International Journal of Mathematics and Computer Research

ISSN: 2320-7167

Volume 13 Issue 05 May 2025, Page no. – 5227-5233

Index Copernicus ICV: 57.55, Impact Factor: 8.615

DOI: 10.47191/ijmcr/v13i5.13

Implementation of Fuzzy Possibilistic C-Means with Optimal Membership of Fuzzy C-Means for Stunting Management in Central Java Province

Falidazia Hasanah Faizana[1], Puspita Kartikasari[2], Deby Fakhriyana[3]

[1,2,3]Department of Statistics, Universitas Diponegoro, Indonesia

ARTICLE INFO

Published Online:
26 May 2025

Corresponding Author:
Puspita Kartikasari

ABSTRACT

Stunting is a serious problem makes children vulnerable disease and reduced productivity. According to Indonesian Health Survey (2023), stunting rate Indonesia in 2023 was 21.5%. The target set in 2020-2024 National Medium-Term Development Plan of 14% and WHO standard below 20% have still not been achieved. Based on Indonesian Health Survey (2023), prevalence stunting in Central Java Province in 2023 has decreased only 0.1% to 20.7%. Therefore, it is necessary to evaluate acceleration stunting handling from achievement more focused and targeted Special Index for Stunting Management (IKPS) indicators, one of which is through clustering analysis. The data used is the indicators IKPS of districts/cities in Central Java Province from the official website of the Central Bureau of Statistics (BPS) in 2023. The data contains outliers because the acceleration rate of stunting reduction varies in each region. Fuzzy Possibilistic C-Means algorithm with optimal membership of Fuzzy C-Means which is able to handle outlier data, is used in this research. The clustering results using the algorithm will be validated using the Davies Bouldin Index (DBI) to find the most optimal cluster. The validated shows the optimal cluster with 5 clusters and a DBI value of 1.520291.

KEYWORDS: Stunting, Clustering, Fuzzy C-Means, Fuzzy Possibilistic C-Means, Davies Bouldin Index

I. INTRODUCTION

Stunting is a serious problem that makes children vulnerable to disease, has impaired cognitive development, and reduces productivity. The Indonesian Health Survey states that the prevalence of stunting in Indonesia in 2023 decreased by 0.1% compared to 2022 to 21.5% [1]. A similar decrease of 0.1% also occurred in Central Java Province, where the stunting prevalence rate in 2023 reached 20.7% from 20.8% in 2022 [2]. These conditions indicate that both at the national and regional levels, greater and more effective efforts are needed to achieve the stunting prevalence target of 14% according to the 2020-2024 National Medium-Term Development Plan and meet the Word Health Organization (WHO) standard of below 20% [3].

Presidential Regulation of the Republic of Indonesia Number 72 of 2021 concerning Acceleration of Stunting Reduction is one of the government's efforts in handling stunting. These efforts will be evaluated through the Special Index for Stunting Handling (IKPS) instrument. IKPS is designed to compare the development of stunting intervention coverage at the national, provincial, and district/city levels [4]. IKPS at the district/city level consists of five dimensions including health, nutrition, housing, education, and social protection. Each region has different characteristics of each IKPS dimension. Therefore, stunting management policies to achieve RPJMN targets need to adjust the characteristics of each region to be more targeted, rather than using a uniform approach for all regions. One of the statistical methods for grouping each region based on the characteristics of the IKPS instrument is cluster analysis.

