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CLUSTERING OF DISTRICTS IN CENTRAL JAVA ACCORDING TO PEOPLE'S WELFARE INDICATORS USING WARD'S METHOD

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Abstract: *Improving people's welfare has always been a primary goal of national development initiatives. Community welfare refers to a condition in which citizens can adequately meet their material and spiritual needs. In Central Java Province, out of a total population of 37.03 million, approximately 3.83 million people live in poverty. Moreover, the province has a population density of 1,120 people per square kilometer and ranks third in the number of people living in poverty in Indonesia. This study aimed to classify the regencies and cities in Central Java based on community welfare indicators. The indicators employed include the Open Unemployment Rate (UR), Labor Force Participation Rate (LFPR), poverty rate, Human Development Index (HDI), and District Minimum Wage (DMW). Ward's Agglomerative Hierarchical Clustering method was used for the analysis. The final analysis revealed that the optimal number of clusters is six. Specifically, the first cluster comprises 13 regencies/cities; the second, 8; the third, 3; the fourth, 1; and the fifth and sixth clusters consist of 5 regencies/cities each.*

***Keywords*:** *Cluster Analysis, Community Welfare, Ward's.*

1. INTRODUCTION

In the fourth paragraph of the Preamble to the 1945 Constitution, it is clearly stated that the national goals that Indonesia aims to achieve are "to protect the entire nation and all the blood spilt in Indonesia, to advance the general welfare, to educate the nation's life, and to participate in implementing world order based on independence, eternal peace, and social justice" [1]. This indicates that the welfare of the people is one of the important indicators in determining the success level of a region in developing the welfare of its community [2], [3]. The welfare of the people in a region is an achievement attained by the community, which is obtained from various efforts, including the economic activities and endeavours of that community [4].

Central Java is one of the 38 provinces in Indonesia. The province of Central Java consists of 35 regencies/cities, including 29 regencies and 6 cities [5]. According to data from BPS Central Java, the population of Central Java in 2022, based on the Interim Population Projection 2020-2023, was recorded at 37.03 million people. The number of poor people in Central Java Province in 2022 was 3,831.44 million people (10.93%), which shows a decrease compared to the poor population in 2021, which was 4,109.75 million people (11.79%) [6]. Although poverty and unemployment rates have decreased, job opportunities have not been able to absorb the annual growth of the workforce. BPS Central Java recorded that the total workforce increased from 18.96 million people in 2021 to 19.47 million people in 2022. Meanwhile, the number of unemployed decreased from 1.13 million people in 2021 to 1.08 million people in 2022 [7]. Therefore, development programs are needed to improve the welfare of the people.

One of the prerequisites for achieving the success of a development program heavily depends on the accurate identification of target groups and target areas [8]. Multivariate analysis can be used for this identification process, specifically through cluster analysis [9], [10], [11]. Cluster analysis is a statistical method used for data grouping [12]. In this grouping, a measure is used to explain the proximity between data points to elucidate the simple group structure from complex data, which is the distance measure [13]. Generally, there are two methods in data cluster analysis: hierarchical and non-hierarchical [14]. Several methods in hierarchical cluster analysis include Single Linkage, Complete Linkage, Average Linkage, Ward's, and Centroid, using the Euclidean distance measure [15].

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This study uses Ward's method to obtain clusters with the smallest possible variance. The measure used in Ward's method is the Sum of Square Error among variables [16].

2. RESEARCH METHODS

2.1. Data Normalization

Data normalization is the scaling of input values so that the input data falls within a certain range, ensuring that the value range of each variable is not too disparate [17]. Variables with large values influence classification predictions more than those with small values. To avoid this issue, variable normalization techniques can be used so that all variables vary within the same range. If process variables are not normalized, there is a possibility that one variable may dominate the classifier. The way to determine normalization values is by calculating the variance and the mean of each variable used in the study, as presented in the following equation [18].

$$\bar{x}_k = \frac{1}{N}\sum_{i=1}^{N} x_{ik} \tag{1}$$

$$\sigma_k = \sqrt{\frac{1}{N-1}\left(\Sigma_{i=1}^{N}\,\bar{x}_i\right)^2} \tag{2}$$

$$\hat{x}_{ik} = \frac{x_{ik} - \bar{x}_k}{\sigma_k} \tag{3}$$

where

$\bar{x}_k$: Mean of the variable to k

σ_k : Variance of the variable ke-k;

