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Research Article

Particle Swarm Optimization-Enhanced DBSCAN for Clustering Malnutrition Data on Java Island, Indonesia

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Abstract

This manuscript proposes an approach that uses the Particle Swarm Optimization (PSO) algorithm to optimize the parameters of the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method in mapping the spatial pattern of malnutrition in Java. Results showed that with a Silhouette Coefficient value close to 1 (0.134) and the lowest Davies-Bouldin Index (1.80), PSO successfully determined the optimal epsilon (eps) value of 1.76 and the optimal minimum number of points of 3. Index validation showed that DBSCAN could map the study area into three clusters that reflected the level of malnutrition, where 82 districts/cities were included in Cluster 0, 5 districts/cities in Cluster 1, and 3 districts/cities in Cluster 2. In contrast, 29 districts/cities were identified as noise. This finding confirms that the PSO approach in optimizing DBSCAN parameters can improve the method's effectiveness in handling complex cases such as malnutrition in a geospatial context.

Keywords : *PSO · DBSCAN · Clustering · Malnutrition*
MSC2020 : *68W40 · 92C30 · 90C59 · 62H30*

1. Introduction

Machine Learning, a branch of artificial intelligence, has emerged as a powerful tool for training computer systems to learn autonomously without the need for explicit programming, according to the original conception introduced by Arthur Samuel. Algorithms in machine learning are designed and analyzed to give computers the ability to acquire knowledge autonomously and overcome the limitations inherent in conventional programming approaches [1–4].

One commonly used machine learning method is cluster analysis [5–7]. Cluster analysis is one of the techniques in data mining that belongs to the unsupervised learning category, where the concept is that the machine learning process is performed without external guidance. In this context, machine algorithms automatically identify patterns in data using only existing feature information to distinguish one item from another, using a clustering approach [8–10].

Clustering is the process of grouping data into specific clusters that pay attention to the similarity of data characteristics between one data and another. Characteristics between data and one another. One method that exists in clustering is Density-Based Spatial Clustering of Application with Noise (DBSCAN). DBSCAN is an algorithm that performs a clustering process based on the density of the existing data. The concept of density in the DBSCAN method is seen from the parameter values used. DBSCAN can form several clusters that have irregular and random shapes, not consistently round. The algorithm can also quickly form clusters even when noise surrounds some clusters. DBSCAN can effectively identify clusters with various shapes and recognize noise points in the data [11–13].

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DBSCAN has been shown to have drawbacks in its implementation, especially when the data shows significant density variation between groups. This challenge arises due to using the same density parameter for all groups in DBSCAN, which is not always optimal for each group individually [14, 15]. To solve that condition, an approach with an optimization algorithm is needed to optimize the determination of parameters in implementing the DBSCAN algorithm. To solve this problem, this research applies a metaheuristic algorithm, specifically Particle Swarm Optimization (PSO). The purpose of applying the PSO algorithm is to improve the efficiency of determining parameters on the cluster [16, 17]. In addition, PSO was also chosen because of its flexibility in handling various optimization problems and its ability to achieve global solutions [18].

Based on the explanation related to the PSO algorithm and the DBSCAN method, the researcher will apply these methods in the Malnutrition case study. Will apply these methods in the Malnutrition case study. According to the World Health Organization, in 2020, out of 180 countries that experience child health and welfare problems, Indonesia is ranked 117^{th}. The problem of malnutrition in toddlers is a nutritional condition characterized by physical responses such as having minimal endemic on both feet, BW/TB less than -3 standard deviations, and upper arm circumference (LILA) less than 12.5 at the age of 6-59 months. One of the causes of malnutrition can be the Socioeconomic conditions of an area through economic development and community behaviour [19]. and also community behavior [20, 21]. This is seen as congruent in the developed and developing regions of developing regions in Indonesia, namely the island of Java, because the island of Java is seen to have a variation in the density of factors affecting malnutrition. to have a variation in the density of factors affecting malnutrition. Java Island has six provinces that have experienced urbanization, including the Province of Banten Province, DKI Jakarta Province, Yogyakarta Special Region Province, East Java Province, West Java Province, and West Java Province. East Java, West Java, and Central Java. Urbanization in an area will greatly impact social behaviour and economic development [22, 23], according to data from the Nutrition Status Survey Indonesia (SSGI) 2022 (Pada [24]). The percentage of malnutrition and undernutrition in toddlers reached 7.7%. Wasting in toddlers reached 7.9% for Banten Province, 8.0% for DKI Jakarta, 7.4% in the province of Yogyakarta Special Region, and 7.2% in the province.

