International Journal of Natural Science and Engineering.
Volume 6 Nomor 3 2022, pp 110-121
P-ISSN: 2615-1383 E-ISSN : 2549-6395
DOI: https://doi.org/10.23887/ijnse.v6i3.53048

Implementation of Fuzzy C-Means in Clustering Stunting Prone Areas

Ratna Dwi Christyanti[1]*, Dady Sulaiman[2], Adymas Putro Utomo[3], Muhammad Ayyub[4]

[1,4] Mathematics, Universitas Kaltara, Tanjung Selor, Indonesia
[2] Physics, Universitas Kaltara, Tanjung Selor, Indonesia
[3] Agrotechnology, Universitas Kaltara, Tanjung Selor, Indonesia
*Corresponding author: ratnadwichristyantii@gmail.com

Abstrak

Stunting adalah suatu masalah gizi kronis yang terjadi pada balita, yang diartikan berdasarkan tinggi badan menurut umur (TB/U) yang kurang dari negatif dua standar deviasi atau tinggi badan balita lebih pendek daripada yang seharusnya. Stunting adalah suatu masalah gizi kronis yang terjadi pada balita, yang ditandai dengan tinggi badan lebih pendek dibandingkan dengan tinggi badan anak seusianya. Kabupaten Bulungan menjadi satu dari 160 kabupaten kota di Indonesia yang diintervensi untuk fokus melakukan penurunan stunting. Berdasarkan permasalahan tersebut, penelitian ini bertujuan untuk mengetahui cluster tingkat kerawanan stunting di Kabupaten Bulungan. Metode yang digunakan adalah Fuzzy C-Means (FCM). Hasil dari penetian ini adalah wilayah yang berada pada cluster 1 memiliki tingkat kerawan tinggi karena memiliki tingkat kecukupan posyandu (aktif) yang terendah dan tingginya kejadian BBLR pada bayi, cluster 2 memiliki tingkat kerawanan sedang karena memiliki tingkat kecukupan puskesmas, kecukupan posyansdu (aktif), kecukupan dokter, kecukupan tenaga ahli gizi, kecukupan bidan, persentase BBLR yang sedang, dan cluster 3 memiliki tingkat kerawanan rendah karena memiliki tingkat rata-rata persentase BBLR tergolong rendah dan tingginya tingkat kecukupan posyandu (aktif) di wilayah tersebut.

***Kata kunci**: Stunting, Clustering, Fuzzy C-Means (FCM)*

Abstract

Stunting is a chronic nutritional problem that occurs in toddlers, defined based on height for age (TB/U) which is less than two negative standard deviations or a toddler's height is shorter than it should be. Stunting is a chronic nutritional problem in toddlers, characterized by a shorter height than the height of children his age. Bulungan Regency is one of 160 urban regencies in Indonesia that is intervened to focus on reducing stunting. Based on these problems, this study aims to determine the cluster of stunting vulnerabilities in Bulungan Regency. The method used is Fuzzy C-Means (FCM). The results of this study are that the area in cluster 1 has a high level of vulnerability because it has the lowest level of adequacy of posyandu (active) and high incidence of LBW in infants, cluster 2 has a moderate level of vulnerability because it has an adequate level of puskesmas, adequacy of posyandu (active), the adequacy of doctors, the adequacy of nutritionists, the adequacy of midwives, the percentage of moderate LBW, and cluster 3 have a low level of vulnerability because they have a low average percentage of LBW and a high level of adequacy of posyandu (active) in the area.

Keywords: Stunting, Clustering, Fuzzy C-Means (FCM)

1. INTRODUCTION

Stunting is a chronic nutritional problem that occurs in toddlers, which is defined based on height for an age that is less than negative two standard deviations (<-2SD) or a toddler's height is shorter than it should be (Antunes et al., 2022; Cahyono et al., 2016). A toddler is said to be stunted if the value of the ratio between height and the standard value of a toddler is below normal than it should be (Wulandari & Kurniawan, 2019). There are several determining factors for children under five who experience stunting, namely the nutritional intake factor in children and genetic factors, in other words, following the short

History:
Received : September 10, 2022
Revised : September 12, 2022
Accepted : October 13, 2022
Published : October 25, 2022

Publisher: Undiksha Press

stature of parents (Lestari et al., 2014; Paintsil et al., 2022). The stunting prevalence rate compares a nutritional problem between one region and another.

The stunting prevalence rate is the percentage of children under five who experience a stunting event in a certain period of the overall population of children under five in a certain area and period (Hadi, 2017; Singh et al., 2022). Fuzzy logic is a logic theory developed to overcome the concept of value between true and false (Fadillah et al., 2018; Radja et al., 2020). Fuzzy logic uses a value between 0 and 1 which describes the degree of confidence/truth of logic, also called membership degree. The greater the value of the membership degree (closer to 1), the greater the trust/truth value (Praja et al., 2017). In group analysis, the data is grouped into several clusters based on the similarity of the characteristics of each data in the existing groups (Prasetyo, 2012).