$\hat{x}_{ik}$: Normalization of the-i data point on the-k variable

2.2. Multicollinearity Testing

Grouping objects into clusters with similar characteristics using the Agglomerative Hierarchical Clustering Ward's method requires the assumption of independence among the variables (attributes) used. The presence of a linear relationship among some or all variables (multicollinearity) causes significant issues [19], [20]. To determine whether a variable has a linear relationship, the Variance Inflation Factor (VIF) value can be used [21], [22]. The equation for calculating the VIF value is formulated as follows:

$$VIF = \frac{1}{1-R^2} \tag{4}$$

The VIF value is used as a criterion to detect multicollinearity in linear regression involving more than two independent variables. The decision-making criteria for the multicollinearity test are as follows: if the VIF value is less than 10, there is no multicollinearity. However, if the VIF value is 10 or greater, then multicollinearity is present [23].

2.3. Agglomerative Hierarchical Clustering Ward's (AHCW)

Cluster analysis is used to group a dataset into several clusters that share similar characteristics and data. One commonly used cluster analysis method for grouping data is hierarchical clustering [24]. Hierarchical clustering can be performed in two directions: dividing from the highest-level cluster down to the smallest data objects, or by combining individual points into clusters at the highest level. AHCW (Agglomerative Hierarchical Clustering Ward) is a method that processes from the lowest data objects to form the highest-level cluster [25], [26].

Euclidean distance is a measure of the straight-line distance between objects. For example, the distance between object *i* and object *j* can be denoted by d_{ij} with $k = 1, 2, \ldots, p$ for the *k* variable. The value of d_{ij} is obtained from the following calculation [24], [27]:

$$d_{ij} = \sqrt{\sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2} \quad (5)$$

The measure used in the AHCW method to evaluate the goodness of the model is the Sum of Square Error (SSE) with the following equation [25], [26], [28]:

$$SSE = \sum_{j=1}^{p} \left[\Sigma_{ij}^{n}\ x_{ij}^2 - \frac{1}{n}\left(\Sigma_{ij}^{n} X_{ij}\right)^2\right] \quad (6)$$

where

X_{ij} : The i data point on the j variable

p : The number of measured variables

n : The number of objects in the formed cluster

2.4. Silhouette Coeficent

2.5. The Silhouette Coefficient is an internal validation measure where object placement within each cluster is evaluated by comparing the average distance of objects within the same cluster to those in different clusters. The Silhouette Coefficient value can be calculated using the following equation [29], [30]:

$$sil\ (c) = (k)\frac{1}{|k|}\ \Sigma_{i=1}^{k}\ sil\ (c_i) \quad (7)$$

(1)

2.6. Research Data

The data used in this study consist of the Unemployment Rate, Economically Active Participation Rate, poverty rate, and Human Development Index in Central Java Province in 2022, obtained from the Central Bureau of Statistics (BPS) of Central Java, and Regional Minimum Wage in Central Java Province in 2022, acquired from the Central Java Province Manpower and Transmigration Office.

2.7. Research Steps

The steps in the research to form regional groups in Central Java according to indicators of public welfare are as follows:

1. Collecting data on indicators of public welfare such as unemployment rate, economically active participation rate, poverty rate, human development index, and regional minimum wage;
2. Conducting descriptive statistical analysis to understand the data used in the study;
3. Normalizing the data;
4. Conducting multicollinearity examination on the variables (attributes) used in the study;
5. Calculating Euclidean distance between research objects. In this case, the research objects are Districts/Cities in Central Java;
6. Clustering process considering the criterion of minimizing the Sum of Square Error (SSE);
7. Performing evaluation to determine the optimal number of clusters to be used.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics of Public Welfare Indicators

Descriptive statistics of public welfare indicators based on the unemployment rate, economically active participation rate, poverty, human development index, and regional minimum wage in Central Java Province in 2022 are presented in Table 1.

