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Application Of The Fuzzy C-Means Method In Elderly Health Analysis At The Blitar Regency Elderly Home

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Abstract

The increasing number of elderly population requires a structured health assessment to support the determination of appropriate interventions in elderly care facilities. This study aims to identify the health patterns of elderly in elderly care facilities in Blitar Regency using Fuzzy C-Means (FCM) and evaluate the validity of clusters using Partition Coefficient (PC). This is an applied research with a sample of 90 elderly from three elderly care facilities. Data were collected through interviews, observations, and measurements of weight, height, blood pressure, blood sugar, BMI, MAP, and PP. The analysis was performed using Min-Max Normalization, FCM, and PC validation. The results showed three clusters, namely healthy (40%), alert (11.11%), and high risk (48.89%), with a PC value of 0.7535 indicating good cluster quality. The findings indicate that FCM is able to identify variations in elderly health conditions. In conclusion, FCM and PC validation can support monitoring and determining the priority of elderly health interventions.

Keywords*: *Fuzzy C-Means, Health, Clustering, Elderly, Nursing Home

INTRODUCTION

Indonesia is experiencing an increase in the number of elderly people, indicating a shift in demographic structure. According to data from the Central Statistics Agency (BPS), the number of elderly people is estimated to reach 32.56 million by 2023, or 12.90% of the total population. Most provinces have an elderly percentage exceeding 7%, while Yogyakarta, East Java, Bali, and Central Java have reached over 10%. Yogyakarta has the highest elderly percentage, at 16.69% (Nindya, 2023). This situation demonstrates the need for government and public attention to fulfilling the needs and rights of the elderly.

The increasing proportion of elderly people, coupled with increasing life expectancy, indicates that Indonesia is moving towards an aging population. The Central Statistics Agency (BPS) (2023) stated that "The increasing proportion of elderly people, coupled with increasing life expectancy, indicates that Indonesia is moving towards an aging population. This means that a more friendly and comprehensive health care system is needed for the elderly." This condition also occurs in Blitar Regency, which has a productive age population percentage of 69.56% and elderly population of 14.44% (BPS, Blitar Regency, 2021). The relatively large number of elderly people demonstrates the importance of improving the welfare and health of the elderly.

One form of service for the elderly in Blitar Regency is a nursing home, which provides housing, healthcare services, care, and activities to support their quality of life (Septiarini et al., 2019). However, managing the health of the elderly still faces challenges, particularly in implementing health intervention programs and recording data. The manual and non-computerized recording system limits the use of health data for analysis.

This problem is also related to the uneven distribution of intervention programs for the health of the elderly, resulting in a suboptimal health analysis process. Based on data from the Blitar Regency Social Service (2023), there are four nursing homes in several sub-districts, consisting of three privately owned and one owned by the East Java Provincial Government. This research was conducted at three nursing homes: the Baitul Miftahul Janah Nursing Home, the Griya Sakinah Nursing Home of the As Sakinah Foundation, and the Al Hikmah Nursing Home. This situation demonstrates the need for a method that can group elderly health data in a more structured manner.

The Fuzzy C-means method can be used to cluster elderly health data. A study by Suyaana et al. (2024) entitled "Using a Fuzzy Expert System to Determine Drug Dosage in the Elderly" used Fuzzy C-means to determine drug dosage in the elderly. The results of this study indicate that this method can help understand elderly health problems and support the determination of more targeted therapies. In this study, Fuzzy C-means was applied to identify elderly health patterns and groups and its accuracy was measured using the Partition Coefficient method.

This study aims to apply the Fuzzy C-means method to identify patterns and health groups of elderly people in elderly care facilities in Blitar Regency and determine the degree of membership of each individual in the cluster. This study also aims to analyze the accuracy level of the Fuzzy C-means method using the Partition Coefficient. The urgency of this research lies in the need for a more structured health data analysis amidst the increasing number of elderly people and the limitations of health records in elderly care facilities. The novelty of this research lies in the application of Fuzzy C-means to analyze elderly people's health in three elderly care facilities in Blitar Regency with accuracy measurements using the Partition Coefficient.

RESEARCH METHODS

This study uses applied research that aims to apply scientific methods to solve health problems of the elderly in elderly care facilities in Blitar Regency. Data collection was carried out through surveys, interviews, observations, and measurements, then the data was analyzed using the Fuzzy C-means method to group the health conditions of the elderly based on predetermined parameters. The results of the analysis are used to provide an overview of the health conditions of the elderly as a basis for supporting health services. According to Siswanto et al. (2020), applied research is a way or method to find solutions to solve problems or phenomena that are currently occurring. The study was conducted at the Baitul Miftakul Janah Elderly Home, the Al Hikmah Elderly Home, and the Griya Sakinah Elderly Home of the As Sakinah Foundation in Blitar Regency from November 22, 2024, to April 25, 2025.

The research instruments used included interview guidelines, observation guidelines, and measurement guidelines. Interviews were conducted with the owners and residents of the shelter to obtain demographic and health data. Observations were used to determine physical activity, eating habits, living conditions, shelter facilities, and the location of the shelter to health services. Measurements were made of weight, height, systolic blood pressure, diastolic blood pressure, blood sugar levels, BMI, MAP, and PP. The tools used included a digital scale, a stadiometer, a sphygmomanometer, and a digital blood sugar tester. The research instruments were tools used to collect and analyze research data (Priadana & Sunarsi, 2021). Data analysis was carried out through statistical analysis to obtain minimum, maximum, and range values, normalization using Min-Max Normalization, application of Fuzzy C-means with three clusters: healthy, alert, and high risk, and validation testing using Partition Coefficient (PC).

The research population was elderly people residing in elderly care institutions in Blitar Regency, specifically in Baitul Miftakul Janah Elderly Care Institution, Al Hikmah Elderly Care Institution, and Griya Sakinah Elderly Care Institution of As Sakinah Foundation. The research sample consisted of elderly data obtained through interviews, observations, and direct measurements at the three care institutions. The data used in the analysis process included body weight, height, systolic blood pressure, diastolic blood pressure, blood sugar levels, BMI, MAP, and PP as parameters in the clustering process using Fuzzy C-means.

The research procedure was carried out through the stages of problem identification, problem formulation, literature study, data collection, data processing, application of Fuzzy C-means, validation testing, and preparation of conclusions. Data obtained through interviews, observations, and measurements were first analyzed to obtain minimum, maximum, and range values, then normalized using Min-Max Normalization. The normalized data were processed using Fuzzy C-means through partition matrix initialization, cluster center calculation, Euclidean distance, membership value update, and iteration until reaching convergence of 0.00001. The clustering results were then tested using the Partition Coefficient to evaluate the quality of the clustering of elderly health conditions.