Clustering is unsupervised (Kusuma & Agani, 2015; Selvi & Ashwin, 2016). Clustering is a data mining technique that aims to assign objects into a collection of groups called clusters so that each object member of the same cluster will have more similar characteristics than objects from different clusters. There are two types of clustering techniques: hard and fuzzy. In the hard clustering technique, each data element must be a member or not a cluster member. In contrast, in the fuzzy clustering technique, each data element can be a member of several clusters with different membership values (Wulandari & Kurniawan, 2019). Fuzzy Clustering is also known as soft Clustering, data elements that can be owned by more than one cluster. A fuzzy cluster is defined as a soft version of K-Means, so it is also referred to as Fuzzy C-Means Clustering, combining fuzzy techniques with K-means clustering techniques (Selvi & Ashwin, 2016).

One method (algorithm) developed in fuzzy clustering analysis is the Fuzzy C-Means (FCM) method. The FCM algorithm is an iterative algorithm that finds clusters in the data and uses the concept of fuzzy membership (Ghogge, 2014; Jayanti & Hartati, 2012). The FCM algorithm is an algorithm to determine the cluster center and then groups the cluster data based on the proximity of the attributes to the cluster center (Ditendra et al., 2020). This FCM method uses a fuzzy grouping model so that data can be members of all classes or clusters formed with degrees or membership levels that are between 0 to 1 (Nidyashofa & Istiawan, 2017). This method resembles the K-Means method because FCM is based on fuzzy logic and the K-Means method, where each point is entered into a group based on its membership value (Kurniawan & Haqiqi, 2015). The basic concept of the FCM algorithm is to determine the cluster's center, which will mark each cluster's average location. In the initial conditions, the cluster center is still not accurate, and each data has a degree of membership for each cluster. By repeatedly improving the cluster center and the membership value of each data, it can be seen that the cluster center will move to the right location. This iteration is based on the minimization of the objective function, which describes the distance from each data point to the center of each cluster weighted by the degree of membership of the data point (Efiyah, 2014; Kurniawan & Haqiqi, 2015).

The problem of stunting is currently the focus of the North Kalimantan Provincial Government. It is known that the prevalence of stunting in Kaltara in 2018 was 26.9% and in 2019 was 26.25%. The solution to this problem is to determine the focus location (locus) for handling stunting malnutrition problems in the Kaltara region. The problem of stunting is currently the focus of the North Kalimantan Provincial Government. It is known that the prevalence of stunting in Kaltara in 2018 was 26.9%, and in 2019 was 26.25%. The solution to this problem is to determine the focus location (locus) for handling stunting malnutrition problems in the Kaltara region (Fonseka et al., 2022; Iqbal & Ferdiany, 2019). Meanwhile, the regional government of Bulungan Regency made the stunting management plan one of the priority programs for Bulungan Regency. It was due to the high stunting rate in Bulungan Regency in 2019, and the number of stunted children in Bulungan Regency in 2019 was

1,235 children or 24.76% of the total number of children under five (Nurjanah & Nugroho, 2020).

A previous study also implemented a website-based Fuzzy C-Means method, requiring an internet network to access it (Ardianti, 2019). In this research, the method implemented is the desktop-based Fuzzy C-Means method with the help of Scilab software so that it does not require an internet network and is visualized using the Scilab GUI. Scilab resembles Matlab software with the same function to perform numerical computations and data visualization (Supriyadi & Wijayati, 2020). Initially, Scilab software developers were INRIA and ENPC, but now Scilab software developers are under the Scilab consortium (Priambodo & Sony, 2019). Therefore, this study aims to determine the clustering level of stunting susceptibility in an area using the Fuzzy C-Means method and perform a clustering simulation using secondary data obtained from the health office in 2021 with the help of GUI Scilab. The Scilab GUI is linked to Microsoft Excel so data can be modified. Implementing the desktop is expected to be an alternative in data clustering without using the internet network (online).

Implementing Open Source-based Scilab Software was certainly very easy to perform Clustering analysis using the Fuzzy C-Means method. The friendly interface makes the Scilab GUI easier for anyone to use. Developing a Clustering application using a GUI-based Scilab is expected to provide convenience to the North Kalimantan Provincial Government and the Bulungan Regency Government in efforts to deal with stunting.