Table 1. Summary of Statistics on People's Welfare Indicators in Central Java Province

Variable	Maximum		Minimum	
	Regency/City	Value	Regency/City	Value
Unemployment Rate	Tegal Regency	9.64%	Rembang Regency	1.76%
Economically Active Participation Rate	Magelang Regency	79.57%	Banyumas Regency	64.75%
poverty	Kebumen Regency	16.41%	Semarang City	4.25%
Human Development Index	Salatiga City	84.35%	Brebes Regency	67.03%
Regional Minimum Wage	Semarang City	IDR 2,835,021.29	Banjarnegara Regency	IDR 1,819,835.17

Source: processed data (2022)

Based on the analysis presented in Table 1, it was found that Tegal Regency had the highest unemployment rate in Central Java in 2022, with a percentage of 9.64. However, the area with the most poor residents was Kebumen Regency, with a percentage of 16.41. Additionally, the highest Labor Force Participation Rate was in Magelang Regency, at 79.57%; the highest Human Development Index was in Salatiga City, at 84.35; and the highest Minimum Wage was in Semarang City, at IDR 2,835,021.29. Therefore, this study aims to form clusters or groups of regions in Central Java, where the final results will illustrate the characteristics of each group formed.

3.2. Data Normalization

Table 1 shows that the variables Unemployment Rate, Labor Force Participation Rate, Poverty, and Human Development Index are presented in percentage (%). However, the Minimum Wage variable is presented in Rupiah (IDR). The significant difference in data ranges can affect the final clustering results. Therefore, the researcher performed data normalization calculations as follows:

$$\hat{x}_{11} = \frac{x_{11} - \bar{x}_1}{\sigma_1} = \frac{9.62 - 5.345429}{1.966043} = 2.174200$$

$$\hat{x}_{21} = \frac{x_{21} - \bar{x}_1}{\sigma_1} = \frac{6.05 - 5.345429}{1.966043} = 0.358370$$

$$\vdots$$

$$\hat{x}_{355} = \frac{x_{355} - \bar{x}_5}{\sigma_5} = \frac{2005930.52 - 2052652.755143}{208927.936229} = -0.223628$$

3.3. Multicollinearity Checking

Multicollinearity examination between the variables/indicators used in the clustering was conducted by checking the VIF values. The results of the VIF calculations for each indicator are presented in Table 2.

Table 2. VIF calculation results for each indicator

Variable	VIF
Unemployment Rate	1.592883
Economically Active Participation Rate	1.508529
Poverty	2.269185
Human Development Index	2.267799
Regional Minimum Wage	1.650218

Based on Table 2, the VIF values for each variable used in the study are less than 10. This indicates that there is no multicollinearity between the variables. Therefore, all five variables will be used to cluster the regencies/cities in Central Java based on poverty characteristics.

3.4. Agglomerative Hierarchical Clustering Ward's (AHCW)

The Euclidean distance calculation between observation objects is performed using Equation 5, which is simulated with the following calculation:

$$d_{12} = \sqrt{(2.174200 - 0.358370)^2 + (-1.569306 + 1.827321)^2 + \cdots + (0.852345 + 0.332128)^2}$$

$$d_{12} = \sqrt{5.315282} = 2.305490$$

The results of calculating the Euclidean distance between observation objects are presented in Table 3.

Table 3. Results of calculating the distance between objects using the Euclidean method

Objects (i,j)	**1**	**2**	**3**	**4**	⋯	**35**
1	0	2.305490	3.616779	3.463185	⋯	2.520458
2	2.305490	0	2.766942	2.594598	⋯	2.012087
3	3.616779	2.766942	0	1.114936	⋯	3.129340
4	3.463185	2.594598	1.114936	0	⋯	3.112468
⋮	⋮	⋮	⋮	⋮	⋱	⋮
35	2.520458	2.012087	3.129340	3.112468	⋯	0

Based on Table 3, the calculated Euclidean distance between object d_{12}, or the distance between Cilacap Regency and Banyumas Regency, is 2.305490. Meanwhile, the Euclidean distance between object d_{13}, or the distance between Cilacap Regency and Purbalingga Regency, is 3.616779. This indicates that the Cilacap Regency has welfare characteristics that are more similar to those of the Banyumas Regency than those of the Purbalingga Regency. After calculating the Euclidean distances between objects, the next step is to form groups by calculating the SSE value. The results of cluster formation based on the SSE values are visualized with a dendrogram, as shown in Figure 1.