RESULTS AND DISCUSSION

Data Normalization

Table 1. Difference Table

No.	Parameter	Minimum	Maximum	Range
1.	BB	30	72	42
2.	TB	123	172	49
3.	TDS	90	204	144
4.	TDD	60	129	69
5.	KGD	89	431	342
6.	BMI	14.3	29.7	15.4
7.	FOLDER	70	148.7	78.7
8.	PP	18	99	81

Table 2. Example of Data Normalization

Parameter	Manual Calculation
X1	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(40 - 30)}{(72 - 30)} = \frac{10}{42} = 0.2381$
X2	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(149 - 123)}{(172 - 123)} = \frac{26}{49} = 0.53061$
X3	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(136 - 90)}{(204 - 90)} = \frac{46}{114} = 0.40351$
X4	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(80 - 60)}{(129 - 60)} = \frac{20}{69} = 0.28986$
X5	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(167 - 89)}{(431 - 89)} = \frac{78}{342} = 0.22807$
X6	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(18 - 14.3)}{(29.7 - 14.3)} = \frac{3.7}{15.4} = 0.24026$
X7	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(98.7 - 70)}{(148,7 - 70)} = \frac{28.7}{78.7} = 0.36468$
X8	$\frac{(X - X_{min})}{(X_{max} - X_{min})} = \frac{(56 - 18)}{(99 - 18)} = \frac{38}{81} = 0.46914$

Information :

X1 = BB (Body Weight).
X2 = TB (Height).
X3 = TDS (Systolic Blood Pressure).
X4 = TDD (Diastolic Blood Pressure).
X5 = KGD (Blood Sugar Level).
X6 = BMI (Body Mass Index).
X7 = MAP (Mean Arterial Pressure)
X8 = PP (Pulse Pressure)

Data normalization is performed to ensure that each variable has an equivalent scale before being used in the clustering process. For variable X, normalization is performed using the formula (X−X Min)/(X Max−X Min). Meanwhile, the body weight variable is normalized based on the actual range in the data, for example, body weight between 35 and 80 kilograms, and height is normalized to a range between 135 and 170 centimeters. A similar process is also applied to other variables such as

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blood pressure, blood sugar levels, body mass index (BMI), mean arterial pressure (MAP), and pulse pressure (PP). So that the results of the normalization produce values that are in the range of 0 to 1.

Implementation of Fuzzy C-means

Table 3. Initial matrix initialization

	Random Used						Normalize Each Row			
No.	**µ1**	**µ2**	**µ3**	Total			**µ1**	**µ2**	**µ3**	Total
1.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
2.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
3.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
4.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
5.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
6.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
7.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
8.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
9.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
10.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
11.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
12.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
13.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
14.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
15.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
16.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
17.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
18.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
19.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
20.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
21.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
22.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
23.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
24.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
25.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
26.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
27.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
28.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
29.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
30.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
31.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
32.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
33.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
34.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
35.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
36.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
37.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
38.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
39.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
40.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
41.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
42.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
43.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
44.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
45.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
46.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
47.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
48.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
49.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
50.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
51.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1

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	Random Used						Normalize Each Row			
No.	**µ1**	**µ2**	**µ3**	Total			**µ1**	**µ2**	**µ3**	Total
52.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
53.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
54.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
55.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
56.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
57.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
58.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
59.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
60.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
61.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
62.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
63.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
64.	0.25	0.35	0.4	1			0.25	0.35	0.4	1
65.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
66.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
67.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
68.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
69.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
70.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
71.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
72.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
73.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
74.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
75.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
76.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
77.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
78.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
79.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
80.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
81.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
82.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
83.	0.35	0.4	0.35	1.1			0.318182	0.363636	0.318182	1
84.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
85.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
86.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
87.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
88.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
89.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1
90.	0.4	0.25	0.25	0.9			0.444444	0.277778	0.277778	1

Table 4. Random matrix initialization

No.	**µ1**	**µ2**	**µ3**		No.	**µ1**	**µ2**	**µ3**
1.	0.179478751	0.219280978	0.179478751		46.	0.296296296	0.146401744	0.146401744
2.	0.296296296	0.146401744	0.146401744		47.	0.296296296	0.146401744	0.146401744
3.	0.296296296	0.146401744	0.146401744		48.	0.125	0.207062792	0.252982213
4.	0.179478751	0.219280978	0.179478751		49.	0.296296296	0.146401744	0.146401744
5.	0.179478751	0.219280978	0.179478751		50.	0.296296296	0.146401744	0.146401744
6.	0.296296296	0.146401744	0.146401744		51.	0.179478751	0.219280978	0.179478751
7.	0.296296296	0.146401744	0.146401744		52.	0.179478751	0.219280978	0.179478751
8.	0.179478751	0.219280978	0.179478751		53.	0.179478751	0.219280978	0.179478751
9.	0.179478751	0.219280978	0.179478751		54.	0.179478751	0.219280978	0.179478751
10.	0.179478751	0.219280978	0.179478751		55.	0.296296296	0.146401744	0.146401744
11.	0.296296296	0.146401744	0.146401744		56.	0.125	0.207062792	0.252982213
12.	0.179478751	0.219280978	0.179478751		57.	0.125	0.207062792	0.252982213
13.	0.179478751	0.219280978	0.179478751		58.	0.125	0.207062792	0.252982213
14.	0.296296296	0.146401744	0.146401744		59.	0.125	0.207062792	0.252982213

15.	0.179478751	0.219280978	0.179478751		60.	0.125	0.207062792	0.252982213
16.	0.125	0.207062792	0.252982213		61.	0.296296296	0.146401744	0.146401744
17.	0.125	0.207062792	0.252982213		62.	0.125	0.207062792	0.252982213
18.	0.125	0.207062792	0.252982213		63.	0.125	0.207062792	0.252982213
19.	0.296296296	0.146401744	0.146401744		64.	0.125	0.207062792	0.252982213
20.	0.179478751	0.219280978	0.179478751		65.	0.296296296	0.146401744	0.146401744
21.	0.296296296	0.146401744	0.146401744		66.	0.296296296	0.146401744	0.146401744
22.	0.125	0.207062792	0.252982213		67.	0.296296296	0.146401744	0.146401744
23.	0.179478751	0.219280978	0.179478751		68.	0.296296296	0.146401744	0.146401744
24.	0.296296296	0.146401744	0.146401744		69.	0.296296296	0.146401744	0.146401744
25.	0.296296296	0.146401744	0.146401744		70.	0.296296296	0.146401744	0.146401744
26.	0.296296296	0.146401744	0.146401744		71.	0.296296296	0.146401744	0.146401744
27.	0.179478751	0.219280978	0.179478751		72.	0.296296296	0.146401744	0.146401744
28.	0.179478751	0.219280978	0.179478751		73.	0.179478751	0.219280978	0.179478751
29.	0.125	0.207062792	0.252982213		74.	0.296296296	0.146401744	0.146401744
30.	0.296296296	0.146401744	0.146401744		75.	0.296296296	0.146401744	0.146401744
31.	0.296296296	0.146401744	0.146401744		76.	0.296296296	0.146401744	0.146401744
32.	0.179478751	0.219280978	0.179478751		77.	0.296296296	0.146401744	0.146401744
33.	0.179478751	0.219280978	0.179478751		78.	0.296296296	0.146401744	0.146401744
34.	0.296296296	0.146401744	0.146401744		79.	0.296296296	0.146401744	0.146401744
35.	0.179478751	0.219280978	0.179478751		80.	0.296296296	0.146401744	0.146401744
36.	0.179478751	0.219280978	0.179478751		81.	0.296296296	0.146401744	0.146401744
37.	0.179478751	0.219280978	0.179478751		82.	0.296296296	0.146401744	0.146401744
38.	0.296296296	0.146401744	0.146401744		83.	0.179478751	0.219280978	0.179478751
39.	0.179478751	0.219280978	0.179478751		84.	0.296296296	0.146401744	0.146401744
40.	0.296296296	0.146401744	0.146401744		85.	0.296296296	0.146401744	0.146401744
41.	0.179478751	0.219280978	0.179478751		86.	0.296296296	0.146401744	0.146401744
42.	0.179478751	0.219280978	0.179478751		87.	0.296296296	0.146401744	0.146401744
43.	0.296296296	0.146401744	0.146401744		88.	0.296296296	0.146401744	0.146401744
44.	0.179478751	0.219280978	0.179478751		89.	0.296296296	0.146401744	0.146401744
45.	0.296296296	0.146401744	0.146401744		90.	0.296296296	0.146401744	0.146401744