2. METHODS

In this study, applying the Fuzzy C-Means (FCM) method in stunting prevention aims to determine the clusters of stunting susceptibility in Bulungan Regency. Data collection is done by collecting data sources that support the variables in the problem of stunting. The variables that affect the prevalence of stunting under five in this study are as follows: Adequacy of Puskesmas (X_1) is the ratio of Puskesmas per 100,000 population; Posyandu adequacy (Active) (X_2) is the proportion of villages that have sufficient posyandu; Doctor adequacy (X_3) is the ratio of doctors per 100,000 population; the Sufficiency of nutritionists (X_4) is the ratio of nutritionists per 100,000 population; Midwife sufficiency (X_5) is the ratio of midwives per 100,000 population; the Percentage of LBW (X_6) is the percentage of infants with low birth weight (LBW), which is less than 2,500 grams; Coverage of infant health services (X_7) is the ratio of the number of infants (aged 29 days – 11 months) who receive health services according to standards at least four times to the total number of infants; and Coverage of health services for children under five (X_8) is the ratio of children under five (12–59 months) who receive health services per the standard to the total number of children under five. According to these standards, health services include monitoring growth at least eight times a year, monitoring at least two times a year, and giving vitamin A 2 times a year (Hadi, 2017). These data are secondary data obtained from the Bulungan District Health Office in 2021. Clustering is carried out based on variables that affect stunting prevalence into 3 clusters. The clusters are 1) High, 2) Medium, and 3) Low.

The FCM algorithm is as follows (Kemala et al., 2019). First, the input data to be clustered is a X matrix measuring n x m, where n = the number of data samples and m = the number of variables for each data. x_{ij}= elements in the matrix of the i sample data (i = 1,2,3,…,n), the j variable (j = 1,2,3,…,m). Second, set the number of clusters (c), the power for the partition matrix (w), the maximum iteration $(MaksIter)$, the smallest expected error (ξ), the initial objective function (P_0=0), the initial iteration (t=1). Third, generate random numbers (μ_{ik}, i=1,2,3,…,n; k=1,2,3,…,c), as elements of the initial partition matrix U.

$$U_{n\times c} = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1c} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{n1} & \mu_{n2} & \cdots & \mu_{nc} \end{bmatrix}$$

The elements in the initial partition matrix $U_{n\times c}$ Must satisfy the following conditions:

$$\mu_{ik} = [0,1]$$

$$\sum_{k=1}^{c} \mu_{ik} = 1$$

Calculate the k cluster center: v_{kj}, with k = 1,2,3,…,*c*; and *j* = 1,2,3,…,*m*. v_{kj} is the points from the center of each cluster.

$$V_{c\times m} = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & \ddots & \vdots \\ v_{c1} & \cdots & v_{cm} \end{bmatrix}$$

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

Calculate the objective function in the *t* iteration using the following equation:

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

Calculate the change in the partition matrix using the equation:

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

Check stop condition:

a. If $(|P_t - P_{t-1}| < \xi)\ or\ (t > MaksIter)$ then stop;

b. b. If not, then $t = t + 1$ and repeat starting from step 4 using the updated μ_{ik}.

3. RESULTS AND DISCUSSION

Result

From the data on the prevalence of stunting under five in Bulungan Regency, 12 locations are the main focus, and eight variable factors that influence the prevalence of stunting cases as shown in Table 1.

Table 1. Stunting Prevalence in Bulungan Regency in 2021

Location	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Long Bia	4155.00	4.86	1385.00	4155.00	259.69	2.70	70.83	70.37
Long Bang	3940.00	2.60	1970.00	3940.00	437.78	5.48	105.97	130.69
Tanjung Palas	14059.00	1.03	2811.80	7029.50	520.70	2.33	88.11	71.40
Antutan	3450.00	2.18	1725.00	1725.00	492.86	12.00	81.36	79.63
Long Beluah	6549.00	2.00	2183.00	3274.50	654.90	9.89	49.57	50.90
Pimping	10997.00	0.03	2199.40	5498.50	646.88	8.79	87.83	60.39
Tanah Kuning	15874.00	1.77	5291.33	7937.00	755.90	8.97	106.91	71.58
Tanjung Selor	49565.00	0.68	5507.22	24782.50	1906.35	8.29	94.07	82.26
Bumi Rahayu	6080.00	1.52	1520.00	3040.00	264.35	2.88	102.86	56.09
Salimbatu	12032.00	1.93	6016.00	6016.00	501.33	7.76	103.35	84.90
Sekatak Buji	10040.00	3.32	3346.67	10040.00	436.52	10.55	93.68	77.27
Bunyu	11711.00	2.55	2927.75	11711.00	1064.64	4.19	85.71	94.85

The data in Table 1 will be processed using the Fuzzy C-Means method by setting 3 clusters, including cluster 1 with high indicators, cluster 2 with medium indicators, and cluster 3 with low indicators. Completion of Clustering using the Fuzzy C-Means method is calculated manually only in the initial iteration for the next iteration using Scilab software. The steps for calculating Clustering using the Fuzzy C-Means method. The first step, the input of stunting prevalence data in Bulungan Regency, is presented in Figure 1.

