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THE APPLICATION OF FUZZY LOGIC IN CLUSTERING PROVINCES BASED ON SOCIAL WELFARE, ECONOMIC STATUS, AND HEALTHCARE FACILITIES

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ABSTRACT

Assessing the quality of life across provinces in Indonesia requires a comprehensive evaluation of multiple socio-economic indicators. This study applies Fuzzy Inference Systems (FIS), specifically the Mamdani and Sugeno models, to cluster Indonesian provinces based on five key parameters: Gross Regional Domestic Product (GRDP), crime rate, open unemployment rate, the number of senior high schools, and the number of hospitals. These indicators collectively represent economic status, public safety, employment conditions, educational infrastructure, and healthcare access, fundamental components of social well-being. The use of fuzzy logic allows for nuanced modeling of complex and uncertain data, accommodating both quantitative and qualitative dimensions. Data were obtained from the Indonesian Central Bureau of Statistics and processed using MATLAB's fuzzy logic toolbox. The results show consistent clustering outputs from both FIS approaches, with most provinces falling within the mid-level cluster. The findings highlight regional disparities that can inform targeted development policies. Moreover, while the ecological dimension was not directly modeled, it is recognized as an underlying factor influencing the observed socio-economic patterns. This framework provides a flexible and adaptable method for future studies incorporating environmental variables to support sustainable regional development.

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1. INTRODUCTION

The quality of life in a region is a crucial indicator of its overall development and the well-being of its inhabitants. In a diverse nation like Indonesia, with its unique socio-economic dynamics across different provinces, understanding and accurately assessing the quality of life is not merely an academic exercise but a critical necessity. Disparities in social welfare, economic status, and access to essential services like healthcare and education can lead to significant socio-economic challenges, including inequality, instability, and hindered national progress. Therefore, accurate measurement and comprehensive assessment of quality of life across provinces are essential for identifying these disparities and formulating targeted, strategic interventions that truly improve the lives of citizens. Clustering techniques, in this context, provide a robust method for analyzing complex socio-economic data, allowing for the grouping of provinces based on shared characteristics and needs.

In recent years, Fuzzy Inference Systems (FIS) have gained prominence in handling data characterized by uncertainty and vagueness, particularly in social and economic analyses [1], [2]. Unlike traditional statistical methods, FIS leverages linguistic variables and membership functions to process qualitative and quantitative data, thereby offering a more nuanced interpretation of regional disparities. The application of fuzzy logic in clustering enables the identification of provinces that share similar socio-economic profiles, thus facilitating targeted policy recommendations. Previous studies have demonstrated the effectiveness of fuzzy logic in clustering regional data based on socio-economic indicators. For instance, in [3], FIS was applied to categorize regions based on economic development levels, revealing distinct clusters that required tailored policy responses. Similarly, [4] employed fuzzy logic to classify provinces based on health and education indices, demonstrating the potential of FIS to effectively handle complex datasets.

This study aims to apply fuzzy logic to cluster Indonesian provinces based on five key parameters: Gross Regional Domestic Product (GRDP), crime rate, open unemployment rate, the ratio of senior high schools to teacher count, and the number of hospitals. These parameters were selected due to their comprehensive representation of economic status, safety, employment, education, and healthcare access, which collectively define the quality of life in a region. The data used in this study were obtained from the Indonesian Central Bureau of Statistics (Badan Pusat Statistik), encompassing recent provincial data across the aforementioned parameters.

This paper is structured as follows: Section 2 discusses the methodology employed in the clustering process, including data collection, FIS design, and implementation in MATLAB. Section 3 presents the results, including the derived fuzzy membership functions and the clustering outcomes. Furthermore, Section 3 also provides a comprehensive discussion of the findings, highlighting significant patterns and implications. Finally, Section 4 concludes the study by summarizing the key contributions and suggesting potential directions for further research.

2. RESEARCH METHODS

2.1 The Parameters Input

In this research, several parameters are employed to measure and cluster the quality of life across the provinces of Indonesia. The selection of these parameters is based on theoretical and empirical relevance supported by a range of scholarly papers and literature. The following is a narrative explanation for each parameter:

1. Gross Regional Domestic Product (GRDP): GRDP per capita serves as a significant indicator for measuring the level of economic well-being within a region. According to [5] in their book “Economic Development”, GRDP reflects the total value of goods and services produced within a region over a specific time period, divided by the population. A higher GRDP generally indicates a better level of income and purchasing power among the populace, which in turn can improve access to basic necessities, education, and healthcare services, all of which are crucial components of quality of life [6]. Research by [7] also demonstrates a positive correlation between per capita income and levels of happiness, although this relationship is not always linear and is influenced by other factors.

2. Crime Rate: The crime rate, frequently quantified as the number of criminal offenses committed per 100,000 residents, serves as a significant metric for assessing the level of safety and social order prevalent within a specific geographical area. The magnitude of the crime rate exerts a direct influence on the perceived sense of security and the overall quality of life experienced by the community inhabiting that region. Elevated crime rates demonstrate a negative correlation with a variety of indicators that reflect social well-being. Moreover, scholarly investigation within the discipline of criminology substantiates that a secure environment, characterized by the absence of criminal activity, constitutes a fundamental prerequisite for individuals to engage actively in both economic and social endeavors and, consequently, to experience an enhanced quality of life.

3. Open Unemployment Rate: The open unemployment rate, which is the percentage of the labor force that is without work and actively seeking employment, is a significant indicator of the labor market conditions and social welfare. According to [8], a high unemployment rate can lead to decreased individual income, increased poverty, and other social problems that negatively impact the quality of life. Moreover, prolonged unemployment can result in the loss of skills and human capital, as well as induce psychological and mental health issues. Therefore, a low unemployment rate is indicative of a healthy labor market and contributes positively to the quality of life of the population.

4. Number of Senior High Schools: The number of senior high schools per region can serve as an indicator of access to secondary education. Education, as emphasized by Schultz in [9], is a crucial investment in human capital that significantly contributes to economic development and the improvement of individual and societal quality of life. Senior high school education equips individuals with higher levels of knowledge and skills, enhancing employment opportunities, income, and participation in social and political life. Regions with better access to secondary education tend to have a higher quality of human resources, which ultimately has a positive impact on the overall quality of life.

5. Health Facilities (Hospital): The number of hospitals per region is an important indicator of access to healthcare services. Health is a fundamental dimension of quality of life. Grossman (1972), in "On the Concept of Health Capital and the Demand for Health", highlights the importance of health as human capital that influences individual productivity and well-being. Adequate availability of healthcare facilities, such as hospitals, ensures that the population has access to the medical services needed to maintain and improve their health. Easy access to quality healthcare services significantly contributes to increased life expectancy, reduced mortality rates, and an overall improvement in quality of life.