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Email : editorijhess@gmail.com

Kluster 1 BB

$$
= \frac{\left(\begin{gathered}
(0,179478751 \times 0,238095238) + (0,296296296 \times 0,238095238) + (0,296296296 \times 0,833333333) + \\
(0,179478751 \times 0,785714286) + (0,179478751 \times 0,80952381) + (0,296296296 \times 0,452380952) + \\
(0,296296296 \times 0,5) + (0,179478751 \times 0,785714286) + (0,179478751 \times 0,880952381) + \\
(0,179478751 \times 0,833333333) + (0,296296296 \times 0,214285714) + (0,179478751 \times 0,5) + \\
(0,179478751 \times 0,238095238) + (0,296296296 \times 0,619047619) + (0,179478751 \times 0,19047619) + \\
(0,125 \times 0,523809524) + (0,125 \times 0,5) + (0,125 \times 0,738095238) + \\
(0,296296296 \times 0,238095238) + (0,179478751 \times 0,761904762) + (0,296296296 \times 0,142857143) + \\
(0,125 \times 0,404761905) + (0,179478751 \times 0,452380952) + (0,296296296 \times 0,69047619) + \\
(0,296296296 \times 0,30952381) + (0,296296296 \times 0,357142857) + (0,179478751 \times 0,357142857) + \\
(0,179478751 \times 0,452380952) + (0,125 \times 0,30952381) + (0,296296296 \times 0,761904762) + \\
(0,296296296 \times 0,357142857) + (0,179478751 \times 0,785714286) + (0,179478751 \times 0,738095238) + \\
(0,296296296 \times 0,214285714) + (0,179478751 \times 0,619047619) + (0,179478751 \times 1) + \\
(0,179478751 \times 0,285714286) + (0,296296296 \times 0,738095238) + (0,179478751 \times 0,404761905) + \\
(0,296296296 \times 0,714285714) + (0,179478751 \times 0,619047619) + (0,296296296 \times 0,571428571) + \\
(0,179478751 \times 0,619047619) + (0,296296296 \times 0,19047619) + (0,296296296 \times 0,833333333) + \\
(0,296296296 \times 0,5) + (0,296296296 \times 0,30952381) + (0,296296296 \times 0,619047619) + \\
(0,125 \times 0,357142857) + (0,296296296 \times 0,357142857) + (0,296296296 \times 0,619047619) + \\
(0,179478751 \times 0,166666667) + (0,179478751 \times 0,166666667) + (0,179478751 \times 0,380952381) + \\
(0,179478751 \times 0,523809524) + (0,296296296 \times 0,452380952) + (0,125 \times 0,761904762) + \\
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(0,179478751 \times 0,357142857) + (0,296296296 \times 0,80952381) + (0,296296296 \times 0,738095238) + \\
(0,296296296 \times 0,285714286) + (0,296296296 \times 0,571428571) + (0,296296296 \times 0,357142857) + \\
(0,296296296 \times 0,476190476) + (0,296296296 \times 0,380952381) + (0,296296296 \times 0,261904762) + \\
(0,296296296 \times 0,738095238) + (0,179478751 \times 0,80952381) + (0,296296296 \times 0,5) + \\
(0,296296296 \times 0,595238095) + (0,296296296 \times 0,595238095) + (0,296296296 \times 0,833333333) + \\
(0,296296296 \times 0,595238095) + (0,296296296 \times 0,357142857) + (0,296296296 \times 0,595238095)
\end{gathered}\right)}{\left(\begin{gathered}
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0.296296296 + 0.296296296 + 0.296296296 + 0.296296296 + 0.296296296 + \\
0.296296296 + 0.296296296
\end{gathered}\right)^{1.5}}
$$

$$\frac{\mathbf{10.4092227123838}}{\mathbf{20.9976272524169}} = \mathbf{0.49573328392072}$$

Table 5. Cluster center calculation results

	BB	TB	TDS	TDD	KGD	BMI	FOLDER	PP
µ1	0.4957333	0.6520217	0.2723297	0.1816049	0.1449056	0.4439796	0.2376422	0.3767265
µ2	0.4961143	0.6352961	0.3418801	0.2480143	0.1635814	0.4584333	0.3100397	0.4180413
µ3	0.4904298	0.6369388	0.1816049	0.2634213	0.1676215	0.4501548	0.3250309	0.4223711

Table 6. Euclidean Distance Results

No.	**µ1**	**µ2**	**µ3**	No.	**µ1**	**µ2**	**µ3**
1.	0.4279473	0.3747474	0.4199843	46.	0.1934449	0.2321397	0.2379331
2.	0.3890818	0.4580901	0.4306038	47.	0.2744604	0.332798	0.3205531
3.	0.5312185	0.5427847	0.558935	48.	1.1231692	0.9954158	1.0756991
4.	0.5432635	0.5051184	0.5575413	49.	0.2580105	0.3388985	0.3053686
5.	0.811249	0.7447991	0.8115273	50.	0.3204359	0.3376257	0.3570207
6.	0.3858128	0.4277008	0.4061006	51.	0.246118	0.2215722	0.2692917