Cluster analysis is a statistical method used for clustering objects (instances) into several segments (clusters) based on similarities with other objects (instances) [5]. Cluster analysis has various methods, including Fuzzy C-Means (FCM) and Fuzzy Possibilistic C-Means (FPCM). FCM is one of the cluster analysis methods in which the existence of each object (data) in a segment (cluster) is determined by the membership value of the data. FPCM is a cluster analysis method resulting from the development of the FCM method which integrates FCM with Possibilistic C-Means (PCM). FPCM has several advantages, one of which is able to overcome the problems of two algorithms, in FCM in the form of noise data and PCM in the form of coincident cluster problems when clustering [6]. FCM and FPCM methods are partition-based data clustering methods. The first step in the partition-based method is to determine the number of segments (clusters) to be formed. The solution to determine the optimal number of segments (clusters) in cluster analysis modeling is cluster validation. Davies Bouldin Index (DBI) is one of the cluster validations based on the distance between the cluster centers of each cluster and the distance between objects in the cluster [7]. Referring to the conditions that have been described, researchers conducted a study of stunting clustering with IKPS indicators using the FPCM method with optimal membership from FCM. This approach was chosen because FPCM is able to handle data containing noise. The method cannot find the most optimal number of clusters, so the results are validated using DBI. This study aims to apply the FPCM method with optimal membership of FCM, validate the FPCM cluster results with DBI, and profile the clustering of districts/cities in Central Java based on IKPS indicators in 2023.

II. THEORETICAL FRAMEWORK

A. *Outlier*

The first step in this research is Exploratory Data Analysis (EDA). EDA is done to look for data patterns. One form of EDA is outlier detection. Outliers are data whose characteristics are very different from the majority of other data. Outliers in high-dimensional data cannot be detected through univariate or bivariate plots [8]. Outlier detection in this study uses the squared Mahalanobis distance measurement because the data used is multivariate data. The squared Mahalanobis distance equation can be seen in the equation below.

$$d^2_{MD(i)} = (\boldsymbol{x_{ij}} - \boldsymbol{\overline{x}_j})\boldsymbol{\Sigma^{-1}}(\boldsymbol{x_{ij}} - \boldsymbol{\overline{x}_j})^{\boldsymbol{T}};\ i = 1, 2, 3, \dots, n$$

where $d^2_{MD(i)}$ is the squared Mahalanobis distance of the i-th object, $\boldsymbol{x_{ij}}$ is the data vector of the i-th object for each j-th variable, $\boldsymbol{\overline{x}_j}$ is the mean vector of each j-th variable, and $\boldsymbol{\Sigma}$ is the covariance matrix. The i-th object is an outlier if $d^2_{MD(i)} > \chi^2_{\alpha;p}$, where $\chi^2_{\alpha;p}$ is the chi-square value with a free degree (*df*) of p variables with a significance level of α.

B. *Cluster Analysis*

Cluster analysis is the process of dividing a set of observation data or objects into segments (clusters) where each data (object) in one segment has the same characteristics (homogeneous), while between segments have different characteristics (heterogeneous) [9]. A commonly used method in assessing the similarity between two objects in cluster analysis is the distance measure. Euclidean distance is the distance measure most often used in cluster analysis [10]. This distance is applied when the data used has the same measurement scale and is not correlated with each other. The euclidean distance equation can be seen in the equation below.

$$d_{euc}(x_i, v_k) = \sqrt{\sum_{j=1}^{p}\left(x_{ij} - v_{kj}\right)^2}$$

where $d_{euc}(x_i, v_k)$ is the value of the Euclidean distance between the observation data of the i-th object and the k-th cluster center, x_{ij} is the observation data of the i-th object in the j-th variable, and v_{kj} is the cluster center of the k-th object in the j-th variable.

C. *Cluster Analysis Assumptions*

The characteristics of a good cluster are high homogeneity (similarity) between members in one cluster and high heterogeneity (difference) between clusters. The assumption test in cluster analysis is the non-multicollinearity test. Multicollinearity is a condition where there is a correlation between variables. It is recommended that the variables do not indicate the presence of multicollinearity (non-multicollinearity) in cluster analysis. Multicollinearity detection can be applied through several methods, one of which is the Variance Inflation Factor (VIF). The equation for calculating the VIF value of each variable can be seen in the equation below.

$$VIF_j = \frac{1}{1 - R_j^2}$$

where VIF_j is the VIF value of the j-th variable and R_j^2 is the coefficient of determination between the j-th variable and other independent variables. Variables are indicated to have multicollinearity if the VIF value is more than 10 [11].