East Java, 6.0% in West Java, and 7.9% in Central Java. Central Java. The prevalence of wasting in the six provinces on the island of Java still exceeds the WHO wasting standard of $< 5\%$. Different factors affecting malnutrition in toddlers result in different prevalence rates between provinces. Different prevalence rates between each province. Therefore, a general grouping is needed to see the characteristics of the factors that cause malnutrition in toddlers. The grouping that will be done is based on the similarity characteristics of the factors that cause malnutrition in toddlers; the grouping will be based on the characteristics of the factors that cause malnutrition in the 119 districts/cities on the island of Java. 119 districts/cities on the island of Java.

2. Method

The research variables used in this study are related to the factors that influence malnutrition. Eight variables were used, and they are described in Table 1.

Table 1. Research variables

Variable	Description	Scale
X_1	Percentage of Toddlers who are Exclusively Breastfed	Ratio
X_2	Percentage of Infants with Low Birth Weight (LBW)	Ratio
X_3	Percentage of Toddlers Receiving Complete Basic Immunization	Ratio
X_4	Number of Active Integrated Service Post	Ratio
X_5	Percentage of Households with Access to Healthy Sanitation	Ratio
X_6	Percentage of Households with Access to Adequate Drinking Water	Ratio
X_7	Percentage of Households with Adequate Housing	Ratio
X_8	Number of Poor People	Ratio