$$X_{12\times 8}=\begin{bmatrix} 4155,00 & 4,86 & 1385,00 & 4155,00 & 259,69 & 2,70 & 70,83 & 70,37 \\ 3940,00 & 2,60 & 1970,00 & 3940,00 & 437,78 & 5,48 & 105,97 & 130,69 \\ 14059,00 & 1,03 & 2811,80 & 7029,50 & 520,70 & 2,33 & 88,11 & 71,40 \\ 3450,00 & 2,18 & 1725,00 & 1725,00 & 492,86 & 12,00 & 81,36 & 79,63 \\ 6549,00 & 2,00 & 2183,00 & 3274,50 & 654,90 & 9,89 & 49,57 & 50,90 \\ 10997,00 & 0,03 & 2199,40 & 5498,50 & 646,88 & 8,79 & 87,83 & 60,39 \\ 15874,00 & 1,77 & 5291,33 & 7937,00 & 755,90 & 8,97 & 106,91 & 71,58 \\ 49565,00 & 0,68 & 5507,22 & 24782,50 & 1906,35 & 8,29 & 94,07 & 82,26 \\ 6080,00 & 1,52 & 1520,00 & 3040,00 & 264,35 & 2,88 & 102,86 & 56,09 \\ 12032,00 & 1,93 & 6016,00 & 6016,00 & 501,33 & 7,76 & 103,35 & 84,90 \\ 10040,00 & 3,32 & 3346,67 & 10040,00 & 436,52 & 10,55 & 93,68 & 77,27 \\ 11711,00 & 2,55 & 2927,75 & 11711,00 & 1064,64 & 4,19 & 85,71 & 94,85 \end{bmatrix}$$

Figure 1. First Step, Input Stunting Prevalence Data in Bulungan District

The second step is to determine the parameters to be used in the Fuzzy C-Means method, namely the number of clusters (c) = 3, the power (w) = 2, the maximum iteration (MaxIter) = 100, the smallest error (ξ) = 1e-5, the initial function objective (P_{t-1}) = 0, and initial iteration (t) = 1. The third step, generating random numbers μ_{ik} as elements of the initial partition matrix U_0, i = rows (number of data), and k = column (number of the cluster) is presented in Figure 2.

$$U_0 = \begin{bmatrix} 0,26 & 0,40 & 0,34 \\ 0,12 & 0,64 & 0,24 \\ 0,53 & 0,12 & 0,35 \\ 0,02 & 0,11 & 0,87 \\ 0,40 & 0,53 & 0,07 \\ 0,87 & 0,10 & 0,03 \\ 0,32 & 0,53 & 0,15 \\ 0,44 & 0,35 & 0,21 \\ 0,20 & 0,29 & 0,51 \\ 0,18 & 0,71 & 0,11 \\ 0,20 & 0,29 & 0,51 \\ 0,87 & 0,10 & 0,03 \end{bmatrix}$$

Figure 2. Generating Random Numbers μ_{ik}

The fourth step is to calculate the center value of each cluster in the first iteration by calculating the value of each point, namely v_{kj} by k = row (number of clusters) and j = column (number of variables). The results are obtained in Figure 3.

$$V_{3\times 8} = \begin{bmatrix} 14221,881 & 1,4303844 & 2919,7112 & 9074,398 & 842,89746 & 6,3953331 & 86,178704 & 75,122758 \\ 11426,601 & 2,2465758 & 3729,5444 & 6534,5346 & 604,718 & 7,2690921 & 92,68176 & 84,568893 \\ 7221,5068 & 2,3229797 & 2194,8649 & 4614,6148 & 474,16314 & 8,5698884 & 88,041436 & 75,999597 \end{bmatrix}$$

Figure 3. Center Value of Each Cluster

The fifth step is calculating the objective function's value in the initial iteration (P_1). By searching $\left[\sum_{j=1}^{8}(x_{ij}-v_{kj})^2\right]$ first, then search

$$\sum_{k=1}^{3}\left(\left[\sum_{j=1}^{8}(x_{ij}-v_{kj})^2\right]\times(\mu_{ik})^2\right) = \begin{bmatrix} 20126351,3435 \\ 29562483,4924 \\ 7818366,6368 \\ 18420966,0734 \\ 25247550,1760 \\ 18021715,3537 \\ 9939331,0091 \\ 608265938,7595 \\ 9165353,8901 \\ 4214422,7847 \\ 12028219,2532 \\ 10412751,6265 \end{bmatrix}.$$

Then $\sum_{i=1}^{12}\sum_{k=1}^{3}\left(\left[\sum_{j=1}^{8}(x_{ij}-v_{kj})^2\right](\mu_{ik})^2\right)$, By adding up each row, we get the value of $P_1 = 773223450,3989$.

The sixth step is to find the value of the change in the partition matrix to obtain the value of the new partition matrix.

$$U_1 = \begin{bmatrix} 0,0648 & 0,1296 & 0,8056 \\ 0,0675 & 0,1363 & 0,7963 \\ 0,6171 & 0,3325 & 0,0504 \\ 0,0960 & 0,1814 & 0,7226 \\ 0,0226 & 0,0571 & 0,9204 \\ 0,1091 & 0,7190 & 0,1719 \\ 0,6667 & 0,2659 & 0,0674 \\ 0,3971 & 0,3331 & 0,2698 \\ 0,0360 & 0,0824 & 0,8816 \\ 0,1766 & 0,7173 & 0,1061 \\ 0,3585 & 0,4677 & 0,1738 \\ 0,6002 & 0,2880 & 0,1118 \end{bmatrix}$$

Seventh step for t = 1 (initial iteration). $P_1 = 773223450,3989$ and $P_{1-1} = 0$, so $|773223450{,}3989| > 1e-5$. Because $|773223450,3989| > 1e-5$ then, for the second iteration, repeat step 4 using the updated μ_{ik}. The results of the next iteration calculation using Scilab software based on the Scilab GUI are presented in Figure 4.

