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Research Article

Sugeno Fuzzy Personality Prediction System: An Approach to Overcoming Psychological Measurement Uncertainty

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Abstract:

Personality prediction is a significant field in psychological measurement, yet it faces challenges due to psychological data's ambiguous and uncertain nature. This study aims to develop a Sugeno-based fuzzy logic system for predicting personality types according to the Myers-Briggs Type Indicator (MBTI). The dataset includes synthetic personality data, incorporating age, introversion, sensing, thinking, and judging. The fuzzification process converts crisp input values into fuzzy variables, which are then processed using predefined fuzzy rules to generate personality predictions. The defuzzification step yields crisp outputs corresponding to MBTI types, demonstrating the system's ability to handle uncertainty and ambiguity effectively. Implementation and evaluation were conducted using Python and LabVIEW, revealing a satisfactory performance with a low error rate of 0.445. This study highlights the potential of fuzzy logic, particularly the Sugeno method, in enhancing accuracy and adaptability in personality prediction, contributing to applications in education, human resource management, and personalized digital services.

Keywords: Fuzzy Logic Sugeno, Uncertainty, MBTI, Psychological Measurements, Personality Prediction
Dataset link: https://www.kaggle.com/datasets/stealthtechnologies/predict-people-personality-types

1. Introduction

Personality prediction is a growing field of research, along with advances in information technology and machine learning. One of the most commonly used approaches in personality analysis is the Big Five personality model or Myers-Briggs Type Indicator (MBTI), which classifies individual personalities based on five main dimensions: extroversion, agreeableness, conscientiousness, openness to experience, and neuroticism [1]. These dimensions describe how individuals respond to situations and their preferences in making decisions and interacting with the environment [2]. MBTI has been widely applied in human resource management, education, and clinical psychology, demonstrating its success in understanding individuals' psychological preferences [3].

However, traditional methods such as interviews and questionnaires have limitations in capturing the complexity of a person's personality, mainly due to the nature of the data, which is often ambiguous and complex to measure objectively [4]. This uncertainty in measurement is due to differences in individual perceptions, variations in question interpretation, and the influence of external factors on responses [5], [6]. In recent years, technology-based approaches such as machine learning and natural language processing (NLP) have been used to overcome these challenges, enabling more in-depth and accurate data analysis [7], [8]. For example, digital data from social media provides a rich source of information for identifying personality patterns using machine learning algorithms [9], [10].

Machine learning-based approaches have shown great potential in improving the accuracy of personality prediction. Previous research successfully developed MBTI-based personality prediction models using text analysis from social media, resulting in higher accuracy rates than traditional methods [11], [12]. However, measuring psychological preferences still faces the challenge of uncertainty, which can affect the prediction results [5]. This uncertainty requires methods that can handle ambiguous data flexibly and adaptively.

Fuzzy logic, introduced by Zadeh in 1965, offers an approach to handle ambiguous data through fuzzy set modeling [13]. With its flexibility in modeling qualitative psychological variables, fuzzy logic has been widely used to improve the accuracy of personality prediction systems [14]. Sugeno's fuzzy method, in particular, is well suited to map ambiguous input variables into concrete outputs through fuzzy rules, making it an efficient tool in MBTI personality type classification [15], [16]. The advantage of this method is its ability to manage incomplete or qualitative data, allowing the system to adapt to input variations [17].

In addition, fuzzy logic has been used to improve prediction accuracy in high-complexity contexts. Research shows that type-2 fuzzy logic can be combined with deep learning models such as Long Short-Term Memory (LSTM) to predict uncertain psychological variables, providing more accurate results in scenarios such as behavioral and personality analysis [13]. This approach shows that integrating fuzzy logic and machine learning can lead to a deeper understanding of personality, especially in complex digital environments [18].

Fuzzy logic has also proven effective in various fields, such as academics and management. A study [19] shows how fuzzy logic can map the relationship between personality variables and individual learning outcomes, providing deeper insight into the influence of personality on academic achievement. With research supporting the superiority of fuzzy logic in handling data uncertainty, this study aims to develop a Sugeno fuzzy-based personality prediction system capable of overcoming ambiguity in psychological data. By utilizing fuzzification techniques, the model is expected to provide more accurate and relevant predictions for information technology applications, such as human resource management, education, and digital service personalization [20].

