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DECISION SUPPORT SYSTEM FOR COMMUNITY WELFARE ASSESSMENT USING FUZZY LOGIC MAMDANI IN PONOROGO REGENCY

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Abstract

The inequality of public welfare is still an important issue in various regions, including Ponorogo Regency. Manual determination of welfare levels often leads to inaccuracies due to subjectivity and limited data coverage. This study develops a Decision Support System (DSS) based on the Mamdani fuzzy logic method to objectively classify the level of community welfare in Ponorogo Regency. The system was built using Python and Streamlit, utilizing secondary data from the Central Statistics Agency (BPS) covering 14 indicators in the education, health, and demographic sectors across 21 sub-districts. The classification results group the sub-districts into three categories: low, medium, and high welfare. Of the 21 sub-districts, seven are classified as high, thirteen as medium, and one as low. The system achieves an accuracy rate of 80.95% when compared to ground truth data, indicating its reliability in reflecting real conditions. To complement this analysis, the Analytical Hierarchy Process (AHP) was applied to determine the relative importance of the indicators, resulting in education (0.54) as the most influential criterion, followed by health (0.30) and demographics (0.16). These findings show that the fuzzy Mamdani method is more suitable for data-driven classification, while AHP provides complementary insights into indicator prioritization. Therefore, this system offers not only a technical tool but also a strategic resource for evidence-based policy formulation by local governments.

Keywords: Decision Support System; Fuzzy Logic; Mamdani; Streamlit; Ponorogo

Abstract

Ketimpangan kesejahteraan masyarakat masih menjadi isu penting di berbagai daerah, termasuk Kabupaten Ponorogo. Penentuan tingkat kesejahteraan secara manual seringkali menimbulkan ketidakakuratan akibat subjektivitas dan keterbatasan cakupan data. Penelitian ini mengembangkan Sistem Pendukung Keputusan (SPK) berbasis metode logika fuzzy Mamdani untuk mengklasifikasikan tingkat kesejahteraan masyarakat di Kabupaten Ponorogo secara objektif. Sistem ini dibangun menggunakan Python dan Streamlit, memanfaatkan data sekunder dari Badan Pusat Statistik (BPS) yang mencakup 14 indikator di sektor pendidikan, kesehatan, dan demografi di 21 kecamatan. Hasil klasifikasi mengelompokkan kecamatan menjadi tiga kategori: kesejahteraan rendah, sedang, dan tinggi. Dari 21 kecamatan, tujuh tergolong tinggi, tiga belas sedang, dan satu rendah. Sistem ini mencapai tingkat akurasi sebesar 80,95% jika dibandingkan dengan data ground truth, yang menunjukkan keandalannya dalam mencerminkan kondisi riil. Untuk melengkapi analisis ini, Proses Hirarki Analitik (AHP) diterapkan untuk menentukan tingkat kepentingan relatif indikator, menghasilkan pendidikan (0,54) sebagai kriteria yang paling berpengaruh, diikuti oleh kesehatan (0,30) dan demografi (0,16). Temuan ini menunjukkan bahwa metode fuzzy Mamdani lebih cocok untuk klasifikasi berbasis data, sementara AHP memberikan wawasan pelengkap dalam penentuan prioritas indikator. Oleh karena itu, sistem ini tidak hanya menawarkan perangkat teknis tetapi juga sumber daya strategis untuk perumusan kebijakan berbasis bukti oleh pemerintah daerah.

Kata Kunci: Sistem Pendukung Keputusan; Logika Fuzzy; Mamdani; Streamlit; Ponorogo

INTRODUCTION

Poverty is a major problem faced by many developing countries, including Indonesia. This problem not only affects economic conditions but also impacts access to education, health care, and other basic needs (Salwa

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Fadhilah Haya dkk., 2022). The government has implemented various poverty alleviation programs, but their implementation often faces various obstacles in the field. According to data from the Central Statistics Agency (BPS) of Ponorogo Regency, the percentage of the poor population in March 2024 was recorded at 9.11%, a decrease compared to the previous year's figure of 9.53% (BPS Ponorogo Regency, 2024). However, the reality on the ground does not fully reflect the program's success, as was the case in Mojorejo Village, Jetis District, Ponorogo Regency. Although various forms of assistance, such as Direct Cash Assistance (BLT), have been distributed, their implementation is often not well-targeted. Social assistance is received by those considered wealthy, while those truly in need are not (Tanzilulloh, 2024).