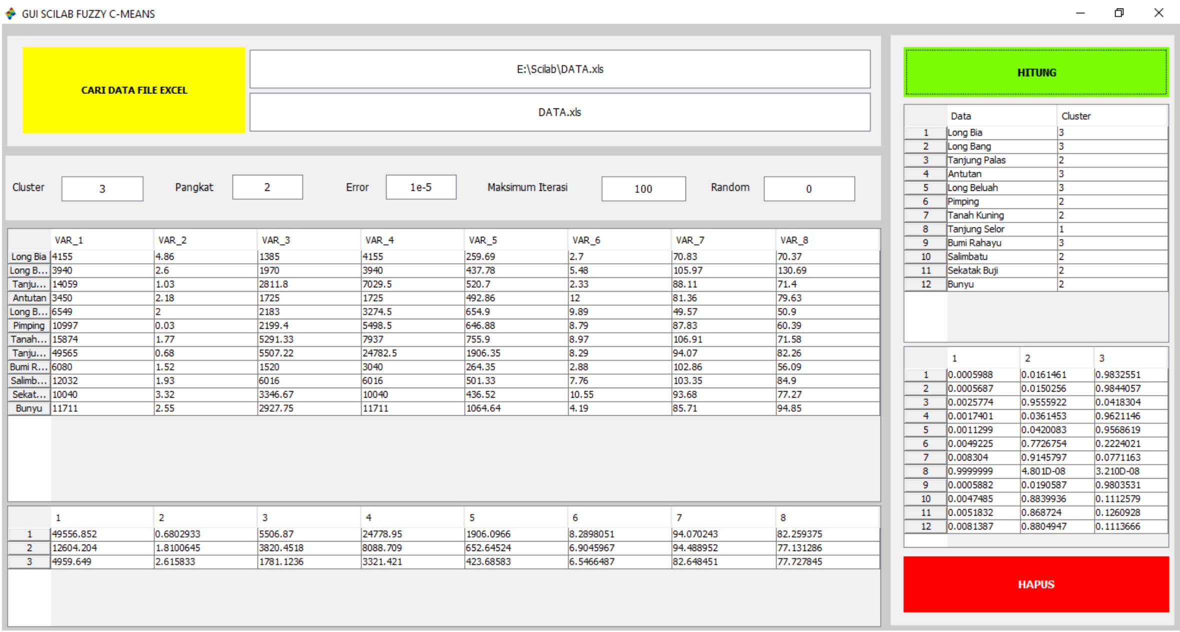

Figure 4. Final Result of Data Calculation

With details below:
Iterasi = 01, Objective Function = 773223450.3989
Iterasi = 02, Objective Function = 630029365.7948
Iterasi = 14, Objective Function = 67432405.5557

$$V_{3\times 8} = \begin{bmatrix} 49556.8520 & 0.6803 & 5506.8700 & 24778.9500 & 1906.0966 & 8.2898 & 94.0702 & 82.2594 \\ 12604.2040 & 1.8101 & 3820.4518 & 8088.7090 & 652.6452 & 6.9046 & 94.4890 & 77.1313 \\ 4959.6490 & 2.6158 & 1781.1236 & 3321.4210 & 423.6858 & 6.5466 & 82.6485 & 77.7278 \end{bmatrix}$$

$$U_{Akhir} = \begin{bmatrix} 0.0006 & 0.0161 & 0.9833 \\ 0.0006 & 0.0150 & 0.9844 \\ 0.0026 & 0.9556 & 0.0418 \\ 0.0017 & 0.0361 & 0.9621 \\ 0.0011 & 0.0420 & 0.9569 \\ 0.0049 & 0.7727 & 0.2224 \\ 0.0083 & 0.9146 & 0.0771 \\ 1.0000 & 0.0000 & 0.0000 \\ 0.0006 & 0.0191 & 0.9804 \\ 0.0047 & 0.8840 & 0.1113 \\ 0.0052 & 0.8687 & 0.1261 \\ 0.0081 & 0.8805 & 0.1114 \end{bmatrix}.$$

From U_{Akhir} obtained the location of the cluster from each location as in Table 2 as follows. Based on Table 2, the cluster results can be obtained as follows.