2. Method

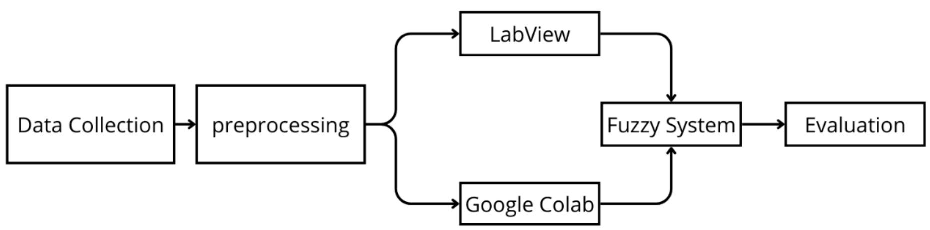


Figure 1. Research Method

This chapter describes the steps used in this research to develop a Sugeno fuzzy logic-based personality type prediction system. The process begins with the use of relevant data sets, followed by the steps of fuzzification to handle data uncertainty, inference to determine predictions based on fuzzy rules, and defuzzification to produce a clearly defined output. Finally, the specifications of the tools and platforms used, namely Google Colab and LabVIEW, are discussed to demonstrate the overall system implementation.

Dataset

The dataset used in this research is the Predict People Personality Types: Synthetic Personality Dataset for Predicting MBTI Types, which is available on the Kaggle platform [21]. This dataset was created to help predict MBTI (Myers-Briggs Type Indicator) personality types from various psychological variables. This dataset contains synthesized data, meaning that it has been artificially designed to mimic real behavioral patterns found in human personality.

Each entry in this data set represents an individual with a number of input variables, such as scores for Introverted, Sensing, Thinking, and Judging, which are part of the MBTI personality dimensions. The output of this data set is one of the 15 MBTI personality types, such as ENTP, INFJ, or ISFP. This dataset has important applications in training machine learning models or fuzzy systems to classify and understand a person's personality type based on relevant psychological input variables [22], [23].

Fuzzification

In the implementation of Sugeno-based fuzzy logic method, the fuzzification process is performed to convert the crisp input or numerical input given by the user into fuzzy values. This fuzzification allows the system to handle ambiguous or uncertain data and categorize it into relevant fuzzy sets. Fuzzy logic is known to be effective in dealing with uncertainty in data that is not well structured or has the nature of ambiguity, especially in psychological contexts such as personality type prediction [24].

a. Input

The input to this system consists of five main variables relevant to the MBTI dimensions, namely Age, Introversion, Sensing, Thinking, and Judging. Age is expressed in integers ranging from 0 to 100 and categorized into three fuzzy sets: young, middle-aged, and old. Meanwhile, the user's level of introversion is expressed on a scale from 0 to 10 and categorized into three fuzzy sets: low, medium, and high. The sensing, thinking, and judging variables also use a 0-10 scale, and each has the same fuzzy categories of low, medium, and high. This fuzzification process helps handle input data that is subjective or uncertain, and categorizes the data into fuzzy sets that are easier for the system to understand [25].

b. Output

In the Sugeno method, this crisp output is generated through a defuzzification process where the crisp value is mapped to one of the 16 MBTI personality types. The 16 personality types are ESFP, INTJ, INFP, INFJ, ENTP, ENFJ, ISFP, ESTJ, ENTJ, ESFJ, ISTJ, ENFP, INTP, ISFJ, ISTP, and ESTP [26]. This personality prediction is based on the four main dimensions of the MBTI, namely Extroversion-Introversion (E/I), Sensing-Navigating (S/N), Thinking-Feeling (T/F), and Judging-Perceiving (J/P). The MBTI has long been used as a valid method for assessing and predicting a person's psychological and behavioral preferences based on these dimensions [27]. Input and output fuzzy system show ini **Table 1**.

Table 1. Input and Output Fuzzy System

Input and Output	Label	Range
Introversion	Low	0-5
	Medium	4-7
	High	6-10
Sensing	Low	0-5
	Medium	4-7
	High	6-10
Thinking	Low	0-5
	Medium	4-7
	High	6-10
Judging	Low	0-5
	Medium	4-7
	High	6-10
Age	Young	0-30
	Middle-Aged	20-60
	Old	50-100
Personality	ESFP, INTJ, INFP, INFJ, ENTP, ENFJ, ISFP, ESTJ, ENTJ, ESFJ, ISTJ, ENFP, INTP, ISFJ, ISTP, dan ESTP	0-15

