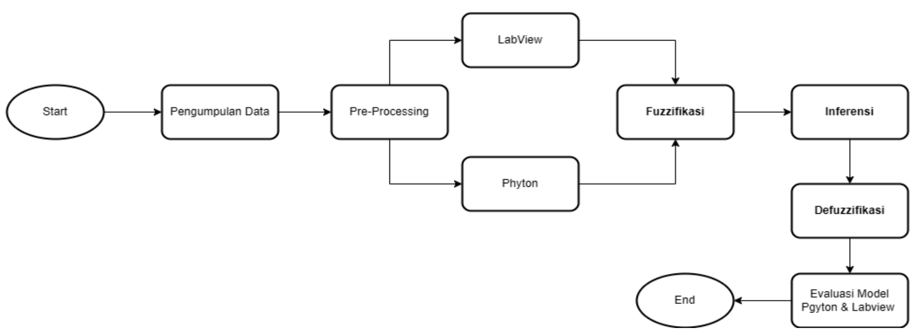


Figure 1. Research Flowchart

This study employs a fuzzy logic approach to develop a system for predicting depression levels based on five key symptom variables: worthlessness, concentration, suicidal ideation, sleep disturbance, and hopelessness. Each variable has the same value range, from 1 to 6, representing severity levels from low to high. The study aims to compare the implementation of the fuzzy model using two different platforms: Python and LabVIEW. The research process begins with data collection, preprocessing, fuzzification of symptoms, inference using fuzzy rules, and defuzzification to produce a crisp output representing the depression level, categorized as No Depression, Mild, Moderate, and Severe.

2.1 Research Design

This research uses a fuzzy logic approach to develop a system for predicting depression levels based on five primary symptom variables: worthlessness, concentration, suicidal ideation, sleep disturbance, and hopelessness. Each variable is measured on a scale from 1 to 6, indicating severity levels from the lowest to the highest. The study compares the implementation of the fuzzy model across two platforms, Python and LabVIEW, for the research flow show in **Figure 1**. The process involves the following steps: data collection, pre-processing, fuzzification of symptoms, inference based on fuzzy rules, and defuzzification to obtain a crisp output indicating the depression level, labelled as No Depression, Mild, Moderate, and Severe.

2.2 Dataset Collection

The dataset used in this study is sourced from the Kaggle platform, containing symptom data with values corresponding to each primary depression-related symptom variable. The dataset includes assessments from respondents on a scale of 1–6, where each number represents the intensity of symptoms, from the mildest to the most severe, for details of dataset show in **Table 1**.

Tabel 1. Dataset Description

No	Variable	Description	Information
1	*Number*	Unique number for each patient	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
2	*Sleep*	Frequency of sleep disturbances	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
3	*Appetite*	Changes in appetite	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
4	*Interest*	Loss of interest in activities	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
5	*Fatigue*	Low levels of fatigue or energy	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
6	*Worthlessness*	Level of fatigue or low energy	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
7	*Concentration*	Difficulty concentrating	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
8	*Agitation*	Physical agitation	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
9	*Suicidal Ideation*	Thoughts of suicide	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
10	*Sleep Disturbance*	Sleep problems	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
11	*Aggression*	Aggressive feelings	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
12	*Panic Attacks*	Panic attack experiences	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
13	*Hopelessness*	Feelings of hopelessness	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
14	*Restlessness*	Feelings of anxiety	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
15	*Low Energy*	Lack of energy	1: *Never*, 2: *Always*, 3: *Often*, 4: *Rarely*, 5: *Sometimes*, 6: *Not at all*
16	*Depression State*	Overall depression status	categorized as *'No depression'*, *'Mild'*, *'Moderate'*, *'Severe'*

The pre-processing steps [12], [13] are performed to clean the data from noise and eliminate irrelevant columns [14], [15], such as several variables that are not included in this fuzzy model. The data is then cleaned of unnecessary characters such as tabs or extra spaces using the `str.strip()` function in Python. Additionally, missing data handling is done by removing incomplete rows or performing data imputation to ensure consistency in the analysis, for the results pre-processing show in **Table 2**. Afterward, the data is formulated to be ready for input into the fuzzy system through the processes of fuzzification, inference, and defuzzification.