7.	0.1020968	0.1933652	0.2073448	52.	0.6424337	0.648327	0.6235411
8.	0.5690098	0.5277707	0.5671582	53.	0.66307	0.6304975	0.6839995
9.	0.6181421	0.6036329	0.6291012	54.	0.6013776	0.641886	0.5988132
10.	0.5528146	0.5338104	0.5914492	55.	0.078632	0.1099938	0.1783807
11.	0.3941574	0.4434899	0.4289959	56.	1.4768202	1.3566022	1.4251112
12.	0.2830483	0.2282478	0.3223822	57.	1.271534	1.1552656	1.2407272
13.	0.4551141	0.4291266	0.4803959	58.	0.9435183	0.8820891	0.9057661
14.	0.4526518	0.5290753	0.4774873	59.	1.1069737	1.0379797	1.0642478
15.	0.6449114	0.6017135	0.6628702	60.	1.0660574	0.9430208	1.0272943
16.	0.5943208	0.5388783	0.5432459	61.	0.1893846	0.2581191	0.2425401
17.	0.8613538	0.7400527	0.8314909	62.	0.8708752	0.7543557	0.8186477
18.	0.4342449	0.3874836	0.4174572	63.	1.2844848	1.1656775	1.2259564
19.	0.4172808	0.4562486	0.4541668	64.	0.8169304	0.7433277	0.7823892
20.	0.7874939	0.7441286	0.7747339	65.	0.3669796	0.4912879	0.4475019
21.	0.5376681	0.5582836	0.5718055	66.	0.5670526	0.6849334	0.6329706
22.	0.85617	0.7619708	0.8533528	67.	0.1846645	0.1808681	0.2533594
23.	0.13207	0.0982596	0.1576196	68.	0.3873576	0.5108088	0.4727512
24.	0.2984328	0.330358	0.3620668	69.	0.5324281	0.653341	0.5990229
25.	0.2957993	0.3269597	0.3124747	70.	0.3369097	0.4016767	0.4143214
26.	0.2406775	0.2817241	0.2932695	71.	0.5460469	0.6586976	0.6045421
27.	0.8762889	0.8570321	0.8673466	72.	0.1844319	0.1705129	0.2510861
28.	0.1571807	0.1909709	0.1830861	73.	0.3402246	0.2499527	0.3344719
29.	0.4245398	0.3577423	0.3894201	74.	0.6289555	0.7304085	0.6882309
30.	0.4280466	0.4224405	0.4568226	75.	0.398059	0.442705	0.4531536
31.	0.1922292	0.2223631	0.2469406	76.	0.3984816	0.4908356	0.4722217
32.	0.3953838	0.3877619	0.4152656	77.	0.267409	0.3667679	0.3395896
33.	0.37118	0.3303729	0.3859273	78.	0.5414446	0.6616516	0.6077558
34.	0.428361	0.4538744	0.45571	79.	0.2573022	0.3572333	0.3254561
35.	0.2276082	0.2037407	0.2802414	80.	0.3409832	0.4270771	0.3978094
36.	0.7048381	0.6931131	0.7289174	81.	0.4654012	0.5115814	0.480189
37.	0.3434225	0.3386065	0.3620935	82.	0.640017	0.7474149	0.7045574
38.	0.5539871	0.6128135	0.5751399	83.	0.5482699	0.5253377	0.5814662
39.	0.4562488	0.46894	0.4404691	84.	0.3455738	0.421032	0.4333347
40.	0.3259264	0.3565673	0.3754574	85.	0.611101	0.6175678	0.6661831
41.	0.3016743	0.2347342	0.3141182	86.	0.4183768	0.5380228	0.5009745
42.	0.3886665	0.3455492	0.3795044	87.	0.5546086	0.6441222	0.6189388
43.	0.4738093	0.5509595	0.5149887	88.	0.2877537	0.382479	0.3569366
44.	0.4641887	0.456562	0.4663655	89.	0.260048	0.3193537	0.3228801
45.	0.4536017	0.4710224	0.4925355	90.	0.299982	0.4121972	0.3986231

Table 7. Update new membership value

No.	μ1	μ2	μ3	No.	μ1	μ2	μ3
1.	0.2646452	0.4500604	0.2852943	46.	0.5210687	0.2512617	0.2276696
2.	0.4572458	0.2379632	0.304791	47.	0.499996	0.231293	0.2687111
3.	0.3658487	0.335648	0.2985033	48.	0.2625034	0.4254981	0.3119985
4.	0.308692	0.4130426	0.2782654	49.	0.5418369	0.1820287	0.2761345
5.	0.2935851	0.4132323	0.2931826	50.	0.406455	0.3297882	0.2637567
6.	0.4037489	0.2673361	0.328915	51.	0.3105529	0.472768	0.2166791
7.	0.8798891	0.0683855	0.0517255	52.	0.3235253	0.3119213	0.3645534
8.	0.2972427	0.401614	0.3011433	53.	0.3219236	0.3937828	0.2842936
9.	0.3298385	0.362713	0.3074486	54.	0.358717	0.2763817	0.3649013
10.	0.3432405	0.3947922	0.2619672	55.	0.7698657	0.2010659	0.0290683
11.	0.4279769	0.2670325	0.3049906	56.	0.2810836	0.3947626	0.3241538
12.	0.2525792	0.5973293	0.1500914	57.	0.2800649	0.4110013	0.3089338
13.	0.3256611	0.4120078	0.2623311	58.	0.286823	0.3754616	0.3377155
14.	0.4267295	0.2286333	0.3446372	59.	0.2886753	0.373425	0.3378997
15.	0.3109886	0.4103795	0.2786319	60.	0.2636516	0.4305937	0.3057548
16.	0.2556217	0.3781974	0.3661809	61.	0.6018495	0.174416	0.2237344

17.	0.2508306	0.4603164	0.288853
18.	0.2667974	0.4208302	0.3123723
19.	0.4145415	0.2900519	0.2954066
20.	0.3010404	0.377591	0.3213686
21.	0.3784985	0.3256131	0.2958884
22.	0.2772183	0.4418844	0.2808972
23.	0.2102313	0.6861416	0.1036271
24.	0.4700305	0.3130206	0.2169489
25.	0.4043792	0.2708944	0.3247264
26.	0.5034598	0.2681702	0.22837
27.	0.3189962	0.3486474	0.3323564
28.	0.4994681	0.229211	0.2713209
29.	0.2274869	0.4511792	0.321334
30.	0.3539815	0.3731493	0.2728692
31.	0.5192895	0.2900252	0.1906853
32.	0.3444969	0.3723919	0.2831113
33.	0.2899329	0.4619747	0.2480924
34.	0.3884836	0.3082264	0.30329
35.	0.3341489	0.5204517	0.1453994
36.	0.339712	0.3632889	0.2969991
37.	0.3487633	0.3690328	0.2822039
38.	0.3954657	0.2641156	0.3404186
39.	0.3281652	0.2940561	0.3777787
40.	0.4413172	0.3080797	0.2506031
41.	0.2184013	0.5958029	0.1857958
42.	0.2702213	0.4325021	0.2972766
43.	0.441804	0.2416381	0.3165579
44.	0.3278719	0.3503349	0.3217931
45.	0.3876824	0.3334329	0.2788848
62.	0.246489	0.4378412	0.3156698
63.	0.2717808	0.4007016	0.3275176
64.	0.2741593	0.3999651	0.3258756
65.	0.5670247	0.1765328	0.2564425
66.	0.4730606	0.2222371	0.3047023
67.	0.422144	0.4587191	0.1191369
68.	0.561351	0.1856305	0.2530184
69.	0.4842217	0.2135643	0.3022141
70.	0.5175559	0.256156	0.2262881
71.	0.4677588	0.2209009	0.3113403
72.	0.3759637	0.5145903	0.109446
73.	0.1817105	0.6237515	0.194538
74.	0.4449758	0.2446543	0.3103699
75.	0.4446363	0.2906277	0.2647361
76.	0.5150797	0.2237501	0.2611702
77.	0.599855	0.169506	0.230639
78.	0.4811452	0.2157619	0.3030929
79.	0.6024829	0.1621479	0.2353691
80.	0.5138339	0.2087994	0.2773667
81.	0.3895099	0.26679	0.3437001
82.	0.4507344	0.2423482	0.3069173
83.	0.3359268	0.3985366	0.2655367
84.	0.5381279	0.244224	0.2176481
85.	0.3749756	0.3595145	0.2655099
86.	0.539937	0.1974289	0.2626341
87.	0.4557197	0.250479	0.2938013
88.	0.5738001	0.1838291	0.2423708
89.	0.5375062	0.236325	0.2261687
90.	0.6245153	0.1751878	0.2002968