D. *Fuzzy Logic*

Fuzzy is defined as something that is fuzzy or vague. Fuzzy logic is usually used to solve various problems with conditions containing noisy elements (outliers), imprecise, uncertainty, and so on [12]. Fuzzy logic has a membership value in the range of 0 to 1. A membership value of 0 indicates an element is not a member of the set, while a membership value of 1 indicates the element is fully a member of the set.

E. *Fuzzy C-Means (FCM)*

FCM is a cluster analysis method in which the presence of each object (data) in a segment (cluster) is determined by the membership value of the data. The FCM algorithm can be seen as follows [13].

1. Enter the observation data (objects) to be clustered into a matrix ***X*** of size *n x p*, where *n* is the total objects (data) and *p* is the total variables of each object. x_{ij} is the observation data of the *i*-th object (*i=1,2,...,n*) with the *j*-th variable (*j=1,2,...,p*).

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix}$$

2. Determine the parameters to be used in FCM modeling, including the number of clusters to be formed (*c*), the

rank/fuzziness value (w), the initial iteration ($l = 1$), the initial objective function ($P_0 = 0$), the maximum iteration (*MaxIter*), and the smallest error limit ($\varepsilon > 0$).

3. Generate random numbers for the initial membership degree $\left(\mu_{ik}^{(0)}\right)$ as elements of the initial partition matrix $\boldsymbol{U}$ of size $n \ x \ c$, where n is the number of objects $(i = 1, 2, \dots, n)$ and k is the number of clusters $(k = 1, 2, \dots, c)$.

$$\boldsymbol{U} = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1c} \\ \vdots & \ddots & \vdots \\ \mu_{n1} & \cdots & \mu_{nc} \end{bmatrix}$$

$$\mu_{ik} \epsilon [0,1] \text{dan} \sum_{k=1}^{c} \mu_{ik} = 1$$

4. Calculate the k-th cluster center (centroid) for the l-th iteration $(v_{kj}^{(l)})$ with equation below.

$$v_{kj}^{(l)} = \frac{\sum_{i=1}^{n} \left(\left(\mu_{ik}^{(l-1)} \right)^{w} x_{ij} \right)}{\sum_{i=1}^{n} \left(\mu_{ik}^{(l-1)} \right)^{w}}$$

5. Calculate the objective function for the l-th iteration (P_l) with the equation below.

$$P_l = \sum_{i=1}^{n} \sum_{k=1}^{c} \left(\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(l)} \right)^2 \right] \left(\mu_{ik}^{(l-1)^{w}} \right) \right)$$

6. Calculate the change in membership matrix with the equation below.

$$\mu_{ik}^{(l)} = \frac{\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(l)} \right)^2 \right]^{-\frac{1}{w-1}}}{\sum_{k=1}^{c} \left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(l)} \right)^2 \right]^{-\frac{1}{w-1}}}$$

7. Checking the stop condition
   a. The process will end or converge if $(|P_l - P_{l-1}| < \varepsilon)$ or $(l > MaxIter)$.
   b. The process will repeat at step 4 if $(|P_l - P_{l-1}| > \varepsilon)$ or $(l < MaxIter)$ until converged.

F. *Fuzzy Possibilistic C-Means (FPCM)*

FPCM is a method of integrating features in FCM and PCM. The method is able to solve the problems of two algorithms, in FCM in the form of noise data and PCM in the form of coincident cluster problems when clustering [14]. The FPCM algorithm can be seen as follows [15].

1. Input the observation data (objects) to be clustered in an $n \ x \ p$ matrix $\boldsymbol{X}$.
2. Determine the parameters to be applied in FPCM modeling, including the number of clusters to be formed (c), relative membership/fuzziness weight value w (real number greater than 1), absolute distinctiveness weight value η (real number greater than 1), initial iteration ($h = 1$), initial objective function ($P_0 = 0$), maximum iteration (*MaxIter*), and smallest error ($\varepsilon > 0$).
3. Call the final results of the relative membership matrix elements (μ_{ik}) and cluster centers $\left(v_{kj}\right)$ from the FCM results to find the $n \ x \ c$ dimension absolute distinctiveness matrix values.