From an ecological standpoint, environmental quality may act as a latent variable influencing all five selected parameters. For instance, poor air quality and pollution can lead to higher disease prevalence, thus burdening hospital infrastructure and diminishing overall health outcomes. Similarly, ecological degradation can affect local economies, especially in regions dependent on agriculture, fisheries, or natural resources, ultimately reflected in GRDP and employment rates. Educational access can also be hindered in ecologically vulnerable areas due to infrastructure damage or relocation. Therefore, while this study does not explicitly model ecological data, it is important to acknowledge that ecological dynamics form an implicit backdrop to the socio-economic indicators used in this clustering model. This observation opens the opportunity for interdisciplinary expansion of future studies, combining ecological metrics with fuzzy logic frameworks to yield more comprehensive regional classifications.

By considering these five parameters collectively, this research aims to provide a comprehensive understanding of the quality of life across various provinces in Indonesia and to identify interesting clustering patterns for further analysis. Additionally, it is noteworthy that the ecological dimension serves as a contextual backdrop that can influence each of the parameters discussed. For instance, regions with poor environmental quality may experience increased health issues, thereby affecting the overall impact of healthcare facilities. Similarly, areas with declining environmental conditions may face challenges in sustaining economic productivity, thereby impacting GRDP. Addressing ecological concerns can, therefore, serve as a complementary strategy to further enhance the quality of life by mitigating potential adverse effects on economic well-being, social stability, education, and health outcomes.

2.2 Cluster Analysis

Cluster analysis stands as a prominent technique within multivariate analysis, serving the purpose of grouping objects based on specific characteristics or attributes they possess. In its process, objects exhibiting a high degree of similarity are aggregated into the same cluster, while those differing significantly are allocated to distinct groups. A cluster can be defined as a collection of objects sharing particular similarities, thereby indicating that objects within the same group tend to possess analogous characteristics. Consequently, the primary objective of cluster analysis is to form several clearly distinct groups, enabling each group to be more readily identified based on the common characteristics shared by its members [10].

In determining the clusters, data requiring processing are necessary. The data utilized in this study are secondary data sourced from the Indonesian Central Bureau of Statistics (Badan Pusat Statistik). Specifically, data for GRDP (Gross Regional Domestic Product) were obtained from [11], with the selected data pertaining to Provincial GRDP at 2010 Constant Market Prices by Regency/Municipality. Crime rate data were sourced from [12], and the chosen data represent crime figures by province. Open unemployment rate data were acquired from [13]. The comparison of the number of teachers to the number of senior high schools was derived from [14]. Lastly, data concerning the number of hospitals by province were obtained from [15]. To mitigate complexity in the data analysis process, we opted to include only data on the number of general hospitals.

2.3 Fuzzy Inference System

The fuzzy inference system (FIS) employs logical reasoning to convert input elements into output, effectively managing uncertainties expressed through terms like “significant impact” or “level of concern” [12]. Such uncertainties arise from human judgment and are commonly articulated using linguistic variables, particularly in applications such as quality of life. The two primary inference methods in FIS are Mamdani and Takagi–Sugeno. Unlike Mamdani, the Sugeno method incorporates constant functions instead of fuzzy sets in the consequent part of the rule base. Both approaches utilize membership functions such as triangular, Gaussian, or trapezoidal for inputs; however, Mamdani applies these functions to outputs as well, whereas Sugeno employs singleton functions.

An FIS framework comprises three essential components: fuzzification, inference rules, and defuzzification. Fuzzification translates numerical data into fuzzy-set membership values, signifying categories like low or high [16]. The significance of each variable is embedded in the rule structure. Once fuzzified, inputs are processed using fuzzy operators to evaluate rule strength, which is then integrated with output membership functions. The aggregated results yield a fuzzy output, which is subsequently converted into a crisp value through defuzzification. Methods such as centroid, area bisector, and the largest of maxima (LOM) are utilized in Mamdani FIS, while Sugeno employs weighted sum (wtsum) or weighted average techniques. Finally, the fuzzy output is transformed into a definite crisp value [17], [18], [19], [20]. The FIS structure is illustrated in Fig.1.

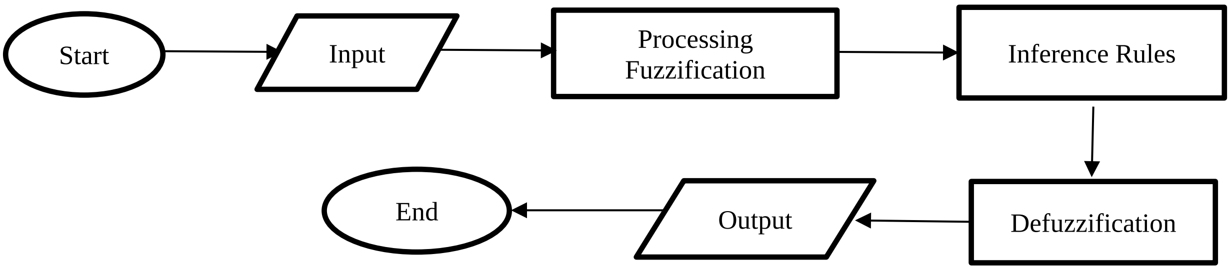

Figure 1. The FIS Structure

An illustration of the procedural flow for both Mamdani and Sugeno techniques is presented in Fig. 2, highlighting the three constituent phases of each method. The fundamental distinction between the Mamdani and Sugeno paradigms lies in the defuzzification procedure. Notably, the Sugeno FIS utilizes weighted sum and weighted average methodologies for defuzzification.

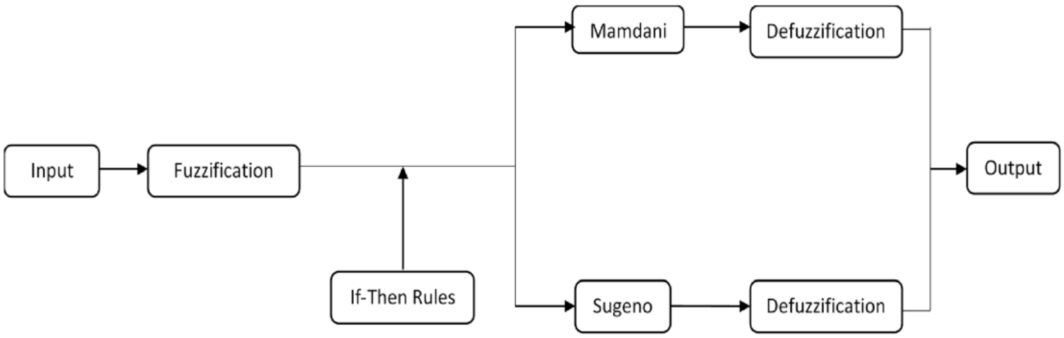

Figure 2. The Process Flowcharts for The Mamdani and Sugeno Fuzzy Inference Systems (FIS)

The diagram in Fig. 2 illustrates the general structure of a fuzzy inference system (FIS), which processes input data to produce a crisp output through a sequence of well-defined steps.