Inference Engine

The inference process in this fuzzy system is based on fuzzy rules defined in CSV files, where each rule combines various input variables to determine the output. These fuzzy rules are formulated based on a combination of fuzzy values on input variables such as age, introvert, feeling, thinking, and judging. For example, a rule might look like this: If Age is "young" and Introversion is "high" and Sensing is "low" and Thinking is "high" and Judging is "medium", then the personality is ENTP. These rules are taken from the CSV file and implemented in the code to run the inference process using the Sugeno method. Under the Sugeno method, each fuzzy rule can produce a linear or constant output function, which helps to minimize the complexity of inference and improve the efficiency of handling fuzzy inputs [28], [29]. To extract these rules from a .csv file and set up the fuzzy rules used in the system, the following code is used:

Algorithm 1 Pseudocode to create fuzzy rules

```
def generate_sugeno_rules_from_csv(rules_df, personality_map):
    fuzzy_rules = []
    for _, row in rules_df.iterrows():
    rule = {
         "age_term": row['Age'],
         "introversion_term": row['Introversion'],
         "sensing_term": row['Sensing'],
         "thinking_term": row['Thinking'],
         "judging_term": row['Judging'],
          "output": personality_map.get(row['Personality'], 0)
        }
        fuzzy_rules.append(rule)
       return fuzzy_rules
import pandas as pd
file_path = '/content/Updated_Personality_Rules_No_Unknown.csv'
updated_personality_rules = pd.read_csv(file_path)
PERSONALITY_MAP = {
    'ESFP': 0, 'INTJ': 1, 'INFP': 2, 'INFJ': 3,
    'ENTP': 4, 'ENFJ': 5, 'ISFP': 6, 'ESTJ': 7,
    'ENTJ': 8, 'ESFJ': 9, 'ISTJ': 10, 'ENFP': 11,
    'INTP': 12, 'ISFJ': 13, 'ISTP': 14, 'ESTP': 15
 }
```

In this code, the generate_sugeno_rules_from_csv function reads the rules from a CSV file using the pandas library. Each rule is defined by the fuzzy terms for variables such as Age, Introversion, Sensing, Thinking, and Judging, and the corresponding Personality Type (e.g., ENTP, ISFP). These rules are then appended to a list that can be used in the inference process. By using this feature, the fuzzy rules in the CSV file are dynamically incorporated into the system, allowing for easy updates and scalability of the fuzzy logic model. The PERSONALITY_MAP dictionary is used to map the personality types to corresponding integer values, which are used as the output of the fuzzy rules.

Defuzzification

The defuzzification method used in this system is the Sugeno method. In this method, the output of the fuzzy system in the form of a crisp value is calculated as a weighted average of all the activated rules. Each rule has a singleton output, and the final value is determined by taking the weighted average of these outputs based on the membership degree of each activated rule. With Sugeno's approach, the system becomes more efficient in handling the many outputs required to predict MBTI personality types because the defuzzification process uses a weighted average method that avoids the complexity found in traditional defuzzification methods [30], [31].

Tool and Platform Specifications

In this research, two main platforms are used to implement and run the fuzzy system, namely Google Colab and LabVIEW. Both play an important role in comparing the performance and results of the Sugeno-based fuzzy system implementation. Colaboratory, another name for Google Colab, is a cloud-based platform specifically designed for data science and machine learning studies. The platform is ideal for building fuzzy logic systems and performing computational activities that require GPU acceleration, as it provides a free and scalable environment in which to run Python code. A number of libraries, including scikit-learn and scikit-fuzzy, are supported by Colab and are required for implementing fuzzy logic and machine learning. Because it is cloud-based, users can perform a variety of operations, ranging from basic educational tools to sophisticated machine learning models, without having to set up a local computer for complex computations [32]. In addition, studies have shown that Google Colab is very effective at clustering tasks and other machine learning processes that benefit from an accessible cloud environment. Other benefits include easy code sharing and collaboration, and integration with Google Drive for easily accessible data storage [33]. LabVIEW is a powerful visual programming language widely used for simulation and hardware interfacing in automation and control systems. The Fuzzy Logic Toolkit, which allows users to design, model, and implement fuzzy controllers for various real-world applications, facilitates the integration of fuzzy logic systems. LabVIEW is often used in educational environments to teach students about fuzzy logic and control systems because of its graphical nature, which simplifies the process of creating fuzzy control systems. For example, LabVIEW is a perfect tool for learning and using fuzzy control theory because of its user-friendly interface, which makes it easy to manipulate fuzzy rules and membership functions [34]. In addition, LabVIEW is used in industry and academia for remote laboratory experiments, enabling data acquisition and remote control through its interface with PLCs and OPC protocols [35]. In this research, LabVIEW will be used as a comparison with the fuzzy system created using Google Colab because of its flexibility and graphical interface that allows visualization and direct interaction with the fuzzy model.