Table 2. Dataset After Preprcessing

No	*Worthlessness*	*Concentration*	*Suicidal Ideation*	*Sleep Disturbance*	*Hopelessness*	*Low Energy*	*Depression State*
1	5	1	5	1	5	5	*Mild*
2	1	5	1	5	1	1	*Moderate*
…	…	…	…	…	…	…	...
540	2	2	2	2	2	2	*Moderate*

2.3 Data Analysis Method

The data analysis process is carried out through several stages, including fuzzification, inference, and defuzzification [16], [17]. Each input variable is mapped into a fuzzy membership function to convert crisp values into fuzzy values. Then, fuzzy rules are applied to determine the fuzzy output based on the combination of inputs. This inference process activates the predefined fuzzy rules. Afterward, the fuzzy results are converted back into crisp values through the defuzzification process. Below is a more detailed explanation of each stage:

1. Fuzzification

   At the fuzzification stage, each main symptom variable is formulated in the form of a membership function, which is divided into three categories: Low, Moderate, and High. The membership function used is the triangular membership function, which is commonly used in fuzzy logic due to its simplicity in representing membership degrees. **Table 3** is the input table and labels used:

Table 3. Membership of Each Input Variable

Variable	Range Crisp Input	Label Fuzzy	Membership Function (Range Fuzzy)
Worthlessness	1-6	*Low*	[1, 1, 3]
		Moderate	[1,3,6]
		High	[3, 6, 6]
Concentration	1-6	*Low*	[1, 1, 3]
		Moderate	[1,3,6]
		High	[3, 6, 6]
Suicidal Ideation	1-6	*Low*	[1, 1, 3]
		Moderate	[1,3,6]
		High	[3, 6, 6]
Sleep Disturbance	1-6	*Low*	[1, 1, 3]
		Moderate	[1,3,6]
		High	[3, 6, 6]
Hopelessness	1-6	*Low*	[1, 1, 3]
		Moderate	[1,3,6]
		High	[3, 6, 6]

This triangular membership function is defined by three main points: the starting point, the peak point, and the end point. For example, the membership function for the Low category on the worthlessness variable takes the shape of a triangle with a value range of [1, 1, 3], where the membership value is 1 at point 1 and decreases to 0 at point 3. The general formula for the triangular membership function is as follows:

$$\mu_{segitiga}(x;a,b,c) = \begin{cases} 0 & jika\ x \leq a \\ \dfrac{x-a}{b-s} & jika\ a < x \leq b \\ \dfrac{c-x}{c-b} & jika\ b < x \leq c \\ 0 & jika\ x \geq c \end{cases} \quad (1)$$

2. Inference Engine

Inference is the process where the predefined fuzzy rules are used to determine the fuzzy output based on the fuzzy input values generated from fuzzification [18], [19]. In this study, a total of 243 rules are applied based on the fuzzy combinations of five input variables. Each rule has an "IF-THEN" condition that determines the output category, whether it is No Depression, Mild, Moderate, or Severe.
Below are some examples of the fuzzy rules used.

a. If Worthlessness is Low and Concentration is Low and Suicidal Ideation is Low and Sleep Disturbance is Low and Hopelessness is Low, Then Depression Level is No Depression.
b. If Worthlessness is Moderate and Concentration is Moderate and Suicidal Ideation is Moderate and Sleep Disturbance is Moderate and Hopelessness is Moderate, Then Depression Level is Moderate.
c. If Worthlessness is High and Concentration is High and Suicidal Ideation is High and Sleep Disturbance is High and Hopelessness is High, Then Depression Level is Severe.
d. If Worthlessness is High and Concentration is High and Suicidal Ideation is Low and Sleep Disturbance is Moderate and Hopelessness is High, Then Depression Level is Severe.