1. Input: The process begins with the input, which consists of real-world data or variables requiring evaluation.
2. Fuzzification: In this stage, the input data is transformed into fuzzy sets using appropriate membership functions. These membership functions can be triangular, Gaussian, trapezoidal, or singleton types, depending on the application and desired precision.
3. Fuzzy If-Then Rules: Following fuzzification, the system consults a comprehensive set of fuzzy IF-THEN rules, also known as the rule base. These rules form the core knowledge base of the FIS, typically formulated by domain experts or derived through data learning.
4. Fuzzy Rule Evaluation: The fuzzified inputs are then evaluated using a set of fuzzy IF-THEN rules. These rules define the relationship between input variables and corresponding output actions in linguistic terms.
5. Inference Mechanism: The fuzzy rule evaluation proceeds through one of two inference methods:
   a. Mamdani Inference: This method interprets the rules by producing fuzzy outputs, which are then aggregated and passed on to the defuzzification stage.
   b. Sugeno Inference: In contrast, this method generates outputs in the form of mathematical functions of the input variables, making it more suitable for optimization and adaptive techniques.
6. Defuzzification: The final step involves converting the fuzzy output back into a crisp, real-world value using defuzzification techniques. For Mamdani inference, common defuzzification methods include the Centroid, Bisector, LOM (Largest of Maximum), MOM (Mean of Maximum), and SOM (Smallest of Maximum). For Sugeno inference, techniques such as weighted average (wtaver) and weighted sum (wtsum) are employed.
7. Output: The result of the defuzzification process is a precise output value, suitable for direct application or further processing in decision-making systems.

3. RESULTS AND DISCUSSION

In this section, we will present the calculations for determining the fuzzy functions and will also display the output results for several predetermined samples.

3.1 Fuzzification

Prior to formulating the fuzzy functions, we first performed a clustering of each parameter utilized in this study. The rule governing the classification division is that a higher cluster level number corresponds to a more favorable condition. The Fuzzy Functions displayed in Table 1 until Table 5 and also Table 7 are defined as a mapping from elements within the universe of discourse (crisp input) to degrees of membership within a fuzzy set.

Firstly, the GRDP of provinces in Indonesia for 2018-2022. For the GRDP at constant prices factor, we initially determined the national average value. The calculated national average is 356 trillion Rupiah. Subsequently, the provinces were divided into two groups: provinces with a GRDP below 356 trillion Rupiah were categorized into the ‘lower’ group, and those with a GRDP greater than or equal to 356 trillion Rupiah were placed into the ‘upper’ group. Following this initial division, the lower and upper bounds of each of these two groups were further identified, resulting in a final division into four groups and the fuzzy function in Table 1 as follows:

GRDP over constant price parameter (in trillion rupiah):

1. $x \leq 121$,
2. $121 < x \leq 356$,
3. $356 < x \leq 983$,
4. $x > 983$.

Table 1. The Fuzzy Function of GRDP

GRDP over Constant Price	Fuzzy Function	Domain
Cluster Level 1	1	$0 \leq x \leq 86$
	$\frac{171-x}{85}$	$86 \leq x \leq 171$
	0	$x \geq 171$
Cluster Level 2	0	$x \leq 36$ or $x \geq 406$
	$\frac{x-36}{124}$	$36 \leq x \leq 160$
	1	$160 \leq x \leq 284$
	$\frac{406-x}{122}$	$284 \leq x \leq 406$
Cluster Level 3	0	$x \leq 110$ or $x \geq 1333$
	$\frac{x-110}{408}$	$110 \leq x \leq 518$
	1	$518 \leq x \leq 926$
	$\frac{993-x}{407}$	$926 \leq x \leq 1333$
Cluster Level 4	0	$x \leq 458$
	$\frac{x-458}{875}$	$458 \leq x \leq 1333$
	1	$x \geq 1333$

Secondly, the crime rate of provinces in Indonesia in 2022. For the crime rate parameter, the first and third quartiles were utilized, yielding values of 65 and 130. Consequently, the resulting group divisions are as follows:

Crime Parameters (crime rate / 100.000 people):

1. $x > 130$ people,
2. $65 < x \leq 130$ people,
3. $x \leq 65$ people.

Following the aforementioned categorization, we developed the fuzzy function in Table 2 as follows:

Table 2. The Fuzzy Function of Crime Rate

Crime Rate (/100.000 people)	Fuzzy Function	Domain
Cluster Level 1	0	$x \leq 120$
	$\frac{x-120}{60}$	$120 \leq x \leq 180$
	1	$x \geq 180$
Cluster Level 2	0	$x \leq 55$ or $x \geq 140$
	$\frac{x-55}{28}$	$55 \leq x \leq 83$
	1	$83 \leq x \leq 111$

Crime Rate (/100.000 people)	Fuzzy Function	Domain
Cluster Level 3	$\frac{111-x}{29}$	$111 \le x \le 140$
	0	$x \ge 101$
	$\frac{x-75}{26}$	$75 \le x \le 101$
	1	$0 \le x \le 75$

Thirdly, the open unemployment of provinces in Indonesia. Subsequently, for the open unemployment rate parameter, the group divisions were established as follows:

Open Unemployment Rate (Percentage of Population):

1. $x > 6.5$,
2. $5 < x \le 6.5$,
3. $4 < x \le 5$,
4. $x \le 4$.

Following the aforementioned categorization, we developed the fuzzy function in Table 3 as follows:

Table 3. The Fuzzy Function of Open Unemployment Rate

The Open Unemployment Rate	Fuzzy Function	Domain
Cluster Level 1	0	$x < 5.5$
	$\frac{x-5.5}{1}$	$5.5 \le x \le 6.5$
	1	$x \ge 6.5$
Cluster Level 2	0	$x \le 4$ or $x \ge 6.5$
	$\frac{x-4}{1.25}$	$4 \le x \le 5.25$
	1	$5.25 \le x \le 6.5$
	$7.5 - x$	$6.5 \le x \le 7.5$
Cluster Level 3	0	$x \le 3$ or $x \ge 5$
	$x - 3$	$3 \le x \le 4$
	1	$4 \le x \le 5$
	$5 - x$	$5 \le x \le 6$
Cluster Level 4	0	$x \ge 5$
	$\frac{5-x}{2.5}$	$2.5 \le x \le 5$
	1	$x \le 2.5$

The selection of the number of senior high schools (SMA) as the sole education parameter in this research stems from its critical role in preparing individuals for advanced education or the competitive labor market, thus significantly impacting a region's human capital and long-term economic potential. While acknowledging the importance of earlier education levels, focusing on SMA provides a relevant proxy for more developed human resources. This choice also prioritizes model simplicity, as the inclusion of additional education parameters across different levels could substantially increase complexity and potential multicollinearity within a model already encompassing economic, safety, employment, and health dimensions. Therefore, concentrating on senior high schools allows for a focused analysis of a key educational stage with significant implications for overall quality of life, while maintaining a parsimonious model structure for clearer interpretation. Our classification of the number of senior high schools is as follows

Education Parameter (The quantity of senior high schools):

1. $x \le 104$,
2. $104 < x \le 208$,
3. $208 < x \le 312$,
4. $x \ge 312$.