Identification of poor communities is still largely done manually, making it prone to inaccuracies in decision-making (Kurniadi dkk., 2022). To address this, a Decision Support System (DSS)-based approach with *fuzzy logic* is considered capable of handling uncertainty in social data and increasing decision-making efficiency (Reza dkk., 2024; Rifai & Fitriyadi, 2023). *Fuzzy logic* is used because it can handle uncertain data. In many cases, a person's welfare status is not simply "prosperous" or "not prosperous," but rather falls within a range such as "high," "medium," or "low" (Januharsa dkk., 2024). This method has proven effective in various studies, including in determining eligibility for social assistance and predicting recipients of the Family Hope Program (Kurniadi dkk., 2022).

Fuzzy logic based systems have also been applied in the assessment of uninhabitable houses, welfare evaluations based on economic indicators, and other parameter-based decision-making (Januharsa dkk., 2024). Such systems offer advantages in terms of transparency, efficiency, and reduced subjectivity in decision-making (Kusuma & Tristianto, 2024). One type of *fuzzy logic* used in this study is the *Mamdani method*, known for its ability to handle easily understood *IF-THEN linguistic rules. Mamdani fuzzy* is more suitable for systems that require expert logic-based reasoning and intuitive knowledge representation. Furthermore, this method is capable of producing more stable and flexible outputs than other approaches such as *Sugeno fuzzy*, especially when the data used is complex and multidimensional (Kurniadi dkk., 2022; Kusuma & Tristianto, 2024).

Based on these previous studies, it can be seen that fuzzy logic has been successfully applied in several domains such as social assistance eligibility, housing assessment, and welfare evaluation based on economic indicators. However, these studies are generally limited to specific indicators or narrow case studies, so the results have not provided a comprehensive welfare assessment at the regional level. Therefore, this study aims to develop a fuzzy logic-based *Decision Support System* (DSS) to assess the level of community welfare in Ponorogo Regency in a more measurable and objective manner. The system integrates 14 indicators from education, health, and demographic data provided by the Central Statistics Agency (BPS), and classifies welfare into three categories: low, medium, and high. The results indicate that most sub-districts fall into the medium category, reinforcing the urgency of data-driven social policy evaluation. The novelty of this study lies in the comprehensive use of multi-sectoral indicators at the sub-district level and the implementation of the system using *Python* with a *Streamlit* interface for interactive visualization.

RESEARCH METHODS

This research was conducted to design and develop a Decision Support System (DSS) based on *Mamdani fuzzy logic* to classify the level of community welfare in Ponorogo Regency. This system was built using the *Python programming language* and the *scikit-fuzzy library, and is equipped with a Streamlit-* based visual interface to facilitate user input and interpretation of results.

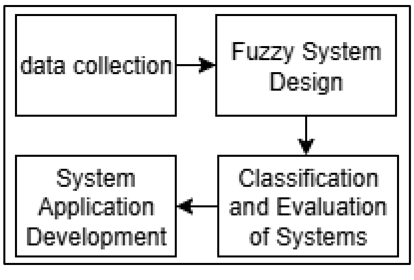

Figure 1. Research Process

This research was conducted through four main stages as follows:

1. Data collection

Data were collected from annual statistical documents published by BPS Ponorogo Regency.

1.1 Data Set and Indicators

To support the welfare classification process using *fuzzy logic*, 14 main indicators were used, grouped into three categories: education, health, and demographics. The following data reflects the actual conditions of all 21 sub-districts in Ponorogo Regency. This table is presented separately by indicator category for greater systematic and easier understanding.

a. Health Indicators

Health indicators are one of the key components in *fuzzy logic* based community welfare assessments. The availability and accessibility of healthcare services reflect the extent to which local governments can fulfill the population's basic health needs. Facilities such as hospitals, community health centers, clinics, and pharmacies play a direct role in maintaining and improving people's quality of life. In the context of *fuzzy logic*, each type of facility can be assigned a weight or membership value representing its level of availability. These values are then processed through *fuzzy* rules to produce a welfare classification that is more adaptive to real-world conditions. Therefore, health indicators are not merely seen as statistical data but also as a reflection of social responsibility and the effectiveness of public service delivery in a given region.