Algorithm 1 Pseudocode to create 243 fuzzy rules

```
START
fuzzy_labels = ['Low', 'Moderate', 'High']
rules = []
for worth in fuzzy_labels:
    for conc in fuzzy_labels:
        for suicide in fuzzy_labels:
            for sleep in fuzzy_labels:
                for hope in fuzzy_labels:
                    depression_level = determine_depression (worth, conc, suicide, sleep, hope)
                    rules.append (f"IF Worthlessness is {worth} AND Concentration is {conc} "
                        f"AND Suicidal Ideation is {suicide} AND Sleep Disturbance is {sleep} "
                        f"AND Hopelessness is {hope} THEN Depression is {depression_level}")
```

The `determine_depression()` function determines the output based on the frequency of High and Moderate occurrences in the input variable combinations. This function follows the logic that the more High or Moderate categories present, the higher the depression level that is produced.

3. Defuzzification:

The defuzzification process is the final stage in the fuzzy system, where the fuzzy output is converted back into a crisp or concrete value that can be interpreted [20], [21]. Defuzzification is performed using the centroid method, which calculates the center of mass of the fuzzy area generated [22]. The resulting crisp value represents the predicted depression level based on the given inputs. The centroid formula is as follows:

$$Crisp\ Output = \frac{\sum \mu(x) \cdot x}{\sum \mu(x)} \quad (2)$$

Where is the fuzzy membership degree for a certain output value. Based on the defuzzification result, the generated value will be mapped into the depression level labels as follows:

No Depression = 0-25

Mild = 25-50
Moderate = 50-75
Severe = 75-100

Thus, defuzzification results in a definite (crisp) value that is interpreted as No Depression, Mild, Moderate, or Severe. This value is the final output of the model and will be compared between two platforms (Python and LabVIEW) to assess the consistency of the depression level prediction results.

3. Results and Discussion:

Results

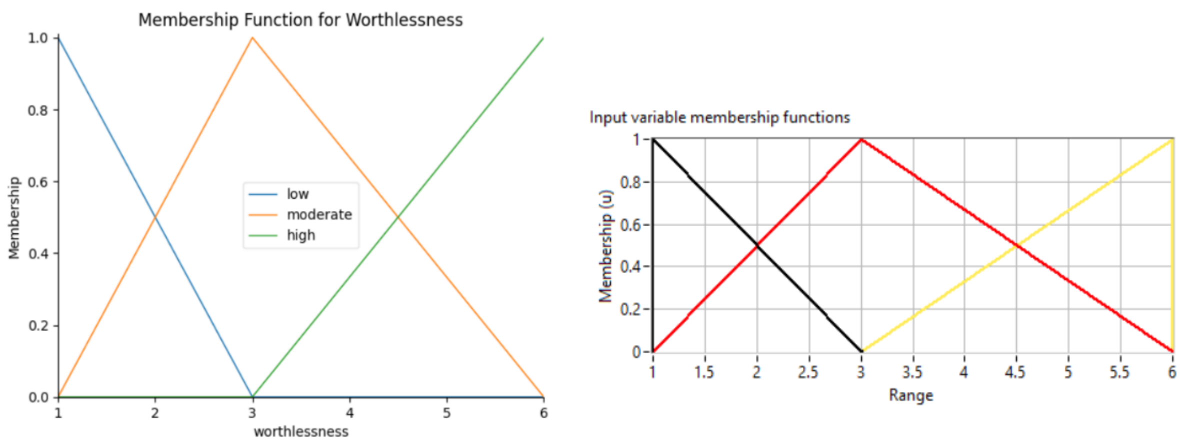
The fuzzification implementation stage in this study is carried out by converting the numerical values of each symptom variable into fuzzy values according to the predefined membership functions. Variables such as Worthlessness, Concentration, Suicidal Ideation, Sleep Disturbance, and Hopelessness are classified into three categories: Low, Moderate, and High using the triangular membership function. For example, a worthlessness value between 1 and 6 is classified as Low (range [1, 1, 3]), Moderate (range [1, 3, 6]), or High (range [3, 6, 6]), where each value receives a proportional membership degree. This fuzzification stage is crucial for converting quantitative data into linguistic data that can be further processed in fuzzy rules. The image below shows the membership functions for each input variable.