Table 8. Convergence value of iteration 43

Iteration 43					
No.	Name	K1	K2	K3	Max Difference
1.	congregation	1.93845E-06	1.63246E-06	3.57091E-06	3.57091E-06
2.	Khodijah	2.7775E-08	2.02898E-08	7.48524E-09	2.7775E-08
3.	Warti	7.17862E-07	1.403E-07	5.77562E-07	7.17862E-07
4.	Katinah	2.51804E-06	7.47003E-07	1.77103E-06	2.51804E-06
5.	Kayatin	6.24097E-06	3.98712E-06	2.25385E-06	6.24097E-06
6.	Sukinah	4.09869E-06	5.14905E-08	4.0472E-06	4.09869E-06
7.	Sarinten	1.4378E-05	4.7873E-08	1.44259E-05	1.44259E-05
8.	Suminah	2.87339E-06	8.97432E-07	1.97595E-06	2.87339E-06
9.	Tuminem	1.63139E-06	4.80952E-07	1.15044E-06	1.63139E-06
10.	Sutiani	1.14487E-06	4.34714E-07	7.10159E-07	1.14487E-06
11.	Tukinem	2.11411E-07	5.60327E-08	2.67443E-07	2.67443E-07
12.	Ngatemi	2.81911E-06	3.12175E-08	2.85033E-06	2.85033E-06
13.	Cynthia	1.56305E-06	1.15469E-06	2.71774E-06	2.71774E-06
14.	Wiwik Pujiati	1.28518E-05	1.35818E-07	1.2716E-05	1.28518E-05
15.	Messiah	1.45602E-06	3.28843E-06	4.74445E-06	4.74445E-06
16.	Leginem	1.72023E-07	9.5893E-07	7.86908E-07	9.5893E-07
17.	Suparti	2.03723E-07	1.90923E-07	1.28001E-08	2.03723E-07
18.	Arnanik	1.35616E-07	1.33072E-07	2.54382E-09	1.35616E-07
19.	Ramini	6.07535E-08	9.44096E-08	3.3656E-08	9.44096E-08
20.	Katini	1.26836E-06	8.29105E-07	4.39259E-07	1.26836E-06
21.	Painah	1.21804E-06	5.44912E-07	1.76295E-06	1.76295E-06
22.	Mesinem	1.28109E-06	1.48399E-07	1.42948E-06	1.42948E-06
23.	Siti Maunah	1.50222E-06	3.73552E-08	1.46487E-06	1.50222E-06
24.	Sri Martini	8.12185E-08	1.90089E-09	7.93176E-08	8.12185E-08
25.	Painem	3.39898E-07	4.69687E-08	3.86867E-07	3.86867E-07

Iteration 43					
No.	Name	K1	K2	K3	Max Difference
26.	Umi Kholifatin	2.76051E-07	3.75205E-08	3.13572E-07	3.13572E-07
27.	Wiwik Kanapiah	2.82155E-06	4.49951E-08	2.86654E-06	2.86654E-06
28.	Sukatemi	3.48432E-06	1.4212E-08	3.49853E-06	3.49853E-06
29.	Saini	3.23761E-06	1.63065E-06	4.86826E-06	4.86826E-06
30.	Hendrik Widya A	6.61663E-07	9.44917E-08	5.67171E-07	6.61663E-07
31.	Sholehani	1.99775E-07	1.49934E-08	2.14768E-07	2.14768E-07
32.	Concerned	1.52891E-07	3.03005E-08	1.2259E-07	1.52891E-07
33.	Murtini	6.88028E-07	1.19473E-07	5.68555E-07	6.88028E-07
34.	Paini	1.05202E-06	2.47208E-07	1.29923E-06	1.29923E-06
35.	Nur Sarah	3.30134E-07	9.78482E-10	3.29156E-07	3.30134E-07
36.	Uswatun	1.57868E-06	6.47627E-07	9.31057E-07	1.57868E-06
37.	Tumiratin	1.73463E-06	2.90973E-07	2.02561E-06	2.02561E-06
38.	Katinem	4.39792E-06	1.36365E-07	4.26155E-06	4.39792E-06
39.	Seeds	2.05324E-06	1.95635E-07	1.85761E-06	2.05324E-06
40.	Wiwin	3.51587E-09	1.02486E-09	2.491E-09	3.51587E-09
41.	Endang Sukamti	2.15806E-06	2.38471E-07	1.91959E-06	2.15806E-06
42.	Riati	3.34096E-06	2.79075E-07	3.06188E-06	3.34096E-06
43.	Suryati	6.15135E-06	9.61631E-08	6.05518E-06	6.15135E-06
44.	Mesiyem	1.62618E-06	6.24043E-07	2.25023E-06	2.25023E-06
45.	Mujiatun	1.59548E-07	3.04307E-08	1.29118E-07	1.59548E-07
46.	Suratun	7.96392E-06	2.94766E-08	7.93444E-06	7.96392E-06
47.	Marjatik	3.03396E-08	5.98612E-09	3.63257E-08	3.63257E-08
48.	Sunarmi	4.20252E-07	5.48967E-07	1.28716E-07	5.48967E-07
49.	Tonah	4.33709E-07	6.8605E-09	4.4057E-07	4.4057E-07
50.	Sumiati	1.30657E-06	1.55331E-07	1.4619E-06	1.4619E-06
51.	Enjoy Nisa	4.67127E-07	2.89071E-08	4.3822E-07	4.67127E-07
52.	Musringah	5.38474E-08	8.15502E-07	8.6935E-07	8.6935E-07
53.	Boinah	1.39079E-06	2.69731E-06	4.0881E-06	4.0881E-06
54.	Jaytun	4.27321E-06	8.77594E-08	4.18545E-06	4.27321E-06
55.	Umi Salamah	1.26661E-05	4.53577E-08	1.26207E-05	1.26661E-05
56.	Liskacinem	5.07356E-07	4.96464E-07	1.08921E-08	5.07356E-07
57.	Suprianto	9.67701E-07	1.24778E-06	2.80081E-07	1.24778E-06
58.	Wagiyem	6.2915E-08	5.9622E-06	6.02511E-06	6.02511E-06
59.	Sri Munastri	2.08914E-07	2.51288E-06	2.30396E-06	2.51288E-06
60.	Sawn	2.1024E-07	2.74806E-07	6.4566E-08	2.74806E-07
61.	Kusmiati	9.07637E-06	4.28369E-08	9.1192E-06	9.1192E-06
62.	Siti Alimah	2.37462E-07	7.67614E-07	5.30152E-07	7.67614E-07
63.	Marinem	4.72188E-08	2.27852E-07	2.75071E-07	2.75071E-07
64.	Lasimah	1.62424E-07	7.31267E-06	7.15025E-06	7.31267E-06
65.	Darman	6.09874E-06	8.73733E-08	6.18611E-06	6.18611E-06
66.	Imam Mustafa	1.03925E-05	9.94317E-08	1.04919E-05	1.04919E-05
67.	Kelvin	5.23459E-06	4.17649E-08	5.19283E-06	5.23459E-06
68.	Endras Sunartoyo	1.9265E-05	7.09935E-08	1.91941E-05	1.9265E-05
69.	Greetings	5.88282E-06	1.03538E-07	5.98636E-06	5.98636E-06
70.	Seminar	9.27981E-07	2.76212E-08	9.0036E-07	9.27981E-07
71.	Sumiran	3.44269E-06	5.58772E-08	3.49857E-06	3.49857E-06
72.	Sumarto	3.80453E-06	5.72566E-08	3.74727E-06	3.80453E-06
73.	June	2.97104E-06	1.74413E-06	4.71518E-06	4.71518E-06
74.	Hengki	9.06629E-06	2.54484E-07	8.8118E-06	9.06629E-06
75.	Mukiat	5.7895E-06	2.48705E-07	5.5408E-06	5.7895E-06
76.	Imron	1.05406E-06	1.51877E-08	1.06925E-06	1.06925E-06
77.	Edo Kurniawan	2.30574E-05	2.87629E-08	2.30286E-05	2.30574E-05
78.	Suroso	5.90013E-06	1.06675E-07	6.00681E-06	6.00681E-06
79.	Slamet	9.60064E-06	1.0687E-07	9.70751E-06	9.70751E-06
80.	Miswanto	2.89013E-06	8.03502E-08	2.97048E-06	2.97048E-06
81.	Agus	7.334E-07	6.83861E-08	6.65014E-07	7.334E-07