Table 1. Health Data

No.	Subdistrict	H	MH	P	CHC	ACHC	PH
1.	Ngrayun	0	0	5	1	3	1
2.	Slahung	0	0	1	2	3	3
3.	Bungkal	0	0	2	1	2	6
4.	Sambit	0	0	4	1	4	4
5.	Sawoo	5	0	7	2	3	12
6.	Sooko	0	0	5	2	3	6
7.	Pudak	0	0	1	1	2	2
8.	Pulung	0	0	4	2	4	3
9.	Mlarak	1	0	1	1	2	4
10.	Siman	0	0	1	2	2	5
11.	Jetis	0	0	1	1	2	3
12	Balong	0	0	10	1	3	4
13.	Kauman	1	0	2	1	2	6
14.	Ham	0	0	2	1	2	1
15.	Badegan	0	0	0	1	2	1
16.	Sampung	0	0	0	2	3	3
17.	Sukorejo	0	0	4	1	4	4
18.	Ponorogo	5	0	7	2	3	12
19	Babadan	0	0	5	2	3	6
20.	Jenangan	0	0	0	2	3	5
21.	Ngebel	0	0	0	1	3	0

Table 1 contains data on the number of health facilities in 21 sub-districts, including hospitals (H), maternity homes (MH), polyclinics (P), community health centers (CHC), assistant community health centers (ACHC), and pharmacies (PH).

b. Education Indicators

Education sector data also plays a role in measuring the availability and distribution of formal educational institutions in each sub-district. Education is a fundamental factor in human development because it influences the level of literacy, skills, and competitiveness of human resources in a region. The more numerous and evenly distributed educational facilities are, the greater the community's opportunity to access basic and higher education. In the context of welfare support systems, education data is very useful for assessing a region's long-term potential to improve the quality of life of its people through education.

Table 2. Education Data

No.	Subdistrict	SD	SMP	SMA	SMK	Universities
1.	Ngrayun	16	6	3	1	0
2.	Slahung	5	1	0	1	0
3.	Bungkal	15	6	4	2	0
4.	Sambit	18	5	3	1	0
5.	Sawoo	18	13	11	9	3
6.	Sooko	15	11	4	3	1
7.	Pudak	5	1	0	1	0
8.	Pulung	18	6	2	1	0
9.	Mlarak	15	6	4	2	0
10.	Siman	18	4	3	0	3
11.	Jetis	14	6	5	3	0
12.	Balong	20	8	6	1	0
13.	Kauman	15	6	4	2	0
14.	Ham	13	5	2	1	0
15.	Badegan	10	5	1	1	0
16.	Sampung	12	7	3	1	0
17.	Sukorejo	18	5	3	1	0
18.	Ponorogo	18	13	11	9	3
19.	Babadan	15	11	4	3	1
20.	Jenangan	17	11	6	2	1
21.	Ngebel	8	4	1	0	0

Table 2 contains data on the number of educational facilities in 21 sub-districts, including elementary schools (SD), middle schools (SMP), high schools (SMA and SMK), and universities.

c. Demographic Indicators

In the framework of *fuzzy logic* based welfare assessment, demographic data is used to capture the complexity of a region's social and

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geographical conditions. Population density, number of households, and land area are key indicators for identifying public service pressure and potential access inequality. Densely populated areas often face challenges related to infrastructure capacity, while sparsely populated regions struggle with effective service distribution. Therefore, demographic information is not merely statistical; it serves as a parameter that reflects the actual needs and barriers faced by communities in accessing basic services. Integrating this data into a *fuzzy logic* system allows for more flexible and realistic decision-making tailored to the unique conditions of each area.