3. Result and Discussion

Result

In this section, it will be shown how the research results using Sugeno fuzzy for predicting a person's personality type. There are 3 existing results, namely fuzzyfication results, inference results and defuzzification results. Fuzzyfication will produce fuzzy output, then will go to inference to produce fuzzy output and finally defuzzification is done to get crisp output. The process may look like the following **Figure 2**:

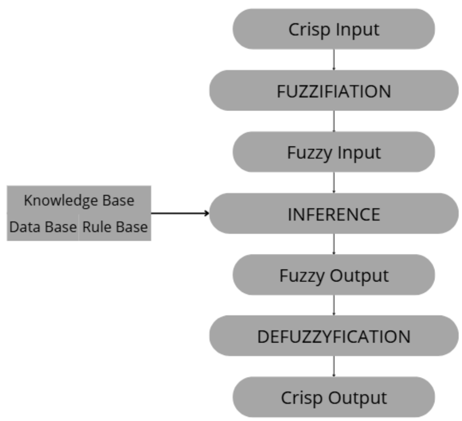
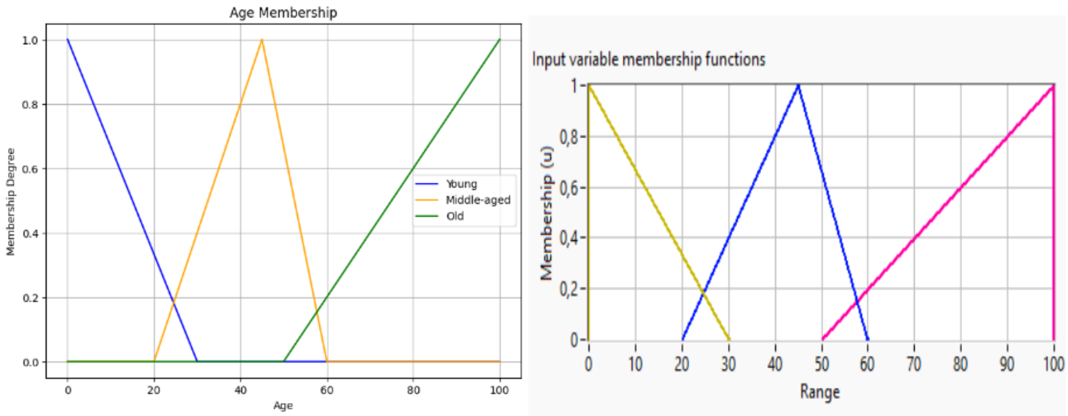


Figure 2. Fuzzy Process

In the fuzzification stage, the collected crisp inputs are transformed into fuzzy inputs through membership functions. This process is done for five main variables, namely age, introversion, feeling, thinking and judging. Each variable has three fuzzy categories, which are used to categorize the input data into more fuzzily defined levels.

1. Age

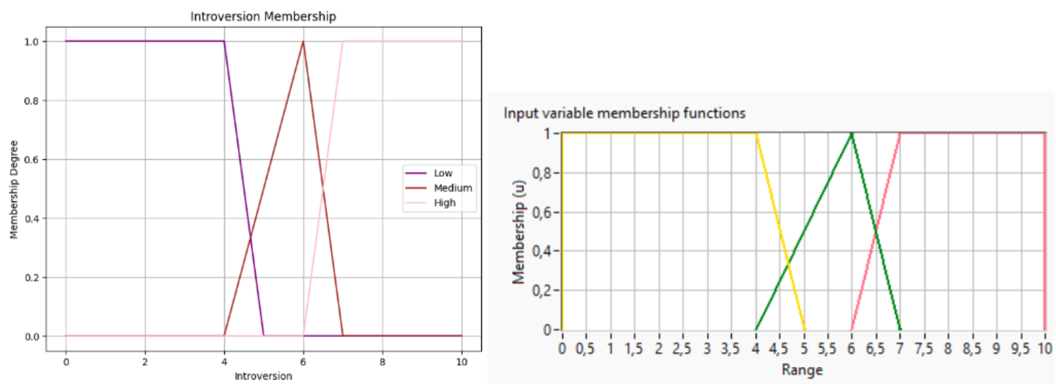
   The age variable is categorized into three fuzzy sets: young, middle-aged, and old. The age membership function is shown in **Figure 3**, where young age has a high membership degree at ages below 20, while old age starts to gain membership degree at ages above 60.