Iteration 43					
No.	Name	K1	K2	K3	Max Difference
82.	Mujito	1.15525E-05	2.25503E-07	1.1327E-05	1.15525E-05
83.	M Basir	5.68658E-08	2.38593E-07	2.95459E-07	2.95459E-07
84.	Sumari	1.15796E-05	2.28025E-08	1.16024E-05	1.16024E-05
85.	Mother	3.43868E-06	3.28003E-07	3.11068E-06	3.43868E-06
86.	Colorful	1.81964E-05	5.64507E-08	1.81399E-05	1.81964E-05
87.	Akabudianto	5.3627E-06	1.91213E-07	5.17148E-06	5.3627E-06
88.	Suyoto	2.20278E-05	9.06514E-08	2.19371E-05	2.20278E-05
89.	Rakub	4.9402E-07	1.06529E-08	5.04672E-07	5.04672E-07
90.	Jamburi	1.81875E-05	1.1078E-07	1.80767E-05	1.81875E-05

Table 9. Calculate the maximum iteration difference

No.	Name	Iteration 42	Iteration 43	Difference Results
1.	congregation	4.84667E-06	3.57091E-06	1.27575E-06
2.	Khodijah	3.77342E-08	2.7775E-08	9.95917E-09
3.	Warti	9.74523E-07	7.17862E-07	2.56661E-07
4.	Katinah	3.41806E-06	2.51804E-06	9.00027E-07
5.	Kayatin	8.47135E-06	6.24097E-06	2.23038E-06
6.	Sukinah	5.56354E-06	4.09869E-06	1.46485E-06
7.	Sarinten	1.95826E-05	1.44259E-05	5.15679E-06
8.	Suminah	3.9004E-06	2.87339E-06	1.02702E-06
9.	Tuminem	2.21456E-06	1.63139E-06	5.83171E-07
10.	Sutiani	1.55413E-06	1.14487E-06	4.09256E-07
11.	Tukinem	3.62975E-07	2.67443E-07	9.55313E-08
12.	Ngatemi	3.86857E-06	2.85033E-06	1.01824E-06
13.	Cynthia	3.68866E-06	2.71774E-06	9.70917E-07
14.	Wiwik Pujiati	1.74442E-05	1.28518E-05	4.59241E-06
15.	Messiah	6.43951E-06	4.74445E-06	1.69506E-06
16.	Leginem	1.30147E-06	9.5893E-07	3.42539E-07
17.	Suparti	2.76517E-07	2.03723E-07	7.27946E-08
18.	Arnanik	1.84214E-07	1.35616E-07	4.85979E-08
19.	Ramini	1.2813E-07	9.44096E-08	3.37204E-08
20.	Katini	1.7217E-06	1.26836E-06	4.53336E-07
21.	Painah	2.39279E-06	1.76295E-06	6.29844E-07
22.	Mesinem	1.94024E-06	1.42948E-06	5.10754E-07
23.	Siti Maunah	2.03944E-06	1.50222E-06	5.37221E-07
24.	Sri Martini	1.10205E-07	8.12185E-08	2.8986E-08
25.	Painem	5.25065E-07	3.86867E-07	1.38198E-07
26.	Umi Kholifatin	4.25539E-07	3.13572E-07	1.11967E-07
27.	Wiwik Kanapiah	3.89089E-06	2.86654E-06	1.02435E-06
28.	Sukatemi	4.74918E-06	3.49853E-06	1.25065E-06
29.	Saini	6.60762E-06	4.86826E-06	1.73936E-06
30.	Hendrik Widya A	8.98205E-07	6.61663E-07	2.36542E-07
31.	Sholehani	2.91476E-07	2.14768E-07	7.67081E-08
32.	Concerned	2.07591E-07	1.52891E-07	5.47001E-08
33.	Murtini	9.33984E-07	6.88028E-07	2.45956E-07
34.	Paini	1.76341E-06	1.29923E-06	4.64179E-07
35.	Nur Sarah	4.48092E-07	3.30134E-07	1.17957E-07
36.	Uswatun	2.14303E-06	1.57868E-06	5.64343E-07
37.	Tumiratin	2.7493E-06	2.02561E-06	7.23696E-07
38.	Katinem	5.96913E-06	4.39792E-06	1.57122E-06
39.	Seeds	2.78712E-06	2.05324E-06	7.33875E-07
40.	Wiwin	4.79641E-09	3.51587E-09	1.28054E-09
41.	Endang Sukamti	2.92934E-06	2.15806E-06	7.71283E-07
42.	Riati	4.53496E-06	3.34096E-06	1.194E-06
43.	Suryati	8.34915E-06	6.15135E-06	2.1978E-06
44.	Mesiyem	3.05419E-06	2.25023E-06	8.03963E-07

No.	Name	Iteration 42	Iteration 43	Difference Results
45.	Mujiatun	2.16632E-07	1.59548E-07	5.70838E-08
46.	Suratun	1.08101E-05	7.96392E-06	2.84618E-06
47.	Marjatik	4.92861E-08	3.63257E-08	1.29604E-08
48.	Sunarmi	7.45068E-07	5.48967E-07	1.96101E-07
49.	Tonah	5.9808E-07	4.4057E-07	1.5751E-07
50.	Sumiati	1.98414E-06	1.4619E-06	5.22233E-07
51.	Enjoy Nisa	6.34107E-07	4.67127E-07	1.6698E-07
52.	Musringah	1.17983E-06	8.6935E-07	3.10482E-07
53.	Boinah	5.54864E-06	4.0881E-06	1.46054E-06
54.	Jaytun	5.80052E-06	4.27321E-06	1.52731E-06
55.	Umi Salamah	1.71928E-05	1.26661E-05	4.5267E-06
56.	Liskacinem	6.88599E-07	5.07356E-07	1.81244E-07
57.	Suprianto	1.69354E-06	1.24778E-06	4.45753E-07
58.	Wagiyem	8.17788E-06	6.02511E-06	2.15277E-06
59.	Sri Munastri	3.41071E-06	2.51288E-06	8.97834E-07
60.	Sawn	3.72967E-07	2.74806E-07	9.81611E-08
61.	Kusmiati	1.23789E-05	9.1192E-06	3.25967E-06
62.	Siti Alimah	1.0419E-06	7.67614E-07	2.74283E-07
63.	Marinem	3.73389E-07	2.75071E-07	9.83184E-08
64.	Lasimah	9.92544E-06	7.31267E-06	2.61277E-06
65.	Darman	8.39737E-06	6.18611E-06	2.21125E-06
66.	Imam Mustafa	1.42417E-05	1.04919E-05	3.74981E-06
67.	Kelvin	7.10587E-06	5.23459E-06	1.87127E-06
68.	Endras Sunartoyo	2.61493E-05	1.9265E-05	6.88429E-06
69.	Greetings	8.12603E-06	5.98636E-06	2.13967E-06
70.	Seminar	1.25977E-06	9.27981E-07	3.31784E-07
71.	Sumiran	4.74906E-06	3.49857E-06	1.25049E-06
72.	Sumarto	5.16429E-06	3.80453E-06	1.35976E-06
73.	June	6.39971E-06	4.71518E-06	1.68453E-06
74.	Hengki	1.23056E-05	9.06629E-06	3.23935E-06
75.	Mukiat	7.85794E-06	5.7895E-06	2.06843E-06
76.	Imron	1.45149E-06	1.06925E-06	3.82241E-07
77.	Edo Kurniawan	3.12976E-05	2.30574E-05	8.24016E-06
78.	Suroso	8.15379E-06	6.00681E-06	2.14698E-06
79.	Slamet	1.31777E-05	9.70751E-06	3.47019E-06
80.	Miswanto	4.03237E-06	2.97048E-06	1.06189E-06
81.	Agus	9.95596E-07	7.334E-07	2.62196E-07
82.	Mujito	1.56805E-05	1.15525E-05	4.128E-06
83.	M Basir	4.00976E-07	2.95459E-07	1.05517E-07
84.	Sumari	1.57492E-05	1.16024E-05	4.14681E-06
85.	Mother	4.6676E-06	3.43868E-06	1.22891E-06
86.	Colorful	2.4699E-05	1.81964E-05	6.50262E-06
87.	Akabudianto	7.27856E-06	5.3627E-06	1.91586E-06
88.	Suyoto	2.98994E-05	2.20278E-05	7.87161E-06
89.	Rakub	6.85122E-07	5.04672E-07	1.8045E-07
90.	Jamburi	2.46861E-05	1.81875E-05	6.49861E-06