Table 2. Location of the Cluster of Each Data

Location	$U_{12\times1}$	$U_{12\times2}$	$U_{12\times3}$	Cluster 1	Cluster 2	Cluster 3
Long Bia	0.0006	0.0161	0.9833			*
Long Bang	0.0006	0.0150	0.9844			*
Tanjung Palas	0.0026	0.9556	0.0418		*	
Antutan	0.0017	0.0361	0.9621			*
Long Beluah	0.0011	0.0420	0.9569			*
Pimping	0.0049	0.7727	0.2224		*	
Tanah Kuning	0.0083	0.9146	0.0771		*	
Tanjung Selor	1.0000	0.0000	0.0000	*		
Bumi Rahayu	0.0006	0.0191	0.9804			*
Salimbatu	0.0047	0.8840	0.1113		*	
Sekatak Buji	0.0052	0.8687	0.1261		*	
Bunyu	0.0081	0.8805	0.1114		*	

Table 3. Total 3 Clusters by Location

No	Subdistrict	Group/cluster	Total
1	Tanjung Selor	1	1 Location
2	Tanjung palas, Pimping, Tanah Kuning, Salimbatu, Sekatak Buji, Bunyu	2	6 Locations
3	Long Bia, Long Bang, Antutan, Long Beluah, Bumi Rahayu	3	5 Locations

From Table 3, it is found that the areas that become cluster 1 are areas with an average level of adequacy of puskesmas (X_1), adequacy of doctors (X_3), adequacy of nutritionists (X_4), adequacy of midwives (X_5), percentage of LBW (X_6), and coverage Health services for children under five (X_8) are high, while the level of Coverage of infant health services (X_7) is moderate and the level of adequacy of posyandu (active) (X_2) is low; in cluster 2 the average level of adequacy of puskesmas (X_1), adequacy of posyandu (active) (X_2), adequacy of doctors (X_3), adequacy of nutritionists (X_4), adequacy of midwives (X_5), percentage of low birth weight (X_6) is moderate, while the level of Coverage of infant health services (X_7) is high and the Coverage of children's health services (X_8) is low; cluster area of 3 regions with an average level of adequacy of puskesmas (X_1), adequacy of doctors (X_3), adequacy of nutritionists (X_4), adequacy of midwives (X_5), percentage of low birth weight (X_6), and Coverage of infant health services (X_7) low, while the level of Coverage of health services for children under five (X_8) is moderate and the level of adequacy of posyandu (active) (X_2) is low.

Table 4. The Average Value of the Variables in Each Cluster

Variable	Average		
	Cluster 1	**Cluster 2**	**Cluster 3**
X_1	49556.8520	12604.2040	4959.6490
X_2	0.6803	1.8101	2.6158
X_3	5506.8700	3820.4518	1781.1236
X_4	24778.9500	8088.7090	3321.4210
X_5	1906.0966	652.6452	423.6858
X_6	8.2898	6.9046	6.5466
X_7	94.0702	94.4890	82.6485
X_8	82.2594	77.1313	77.7278

From Table 4 it can be categorized based on the level of vulnerability, so it can be concluded that the area in cluster 1 has a high level of vulnerability because it has the lowest level of adequacy of posyandu (active) (X_2) and a high incidence of LBW in infants (X_6); cluster 2 has a moderate level of vulnerability because it has an adequate level of puskesmas (X_1), adequacy of posyandu (active) (X_2), adequacy of doctors (X_3), adequacy of nutritionists (X_4), adequacy of midwives (X_5), percentage of low birth weight (X_6) that currently; and cluster 3 has a low level of vulnerability. After all, it has a low average percentage of LBW (X_6) and a high level of adequacy of posyandu (active) (X_2) in the area.

Discussion

A toddler is said to be stunted if the value of the ratio between height and the standard value of a toddler is below normal than it should be (Wulandari & Kurniawan, 2019). Based on the values of the parameters used in the Fuzzy C-Means method, the results of the cluster based on the location are as follows cluster 1, namely Tanjung Selor; cluster 2 is Tanjung Palas, Pimping, Tanah Kuning, Salimbatu, Sekatak Buji, Bunyu and cluster 3 is Long Bia, Long Bang, Antutan, Long Beluah, Bumi Rahayu. After getting the locations in each cluster, each cluster will be given a label/category based on the level of vulnerability. The determination of categories is based on the average value of the variables in each cluster. Based on the average value of these variables, it was found that the locations were in cluster 1 with a high level of vulnerability, cluster 2 with a moderate level of vulnerability, and cluster 3 with a low level of vulnerability. Stunting must be considered seriously because it will affect the growth and development of toddlers (Antunes et al., 2022; Cahyono et al., 2016).

Several factors that can cause children to experience stunting are nutritional intake and genetic factors (Fufa, 2022; Paintsil et al., 2022; Wardoyo et al., 2022). Other findings also state that several determinants of children under five who experience stunting are nutritional intake factors in children and genetic factors, in other words, following the short stature of their parents (Lestari et al., 2014; Paintsil et al., 2022). The results of data analysis show that the factors that affect the level of vulnerability to stunting are areas in cluster 1 that have a high level of vulnerability because they have the lowest level of adequacy of posyandu (active) (X_2) and high incidence of LBW in infants (X_6); cluster 2 has a moderate level of vulnerability because it has an adequate level of puskesmas (X_1), adequacy of posyandu (active) (X_2), adequacy of doctors (X_3), adequacy of nutritionists (X_4), adequacy of midwives

(X_5), percentage of low birth weight (X_6) that currently; and cluster 3 has a low level of vulnerability because it has a low average percentage of LBW (X_6) and a high level of adequacy of posyandu (active) (X_2) in the area.