Table 3. Demographic Data

No.	Subdistrict	Including Area (km ^{2})	House holds	Population
1.	Ngrayun	184.76	15 168	56 413
2.	Slahung	90.34	13 965	48 407
3.	Bungkal	54.01	10 372	34 246
4.	Sambit	59.83	10 294	34 957
5.	Sawoo	124.71	14 749	51 941
6.	Sooko	55.33	6 528	22 423
7	Pudak	48.92	2 430	9 159
8.	Pulung	127.55	13 944	46 128
9.	Mlarak	37.20	8 930	36 963
10.	Siman	37.95	12 058	43 678
11.	Jetis	22.41	7 838	28 260
12.	Balong	56.96	11 972	40 665
13.	Kauman	36.61	10 871	37 165
14.	Ham	57.48	10 980	38 470
15.	Badegan	52.35	8 346	29 080
16.	Sampung	80.61	10 275	34 377
17.	Sukorejo	59.58	15 016	51 281
18.	Ponorogo	22.31	20 558	78 583
19.	Babadan	43.93	18 994	68 317
20.	Jenangan	59.44	16 059	53 867
21.	Ngebel	59.50	5 443	19 520

Table 3 contains data on the number of demographic facilities in 21 sub-districts, including area, households, and population.

2. *Fuzzy* System Design

At this stage, the following determinations are made:

2.1 Input variables: education, health, and demographic indicators.

2.2 Output variable: level of community welfare.

2.3 Membership functions: using automf(3) from the *scikit-fuzzy library*, which automatically divides values into three linguistic categories (*poor*, *average*, *good*).

2.4 Fuzzy rules (*rule base*): are composed based on a combination of *AND* and *OR logic* to linguistically map input to output.

3. Classification and Evaluation of Systems

In the *Mamdani fuzzy* classification method, numeric input values (crisp) are converted into *fuzzy* values using the automf(3) membership function, which divides the data into linguistic categories: *poor*, *moderate*, and *good*. The system evaluates all relevant *fuzzy rules* and combines the results into *fuzzy* output. The resulting *fuzzy* values are then converted back into exact numbers using the *Centroid of Area* (COA) method to obtain the final welfare level.

In addition to the *Mamdani fuzzy* method, this study also applies the *Analytical Hierarchy Process* (AHP) for comparison. In AHP, the evaluation begins by constructing a *pairwise* comparison matrix of three main criteria (education, health, and demographics) using *Saaty's* 1–9 scale. The matrix is normalized, and the priority weights are calculated using the *eigenvector method*. A consistency check is performed by calculating the *Consistency Ratio* (CR) to ensure that the *pairwise* comparisons are valid.

4. System Application Development

This system was developed using *Python*, utilizing the *scikit-fuzzy library*. The system interface was designed using *Streamlit* and runs locally on the administrator's device. The following is the login page:

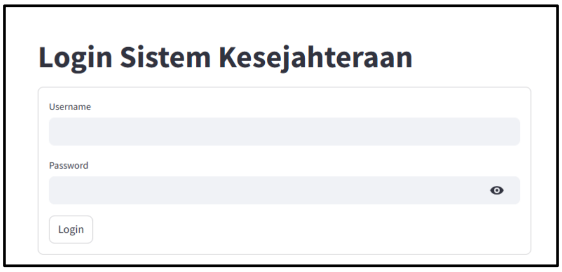

Figure 2. Login Page

Figure 2 shows the system's initial interface, which serves as an authentication gateway for users. Users are required to enter a username and password to access the system, ensuring that only authorized parties can use the welfare classification feature. This aims to maintain data security and prevent unauthorized access.