(a) (b)

Figure 3. Age Membership (a) python, (b) labview

2. Introversion

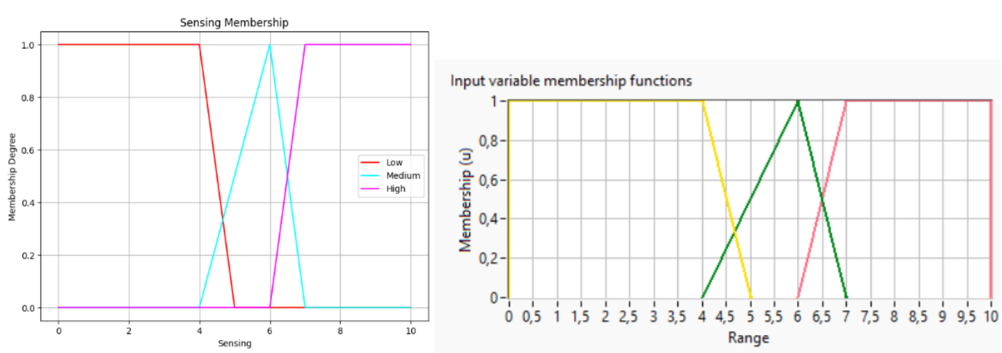


(a) (b)

Figure 4. Introversion Membership (a) python, (b) labview

The introversion variable is divided into three fuzzy categories: low, medium, and high. These membership functions can be seen in **Figure 4**, where the highest degree of membership for low introversion is on a scale of 0-4, and high introversion starts on a scale above 6.

3. Sensing

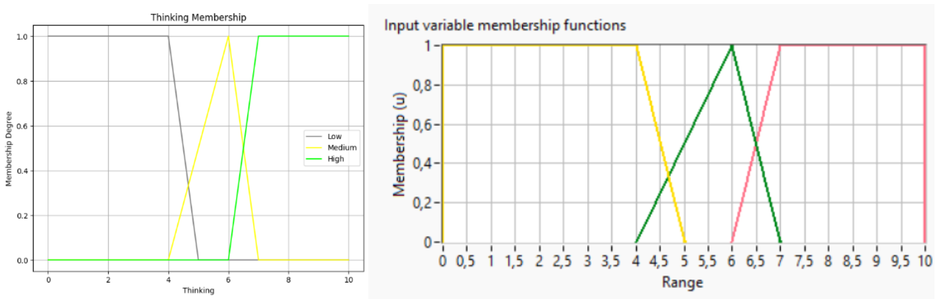


(a) (b)

Figure 5. Sensing Membership (a) python, (b) labview

This variable is also divided into three fuzzy categories: low, medium, and high, as shown in **Figure 5**. Low sensing starts on a scale of 0-4, medium on a scale of 4-6, and high on a scale above 6.

4. Thinking:

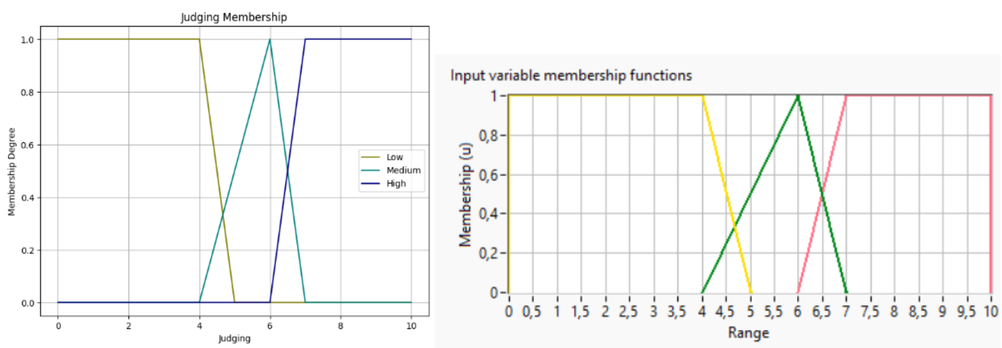


(a) (b)

Figure 6. Thinking Membership (a) Python, (b) LabVIEW

Thinking is similarly categorized into low, medium, and high fuzziness, with membership functions as shown in **Figure 6**. Low thinking has a high degree of membership on a scale of 0-4, and high thinking has a high degree of membership on a scale of 6 and above.