Following the aforementioned categorization, we developed the fuzzy function in Table 4 as follows:

Table 4. The Fuzzy Function of Education Parameter

The Quantity of Senior High School	Fuzzy Function	Domain
Cluster Level 1	1	$0 \leq x \leq 40$
	$\frac{90-x}{50}$	$40 \leq x \leq 90$
	0	$x > 90$
Cluster Level 2	0	$x \leq 70$ or $x \geq 220$
	$\frac{(x-70)}{50}$	$70 \leq x \leq 120$
	1	$120 \leq x \leq 185$
	$\frac{220-x}{35}$	$185 \leq x \leq 220$
Cluster Level 3	0	$x \leq 200$ or $x \geq 325$
	$\frac{x-200}{50}$	$200 \leq x \leq 250$
	1	$250 \leq x \leq 290$
	$\frac{325-x}{35}$	$290 \leq x \leq 325$
Cluster Level 4	0	$x \leq 300$
	$\frac{x-0.0395}{0.00975}$	$300 \leq x \leq 350$
	1	$x \geq 350$

And lastly, for the health parameter, which we took from Badan Pusat Statistik, that is, the total number of hospitals, two classifications were formed as follows:

1. $x \leq 50$,
2. $x > 50$.

Following the aforementioned categorization, we developed the fuzzy function in Table 5 as follows:

Table 5. The Fuzzy Function of Health Parameter

Health Facilities (Hospital)	Fuzzy Function	Domain
Cluster Level 1	1	$0 \leq x \leq 25$
	$\frac{60-x}{35}$	$25 \leq x \leq 60$
	0	$x \geq 60$
Cluster Level 2	0	$x \leq 15$
	$\frac{x-15}{45}$	$15 \leq x \leq 60$
	1	$x \geq 68$

3.2 Rules and Output

To establish the decision-making rules, several stipulations were employed. The first stipulation is that the fuzzy connective used is “and”. Subsequently, each cluster is assigned a weight corresponding to its level; if an input is at cluster level 1, its weight is 1, if at cluster level 2, its weight is 2, and so forth. The third stipulation is that the output weight is determined by the total sum of all input weights. For example, given an input GRDP at cluster level 2, a crime rate at cluster level 1, an open unemployment rate at level 2, an education parameter at level 2, and a health parameter at level 1, then the output weight is $2+1+2+2+1=8$. Consequently, the minimum possible weight is $1+1+1+1+1=5$, and the maximum possible weight is $4+4+4+4+2=18$. Based on this explanation, we categorized the output into 5 clusters with the following group division given in Table 6 as follows:

Table 6. The Clustering of Output

Cluster	Weight
Cluster Level 1	$5 \leq x < 7$
Cluster Level 2	$7 \leq x < 9$

Cluster	Weight
Cluster Level 3	$9 \leq x < 12$
Cluster Level 4	$12 \leq x < 14$
Cluster Level 5	$14 \leq x < 16$
Cluster Level 6	$16 \leq x \leq 18$

Based on the aforementioned group divisions in Table 6 above, the fuzzy functions were also formulated according to the following rules given in Table 7 below:

Table 7. The Fuzzy Function of Output

Output	Fuzzy Function	Domain
Cluster Level 1	1	$5 \leq x \leq 6$
	$\frac{6.5 - x}{0.5}$	$6 \leq x \leq 6.5$
	0	$x \geq 6.5$
Cluster Level 2	0	$x \leq 6$ or ≥ 8.5
	$\frac{x - 6}{0.8}$	$6 \leq x \leq 6.8$
	1	$6.8 \leq x \leq 7.6$
	$\frac{8.5 - x}{0.9}$	$7.6 \leq x \leq 8.5$
Cluster Level 3	0	$x \leq 7.6$ or $x \geq 11.5$
	$\frac{x - 7.6}{1.3}$	$7.6 \leq x \leq 8.9$
	1	$8.9 \leq x \leq 10.2$
	$\frac{11.5 - x}{1,3}$	$10.2 \leq x \leq 11.5$
Cluster Level 4	0	$x \leq 10.2$ or $x \geq 13.5$
	$\frac{x - 10.2}{1,1}$	$10.2 \leq x \leq 11.3$
	1	$11.3 \leq x \leq 12.4$
	$\frac{13.5 - x}{1.1}$	$12.4 \leq x \leq 13.5$
Cluster Level 5	0	$x \leq 12.4$ or $x \geq 15.5$
	$x - 12.4$	$12.4 \leq x \leq 13.4$
	1	$13.4 \leq x \leq 14.4$
	$\frac{13.8 - x}{1.1}$	$14.4 \leq x \leq 15.5$
Cluster Level 6	0	$x \leq 13,8$
	$\frac{x - 13.8}{1.8}$	$13.8 \leq x \leq 15.6$
	1	$15.6 \leq x \leq 18$

3.3 FIS in MATLAB

Once the fuzzy functions have been formulated, the next step involves inputting them into the MATLAB program via the “apps” menu and selecting the “Fuzzy logic designer” option given in Fig. 3.

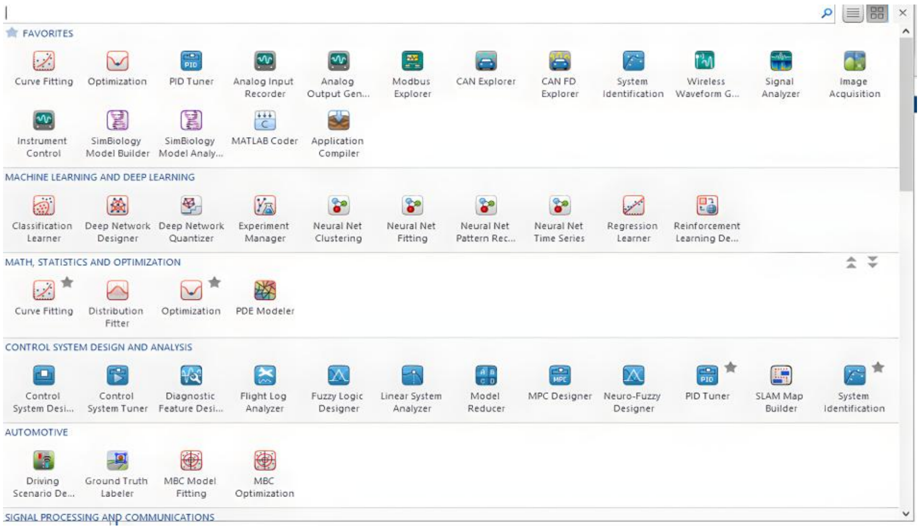

Figure 3. FIS Menu in MATLAB

The MATLAB interface used for data analysis is shown in Fig. 3. For the Fuzzy Inference System, select the Fuzzy Logic Designer menu. Within the Add Variable and Rules menus, the settings are configured according to the established fuzzy function tables that we have formed before. The following are the graphs for each input function.