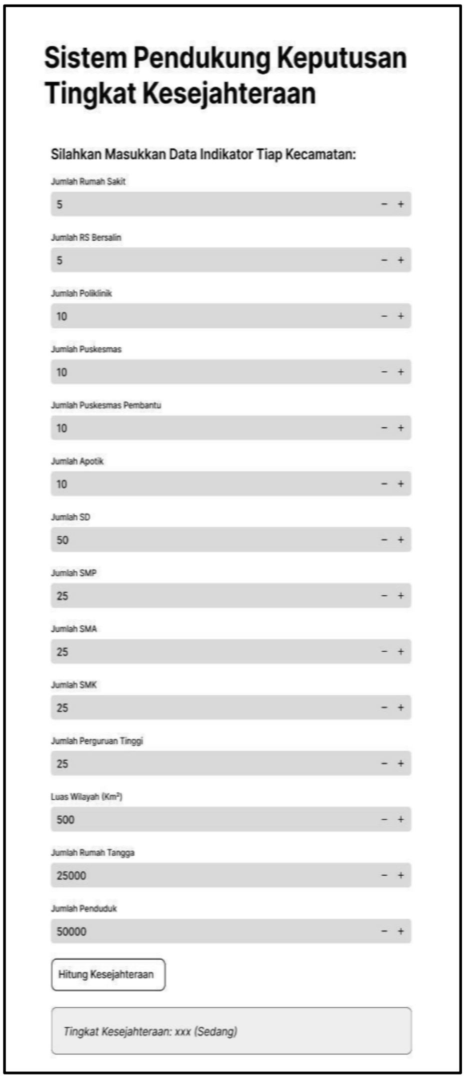

Figure 3. Streamlit Interface Wireframe

Figure 3 depicts the initial design of the system interface designed using *Streamlit*. This view organizes key elements such as input columns for entering welfare indicator data, a process button for running the classification using *Mamdani fuzzy logic*, and an output area that displays the classification results. The wireframe serves as a design guide to ensure the system has a structured, easy-to-understand interface and facilitates user interaction.

In addition to the interface design, the determination of indicator data is an important foundation of this system. The indicators used—covering health, education, and demographic aspects—were chosen because they represent essential dimensions of welfare. Health facilities indicate access to basic services, education facilities reflect opportunities for human capital development, while demographic data capture service burdens and distribution equity. These variables are then transformed into fuzzy inputs and processed to produce a final classification of welfare levels.

Engineering data analysis

Mamdani fuzzy system used in this study consists of five main stages, namely:

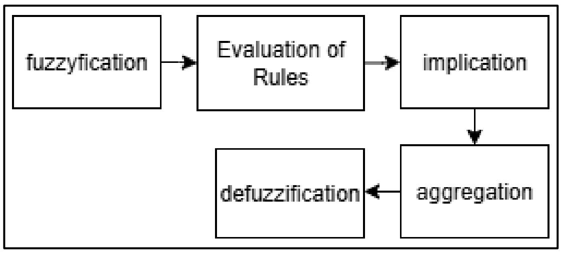

Figure 4. Fuzzy Logic Calculation Process

1. *Fuzzyfication*

This process involves converting numeric (*crisp*) input into *fuzzy value form* using membership functions.

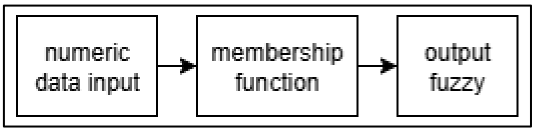

Figure 5. Fuzzyfication Process

In the developed system, each input variable is classified into three *fuzzy* sets: poor, average, and good. Meanwhile, the output welfare level is divided into three fuzzy categories: low, medium, and high.

Triangular Membership Function Equation:
$\mu_A(\ x\ ) = \{0, \frac{x-a}{b-a}\ \frac{c-x}{c-b} \quad x \le a\ atau\ x \ge c\ a < x \le b\ b < x < c$ (1)

Information:

$\mu_A(x)$: Degree of membership of the values $x$in *fuzzy set A*

a, b, c: The starting, middle, and ending points of a triangle function

The value $\mu_A(x)$:is in the range [0,1]

2. Evaluation of Rules

Rule evaluation is the process of calculating the truth value (*firing strength*) of the premises in *the IF part* of a *fuzzy rules.*

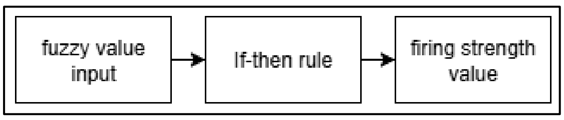

Figure 6. Rule Evaluation Process

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General Format of *Fuzzy Rules*:

IF X_1 is A_1 *AND* X_2 is A_1 THEN Y is B (2)

Operators Used:

AND (Conjunction) minimum

OR (Disjunction) maximum

$$\mu_{rule} = \min(\mu_{X_1}, \mu_{X_2}, \ldots, \mu_{X_n}) \quad (3)$$

3. *Implications*

Implication is the process of determining the shape of the *fuzzy* output (the THEN part) based on the firing strength of the rule premise.