4. CONCLUSION

The results of determining the stunting vulnerability cluster in Bulungan Regency using the parameters of the Fuzzy C-Means method found that the area in cluster 1 has a high vulnerability level because it has the lowest level of adequacy of posyandu (active) and the high incidence of LBW in infants whose location is Tanjung Selor. Cluster 2 has a moderate level of vulnerability because it has adequacy levels of puskesmas, adequacy of posyandu (active), adequacy of doctors, adequacy of nutritionists, adequacy of midwives, moderate percentage of LBW with locations namely Tanjung Palas, Pimping, Tanah Kuning, Salimbatu, Sekatak Buji, sound. Cluster 3 has a low level of vulnerability because it has a low average percentage of LBW and a high level of adequacy of posyandu (active) in the area, with the locations being Long Bia, Long Bang, Antutan, Long Beluah, Bumi Rahayu.

5. ACKNOWLEDGMENTS

The researcher would like to thank the Directorate of Research and Community Service of the Ministry of Education and Culture for the support given to researchers in the form of research funding assistance with the 2022 Beginner Lecturer Research scheme, which supports this research well.

6. REFERENCES

Antunes, J. L. F., Corrêa, E. M., Gallo, C. de O., & Jaime, P. C. (2022). The tendency of stunting among children under five in the Northern Region of Brazil, according to the food and nutrition surveillance system, 2008-2017. *Jornal de Pediatria*. https://doi.org/g/10.1016/j.jped.2022.07.006.

Ardianti, C. R. (2019). *Implementasi Metode Fuzzy C-Means Untuk Klasifikasi Status Gizi Pada Balita Berdasarkan Indeks Antropometri*.

Cahyono, F., Manongga, S. P., & Picauly, I. (2016). Faktor Penentu Stunting Anak Balita Pada Berbagai Zona Ekosistem Di Kabupaten Kupang. *Jurnal Gizi dan Pangan*, *11*(1), 9–18. https://doi.org/10.25182/jgp.2016.11.1.%25p.

Ditendra, E., Monalisa, S., Anderjovi, S., & Lesmana, S. (2020). Klasterisasi Clv Dengan Model Lrfm Menggunakan Algoritma Fuzzy C-Means (Studi Kasus: Pangeran Gym Pekanbaru). *Jurnal Ilmiah Rekayasa dan Manajemen Sistem Informasi*, *6*(1), 109–116. https://doi.org/10.24014/RMSI.V6I1.8535.

Efiyah, U. (2014). *Penerapan algoritma fuzzy C-Means untuk pengelompokan harga gabah di tingkat penggilingan berdasarkan kualitas gabah*. Universitas Islam Negeri Maulana Malik Ibrahim.

Fadillah, A. W., Tejawati, A., & Puspitasari, N. (2018). Penerapan Fuzzy C-Means Pada Curah Hujan Di Kalimantan Timur. *Jurnal Rekayasa Teknologi Informasi (JURTI)*, *2*(1), 82–89. https://doi.org/10.30872/JURTI.V2I1.1426.

Fonseka, R. W., McDougal, L., Raj, A., & Reed, E. (2022). Measuring the impacts of maternal child marriage and maternal intimate partner violence and the moderating effects of proximity to conflict on stunting among children under 5 in post-conflict Sri Lanka. *SSM - Population Health*, *18*. https://doi.org/10.1016/j.ssmph.2022.101074.

Fufa, D. A. (2022). Determinants of stunting in children under five years in dibate district of

Ethiopia: A case-control study. *Human Nutrition & Metabolism*, *30*. https://doi.org/10.1016/j.hnm.2022.200162.

Ghogge, R. (2014). Brain Tumour Detection Using K-means and Fuzzy C-means Clustering Algorithm. *IJSETR*, *3*(7).

Hadi, B. S. (2017). *Pendekatan Modified Particle Swarm Optimization dan Artificial Bee Colony Pada Fuzzy Geographically Weighted Clustering (Studi Kasus Pada Faktor Stunting Balita di Provinsi Jawa Timur*. Institut Teknologi Sepuluh November.

Iqbal, M., & Ferdiany, F. S. (2019). *Kaltara Miliki Kasus Gizi Buruk Terendah se-Kalimantan*. Antara Kaltara.

Jayanti, S., & Hartati, S. (2012). Sistem Pendukung Keputusan Seleksi Anggota Paduan Suara Dewasa Menggunakan Metode Fuzzy Mamdani. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, *6*(1). https://doi.org/10.22146/ijccs.2141.