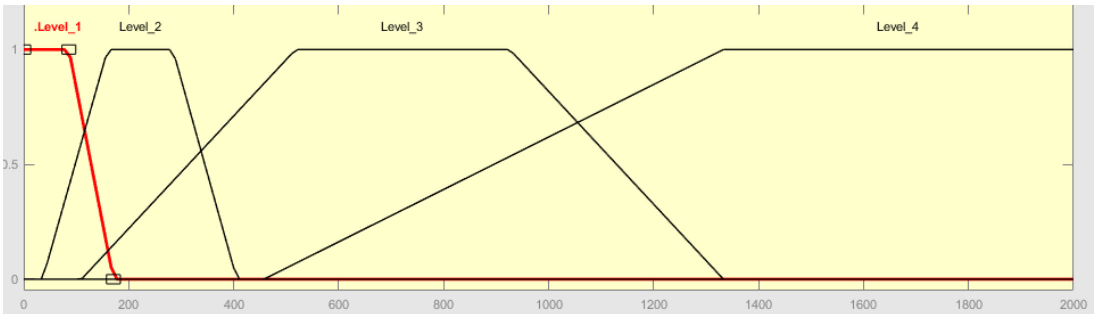

Figure 4. Graphic GRDP Input Function

Based on the fuzzy function in Table 1, we obtained the input graph in MATLAB as shown in Fig. 4 above.

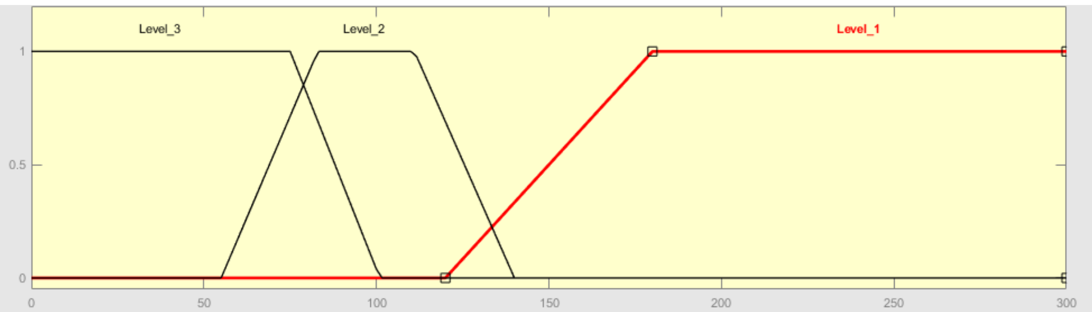

Figure 5. Graphic Crime Rate Input Function

Based on the fuzzy function in Table 2, we obtained the input graph in MATLAB as shown in Fig.5 above.

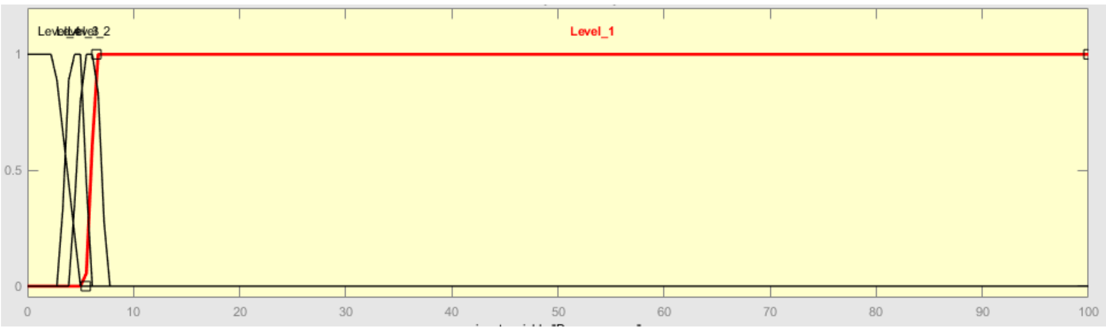

Figure 6. Graphic Open Unemployment Rate Input Function

Based on the fuzzy function in Table 3, we obtained the input graph in MATLAB as shown in Fig. 6 above.

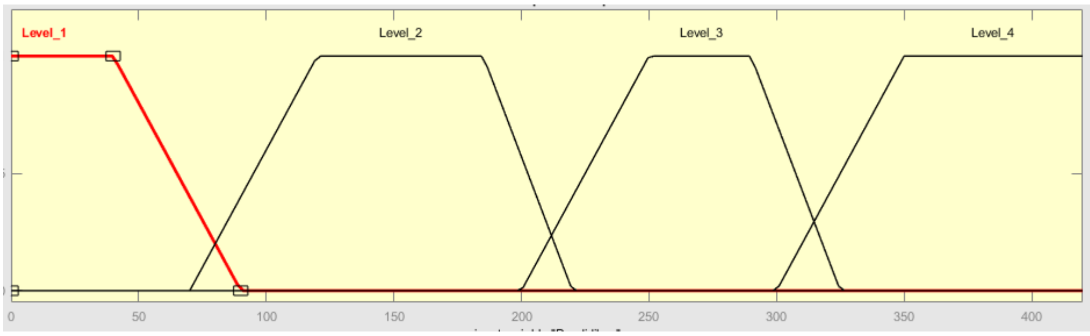

Figure 7. Graphic Education Input Function

Based on the fuzzy function in Table 4, we obtained the input graph in MATLAB as shown in Figure 7 above.

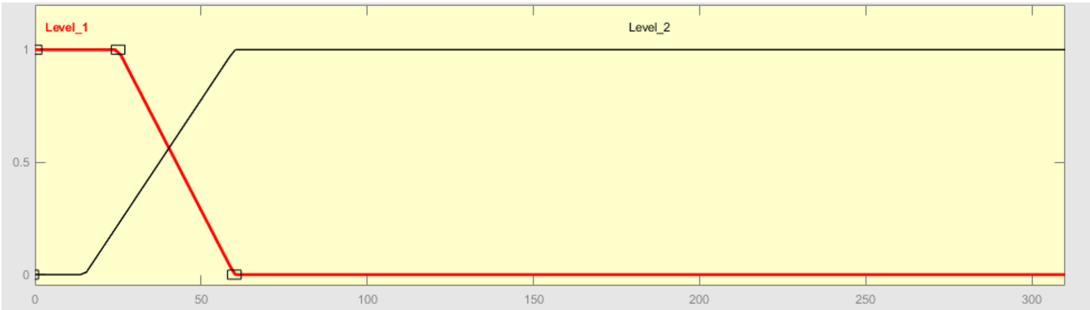

Figure 8. Graphic Health Input Function

Based on the fuzzy function in Table 5, we finally obtained the input graph in MATLAB as shown in Fig. 8 above. Lastly, based on the function in Table 7, the graph of the output function for the Mamdani-type FIS is presented in Fig. 9 below.