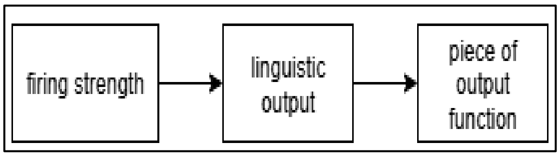


Figure 7. Implication Process

The MIN (minimum) method is used to truncate the output membership function according to the firing strength.

Implication Equation:

$$\mu_{output}(z) = \min(\mu_{premis}, \mu_B(z)) \quad (4)$$

Information:

μ_{premis} : result the result of evaluating the rule premise (also known as the firing strength)
$\mu_B(z)$: membership function of the consequent
$\mu_{output}(z)$: *fuzzy* implication result

4. *Aggregation*

Aggregation is the process of combining all the results of fuzzy implication from the active *fuzzy* rules.

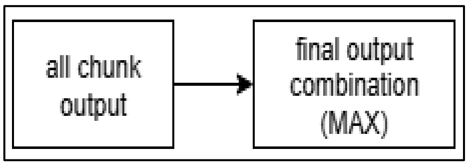


Figure 8. Aggregation Process

Method: the *MAX* (maximum) operator is applied to each z value in the output domain.

Aggregation Equation:

$$\mu_{gabungan}(z) = \max(\mu_{output_1}(z), \mu_{output_2}(z), \mu_{output_3}(z)) \quad (5)$$

The result is a combined *fuzzy* output curve that is ready for the *defuzzification* process.

5. *Defuzzification*

Defuzzification is the process of converting the aggregated *fuzzy* output into a single crisp numerical value that represents the final result of the system.

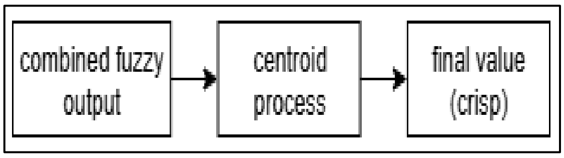


Figure 9. Defuzzification Process

Method Used: *Centroid of Area* (COA), also known as the *Center of Gravity* (COG) method.

Defuzzification Equation:

$$z = \frac{\int_{\alpha}^{\beta} z \cdot \mu(z)\, dz}{\int_{\alpha}^{\beta} \mu(z)\, dz} \quad (6)$$

Information:

Z : *crisp value* of output
$\mu(z)$: degree of membership of the results
the *fuzzy* aggregation
$\propto, \beta$: lower and upper bounds of the output domain (in this system: 0-100)

RESULTS AND DISCUSSION

Inter-regional inequality remains a significant challenge that demands an objective, adaptive, and data-driven assessment approach. Determining the level of community well-being cannot rely on a single indicator alone; instead, it requires a comprehensive and integrated consideration of multiple factors. In this context, *fuzzy logic*-based decision support systems serve a vital role as analytical tools capable of managing uncertainty and multidimensional data, especially in public sector decision-making.

The *Mamdani fuzzy system* employed in this study is designed to classify the level of community welfare based on education, health, and demographic indicators from 21 sub-districts in Ponorogo Regency. *Fuzzification* converts numerical input values into linguistic categories (*poor*, *average*, *good*). Through *rule evaluation* and *fuzzy logic aggregation*, the system calculates a final welfare score for each sub-district. The *defuzzification* process produces a numerical output (*crisp value*), which is then classified into three categories: low, medium, and high.

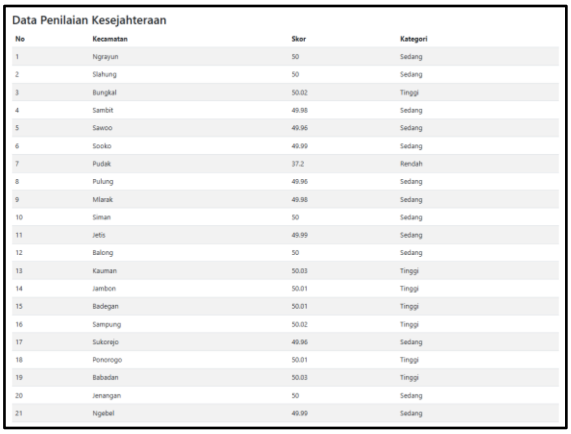
Figure 10. Main Page

The system also features a *Streamlit*-based interactive visual interface that enables users to input data and directly view the classification results. Figure 10 illustrates the system's main page, which displays general information on key welfare indicators, namely access to health care, education services, and demographic conditions. The interface, as shown in Figure 11, reinforces the notion that welfare assessments should be conducted holistically—taking into account not only the number of facilities but also their relevance to population size and other contextual indicators.