5. Judging:



(a) (b)

Figure 7. Judging Membership (a) python, (b) LabVIEW

The last variable, judging, is categorized into low, medium and high fuzzy, with the fuzzification results shown in **Figure 7**. Low judging starts on a scale of 0-4, while the high category is on a scale above 6. To illustrate how the fuzzification process works, let's evaluate the following sample input data: 'age': 22, 'introversion': 4.5, 'Sensing': 6.5, 'Thinking': 4.2, 'Judging': 6.1. The fuzzification process will convert these crisp values into fuzzy inputs based on the predefined membership functions for each variable. Below are the fuzzification results for each input variable:

Table 2. Fuzzification Result

Variable	Input	Membership
Age	30	Young: 0
		Middle-Aged: 1
		Old: 0
Introversion	4.4	Low: 0.74
		Medium: 0.26
		High: 0
Sensing	6.7	Low: 0.00
		Medium: 0.26
		High: 0.74
Thinking	4	Low: 0.98
		Medium: 0.02
		High: 0
Judging	6.7	Low: 0.00
		Medium: 0.33

Variable	Input	Membership
		High: 0.67

In the fuzzy inference stage, the fuzzy rules defined earlier are used to determine the output based on a combination of fuzzy values in the input variables. This process uses the MIN operator to determine the lowest membership degree of the variables involved in each rule, and the final result uses the MAX operator for each fuzzy output. Table 3 inference results for the example input data:

Table 3. Min Inference Engine Operator Results

Rule	Output	Minimum Membership Degree
IF age is Middle-aged AND introversion is Low AND sensing is Medium AND thinking is Low AND judging is Medium	2	0,26
IF age is Middle-aged AND introversion is Low AND sensing is Medium AND thinking is Low AND judging is High	2	0,26
IF age is Middle-aged AND introversion is Low AND sensing is Medium AND thinking is Medium AND judging is Medium	2	0,02
IF age is Middle-aged AND introversion is Low AND sensing is Medium AND thinking is Medium AND judging is High	1	0,02
IF age is Middle-aged AND introversion is Low AND sensing is High AND thinking is Low AND judging is Medium	6	0,33
IF age is Middle-aged AND introversion is Low AND sensing is High AND thinking is Low AND judging is High	6	0,4
IF age is Middle-aged AND introversion is Low AND sensing is High AND thinking is Medium AND judging is Medium	14	0,02
IF age is Middle-aged AND introversion is Low AND sensing is High AND thinking is Medium AND judging is High	13	0,02
IF age is Middle-aged AND introversion is Medium AND sensing is Medium AND thinking is Low AND judging is Medium	2	0,21
IF age is Middle-aged AND introversion is Medium AND sensing is Medium AND thinking is Low AND judging is High	2	0,21
IF age is Middle-aged AND introversion is Medium AND sensing is Medium AND thinking is Medium AND judging is Medium	2	0,02
IF age is Middle-aged AND introversion is Medium AND sensing is Medium AND thinking is Medium AND judging is High	2	0,02
IF age is Middle-aged AND introversion is Medium AND sensing is High AND thinking is Low AND judging is Medium	0	0,21
IF age is Middle-aged AND introversion is Medium AND sensing is High AND thinking is Low AND judging is High	0	0,21
IF age is Middle-aged AND introversion is Medium AND sensing is High AND thinking is Medium AND judging is Medium	0	0,02
IF age is Middle-aged AND introversion is Medium AND sensing is High AND thinking is Medium AND judging is High	9	0,02

Table 4. Max Inference Operator Results

Output	Label	Activation
0	ESFP	0.21
1	INTJ	0.02
2	INFP	0.26
6	ISFP	0.4
9	ESFJ	0.02
13	ISFJ	0.02
14	ISTP	0.02

After the inference process, the final stage is defuzzification using the Sugeno method, where the crisp value is calculated as a weighted average of all activated rules. Each rule has an output and an activation value, and the output with the maximum activation value is selected. If more than one rule has the same activation value, the average of the outputs of the rules is calculated. In the example data, the final result of this defuzzification process is the ISFP personality type, which appears with the highest activation.

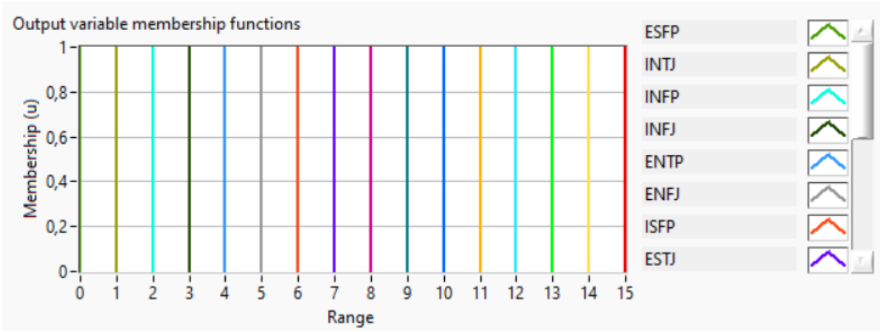


Figure 8. Personality Output Singleton

After obtaining the results of the fuzzy system made, then an evaluation is done using Labview to see what the resulting error rate is. Both are given input 10 times with different inputs in each trial. The final results are recorded and the average error is found. Below is a **Table 5** with the results of 10 trials.