$$\boldsymbol{T} = \begin{bmatrix} t_{11} & \cdots & t_{1c} \\ \vdots & \ddots & \vdots \\ t_{n1} & \cdots & t_{nc} \end{bmatrix}$$

The equation for the initial absolute distinctiveness matrix value can be seen in the following equation.

$$t_{ik}^{(0)} = \frac{\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(l)} \right)^2 \right]^{-\frac{1}{\eta-1}}}{\sum_{i=1}^{n} \left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(l)} \right)^2 \right]^{-\frac{1}{\eta-1}}}$$

4. Calculate the k-th cluster center on the j-th variable for the h-th iteration $(v_{kj}^{(h)})$ with the equation below.
   If $h = 1$, then

$$v_{kj}^{(h)} = \frac{\sum_{i=1}^{n} \left(\mu_{ik}^{(l)^{w}} + t_{ik}^{(h-1)^{\eta}} \right) x_{ij}}{\sum_{i=1}^{n} \left(\mu_{ik}^{(l)^{w}} + t_{ik}^{(h-1)^{\eta}} \right)}$$

   If $h = 2, 3, \dots, q$, then

$$v_{kj}^{(h)} = \frac{\sum_{i=1}^{n} \left(\mu_{ik}^{(h-1)^{w}} + t_{ik}^{(h-1)^{\eta}} \right) x_{ij}}{\sum_{i=1}^{n} \left(\mu_{ik}^{(h-1)^{w}} + t_{ik}^{(h-1)^{\eta}} \right)}$$

5. Calculate the objective function for the h-th iteration with the equation below.
   If $h = 1$, also

$$P_h = \sum_{i=1}^{n} \sum_{k=1}^{c} \left(\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right] \left(\mu_{ik}^{(l)^{w}} + t_{ik}^{(h-1)^{\eta}} \right) \right)$$

   If $h = 2, 3, \dots, q$, also

$$P_h = \sum_{i=1}^{n} \sum_{k=1}^{c} \left(\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right] \left(\mu_{ik}^{(h-1)^{w}} + t_{ik}^{(h-1)^{\eta}} \right) \right)$$

6. Calculate the change in relative membership degree with the equation below.

$$\mu_{ik}^{(h)} = \frac{\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right]^{-\frac{1}{w-1}}}{\sum_{k=1}^{c} \left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right]^{-\frac{1}{w-1}}}$$

7. Calculate the change in absolute degree of distinctiveness with the equation below.

$$t_{ik}^{(h)} = \frac{\left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right]^{-\frac{1}{\eta-1}}}{\sum_{i=1}^{n} \left[\sum_{j=1}^{p} \left(x_{ij} - v_{kj}^{(h)} \right)^2 \right]^{-\frac{1}{\eta-1}}}$$

8. Checking the stop condition
   a. The process will end or converge if $(|P_h - P_{h-1}| < \varepsilon)$ or $(h > MaxIter)$.
   b. The process will repeat at step 4 if $(|P_h - P_{h-1}| > \varepsilon)$ or $(h < MaxIter)$ until converged.

c. Determining the members of each cluster
The ninth step is to determine the members of each cluster. The members of each cluster in Fuzzy Possibilistic C-Means are determined from the element values in the absolute distinctiveness matrix $\boldsymbol{T}$. The higher the value of the absolute distinctiveness matrix element $t_{ik}^{(h)}$, the higher the data is classified as a member of a cluster.

***G.** Davies Bouldin Index (DBI)*

The solution to determine the most optimal number of clusters is to perform cluster validation. DBI is one of the cluster validations based on the distance between the cluster centers of each cluster and the distance between objects in the cluster [16]. The DBI equation can be seen in equation below.

$$DBI = \frac{1}{c}\sum_{k=1}^{c} max_{k\neq q}(R_{k,q});$$

where DBI is the DBI value, $R_{k,q}$ is the ratio between the *k*-th and *q*-th clusters, and *c* is the number of clusters.