This visual approach enhances transparency and improves user understanding of the classification process. Users can not only see the final results but also trace how each variable contributes to the determination of welfare categories. Thus, the system functions not only as an analytical tool but also as an educational resource for policymakers, enabling a more objective and data-driven understanding of regional inequality. This, in turn, encourages more active participation in development planning. Furthermore, users are able to identify priority areas more efficiently and accurately.

Figure 11. Classification System Results

The system interface, as shown in Figure 11, presents the classification results in an intuitive and easy-to-understand visual format. Each sub-district is assigned a welfare score based on the *fuzzy logic* process and subsequently categorized as low, medium, or high.


Data Penilaian Kesejahteraan

No	Kecamatan	Skor	Kategori
1	Ngrayun	50	Sedang
2	Slahung	50	Sedang
3	Bungkal	50.02	Tinggi
4	Sambit	49.98	Sedang
5	Sawoo	49.96	Sedang
6	Sooko	49.99	Sedang
7	Pudak	37.2	Rendah
8	Pulung	49.96	Sedang
9	Mlarak	49.98	Sedang
10	Siman	50	Sedang
11	Jetis	49.99	Sedang
12	Balong	50	Sedang
13	Kauman	50.03	Tinggi
14	Jambon	50.01	Tinggi
15	Badegan	50.01	Tinggi
16	Sampung	50.02	Tinggi
17	Sukorejo	49.96	Sedang
18	Ponorogo	50.01	Tinggi
19	Babadan	50.03	Tinggi
20	Jenangan	50	Sedang
21	Ngebel	49.99	Sedang

Figure 12. Program Classification Results

With this interface, users can perform real-time, data-driven monitoring and evaluation of regional conditions. This significantly supports

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the formulation of more targeted policies, particularly in resource allocation and the improvement of public services. The classification results are presented in tabular form in Figure 12. The system categorizes one sub-district, Pudak, into the low welfare category, 13 sub-districts into the medium category, and 7 sub-districts into the high category. Overall, most sub-districts fall into the *medium* category, indicating a relatively balanced distribution of facilities, although not yet optimal in proportion to the population. For instance, Pudak Sub-district is classified as having low welfare, consistent with demographic data showing a small number of households and residents, along with limited access to education and health facilities. Conversely, Ponorogo Sub-district, which is classified as high welfare, has more extensive education and health infrastructure and a larger population, making it a regional growth center. These findings suggest that equitable development has not yet been fully achieved across all sub-districts. This decision support system (*DSS*) can serve as an objective foundation for setting development priorities toward sustainable regional progress. The system's output also indicates that access to public facilities remains concentrated in specific areas. Therefore, targeted policy interventions are necessary to promote increased welfare in lower-income regions.

Table 4. Ground Truth Data Description

No.	Subdistrict	Results Fuzzy Classification	Real Data
1.	Ngrayun	Medium	Medium
2.	Slahung	Medium	Medium
3.	Bungkal	High	Medium
4.	Sambit	Medium	Medium
5.	Sawoo	Medium	Medium
6.	Sooko	Medium	Medium
7	Pudak	Low	Low
8.	Pulung	Medium	Low
9.	Mlarak	Medium	Medium
10.	Siman	Medium	Medium
11.	Jetis	Medium	Medium
12.	Balong	Medium	Medium
13.	Kauman	High	High
14.	Jambon	High	Medium
15.	Badegan	High	High
16.	Sampung	High	High
17.	Sukorejo	Medium	Medium
18.	Ponorogo	High	High
19.	Babadan	High	High
20.	Jenangan	Medium	Medium
21.	Ngebel	Medium	Low

Comparison with real-world data shows that 17 out of 21 sub-districts have classification results consistent with the ground truth data from BPS Ponorogo Regency (2020), which includes comprehensive indicators of community welfare. Discrepancies were found in Bungkal, Ngebel, Pulung, and Jambon sub-districts. These inconsistencies are likely due to the limited number of input indicators used in the system, which may not fully capture complex socio-economic conditions such as income levels, unemployment rates, or the proportional distribution of facilities relative to geographic area or physical terrain.