Table 5. Comparison of python and LabVIEW

No	Input Variable	Python	LabVIEW	Error
1	22, 4.5, 6.5, 4.2, 6.1	4.89	3.36	1.53
2	55, 4.3, 4.5, 6.2, 7.1	4.85	4.85	0
3	55, 4.3, 4.5, 6.2, 6.1	7.80	7.49	0.30
4	55, 4.3, 6.5, 6.2, 4.1	8.51	9.67	1.15
5	22, 4.3, 6.5, 6.2, 4.1	7.37	7.8	0.43
6	22, 4.3, 4.5, 6.2, 6.1	6.48	6.43	0.05
7	22, 6.3, 4.5, 6.2, 4.1	7.94	7.6	0.34
8	22, 6.3, 6.5, 6.2, 4.5	7.36	7.53	0.17
9	22, 9.3, 4.5, 8.2, 8.5	6.06	6.52	0.46
10	40, 3.3, 9.5, 5.2, 8.5	13	13	0

Table 5 shows the results of experiments with multiple input variables on three systems, namely Python, Labview, and Error. Each row represents an experiment with different input values, consisting of five numerical parameters. The "Python" and "Labview" columns show the results obtained on both systems, while the "Error" column shows the difference between the Python and Labview results.

Table 5 shows that the Python and Labview results are generally quite close, with most of the error values in a relatively small range. For example, in the first experiment with inputs 22, 4.5, 6.5, 4.2, 6.1, the result values obtained were 4.89 for Python and 3.36 for Labview, resulting in an error of 1.53. This shows the difference between the two systems, although the results are almost similar. In the second experiment with inputs 55, 4.3, 4.5, 6.2, 7.1, the results from both systems were identical (4.85), so the error was 0.

The 10th trial with inputs 40, 3.3, 9.5, 5.2, 8.5 showed larger results in both systems (13 for Python and Labview), with an error also of 0, indicating high consistency between the two systems for these inputs. Overall, although there was some variation in the error values between experiments, most experiments showed relatively small differences between the results computed by Python and Labview. This indicates that the two systems provide very similar results to each other, with slight differences that could be due to certain factors in the implementation or computation on each platform.

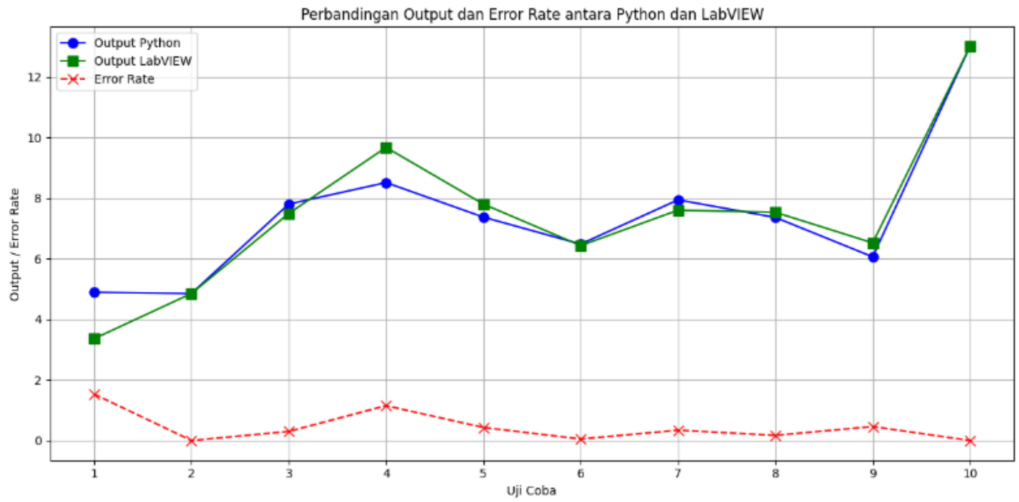


Figure 9. Comparison Chart of Python and LabVIEW Results

After obtaining the experimental data, the average error is calculated by summing all the error values and dividing them by the number of trials, show **Figure 9**. In this case, the total error of all the trials was 4.45588, and since there were 10 trials, the average error was 4.45588 divided by 10, giving a value of 0.445588. Thus, the average error value obtained from this experiment is 0.445588, which shows how large the average difference is between the results calculated using Python and Labview.