***H.** Interpretation of Cluster Results*

Interpretation is the last step in data analysis in this study. Interpretation is done to give a specific name that can reflect the content or characteristics of the cluster and to know the description of each cluster formed from the average value (centroid) of each cluster [17]. The equation for the average value (centroid) of each cluster can be seen in the equation below.

$$m_{kj} = \frac{\sum_{i=1}^{n_k} x_{ijk}}{n_k}$$

where m_{kj} is the average value of the *k*-th cluster center (centroid) on the *j*-th variable, x_{ijk} is the observation data of the *i*-th object on the *j*-th variable in the *k*-th cluster, and n_k is the number of objects in the *k*-th cluster.

III. RESEARCH METHODS

Data on IKPS indicators at the district/city level in all districts/cities of Central Java Province in 2023 were used in this study. The data was taken from the official website publication of the Central Java Provincial Statistics Agency. The variables used in this study are presented in Table I.

TABLE I. RESEARCH VARIABLES

Symbol	*Variable*	*Unit*
X_1	Ever-married women aged 15-49 years who gave birth to a live birth child and were assisted in the delivery process by a health worker at a health facility	%
X_2	Population aged 0-59 months who received complete basic immunizations	%
X_3	Ever-married women aged 15-49 years or their partners who use modern family planning methods	%
X_4	People less than 6 months of age who are exclusively breastfed	%
X_5	Population aged 6-23 months who received complementary food during the day yesterday	%
X_6	Households with access to safe drinking water sources	%
X_7	Households with access to improved sanitation	%
X_8	Participation in preschool education for 3-6 years old	%
X_9	Population with some type of health insurance (BPJS)	%
X_{10}	Households that receive a Prosperous Family Card (KKS)	%

These variables are processed using R tools with the following analysis stages:

1. Collecting data on the indicators that make up IKPS from the official website publication of the Central Java Provincial Statistics Agency.
2. Entering data on the indicators that make up the IKPS of Central Java Province in 2023 in the R Cloud tool.
3. Detecting outlier data using the Mahalanobis distance squared measurement method with a significance level of $\alpha = 5\%$.
4. Testing the assumptions of cluster analysis, namely the non-multicollinearity test. The representative sample assumption is not performed because the data used is population data.
5. Determining the number of clusters (c) as an initial parameter in cluster analysis modeling. The number of clusters used and compared the results are 2, 3, 4, 5, and 6.
6. Perform modeling using FCM.
   a. Determine the parameters used, such as weight value ($w = 2$), initial iteration value ($l = 1$), maximum iteration value ($MaxIter = 10000$), smallest error limit ($\varepsilon = 10^{-5}$), and initial objective function ($P_0 = 0$).
   b. Generate initial random numbers $(\mu_{ik}^{(0)})$ as elements of the initial partition matrix $\boldsymbol{U}$, of size *n x c*, where *n* is the number of objects (data) and *c* is the number of segments (clusters).
   c. Calculate the *k*-th cluster center on the *j*-th variable for the *l*-th iteration ($v_{kj}^{(l)}$).
   d. Calculate the objective function for the *l*-th iteration (P_l).
   e. Calculate the relative membership value of the *i*-th object in the *k*-th cluster for the *l*-th iteration ($\mu_{ik}^{(l)}$).

f. Checking the stop condition:
   1. The process will end or converge if $(|P_l - P_{l-1}| < \varepsilon)$ or $(l > MaxIter)$.
   2. The process will repeat at step 4 if $(|P_l - P_{l-1}| > \varepsilon)$ or $(l < MaxIter)$ until converged.