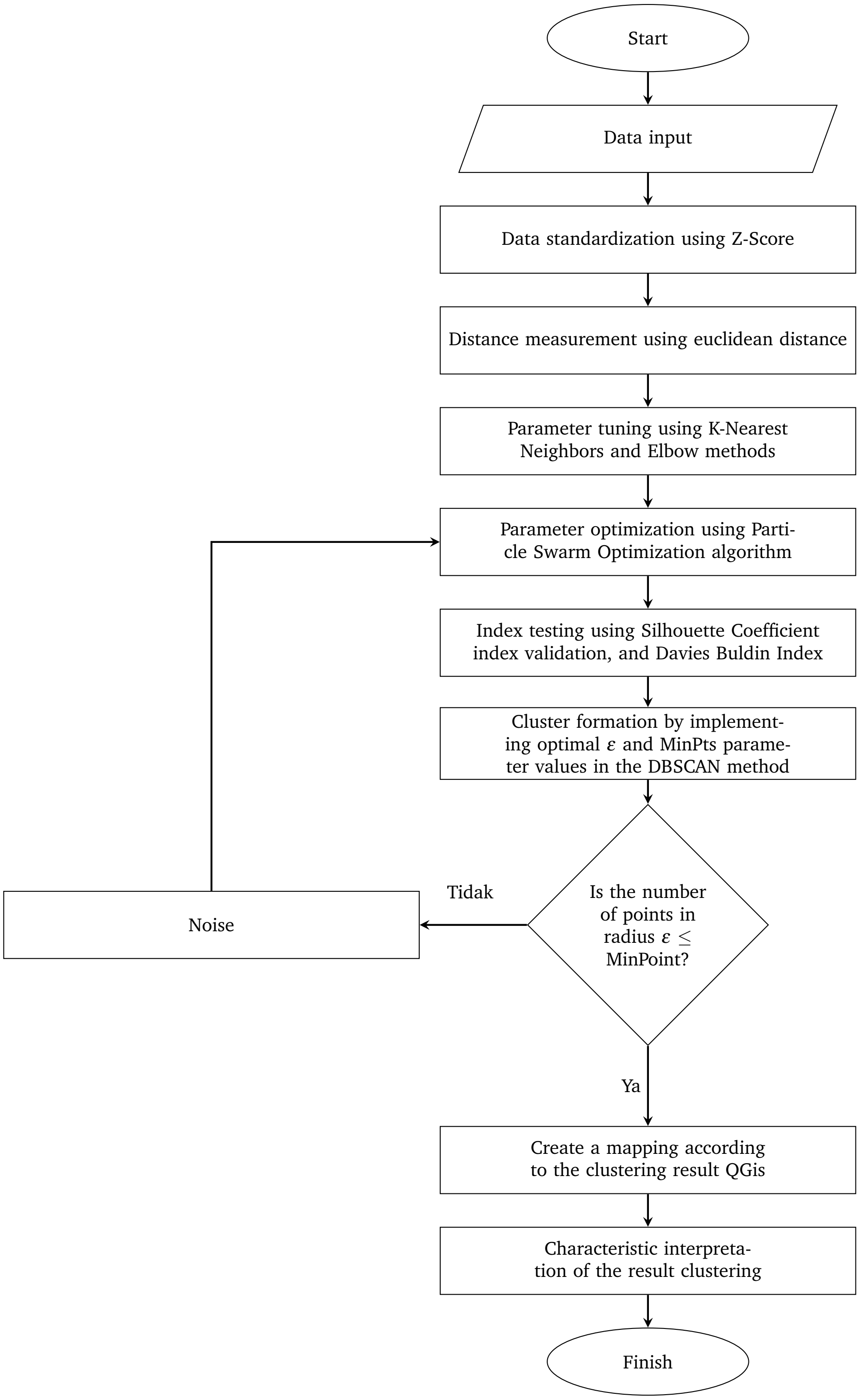

Figure 1. Research flow chart

1. Percentage of Toddlers who are Exclusively Breastfed: The percentage of children in each district/city in Java Island who receive breast milk exclusively from birth to six months of age with

no other food or drink added.
2. Percentage of Infants with Low Birth Weight: Percentage of babies born weighing below 2,500 grams in each district/city in Java Island.
3. Percentage of Toddlers Receiving Complete Basic Immunization: Percentage of infants receiving all basic immunization vaccines (BCG, Hepatitis, DPT, and measles) in each district/city in Java Island.
4. Number of Active Integrated Service Post: The number of active public health and family planning service facilities in each district/city in Java Island, including active health programs and cadres.
5. Percentage of Households with Access to Healthy Sanitation: Percentage of households in Java Island that have sanitation facilities that meet health standards, including safe waste disposal and away from contamination.
6. Percentage of Households with Access to Safe Drinking Water: Percentage of households in Java Island with access to clean, safe drinking water that meets health standards.
7. Percentage of Households with Adequate Housing: Percentage of households in Java Island living in dwellings that meet health, safety, and welfare standards.
8. Number of Poor People: The number of individuals in Java Island who cannot fulfil the basic needs of life such as food, clothing, housing, education, and health services.

This study utilizes secondary data involving 199 districts/cities from six provinces in the Java Island region in 2022, focusing on the prevalence of malnutrition that exceeds the national average. The data used in this study were sourced from the Ministry of Health's SSGI data publication in 2022, the Health Profile publication of the Health Office of Banten, DKI Jakarta, Daerah Istimewa Yogyakarta, East Java, West Java and Central Java Provinces in 2022, and the Statistics Agency publication of Banten, DKI Jakarta, Daerah Istimewa Yogyakarta, East Java, West Java and Central Java Provinces. The data used in this study are the factors that influence malnutrition. The sampling technique is saturated sampling, where all population members are sampled. The stages of this research are described in a flowchart to provide a visual description of the process performed.

3. Results and Discussion

This section discusses the application of the Density-Based Spatial Clustering Application with Noise (DBSCAN) method in clustering malnutrition cases in Java Island in 2022 and the use of the Particle Swarm Optimization (PSO) optimization algorithm to find optimal parameters. This study involved 119 districts/cities in Java Island with eight research variables, a total of 952 data. The data came from the Central Bureau of Statistics publication and the District Health Office in Java Island publications.

3.1. Descriptive Statistics

Table 2 shows a considerable difference in the range of values between variable 1 and the others. It is deemed necessary to standardize the data first to stabilize the variance between variables and prevent data bias that may arise due to different scales.

3.2. Data Standardization

The descriptive statistics results show a considerable difference in the range of values between each value, so it is necessary to carry out a data standardization process to convert the data into a smaller range before the following data analysis process is carried out. In this study, the data standardization process was carried out through the calculation of Z Score, which is presented in Table 3.