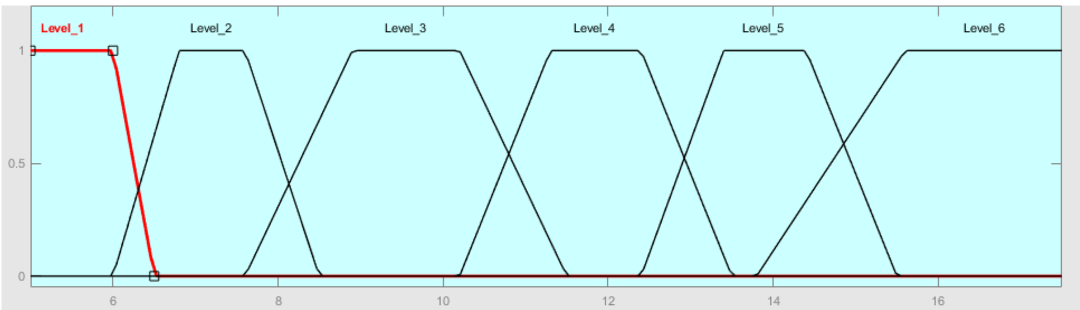

Figure 9. Mamdani Output Type Graphic

Utilizing the convert feature in MATLAB, we can also directly transform the output type from Mamdani to Sugeno, as illustrated in Fig. 10.

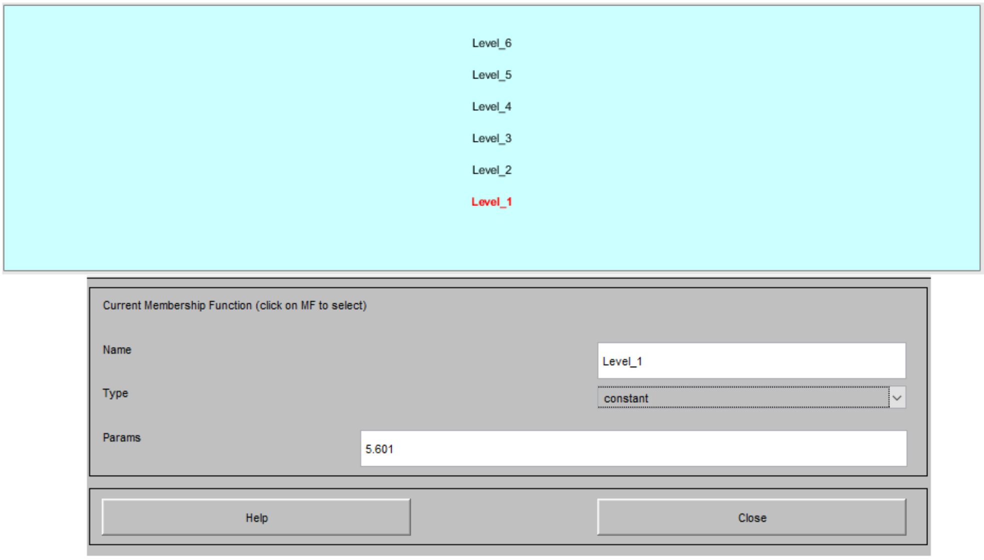

Figure 10. Sugeno Output Type Graphic

Furthermore, the rules menu is also configured in accordance with, as depicted below. The rules menu is also configured according to Table 6, with a total of 384 rules requiring specification. The resulting rule settings within the Fuzzy Logic Designer in MATLAB are illustrated in Fig. 11 below.

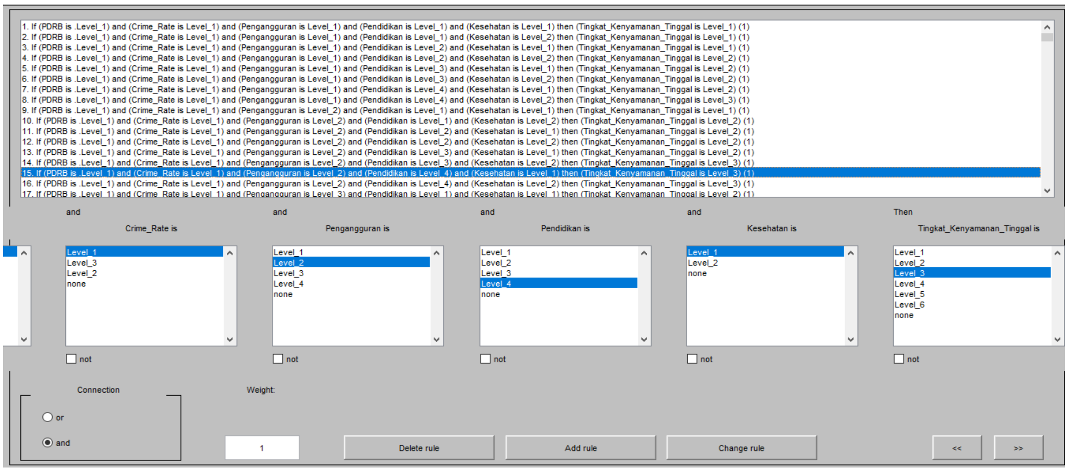

Figure 11. Rules of Fuzzy Inference System

The interface of the Fuzzy Logic Designer's Rules section in MATLAB is displayed in Fig. 11. The rules previously established in Table 6 were subsequently entered into this menu.

3.4 Result

In this section, an experiment will be conducted in Indonesian provinces, with the specifications and the results presented in Table 8 below. The input column (GRDP, Crime Rate, Open Unemployment Rate, Education Parameter, Health Parameter) states the input parameter, and the output column states the result of Mamdani and Sugeno FIS.

Table 8. Table of Cluster Results

Province	Input					Output	
	GRDP	Crime Rate	Open Unemployment Rate	Education Parameter	Health Parameter	Mamdani	Sugeno
Aceh	141	125	6.17	535	64	10.6 (Level 3)	10.3 (Level 3)

Province	Input					Output	
	GRDP	Crime Rate	Open Unemployment Rate	Education Parameter	Health Parameter	Mamdani	Sugeno
Sumatera Utara	574	250	6.16	1075	195	10.7 (Level 3)	11.1 (Level 3)
Sumatera Barat	183	103	6.28	337	49	10.6 (Level 3)	10.6 (Level 3)
Riau	530	110	4.37	455	59	13.5 (Level 4)	13.6 (Level 4)
Jambi	162	104	4.59	239	38	10.8 (Level 3)	10.6 (Level 3)
Sumatera Selatan	343	153	4.63	612	68	11 (Level 3)	11.5 (Level 3)
Bengkulu	49	177	3.59	146	22	8.67 (Level 2)	8.82 (Level 2)
Lampung	258	115	4.52	519	59	12.4 (Level 4)	12.5 (Level 4)
Kepulauan Bangka Belitung	58	108	4.77	71	21	8.4 (Level 2)	8.45 (Level 2)
Kepulauan Riau	190	111	8.23	163	30	8.24 (Level 2)	8.29 (Level 2)
DKI Jakarta	1953	277	7.18	492	141	11.8 (Level 3)	11.8 (Level 3)
Jawa Barat	1590	15	8.31	1711	309	13.9 (Level 4)	13.9 (Level 4)
Jawa Tengah	1050	26	5.57	854	267	14.7 (Level 5)	14.3 (Level 5)
DI Yogyakarta	113	123	4.06	173	60	10.2 (Level 3)	9.89 (Level 3)
Jawa Timur	1758	48	5.49	1518	302	14.8 (Level 5)	14.7 (Level 5)
Banten	484	27	8.09	603	85	11.9 (Level 3)	11.9 (Level 3)
Bali	151	55	4.80	163	65	10.9 (Level 3)	10.9 (Level 3)
Nusa Tenggara Barat	102	122	2.89	343	34	12.5 (Level 4)	12.2 (Level 4)
Nusa Tenggara Timur	73	90	3.54	598	50	11.9 (Level 3)	12.3 (Level 4)
Kalimantan Barat	148	80	5.11	459	45	11..9 (Level 3)	11.6 (Level 3)