Partition Coefficient Validation Testing

Table 10. Calculate the Partition Coefficient results

No.	Name	K1	K2	K3
1.	congregation	0.059752	0.032838	0.90741
2.	Khodijah	0.008105	0.00087	0.991025
3.	Warti	0.972097	0.004023	0.02388
4.	Katinah	0.941657	0.015829	0.042514
5.	Kayatin	0.679372	0.188441	0.132187
6.	Sukinah	0.358904	0.011872	0.629224
7.	Sarinten	0.193294	0.001921	0.804786

No.	Name	K1	K2	K3
8.	Suminah	0.91962	0.022737	0.057643
9.	Tuminem	0.943525	0.013646	0.04283
10.	Sutiani	0.921317	0.020519	0.058165
11.	Tukinem	0.007494	0.00106	0.991445
12.	Ngatemi	0.612008	0.02148	0.366511
13.	Cynthia	0.080458	0.03246	0.887082
14.	Wiwik Pujiati	0.567816	0.012436	0.419749
15.	Messiah	0.164651	0.167297	0.668052
16.	Leginem	0.422864	0.14513	0.432006
17.	Suparti	0.010785	0.981048	0.008167
18.	Arnanik	0.89612	0.021441	0.082438
19.	Ramini	0.022262	0.004058	0.97368
20.	Katini	0.589876	0.179097	0.231027
21.	Painah	0.066828	0.016327	0.916845
22.	Mesinem	0.145281	0.718326	0.136393
23.	Siti Maunah	0.130937	0.003153	0.86591
24.	Sri Martini	0.997043	0.000149	0.002808
25.	Painem	0.011056	0.000876	0.988068
26.	Umi Kholifatin	0.028404	0.001211	0.970385
27.	Wiwik Kanapiah	0.471156	0.117149	0.411695
28.	Sukatemi	0.08885	0.001836	0.909314
29.	Saini	0.143016	0.049914	0.80707
30.	Hendrik Widya A	0.990939	0.001162	0.007899
31.	Sholehani	0.003433	0.00018	0.996387
32.	Concerned	0.991926	0.00102	0.007054
33.	Murtini	0.991563	0.001355	0.007082
34.	Paini	0.039176	0.005687	0.955138
35.	Nur Sarah	0.963912	0.001834	0.034255
36.	Uswatun	0.924954	0.02312	0.051926
37.	Tumiratin	0.047418	0.00574	0.946842
38.	Katinem	0.8139	0.012188	0.173911
39.	Seeds	0.230263	0.021918	0.747819
40.	Wiwin	0.998995	5.73E-05	0.000947
41.	Endang Sukamti	0.95256	0.005192	0.042248
42.	Riati	0.817203	0.018113	0.164684
43.	Suryati	0.750811	0.008573	0.240616
44.	Mesiyem	0.048845	0.012782	0.938373
45.	Mujiatun	0.992359	0.000923	0.006718
46.	Suratun	0.52509	0.0039	0.47101
47.	Marjatik	0.001826	0.000134	0.99804
48.	Sunarmi	0.01144	0.981426	0.007134
49.	Tonah	0.00856	0.000342	0.991098
50.	Sumiati	0.137531	0.007221	0.855248
51.	Enjoy Nisa	0.981992	0.000884	0.017124
52.	Musringah	0.100043	0.040444	0.859513
53.	Boinah	0.160935	0.137026	0.702039
54.	Jaytun	0.197656	0.034146	0.768197
55.	Umi Salamah	0.605588	0.002775	0.391637
56.	Liskacinem	0.04157	0.920118	0.038312
57.	Suprianto	0.036267	0.942212	0.021521
58.	Wagiyem	0.129103	0.395356	0.475541
59.	Sri Munastri	0.173229	0.539328	0.287442
60.	Sawn	0.00703	0.987991	0.00498
61.	Kusmiati	0.174235	0.002758	0.823007
62.	Siti Alimah	0.013686	0.969819	0.016495
63.	Marinem	0.023263	0.95102	0.025717
64.	Lasimah	0.110956	0.468796	0.420248

No.	Name	K1	K2	K3
65.	Darman	0.093978	0.002999	0.903023
66.	Imam Mustafa	0.265454	0.014086	0.72046
67.	Kelvin	0.280672	0.007538	0.71179
68.	Endras Sunartoyo	0.539794	0.006474	0.453732
69.	Greetings	0.137004	0.008095	0.854901
70.	Seminar	0.060241	0.003619	0.936141
71.	Sumiran	0.100026	0.007213	0.89276
72.	Sumarto	0.782158	0.005188	0.212653
73.	June	0.138596	0.050919	0.810486
74.	Hengki	0.742176	0.014853	0.242971
75.	Mukiat	0.884901	0.007619	0.10748
76.	Imron	0.030463	0.002286	0.96725
77.	Edo Kurniawan	0.464718	0.00506	0.530222
78.	Suroso	0.138964	0.008616	0.85242
79.	Slamet	0.117432	0.002886	0.879681
80.	Miswanto	0.044768	0.00275	0.952482
81.	Agus	0.043951	0.007048	0.949
82.	Mujito	0.618684	0.019066	0.36225
83.	M Basir	0.855673	0.040286	0.10404
84.	Sumari	0.327647	0.010448	0.661905
85.	Mother	0.535691	0.080795	0.383514
86.	Colorful	0.494943	0.008316	0.496741
87.	Akabudianto	0.875122	0.007715	0.117163
88.	Suyoto	0.556554	0.005704	0.437742
89.	Rakub	0.010568	0.000724	0.988707
90.	Jamburi	0.687236	0.004024	0.30874