Table 2. Descriptive Statistics Results

	X1	X2	X3	X4	X5	X6	X7	X8
Count	119.0	119.0	119.0	119.0	119.0	119.0	119.0	119.0
Mean	49.95	7.40	85.21	116.42	196.65	94.40	63.81	82.05
STD	25.98	4.80	19.96	75.97	296.78	5.48	16.12	13.19
Min	8.79	0.30	19.24	3.67	1.00	73.27	14.37	45.80
Q1	24.65	3.95	72.40	71.78	1.33	92.92	54.21	77.75
Median	57.50	6.10	90.60	111.03	2.21	95.97	66.75	85.82
Q3	73.95	10.81	99.25	149.13	338.00	98.18	75.34	92.38
Max	93.90	21.08	132.50	474.70	969.00	100.00	90.52	97.72

Table 3. Data Standardization Results

District/City	X1	X2	X3	X4	$\cdots$	X8
Kab. Lebak	-1.4906	2.6230	-1.9540	0.0105	$\cdots$	-1.1160
Kab. Pandeglang	-1.5911	1.6275	-2.6146	-0.0235	$\cdots$	-1.5165
Kab. Tangerang	-1.5454	2.3051	-1.9897	2.0370	$\cdots$	0.3485
Kota Cilegon	-1.5207	0.6634	-2.1210	-1.3215	$\cdots$	0.4315
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Kota Tegal	-1.2567	1.0984	-0.0421	-1.2776	$\cdots$	0.8777

3.3. Distance Measurement

Distance measurement measures how close or far two data points are in feature space. This study's data analysis used the Euclidean distance measurement method, with the calculation results presented in Table 4.

Table 4. Euclidean Distance Results

	1	2	3	4	$\cdots$	119
1	0.0000	1.4642	5.7122	6.8037	$\cdots$	6.6512
2	1.4642	0.0000	5.3115	6.1754	$\cdots$	6.3135
3	5.7122	5.3115	0.0000	4.9718	$\cdots$	4.1893
4	6.8034	6.1754	4.9719	0.0000	$\cdots$	3.7116
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
119	6.6512	6.3134	4.1893	3.7116	$\cdots$	0.0000

4. Parameter Tuning

Parameter tuning is done to find the initial generation value used as a PSO constraint in exploring the optimal parameter search space. Parameter tuning implements the k-Nearest Neighbor (k-NN) method to find the initial generating value of min points. The search results using k-NN are presented in Table 5.

Table 5. Min Points search results using k-NN

Minimum Samples	Shape of Distance Matrix
16	119,119

And to find the initial generation value of epsilon using the elbow method by looking at the point where the decrease in inertia begins to slow down significantly. The search results using elbow are presented in Figure 2.

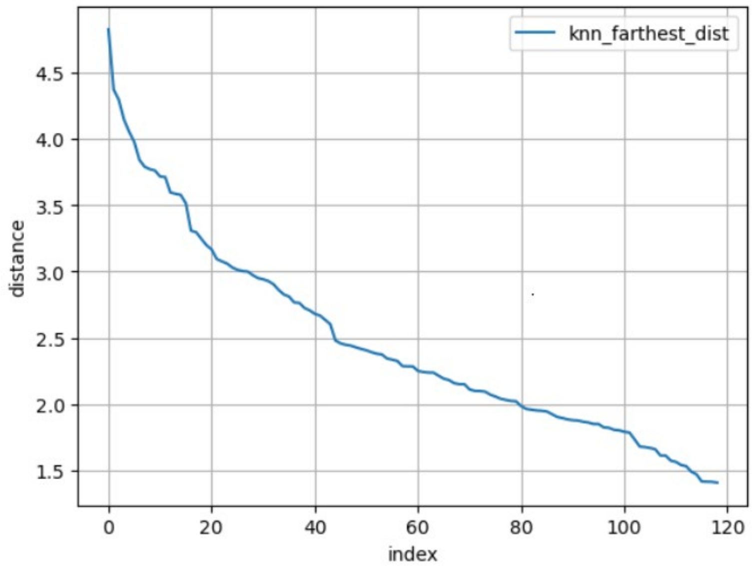

Figure 2. Graph of the results of finding the epsilon value using the elbow

4.1. Particle Swarm Optimization (PSO)

In this stage, the optimal parameters of the epsilon and minimum point values used in the data clustering process using the DBSCAN method are searched. The values obtained through parameter tuning are used as limits in finding parameters for eps and minimum points in the PSO algorithm. The algorithm will iterate and work according to these limits through the objective function used in the search for Gbest as epsilon and Pbest as Minimum Point. In this study, the PSO algorithm iterated 10,100 times. Information on iterations performed by the PSO algorithm is presented in Table 6.