Kemala, R. F., Astuti, I. F., & Maharani, S. (2019). Penerapan Metode Fuzzy C-Means Pada Aplikasi Simulasi TOEFL (Test Of English As A Foreign Language) Berbasis Web (Studi Kasus: Fakultas MIPA Universitas Mulawarman). *Informatika Mulawarman : Jurnal Ilmiah Ilmu Komputer*, *14*(1), 17–20. https://doi.org/10.30872/jim.v14i1.1954.

Kurniawan, R., & Haqiqi, B. N. (2015). Pengelompokan Menggunakan Metode Subtractive Fuzzy C-Mean (Sfcm), Studi Kasus Demam Berdarah Di Jawa Timur. *Statistika*, *3*(2), 22–30.

Kusuma, D. T., & Agani, N. (2015). Prototipe Komparasi Model Clustering Menggunakan Metode K-Means Dan FCM Untuk Menentukan Strategi Promosi : Study Kasus Sekolah Tinggi Teknik-PLN Jakarta. *Jurnal TICOM*, *3*(3), 93460.

Lestari, W., Margawati, A., & Rahfiludin, Z. (2014). Faktor risiko stunting pada anak umur 6-24 bulan di kecamatan Penanggalan kota Subulussalam provinsi Aceh. *Jurnal Gizi Indonesia (The Indonesian Journal of Nutrition)*, *3*(1), 37–45. https://doi.org/10.14710/JGI.3.1.126-134.

Nidyashofa, N., & Istiawan, D. (2017). Penerapan Algoritma Fuzzy C-Means untuk Pengelompokan Kabupaten / Kota di Jawa Tengah Berdasarkan Status Kesejahteraan Tahun 2015. *The 6th University Research Colloquium*, 23–30.

Nurjanah, & Nugroho, E. (2020). *Serius Tangani Stunting, Pemkab Lakukan Aksi*. Koran Kaltara.

Paintsil, J. A., Kofinti, R. E., Koomson, I., & Ameyaw, E. K. (2022). Reducing children's malnutrition by increasing mothers' health insurance coverage: A focus on stunting and underweight across 32 sub-Saharan African countries. *Economic Modelling*, *117*. https://doi.org/10.1016/j.econmod.2022.106049.

Praja, A., Lubis, C., & Herdiwindiati, D. E. (2017). Deteksi Penyakit Diabetes Dengan Metode Fuzzy C-Means Clustering Dan K-Means Clustering. *Computatio : Journal of Computer Science and Information Systems*, *1*(1), 15–24. https://doi.org/10.24912/COMPUTATIO.V1I1.233.

Prasetyo, E. (2012). *Data Mining – Konsep dan Aplikasi Menggunakan MATLAB* (N. WK (red); Edisi 1). Penerbit Andi.

Priambodo, A. S., & Sony, A. (2019). Studi Komparasi Simulasi Sistem Kendali PID Pada Matlab, GNU Octave, SciLab dan Spyder. *Elinvo (Electronics, Informatics, and Vocational Education)*, *4*(2), 169–175. https://doi.org/10.21831/ELINVO.V4I2.28347.

Radja, M., Londa, M. A., & Sara, K. (2020). Penerapan Metode Logika Fuzzy dalam Evaluasi Kinerja Dosen. *Matrix: Jurnal Manajemen Teknologi dan Informatika*, *10*(2). https://doi.org/10.31940/matrix.v10i2.1841.

Selvi, B. K., & Ashwin, M. (2016). FCM : Fuzzy C-Means Clustering – A View in Different Aspects. *IJSRSET*, *2*(1), 469–473.

Singh, K. J., Chiero, V., Kriina, M., Alee, N. T., & Chauhan, K. (2022). Identifying the trend of persistent cluster of stunting, wasting, and underweight among children under five years in northeastern states of India. *Clinical Epidemiology and Global Health*, *18*. https://doi.org/10.1016/j.cegh.2022.101158.

Supriyadi, E., & Wijayati, D. (2020). Penggunaan Scilab Untuk Memperkenalkan Kepada Siswa Smk Tentang Dasar Matematika Dalam Pemrograman Komputer. *GAUSS: Jurnal Pendidikan Matematika*, *03*(02), 11–21. https://doi.org/10.30656/gauss.v3i2.2662.

Wardoyo, S., Nurjazuli, N., & Darundiati, Y. H. (2022). Lead exposure and stunting incidents in children aged 3–5 years in Pontianak City, West Kalimantan, Indonesia. *Toxicologie Analytique et Clinique*, *34*(2). https://doi.org/10.1016/j.toxac.2022.02.006.

Wulandari, S., & Kurniawan, R. (2019). Pengelompokan Kabupaten/Kota Di Jawa Timur Berdasarkan Kasus Stunting Balita Menggunakan Algoritme Fuzzy Particle Swarm Optimization-Fuzzy C-Means. *Jurnal Statistika*, *7*(1), 1–13. https://doi.org/10.26714/jsunimus.7.1.2019.%25p.