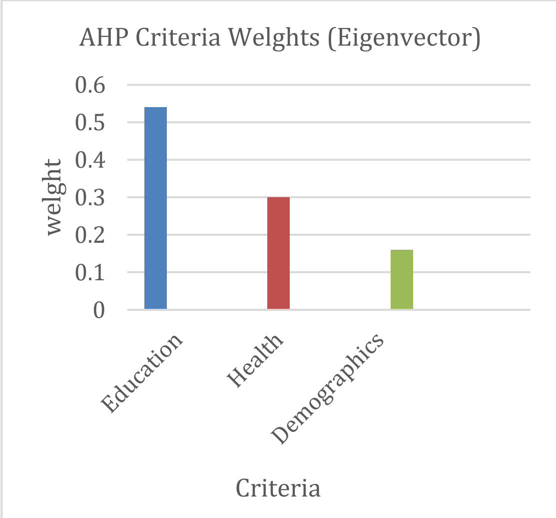

Figure 13. AHP Criteria Weights (Eigenvector)

The *fuzzy Mamdani* system achieves an accuracy rate of 80.95%, calculated from the proportion of correctly classified sub-districts (17 out of 21) when compared with the ground truth data obtained from official BPS records. Classification discrepancies occurred in sub-districts such as Bungkal, Ngebel, Pulung, and Jambon, which may be attributed to limitations in the input data or the fact that the distribution of public facilities is not fully captured by the selected indicators. Despite these inconsistencies, the fuzzy logic system has demonstrated considerable effectiveness in objectively classifying community welfare levels and shows potential as a valuable tool for development evaluation and data-driven social policy formulation. To complement these results, the *Analytical Hierarchy Process* (AHP) was also applied, and the calculation results are presented in Figure 13. The *pairwise* comparison produced consistent results (CR = 0.07 < 0.1), with education identified as the most influential factor (weight = 0.54), followed by health (0.30) and demographics (0.16). Compared with the *fuzzy Mamdani* method, which is superior in handling quantitative and complex field data, AHP is more suitable for determining the relative importance of indicators, although it is highly dependent on subjective judgments. Therefore, this comparison indicates that the *fuzzy Mamdani* method is more appropriate for data-driven classification of community welfare, while AHP serves as a complementary approach to highlight policy priorities.

CONCLUSION AND SUGGESTIONS

Conclusion

This research successfully developed a Decision Support System (DSS) based on the *Mamdani fuzzy logic* method to classify the level of community welfare in Ponorogo Regency. The system utilizes 14 indicators derived from the education, health, and demographic sectors across 21 sub-districts. The classification process was carried out through automatic *fuzzification*, *rule-based inference*, and *defuzzification* using the *Centroid of Area* (COA) method. The results indicate that most sub-districts fall into the medium and high welfare categories, while only one sub-district is classified as low. By considering the ratio of public facilities to population, the system produces more proportional and equitable classification outcomes. The evaluation, conducted against ground truth data, produces an accuracy rate of 80.95%, demonstrating that the system is sufficiently reliable for data-driven decision-making. In addition, the *Analytical Hierarchy Process* (AHP) was applied to determine the relative importance of indicators, resulting in education (0.54) as the most influential criterion, followed by health (0.30) and demographics (0.16). These findings suggest that the *Mamdani fuzzy* method is more suitable for data-driven classification of community welfare, while AHP provides complementary insights into indicator prioritization. Therefore, the combination of both approaches offers not only a technical analytical tool but also a strategic resource for local governments in assessing development and formulating evidence-based social policies.

Suggestion

Future research is recommended to incorporate additional socioeconomic indicators, such as per capita income, unemployment rate, and the *Gini index*, to enhance the comprehensiveness of the classification results. System testing using data from different years is also necessary to evaluate the long-term stability and validity of the model. Furthermore, future studies could develop a hybrid approach by integrating the *Mamdani fuzzy* method with AHP or other *decision-making* and *machine learning* techniques, which may enrich the analysis and further improve classification accuracy.

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