7. Perform modeling using FPCM
   a. Determine the parameters used, such as weight value $(w = 2)$, the absolute distinctiveness weight value $(\eta = 2)$, initial iteration value $(h = 1)$, maximum iteration value $(MaxIter = 10000)$, smallest error limit $(\varepsilon = 10^{-5})$, and initial objective function $(P_0 = 0)$.
   b. Call the relative membership matrix elements (μ_{ik}) and cluster centers (v_{kj}) in the last iteration result of FCM to find the n x c dimension absolute distinctiveness matrix value. The absolute distinctiveness matrix element is the absolute distinctiveness value (t_{ik}) where n is the number of objects (i = *1, 2, ..., n*) and c is the number of clusters (k = *1, 2, ..., c*).
   c. Fix the kth cluster center on the *j*-th variable for the *h*-th iteration $(v_{kj}^{(h)})$.
   d. Calculate the objective function for the *h*-th iteration (P_h).
   e. Fix the relative membership value of the *i*-th object in the *k*-th cluster at the *h*-th iteration $(\mu_{ik}^{(h)})$.
   f. Fix the absolute distinctiveness value of the *i*-th object in the kth cluster at the *h*-th iteration $(t_{ik}^{(h)})$.
   g. Checking the stop condition:
      1. The process will end or converge if $(|P_h - P_{h-1}| < \varepsilon)$ or $(h > MaxIter)$.
      2. The process will repeat at step 4 if $(|P_h - P_{h-1}| > \varepsilon)$ or $(h < MaxIter)$ until converged.
   h. Determine the members in each cluster.

8. Perform cluster validation to determine the optimum number of clusters (c) using the Davies Bouldien Index in FPCM modeling.
9. Interpreting the cluster results.

IV. RESULT AND DISCUSSION

Clustering districts/cities in Central Java Province based on the IKPS indicator in this study goes through several stages including Exploratory Data Analysis (EDA), cluster analysis assumption test, clustering, and cluster profiling. EDA is the initial stage to determine the pattern of data owned, so that it can determine the appropriate cluster method. The EDA performed is outlier detection. Outlier detection in this study uses the squared Mahalanobis distance method. The results of outlier detection state that there are 3 objects, namely Cilacap Regency, Rembang Regency, and Magelang City, which are outlier data. This is because the squared mahalanobis distance on the three objects is greater than the chi-square distribution $(\chi^2_{0.05;10} = 18.307)$ Cilacap Regency at 20.40, Rembang Regency at 19.27, and Magelang City at 24.36.

The second stage in this study is the assumption test. The VIF results state that all variables have a VIF value < 10 namely variable X_1 of 1.46, X_2 of 1.17, X_3 of 1.20, X_4 of 1.10, X_5 of 1.28, X_6 sebesar 1.76, X_7 of 1.38, X_8 of 1.49, X_9 of 1.65, and X_{10} of 1.52. These results indicate that the data is not multicollinear, so the assumptions are met.

The cluster analysis assumption test showed that the data met the requirements to be analyzed using the FPCM method with FCM optimal membership. The value of the cluster center and the relative degree of membership from the last iteration of FCM are used as initial values in the calculation of the cluster center, objective function, and absolute degree of distinctiveness in the FPCM method, which is then validated by DBI. The results of clustering performance using FPCM with FCM optimal membership can be seen in Table II.

TABLE II. FPCM PERFORMANCE RESULTS WITH FCM OPTIMAL MEMBERSHIP

Clusters Formed	*Indicators*		
	Time (seconds)	*Number of Iterations*	*Minimum Objective Function*
2	0.057	31	9083.97
3	0.171	100	6068.88
4	0.437	150	4561.85
5	0.307	111	3604.19
6	7.329	1959	2980.18

Table II shows that the clustering performance results for each cluster formed show variations, both in terms of the time required, the number of iterations, and the minimum value of the objective function. The more clusters formed, the time required increases and the number of iterations tends to increase, while the minimum objective function decreases. The validation results show that the smallest DBI value, 1.520291, is obtained at the number of 5 segments (clusters). Therefore, the optimal number of clusters is 5, with further details presented in Table III.

TABLE III. FPCM CALCULATION USING R CLOUD

Total Cluster	*Fuzzy Possibilistic C-Means*	
	Number of Iterations	*Davies Bouldin Index*
2	31	1.737179
3	100	1.917514
4	150	1.858107
5	111	1.520291
6	1959	1.795470

The next step is to group districts/cities using the FPCM method with a total of 5 clusters. The results of clustering districts/cities in Central Java Province using the FPCM method with optimal FCM membership based on IKPS indicators are presented in Table IV and Figure 1.