1. Fuzzification:

The fuzzification stage in this study involves converting the numerical values of each symptom variable into fuzzy values based on predefined membership functions. Variables such as *Worthlessness*, *Concentration*, *Suicidal Ideation*, *Sleep Disturbance*, and *Hopelessness* are classified into three categories: **Low**, **Moderate**, and **High** using triangular membership functions. For instance, *Worthlessness* values ranging from 1 to 6 are classified as Low ([1, 1, 3]), Moderate ([1, 3, 6]), or High ([3, 6, 6]), with each value assigned a proportional membership degree.

a. This fuzzification process is essential to transform quantitative data into linguistic data, which can be further processed within fuzzy rules. The figure below illustrates the membership functions for each input variable.

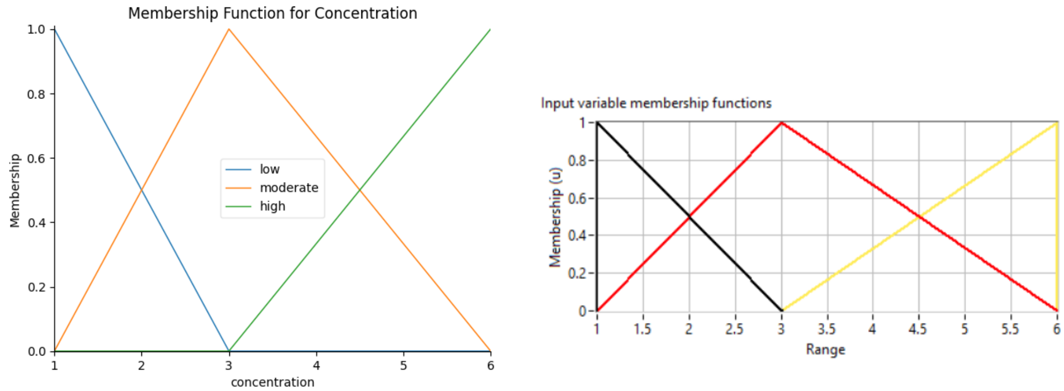
b. Membership Function for the Worthlessness Variable



(a) (b)

Figure 2. Membership function for the Worthlessness variable (a) Python, (b) LabVIEW

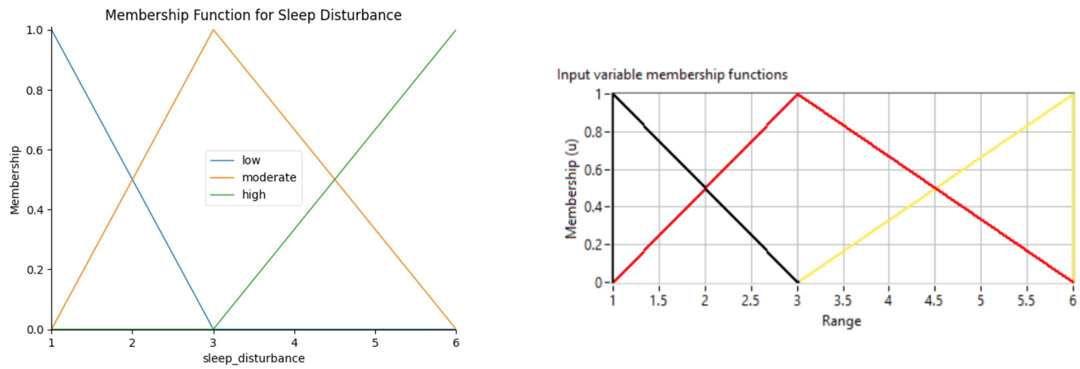
c. Membership Function for the Concentration Variable



(a) (b)

Figure 3. Membership function for the Concentration variable (a) Python, (b) LabVIEW