Province	Input					Output	
	GRDP	**Crime Rate**	**Open Unemployment Rate**	**Education Parameter**	**Health Parameter**	**Mamdani**	**Sugeno**
Kalimantan Tengah	109	91	4.26	242	24	10.8 (Level 3)	10.6 (Level 3)
Kalimantan Selatan	142	118	4.74	205	38	9.51 (Level 3)	9.9 (Level 3)
Kalimantan Timur	506	126	5.71	233	45	10.8 (Level 3)	10.7 (Level 3)
Kalimantan Utara	67	140	4.33	67	11	8.02 (Level 2)	7.32 (Level 2)
Sulawesi Utara	97	249	6.61	230	43	8.69 (Level 2)	8.39 (Level 2)
Sulawesi Tengah	173	169	3.00	232	35	10.4 (Level 3)	10.8 (Level 3)
Sulawesi Selatan	361	166	4.51	599	86	11.2 (Level 3)	11.6 (Level 3)
Sulawesi Tenggara	103	91	3.36	313	36	11.6 (Level 3)	12.3 (Level 4)
Gorontalo	30	208	2.58	70	15	7.24 (Level 2)	7.23 (Level 2)
Sulawesi Barat	34	110	2.34	91	11	9.55 (Level 3)	9.55 (Level 3)
Maluku	33	177	6.88	284	30	8.24 (Level 2)	7.59 (Level 2)
Maluku Utara	40	82	3.98	217	20	10.7 (Level 3)	10.4 (Level 3)
Papua Barat	63	289	5.37	131	20	7.97 (Level 2)	7.74 (Level 2)
Papua	173	186	2.83	256	46	10.8 (Level 3)	11.2 (Level 3)

Based on the clustering results in Table 8, the Mamdani and Sugeno methods consistently produced nearly identical outputs, with differences observed only in East Nusa Tenggara and Southeast Sulawesi. Most provinces in Indonesia were classified into cluster level 3, while several others—such as Bengkulu, Bangka Belitung Islands, Riau Islands, North Kalimantan, North Sulawesi, Gorontalo, Maluku, and West Papua fell into cluster level 2. Provinces including Riau, Lampung, West Java, West Nusa Tenggara, and East Nusa Tenggara were grouped into cluster level 4, and only two provinces, Central Java and East Java, reached cluster level 5. The capital city, DKI Jakarta, was classified into cluster level 3 due to its high crime and open unemployment rates, despite its significantly high GRDP. The results of Table 8 are also presented in Fig. 12 below.

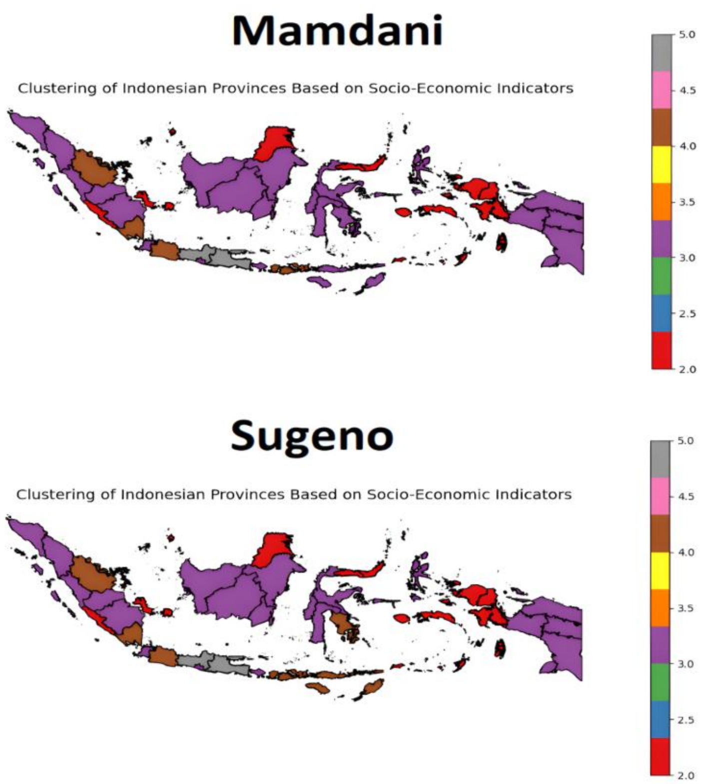

Figure 12. Figure of Cluster Results

In Fig. 12, the red color indicates output level 2, purple output level 3, brown output level 4, and grey output level 5.

4. CONCLUSION

This study successfully clustered Indonesian provinces utilizing both Mamdani and Sugeno Fuzzy Inference Systems (FIS), based on five principal socio-economic indicators: Gross Regional Domestic Product (GRDP), crime rate, open unemployment rate, the number of senior high schools, and the number of hospitals. The consistent outcomes derived from both FIS models affirm the robustness of fuzzy logic in analyzing complex socio-economic data, revealing significant regional disparities wherein the majority of provinces were categorized into a mid-level cluster, while a smaller proportion fell into lower tiers, and only a few attained the highest cluster. This framework offers a flexible methodology for regional quality of life evaluation and presents opportunities for future multidisciplinary investigations, particularly through the integration of ecological variables, to foster more comprehensive and sustainable development policies.

Author Contribution

Hubbi Muhammad: Conceptualization, Data Curation, Formal Analysis, Methodology, Software, Writing - Original Draft. Iik Nurul Fatimah: Funding Acquisition, Investigation, Project Administration, Resources, Supervision, Validation, Visualization, Writing - Review and Editing. All authors reviewed and approved the final version of the manuscript.

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Declarations

The authors declare no competing interests.

REFERENCES

[1] E. H. Mamdani and S. Assilian, “AN EXPERIMENT IN LINGUISTIC SYNTHESIS WITH A FUZZY LOGIC CONTROLLER,” *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1–13, 1975. doi: https://doi.org/10.1016/S0020-7373(75)80002-2

[2] G. Cui, “ANALYSIS ON THE COUNTRY DIFFERENCES OF CSR OF MULTINATIONAL CORPORATIONS BASED ON FUZZY C-MEANS CLUSTERING,” *J. Phys.: Conf. Ser.*, vol. 1533, no. 2, p. 022079, Apr. 2020. doi: https://doi.org/10.1088/1742-6596/1533/2/022079

[3] Zadeh, L. A., “FUZZY SETS,” *Information and Control*, vol. 8, no. 3, pp. 338-353, 1965. doi: https://doi.org/10.1016/S0019-9958(65)90241-X

[4] Takagi, T., and Sugeno, M., “FUZZY IDENTIFICATION OF SYSTEMS AND ITS APPLICATIONS TO MODELING AND CONTROL,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-15, no. 1, pp. 116-132, 1985. doi: https://doi.org/10.1109/TSMC.1985.6313399

[5] M. P. Todaro and S. C. Smith, *ECONOMIC development*, 11th ed. Boston, Mass: Addison-Wesley, 2012.