TABLE IV. OPTIMUM CLUSTERING RESULT WITH FPCM

Cluster	*Number of Members*	*District/City Member*
1	3	Blora, Demak, Kendal
2	11	Klaten, Sukoharjo, Karanganyar, Rembang, Kudus, Tegal City, Pekalongan City, Semarang City, Magelang City, Salatiga City, Surakarta City
3	3	Banjarnegara, Wonosobo, Batang
4	5	Boyolali, Sragen, Pati, Semarang, Pemalang
5	13	Cilacap, Banyumas, Purbalingga, Kebumen, Purworejo, Magelang, Wonogiri, Grobogan, Jepara, Temanggung, Pekalongan, Pemalang, Brebes

Figure 1. Clustering Result Map

Interpretation is the last step in data analysis in this study. Interpretation is done by looking at the values of the centroid of each cluster. These values are presented in Table V below. Referring to Table V, it can be concluded that for ever-married women aged 15-49 years who received assistance in the delivery process by a health worker at a health facility, for people less than 6 months old who are exclusively breastfed, and for households with access to a source of safe drinking water, all three indicators have high averages for all clusters (90% to 100%). However, the average indicator of participation in preschool education for the population aged 3-6 years for all clusters is still quite low (32% to 39%). Based on these conditions, the local government of Central Java Province needs to focus on increasing the participation of preschool education for the population aged 3-6 years in order to reduce the prevalence of stunting.

TABLE V. CENTROID VALUE OF FIVE FPCM CLUSTERS

Cluster	m_{k1}	m_{k2}	m_{k3}	m_{k4}	m_{k5}	m_{k6}	m_{k7}	m_{k8}	m_{k9}	m_{k10}
1	100.000	69.778	70.645	95.040	70.734	98.573	93.691	39.929	79.166	15.907
2	100.000	73.304	74.017	95.720	74.260	92.987	55.310	35.900	60.100	19.577
3	99.762	68.792	65.842	96.232	68.414	96.486	90.356	34.368	62.296	14.568
4	98.855	69.362	70.923	95.939	72.336	91.046	82.678	32.985	64.274	29.909
5	100.000	69.778	70.645	95.040	70.734	98.573	93.691	39.929	79.166	15.907

Based on Table V, the cluster with excellent IKPS indicators is cluster 2. This cluster shows the most superior value compared to other clusters in the delivery process by health workers in health facilities (100%), access to proper drinking water sources (98.58%), access to proper sanitation (93.69%), participation in preschool education (39.93%), and ownership of health insurance (79.16%). As a step to reduce the stunting rate, cluster 5 needs to make various efforts to improve the delivery assistance by health personnel in health facilities, access to decent drinking water sources, and participation in preschool education for the population aged 3-6 years, because all of these indicators have the lowest average compared to other clusters. On the other hand, the average indicator for the Prosperous Family Card (KKS) in this cluster is the highest, indicating the need to improve overall economic welfare. Based on these conditions, cluster 5 can be referred to as a group with poor IKPS.

V. CONCLUSION

Based on the performance results of the FPCM method with FCM optimal membership, it is concluded that the more clusters are formed, the time required and the number of iterations tend to increase, while the minimum objective function decreases. Davies Bouldin Index (DBI) validation results on the FPCM method with FCM optimal membership, it is concluded that the cluster with the number 5 is the most optimal on the IKPS indicator in 2023. This is indicated by the lowest DBI value of 1.520291, which indicates that objects in the same cluster are more compact and between clusters have better separation than the number of other clusters. The less optimal number of clusters formed is 3 clusters with a DBI value of 1.917514.

Cluster 5 is the top priority cluster for the Central Java Provincial Government because the majority of IKPS indicators are the lowest compared to other clusters. Cluster 1 is the second priority cluster because the participation rate of immunization and complementary feeding is still quite low. Cluster 4 is the third priority cluster due to the low level of modern family planning users. Clusters 3 and 2 are the last priority because the overall percentage of IKPS indicators is quite high.