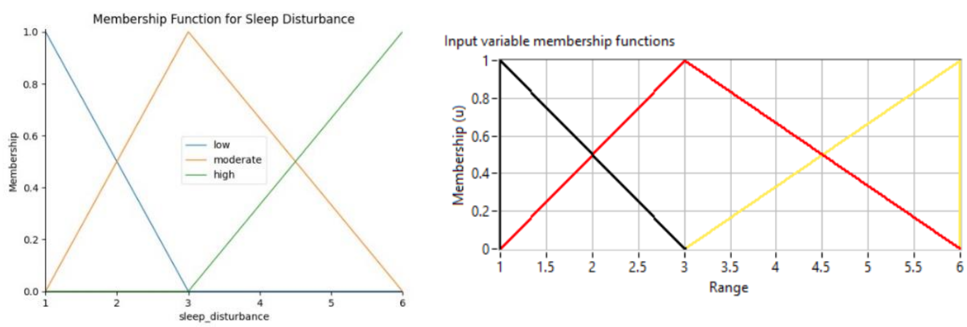
d. Membership Function for the Suicidal Ideation Variable



(a) (b)

Figure 4. Membership function for the Suicidal Ideation variable (a) Python, (b) LabVIEW

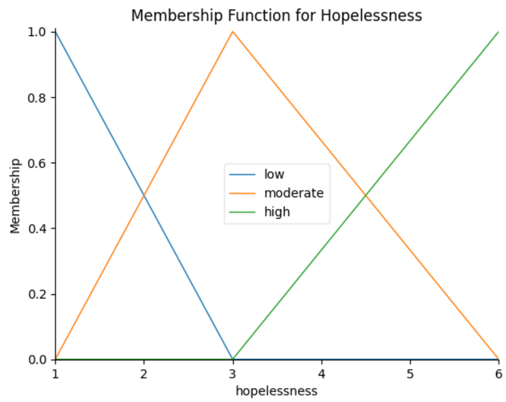
e. Membership Function for the Sleep Disturbance Variable



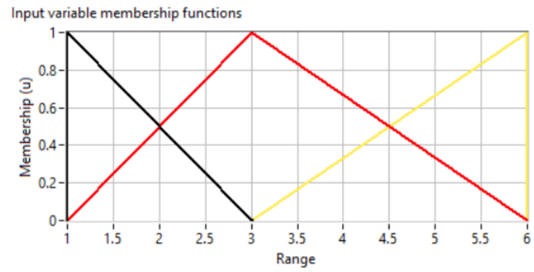
(a) (b)

Figure 5. Membership function for the Sleep Disturbance variable (a) Python, (b) LabVIEW

f. Membership Function for the Hopelessness Variable



(a)



(b)

Figure 6. Membership function for the Hopelessness variable (a) Python, (b) LabVIEW

Figures 2 to **6** show the three fuzzy categories generated: Low, Moderate, and High. For example, if someone has a Worthlessness score of 4, the value will fall into both the Moderate and High categories with specific membership degrees.

2. Inference Engine:

After the fuzzification process, each combination of fuzzy categories from the symptom variables generates an output for the depression level, calculated using the 243 fuzzy rules that have been set. This inference process is carried out in both Python and LabVIEW, with each rule serving to determine the output based on the given combination of symptoms. Below are some examples of the fuzzy rules applied:

Rule 1: If all input variables are in the High category, then the depression level output is Severe.

Rule 2: If most input variables are in the Moderate category, then the depression level output is either Moderate or Mild, depending on the proportion of higher input values.

These rules cover various combinations of inputs, allowing the system to map different patient conditions to the appropriate depression level. Inference is performed for each patient based on their inputs, and the fuzzy output representing the depression level is obtained from the combination of relevant rules [23], [24].

3. Defuzzification:

Defuzzification is the final step in this fuzzy system, where the fuzzy values generated from the inference process are converted into crisp values that can be interpreted quantitatively. The method used is the centroid method, which calculates the center of gravity of the area under the fuzzy output membership function curve [25]–[27].