3.1 Discussion

The results show that the Sugeno fuzzy system successfully maps fuzzy inputs to crisp outputs in personality type prediction with good accuracy, as seen in the defuzzification results leading to the ISFP personality type. The comparison between the Python and LabView results showed consistency with an average error of 0.445588, indicating that both platforms produced almost identical results. This research supports previous findings demonstrating the effectiveness of fuzzy logic in handling ambiguous data in personality analysis, and also shows its potential application in various practical areas such as human resource management, education, and personalization of digital services. This fuzzy logic-based personality prediction system can be used in the recruitment process to assess candidates' compatibility with job roles or corporate culture. In education, the system can help identify students' personality types and tailor a more personalized learning approach. In addition, this research contributes to improving personalization in digital services, where personality insights can be used to enhance the user experience.

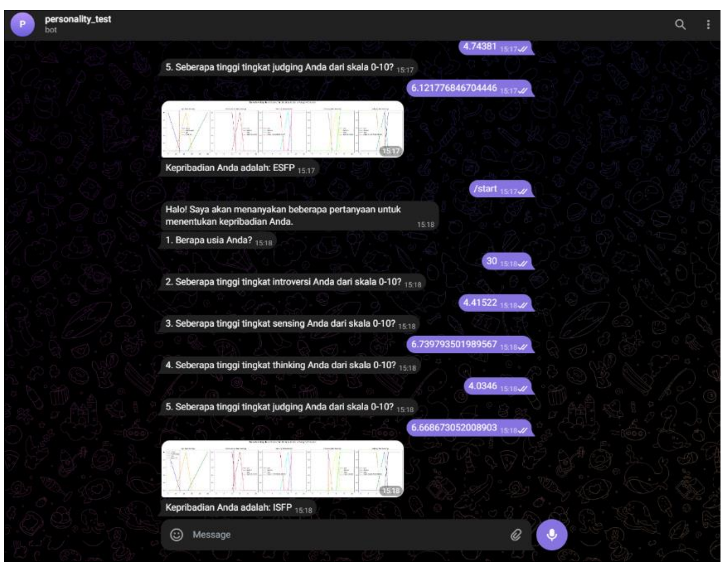


Figure 10. Application of fuzzy system in chatbot

In addition, the development of a Telegram chatbot that integrates this personality prediction system is an important practical application, show in **Figure 10**. By using a fuzzy logic model, the chatbot can assess users' personality types based on their answers to certain questions, and provide more personalized advice or recommendations. This makes the system accessible to a wider audience, allowing individuals to gain insight into their personality type through a simple and interactive platform like Telegram. This integration also highlights the potential use of AI-based personality analysis in everyday applications, ranging from personal growth to increased user engagement in digital services.

However, this study has limitations, such as the use of variables limited to five main dimensions and testing on a relatively small dataset, which may limit the model's ability to generalize to larger populations or different contexts. Therefore, further research is recommended to expand the range of variables used, test the system with more diverse and representative data, and explore more complex integration methods to improve the model's accuracy and flexibility in analyzing personality in different situations.

4. Conclusion

The conclusion of the research on personality type prediction using the Fuzzy Sugeno method shows that the fuzzification process successfully converts crisp input values into fuzzy values for five main variables (age, introversion, sensing, thinking, and judging). Each variable has three fuzzy categories that form the basis for clustering the input data, with the fuzzification results providing unambiguous membership degrees for each category. The inference stage successfully applies predefined fuzzy rules, where a combination of fuzzy values from the inputs is used to determine the output, considering the lowest membership degree of each rule. The defuzzification process using the Sugeno method produced a consistent crisp value of 3.36, which was mapped to the INFJ personality type. The evaluation using LabVIEW showed a difference in output between the fuzzy system and the results from LabVIEW, with an average error rate of 0.445588, indicating that despite the difference, the fuzzy system still performed well in predicting personality based on the given input. This research demonstrates the potential of applying fuzzy methods in the field of psychology to predict personality types, and with further development, these methods can be adapted for broader applications, including psychological assessment and the development of more personalized and accurate assessment tools. Overall, this research proves that the Fuzzy Sugeno Method is an effective tool for predicting personality types, with a structured process and reliable results, paving the way for further research and application development using fuzzy approaches in psychology.

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