Table 6. PSO Iteration Information

Iterasi	Epsilon	Minimum Point	Fungsi Tujuan
1	1.80	3	0.0
3	1.77	3	0.8991596638655462
6	1.78	3	0.8991596638655462
8	1.79	3	0.8991596638655462
33	1.70	3	0.5294117647058824
40	1.69	3	0.3949579831932773
41	1.76	3	0.9663865546218487
45	1.67	3	0.5126050420168067
⋮	⋮	⋮	⋮
10100	1.74	3	0.9663865546218487

The Silhouette Coefficient value closest to one is 0.13449014298569087, while the smallest Davies-Bouldin Index value is 1.8014595350863065. Several combinations of epsilon and minimum point values produce the same calculations for the Silhouette Coefficient and Davies-Bouldin Index. However, it should be emphasized that in this study, the search for optimal parameters using the PSO algorithm also considered the highest objective function value. Therefore, by considering the validation results of these indices as well as the highest objective function value, it can be concluded that the optimal parameters generated by the PSO algorithm, namely epsilon: 1.76 and minimum points : 3 at the 41st iteration, can be used as parameters in the data clustering process using the DBSCAN method.

4.2. Cluster Formation

Cluster formation in the DBSCAN method uses optimal parameters generated by the PSO algorithm and tested for validation index. The optimal parameter values obtained are an eps value of 1.76 and a minimum point of 3. The data clustering process is presented in Table 7.

Table 7. The region based on cluster 0, 1, 2, and cluster noise

Cluster	District/City
Cluster 0	Kab. Serang, Kota Tangerang, Jakarta Selatan, Jakarta Timur, Kab. Bantul, Kab. Gunung Kidul, Kab. Sleman, Kota Yogyakarta, Kab. Ponorogo, Kab. Tulungagung, Kab. Blitar, Kab. Kediri, Kab. Malang, Kab. Lumajang, Kab. Jember, Kab. Banyuwangi, Kab. Probolinggo, Kab. Pasuruan, Kab. Siduarjo, Kab. Mojokerto, Kab. Jombang, Kab. Nganjuk, Kab. Madiun, Kab. Magenta, Kab. Ngawi, Kab. Bojonegoro, Kab. Tuban, Kab. Gresik, Kab. Sumenep, Kota Kediri, Kota Blitar, Kota Malang, Kota Probolinggo, Kota Pasuruan, Kota Mojokerto, Kota Madiun, Kota Surabaya, Kota Batu, Kab. Bandung, Kab. Ciamis, Kab. Kuningan, Kab. Majalengka, Kab. Sumedang, Kab. Indramayu, Kab. Subang, Kab. Purwakarta, Kab. Karawang, Kab. Bekasi, Kota Cirebon, Kota Bekasi, Kota Cimahi, Kota Banjar, Kab. Cilacap, Kab. Banyumas, Kab. Prubalingga, Kab. Kebumen, Kab. Purworejo, Kab. Magelang, Kab. Boyolali, Kab. Klaten, Kab. Sukoharjo, Kab. Wonogiri, Kab. Karanganyar, Kab. Sragen, Kab. Grobogan, Kab. Blora, Kab. Jepara, Kab. Demak, Kab. Semarang, Kab. Temanggung, Kab. Kendal, Kab. Batang, Kab. Pekalongan, Kab. Pemalang, Kab. Tegal, Kab. Brebes, Kota Mangelang, Kota Surakarta, Kota Salatiga, Kota Semarang, Kota Pekalongan, Kota Tegal.
Cluster 1	Kab. Bondowoso, Kab. Situbondo, Kota Sukabumi, Kota Bandung, Kota Tasikmalaya.
Cluster 2	Kab. Sukabumi, Kab. Tasikmalaya, Kab. Bandung Barat.
Cluster Noise	Kab. Lebak, Kab. Pandeglang, Kab. Tangerang, Kota Cilegon, Kota Serang, Kota Tangerang Selatan, Jakarta Pusat, Jakarta Utara, Jakarta Barat, Kepulauan Seribu, Kab. Kulon Progo, Kab. Pacitan, Kab. Trenggalek, Kab. Lamongan, Kab. Bangkalan, Kab. Sampang, Kab. Pamekasan, Kab. Bogor, Kab. Cianjur, Kab. Garut, Kab. Cirebon, Kab. Pangandaran, Kota Bogor, Kota Depok, Kab. Banjarnegara, Kab. Wonosobo, Kab. Rembang, Kab. Pati, Kab. Kudus.