Figure 7 shows the membership function for the Depression variable, indicating the defuzzification results:

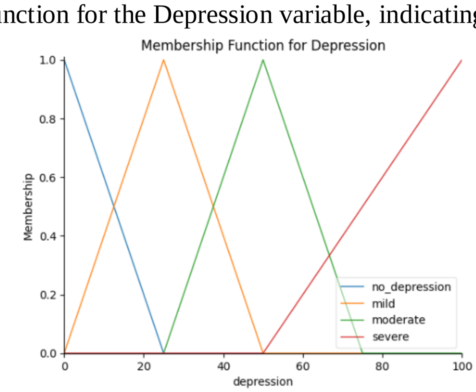


Figure 7. Membership function for the Hopelessness variable (a) Python, (b) LabVIEW

This membership function divides the depression level into four categories: No Depression (0-25), Mild (25-50), Moderate (50-75), and Severe (75-100). The final result of defuzzification is a crisp value that is mapped to one of these categories based on the patient's condition.

4. Comparison Analysis: To evaluate the performance of both models, several experiments were conducted with various combinations of input values representing different intensities of symptoms. In Experiment 1, the defuzzification result in Python produced a depression level of 37.5, classified as Mild, while the result from LabVIEW was 37.4966, with an error of 0.0034. Experiment 2 showed a defuzzification result of 8.333 in Python (classified as No Depression) and 8.34447 in LabVIEW, with an error margin of 0.0111. In Experiment 3, Python produced a value of 60.748, classified as Moderate, while LabVIEW produced 60.7447, with an error of 0.0041. The results of these three experiments are presented in tables and graphs to clarify the differences and error margins between the platforms.

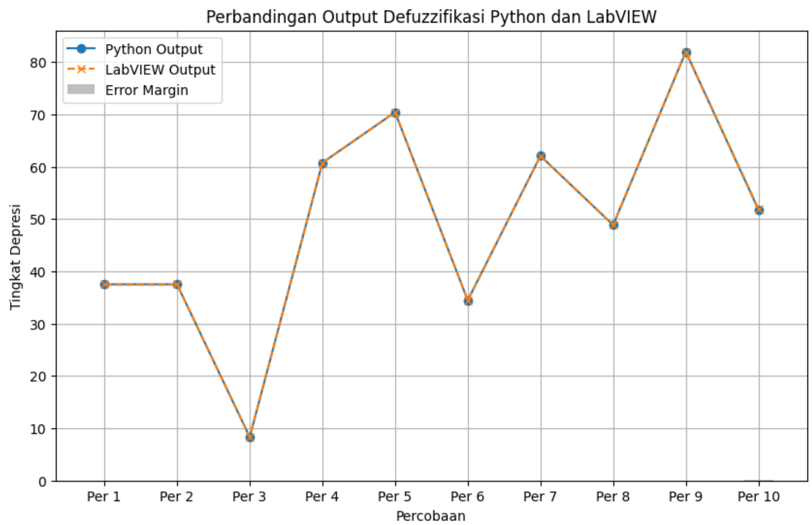


Figure 8. Comparison Graph of Defuzzification Results in Python and LabVIEW

Figure 8 shows the comparison of depression level defuzzification results between the Python and LabVIEW implementations for each experiment. The blue line with circular markers represents the results from Python, while the orange line with cross markers represents the results from LabVIEW. In addition, the margin of error for each experiment is displayed as grey bars, showing the small differences between the results in each trial. This visualization demonstrates that the difference between the two platforms is minimal, indicating consistency in the depression level prediction results.

Discussion

Table 4. Experiment Results

Test	Symptom Input	Python (Output)	LabVIEW (Output)	Depression Label	Erorr Rate
1	2, 2, 2, 3, 4	37.5	37.4966	Mild	0.0034
2	1, 2, 3, 4, 5	37.5	37.4966	Mild	0.0034
3	1, 1, 1, 1, 1	8.3333	8.34447	No Depression	0.0111
4	4, 4, 6, 4, 6	60.7487	60.7447	Moderate	0.0041
5	5, 6, 5, 6, 4	70.4106	70.4114	Mild	0.0008
6	1, 2, 3, 1, 2	34.4697	34.4618	Moderate	0.0079
7	4, 5, 6, 2, 3	62.0596	62.0566	Moderate	0.003
8	2, 2, 4, 4, 6	48.8465	48.8508	Mild	0.0043
9	6, 6, 4, 4, 6	81.9444	81.9398	Severe	0.0046