REFERENCES

1. Kementerian Kesehatan Republik Indonesia. 2024 Dukung Survei Status Gizi Untuk Masa Depan Indonesia. Available: https://sehatnegeriku.kemkes.go.id/baca/rilismedia/20230125/3142280/prevalensi-stunting-di-indonesia-turun-ke-216-dari-244/ (accessed on September 5, 2024).
2. Bappeda. 2024 TPPS Jateng Laksanakan Penilaian Kinerja Percepatan Penurunan Stunting. Available: https://bappeda.jatengprov.go.id/tpps-jateng-laksanakan-penilaian-kinerja-percepatan-penurunan-stunting/#:~:text=Ia%20menambahkan%2C%20hasil%20Survey%20Kesehatan,kabupaten%2Fkota%20lebih%20nampak%20fluktuasinya (accessed on September 5, 2024).
3. Kementerian Kesehatan Republik Indonesia. 2023. Prevalensi Stunting di Indonesia Turun ke 21,6% dari 24,4%. Available: https://sehatnegeriku.kemkes.go.id/baca/rilismedia/20230125/3142280/prevalensi-stunting-di-indonesia-turun-ke-216-dari-244/ (accessed on September 5, 2024).
4. BPS Jawa Tengah. 2024. Publikasi Badan Pusat Statistik Provinsi Jawa Tengah. Available: https://jateng.bps.go.id/id (accessed on August 25, 2024).
5. Primartha, R. 2021 Algoritma Machine Learning. Bandung: Informatika.
6. Ozdemir, O. dan Kaya, A., "Comparison of FCM, PCM, FPCM, and PFCM Algorithms in Clustering Method", Journal of Scremce and Engineering, vol. 19, pp. 92-102, 2019.
7. Xiao, J., Lu, J., Xiangyu, L., "Davies Bouldin Index based hierarchical initialization K-Means", Intelligent Data Analysis, vol. 21, no. 6, pp. 1327-1338, 2017.
8. Johnson, R. A. and Wichern, D. W. 2007 Applied Multivariate Statistical Analysis. New Jersey: Pearson
9. Fitriana, R., Habyba, A. N., and Febriani, E. 2022 Data Mining dan Aplikasinya. Jawa Tengah: Wawasan Ilmu.
10. Raja, N. A., Tinungki, G. M., dan Sirajang, N., "Implementasi Algoritma Centroid Linkage dan K-Medoids dalam Mengelompokkan Kabupaten/Kota di Sulawesi Selatan Berdasarkan Indikator Pendidikan", Journal of Statistics and Its Application, vol. 5, no. 1, pp. 61-74, 2024.
11. Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. 2010 Multivariate Data Analysis, Seventh edition. New Jersey: Prentice Hall International, Inc.
12. Wahyuni, I. 2021 Logika Fuzzy Tahani. Sleman: Komojoyo Press.
13. Kusumadewi, S. and Purnomo, H. 2004 Aplikasi Logika Fuzzy untuk Pendukung Keputusan. Yogyakarta: Graha Ilmu.
14. Ozdemir, O. dan Kaya, A., "Comparison of FCM, PCM, FPCM, and PFCM Algorithms in Clustering Method", Journal of Scremce and Engineering, vol. 19, pp. 92-102, 2019.
15. Nida, K., Hayati, M. N., and Goejantoro, R., "Implementasi Metode Fuzzy Possibilistic C-Means pada Pengelompokan Provinsi di Indonesia Berdasarkan Data Jumlah Kejadian dan Dampak Bencana Banjir", Jurnal of Mathematics Education and Science, vol. 7, no. 1, pp. 33-42, 2024.
16. Septiani, I. W., Fauzan, A. C., and Huda, M. M., "Implementasi Algoritma K-Medoids dengan Evaluasi Davies-Bouldin-Index Untuk Klasterisasi Harapan Hidup Pasca Operasi pada Pasien Penderita Kanker Paru-Paru", *Jurnal Sistem Komputer dan Informatika (JSON)*, vol. 3, no. 4, pp: 556, 2022.
17. Simamora, B. 2005 Analisis Multivariat Pemasaran. Jakarta: PT. Gramedia Pustaka.