Fuzzy C-means Core Program

```
import numpy as np
from sklearn.cluster import KMeans

class FuzzyCMeans:
    def __init__(self, n_clusters=3, m=1.5, max_iter=1000, tol=1e-5,
random_seed=42):
        self.n_clusters = n_clusters
        self.m = m  # Fuzziness parameter
        self.max_iter = max_iter
        self.tol = tol
        self.random_seed = random_seed

    def fit(self, X):
        """Fungsi utama untuk melakukan clustering"""
        n_samples, n_features = X.shape

        # Inisialisasi membership matrix menggunakan K-Means
        kmeans = KMeans(n_clusters=self.n_clusters,
                        random_state=self.random_seed,
                        n_init=10)
        initial_labels = kmeans.fit_predict(X)

        # Buat membership matrix awal
        self.U = np.zeros((n_samples, self.n_clusters))
        for i in range(n_samples):
            self.U[i, initial_labels[i]] = 0.9
            remaining = 0.1
            for j in range(self.n_clusters):
                if j != initial_labels[i]:
                    self.U[i, j] = remaining / (self.n_clusters - 1)
```

```
import numpy as np
from sklearn.cluster import KMeans

class FuzzyCMeans:
    def __init__(self, n_clusters=3, m=1.5, max_iter=1000, tol=1e-5,
random_seed=42):
        self.n_clusters = n_clusters
        self.m = m  # Fuzziness parameter
        self.max_iter = max_iter
        self.tol = tol
        self.random_seed = random_seed

    def fit(self, X):
        """Fungsi utama untuk melakukan clustering"""
        n_samples, n_features = X.shape

        # Inisialisasi membership matrix menggunakan K-Means
        kmeans = KMeans(n_clusters=self.n_clusters,
                        random_state=self.random_seed,
                        n_init=10)
        initial_labels = kmeans.fit_predict(X)

        # Buat membership matrix awal
        self.U = np.zeros((n_samples, self.n_clusters))
        for i in range(n_samples):
            self.U[i, initial_labels[i]] = 0.9
            remaining = 0.1
            for j in range(self.n_clusters):
                if j != initial_labels[i]:
                    self.U[i, j] = remaining / (self.n_clusters - 1)
```

```
            # Cek konvergensi
            if np.linalg.norm(U_new - self.U) < self.tol:
                break
               self.U = U_new

        # Assign cluster berdasarkan membership tertinggi
        self.labels_ = np.argmax(self.U, axis=1)
        return self
```

Partition Coefficient Core Program

```
import numpy as np

def calculate_partition_coefficient(membership_matrix):
    """
    Menghitung Partition Coefficient (PC)
    PC = (1/N) x sum(sum(uij^2))

    Nilai PC berkisar antara 1/c (terburuk) sampai 1 (terbaik)
    dimana c adalah jumlah cluster

    Parameters:
    membership matrix: array 2D, matriks keanggotaan fuzzy (c x n)
```

```
        Returns:
    float: nilai PC antara 0 sampai 1
    """
    # Jumlah data (n)
    N = membership_matrix.shape[1]

    # Hitung PC
    pc = np.sum(membership_matrix xx 2) / N

    return pc

def interpret_pc(pc_value, n_clusters):
    """
    Interpretasi nilai Partition Coefficient

    Parameters:
    pc_value: nilai PC yang dihitung
    n_clusters: jumlah cluster

    Returns:
    tuple: (kategori, warna)
    """
    # Nilai acak terburuk (1/c)
    worst_case = 1/n_clusters

    if pc_value > 0.7:
        return "BAIK", "green"
    elif pc_value > (0.5 + worst_case)/2:  # Pertengahan antara
acak dan baik
        return "CUKUP", "orange"
    else:
        return "BURUK", "red"
```

Discussion

Fuzzy C-means Analysis

Research by Violán et al. (2019) demonstrated that the Fuzzy C-Means (FCM) method is effective in identifying chronic disease patterns in the elderly, by forming eight clinically meaningful multimorbidity clusters. This is in line with the study by Krasnov et al. (2023) who applied FCM to medical image-based breast cancer detection, where FCM was shown to improve tumor segmentation accuracy compared to conventional methods.

This study strengthens these findings by implementing FCM on elderly health data in Blitar Regency. The clustering results show three main categories: Healthy (40%), Alert (11.11%), and High Risk (48.89%). For example, data on an elderly with blood pressure of 154/80 mmHg, blood sugar of 222 mg/dL, and a BMI of 28.3 falls into the high-risk cluster, with a membership degree approaching 1 in that cluster. This condition indicates potential complications such as hypertension and diabetes.

A high degree of membership in a cluster indicates specific health tendencies. For example, an elderly person with a μ value of 0.92 in the healthy cluster has a low probability of developing degenerative diseases, while a μ value of 0.88 in the high-risk cluster indicates the need for immediate medical intervention. Thus, the application of FCM in this study provides a realistic picture of the variations in health conditions of the elderly and can also serve as a basis for community health centers and nursing home managers to determine more targeted intervention strategies.

Analysis of Partition Coefficient Validation Results

According to Rohmah & Saputro (2020), a Partition Coefficient (PC) value of 0.762 indicates good cluster quality. Research by Verma et al. (2023) also confirms that a high PC indicates clear cluster separation with low overlap.

In this study, the Partition Coefficient validation results yielded a PC value of 0.7535, which is considered good. Of the 90 individuals, 46 elderly individuals (51.11%) had a certainty index above 0.3, indicating stable and reliable clustering results. However, some data had ambiguous membership values, indicating the need for additional data collection or further medical examination.

This finding reinforces the consistency of the clustering results, as the PC values obtained were identical both in manual calculations and using the custom Python program function. This demonstrates that the applied FCM method is capable of producing valid results, although further evaluation is needed for individuals with ambiguous membership. Thus, the integration of FCM and PC evaluation can be an effective tool to support decision-making in elderly healthcare services at the nursing home and community health center levels.

CONCLUSION

Based on the research results, the application of the Fuzzy C-Means (FCM) method was able to group the health conditions of 90 elderly people in three nursing homes in Blitar Regency into three categories: healthy (40%), alert (11.11%), and high risk (48.89%). These results indicate that the high-risk group constitutes the largest proportion and therefore requires more attention in health monitoring and services. The degree of membership in each cluster can also describe the level of health condition tendencies of each elderly person more flexibly. Validation using the Partition Coefficient produced a PC value of 0.7535, which is categorized as good, and shows consistency between manual calculations and the custom Python program. Practically, the clustering results can be used by nursing home and community health center managers as a basis for identifying elderly people who require more intensive monitoring and determining health intervention priorities according to their group characteristics.

This study has limitations because the data used were from 90 elderly residents in three nursing homes in Blitar Regency, so the clustering results cannot be broadly generalized to elderly populations in other regions. Furthermore, some individuals showed ambiguous membership values, so interpretation of the clustering results still requires further medical examination and assessment.

Future research is recommended to use a larger sample size, involve more nursing homes or regions, and include relevant health parameters and social factors to more comprehensively describe the characteristics of each cluster. Development of a digital-based system that integrates FCM with periodic health data can also be carried out to support continuous monitoring of elderly conditions and assist health workers and nursing home managers in making more targeted decisions.

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