Test	Symptom Input	Python (Output)	LabVIEW (Output)	Depression Label	Erorr Rate
10	1, 2, 6, 4, 5	51.7798	51.9576	Moderate	0.1778

The results from Table 4 show that the fuzzy model in Python and LabVIEW produce very similar results, with very small error margins in each experiment. The visualization graph of the membership function for each symptom and the depression level output is also displayed to illustrate the degree of membership for each input value, showing how each input is interpreted within the fuzzy context. This visualization provides a clear view of how the fuzzy process converts numerical data into linguistic information that can be processed in the fuzzy model.

In the results interpretation stage, the small differences between the outputs in Python and LabVIEW indicate that both platforms are capable of generating similar depression level estimates with high accuracy. The small errors that occur may be due to differences in the centroid function implementation algorithms on each platform, although overall, both platforms can produce consistent results. The small margin of error suggests that the difference between Python and LabVIEW is not significant in this context, so both platforms can be considered effective in applying the fuzzy model for depression level prediction. When compared to previous studies, these results show that fuzzy logic is a reliable method for analysing depression levels based on key symptoms that are subjective and often overlapping. Previous studies also show that fuzzy logic is effective in handling ambiguous and unstructured data, which is consistent with the results of this study. For example, [28] in their research applied the Mamdani Fuzzy method to detect work-related depression levels in elementary school teachers, using the Body Mass Index (BMI) and PHQ-9 scores as the main input variables. This finding reinforces the relevance of fuzzy logic in addressing uncertainty in clinical data, which often exhibits ambiguous characteristics.

Although the results of this study are promising, there are several limitations that need to be considered. One of them is the accuracy of the tool, which is influenced by the selection of membership functions and the rules set, which can directly affect the defuzzification results. The subjective nature of rule-setting and membership definitions also allows for variation in outcomes depending on the perception or domain knowledge of the model developer. Furthermore, since this model is limited to five key symptom variables, there is a limitation in capturing the full complexity of depression conditions. Future research is encouraged to add more relevant clinical variables or combine techniques such as machine learning to improve the accuracy and generalization ability of this model.

4. Conclusion

The results of this study show that both platforms are capable of producing very similar depression level predictions, with very small error margins in each experiment. The error margin below 0.01 between Python and LabVIEW confirms that both platforms generate nearly identical and consistent predictions despite slight differences in their internal computational approaches. This indicates that both Python and LabVIEW are accurate and reliable platform choices for applying fuzzy models in the context of depression level prediction. These results are relevant for further research and practical applications, where fuzzy models can be used as tools for the initial assessment of depression conditions in clinical settings. Additionally, this study reinforces the evidence that fuzzy logic is an effective approach for handling uncertainty in clinical data, particularly in mental health conditions, which often lack clear-cut category boundaries. The fuzzy model used in this study successfully addressed ambiguities in the assessment of symptoms that are poorly structured, and it generated results that can be interpreted within a clinical context. This aligns with previous studies that highlight the advantages of fuzzy logic in dealing with subjective and uncertain data, especially in the field of mental health.

However, this study has some limitations that need to be addressed. One limitation is the subjectivity in defining membership functions and fuzzy rules, which, although based on general principles, are still influenced by the perceptions of the model developers. Additionally, this study only covers five key symptom variables and does not take into account other complexities that may affect an individual's depression level, such as environmental factors or additional psychological variables. Future research is encouraged to add more relevant variables or combine this fuzzy model with machine learning approaches to improve accuracy and predictive power. Overall, this study contributes to the development of an accurate and reliable fuzzy logic-based prediction tool and strengthens the evidence for the effectiveness of fuzzy models in mental health analysis. The findings of this research are expected to serve as a foundation for further development and practical application in the early diagnosis of depression. These findings also open opportunities for applying similar models in various clinical or psychological contexts, with the potential to create diagnostic tools that are accessible, efficient, and technology-based.

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