[6] S. Anand and M. Ravallion, “HUMAN DEVELOPMENT IN POOR COUNTRIES: ON THE ROLE OF PRIVATE INCOMES AND PUBLIC SERVICES,” *Journal of Economic Perspectives*, vol. 7, no. 1, pp. 133–150, Feb. 1993. doi: https://doi.org/10.1257/jep.7.1.133

[7] R. A. Easterlin, “DOES ECONOMIC GROWTH IMPROVE THE HUMAN LOT? SOME EMPIRICAL EVIDENCE,” *Nations and Households in Economic Growth*, pp. 89–125, 1974. doi: https://doi.org/10.1016/B978-0-12-205050-3.50008-7

[8] O. Blanchard and D. R. Johnson, *MACROECONOMICS*, Sixth Edition. Boston: Pearson, 2013.

[9] T. W. Schultz, “INVESTMENT IN HUMAN CAPITAL,” *The American Economic Review*, vol. 51, no. 1, pp. 1-17, 1961.

[10] A. Ersawahyuni, S. Martha, and H. Perdana, “PENGELOMPOKAN INDEKS PEMBANGUNAN MANUSIA DI INDONESIA MENGGUNAKAN METODE K-MEDOIDS DENGAN EVALUASI DAVIES BOULDIN INDEX,” *Buletin Ilmiah Math. Stat dan Terapannya (Bimaster)*, vol. 14, no. 2, pp. 207–216, 2025.

[11] B. P. S. Indonesia, “PRODUK DOMESTIK REGIONAL BRUTO KABUPATEN_KOTA DI INDONESIA 2018-2022.”14 June 2023, [Online]. Available: https://www.bps.go.id/id/publication/2023/06/14/99ca8a81cd97e69dc04a31bc/produk-domestik-regional-bruto-kabupaten-kota-di-indonesia-2018-2022.html [Accessed: May 24, 2025].

[12] B. P. S. Indonesia, “STATISTIK KRIMINAL 2022.” 30 Nov. 2022, [Online]. Available: https://www.bps.go.id/id/publication/2022/11/30/4022d3351bf3a05aa6198065/statistik-kriminal-2022.html [Accessed: May 24, 2025].

[13] B. P. S. Indonesia, “TINGKAT PENGANGGURAN TERBUKA (TPT) DAN TINGKAT PARTISIPASI ANGKATAN KERJA (TPAK) MENURUT PROVINSI, 2023 - TABEL STATISTIK.” 20 Feb. 2023, [Online]. Available: https://www.bps.go.id/id/statistics-table/3/V2pOVWJWcHJURGg0U2pONFJYaExhVXB0TUhacVFUMDkjMw==/tingkat-pengangguran-terbuka--tpt--dan-tingkat-partisipasi-angkatan-kerja--tpak--menurut-provinsi--2022.html?year=2022 [Accessed: May 24, 2025].

[14] B. P. S. Indonesia, “JUMLAH SEKOLAH, GURU, DAN MURID SEKOLAH MENENGAH ATAS (SMA) DI BAWAH KEMENTERIAN PENDIDIKAN, KEBUDAYAAN, RISET, DAN TEKNOLOGI MENURUT PROVINSI, 2024/2025 - TABEL STATISTIK.” 17 Feb. 2023, [Online]. Available: https://www.bps.go.id/id/statistics-table/3/YTFsRmNubEhOWE5ZTUZsdWVHOHhMMFpPWm5VMFp6MDkjMw==/jumlah-sekolah--guru--dan-murid-sekolah-menengah-atas--sma--di-bawah-kementerian-pendidikan--kebudayaan--riset--dan-teknologi-menurut-provinsi--2022.html?year=2022 [Accessed: May 24, 2025].

[15] B. P. S. Indonesia, “JUMLAH RUMAH SAKIT UMUM, RUMAH SAKIT KHUSUS, PUSKESMAS, KLINIK PRATAMA, DAN POSYANDU MENURUT PROVINSI, 2020 - TABEL STATISTIK.” 23 Feb. 2022, [Online]. Available: https://www.bps.go.id/id/statistics-table/3/YmlzemNGUkNVblZLVVhOblREWnZXbkEzWld0eVVUMDkjMw==/jumlah-rumah-sakit-umum--rumah-sakit-khusus--puskesmas--klinik-pratama--dan-posyandu-menurut-provinsi--2018.html?year=2020 [Accessed: May 24, 2025].

[16] O. R. Putri, W. Sudarwati, S. Wardah, and U. Marfuah, “APLIKASI SISTEM INFERENSI FUZZY METODE MAMDANI UNTUK MEMPREDIKSI JUMLAH PRODUKSI PAKAIAN PADA INDUSTRI KREATIF FESYEN,” *Semnastek*, April 2024.

[17] F. Bellini, Y. Barzegar, A. Barzegar, S. Marrone, L. Verde, and P. Pisani, “SUSTAINABLE WATER QUALITY EVALUATION BASED ON COHESIVE MAMDANI AND SUGENO FUZZY INFERENCE SYSTEM IN TIVOLI (ITALY),” *Sustainability*, vol. 17, no. 2, p. 579, Jan. 2025. doi: https://doi.org/10.3390/su17020579

[18] J. Chen, C. Yang, G. Xu, and L. Ning, “IMAGE SEGMENTATION METHOD USING FUZZY C MEAN CLUSTERING BASED ON MULTI-OBJECTIVE OPTIMIZATION,” *J. Phys.: Conf. Ser.*, vol. 1004, p. 012035, Apr. 2018. doi: https://doi.org/10.1088/1742-6596/1004/1/012035

[19] Z. Zhang, “ALGORITHM FOR EVALUATING THE STABILITY OF MECHANICAL STRUCTURE OF A TRIPHIBIAN ROBOT BASED ON REDUCED-DIMENSIONAL FUZZY C-MEAN CLUSTERING,” *Eng. Res. Express*, vol. 7, no. 2, p. 025550, Jun. 2025. doi: https://doi.org/10.1088/2631-8695/add4c9

[20] A. M. Husein, M. Harahap, S. Aisyah, W. Purba, and A. Muhazir, “THE IMPLEMENTATION OF TWO STAGES CLUSTERING (K-MEANS CLUSTERING AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM) FOR PREDICTION OF MEDICINE NEED BASED ON MEDICAL DATA,” *J. Phys.: Conf. Ser.*, vol. 978, p. 012019, Mar. 2018. doi: https://doi.org/10.1088/1742-6596/978/1/012019

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