Based on Table 7, cluster 0 consists of 82 districts/cities, cluster 1 consists of 5 districts/cities, cluster 2 consists of 3 districts/cities, and 29 districts/cities are defined as noise/outliers. The number of members of cluster 0 dominates compared to clusters 1 and 2. Figure 3 maps the clustering results based on the factors that cause malnutrition across 119 districts/cities in the Java Island region. The light pink districts/cities are in cluster 0, the electric pink districts/cities are in cluster 1, the purple districts/cities are in cluster 2, and the maroon districts/cities are defined as noise/outliers.

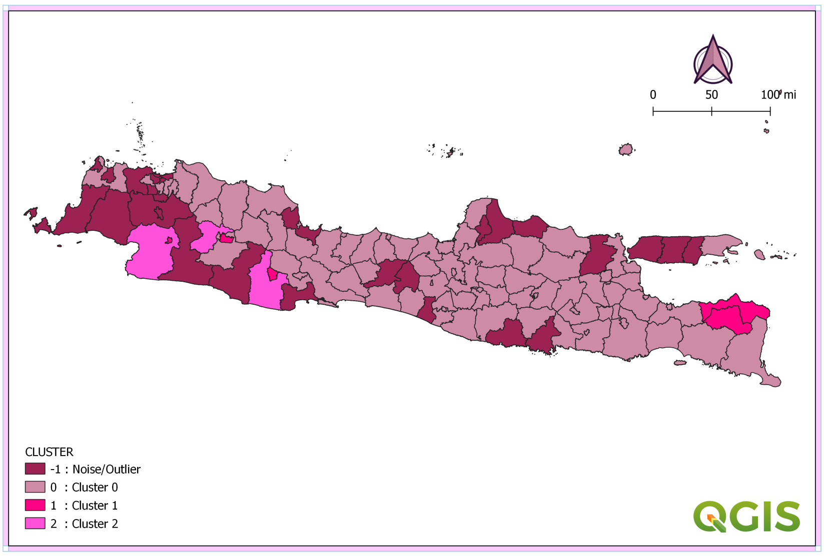

Figure 3. Map of Malnutrition Grouping in Java Island region

4.3. Interpretation of Cluster Formation Results

Based on the centroid value, it can be seen that cluster 0 consists of districts/cities where the percentage of infants with low birth weight (BBLR) (X2) and the number of poor people (X8) is highest compared to cluster 1 and cluster 2. Cluster 1 consists of districts/cities with the percentage of toddlers who get exclusive breastfeeding (X1), the percentage of households that have access to healthy sanitation (X5), and the percentage of households that have access to proper drinking water (X6) is highest compared to cluster 0 and cluster 2. For districts/cities that are members of cluster 2, the areas with the highest percentage of toddlers getting complete basic immunization (X3), the number of active Integrated Service Posts (X4), and the percentage of households having decent housing (X7) compared to cluster 0 and cluster 1.

Table 8. DBSCAN Cluster Centroid Value

Variabel	*Cluster* 0	*Cluster*1	*Cluster*2
X1	0.007039	0.987767	0.742937
X2	-0.072379	-0.484820	-0.717663
X3	0.097121	0.525896	1.104820
X4	-0.077207	-0.453350	0.946608
X5	-0.262163	-0.170638	-0.657596
X6	0.243349	0.520163	-1.314642
X7	0.366792	-1.416725	1.513445
X8	0.293531	-2.373547	-1.967091

5. Conclusions

In clustering districts/cities in the Java Island region in 2022 based on the factors that cause malnutrition cases using the PSO optimization algorithm in determining the optimal DBSCAN parameters. The parameters that are considered to be able to perform well, namely at the value of $\varepsilon = 1.76$ and Min Points $= 3$ with the resulting cluster totalling 3 clusters, and there is noise/outliers. These parameters work well, as evidenced by the calculation of the validation index with a Silhouette Coefficient value of 0.13449014298569087 and the Davies-Bouldin Index of 1.8014595350863065. The good performance of the PSO algorithm in determining DBSCAN parameters can be seen through the results of clustering districts/cities in the Java Island region in 2022 based on factors that cause malnutrition, which results in 3 clusters being formed. Cluster 0 consists of 82 districts/cities, cluster 1 consists of 5 districts/cities, and cluster 2 consists of 3 districts/cities. The characteristic results of each cluster formed show that the districts/cities with the highest malnutrition cases are in Cluster 0, and the districts/cities with the lowest malnutrition cases are in Cluster 2.

Supplementary Information

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Conflict of interest. The authors declare no conflict of interest.

Data availability. The data supporting this research are available in [21, 24].

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