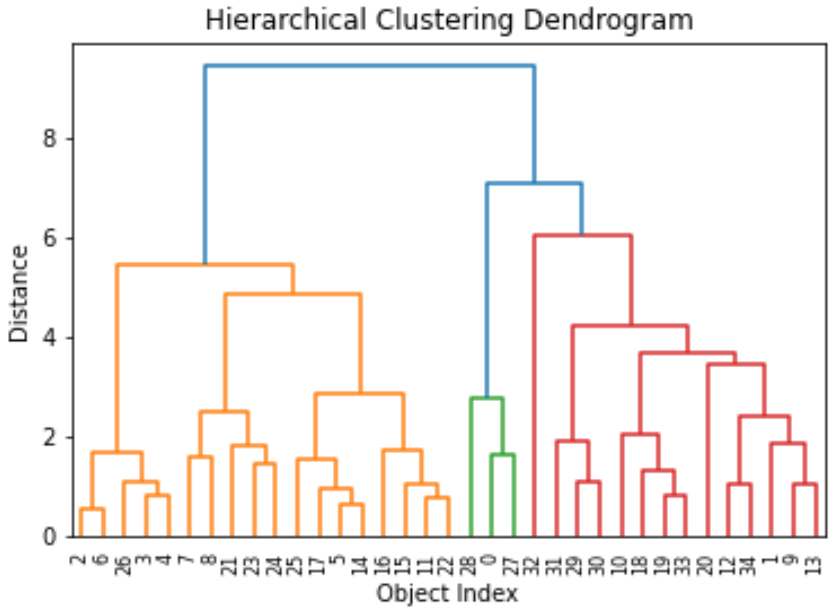

Figure 1. Dendroman Grouping Districts/Cities Based on the People's Welfare Index

Based on Figure 1, it can be seen that object 2, or Banyumas Regency, has characteristics similar to those of object 6, or Purworejo Regency. Additionally, object 2, or Banyumas Regency, has more similar characteristics to object 3, or Purbalingga Regency, compared to object 7, or Wonosobo Regency. This is because the distance between object 2 and object 3 is smaller than between object 2 and object 7. Based on the dendrogram diagram,

the grouping of each regency/city is arranged into 5 scenarios. Scenario 1 consists of 2 clusters, scenario 2 consists of 3 clusters, scenario 3 consists of 4 clusters, scenario 4 consists of 5 clusters, and scenario 5 consists of 6 clusters. The results of the group formation for each scenario are presented in Table 4.

Table 4. Formation Results of Groups for Each Scenario

No	Regency/City	2 Cluster	3 Cluster	4 Cluster	5 Cluster	6 Cluster
1	Cilacap Regency	1	3	3	3	3
2	Banyumas Regency	1	1	2	2	1
3	Purbalingga Regency	2	2	1	5	5
4	Banjarnegara Regency	2	2	1	5	5
5	Kebumen Regency	2	2	1	5	5
6	Purworejo Regency	2	2	1	1	2
7	Wonosobo Regency	2	2	1	5	5
8	Magelang Regency	2	2	1	1	6
9	Boyolali Regency	2	2	1	1	6
10	Klaten Regency	1	1	2	2	1
11	Sukoharjo Regency	1	1	2	2	1
12	Wonogiri Regency	2	2	1	1	2
13	Karanganyar Regency	1	1	2	2	1
14	Sragen Regency	1	1	2	2	1
15	Grobogan Regency	2	2	1	1	2
16	Blora Regency	2	2	1	1	2
17	Rembang Regency	2	2	1	1	2
18	Pati Regency	2	2	1	1	2
19	Kudus Regency	1	1	2	2	1
20	Jepara Regency	1	1	2	2	1
21	Demak Regency	1	1	2	2	1
22	Semarang Regency	2	2	1	1	6
23	Temanggung Regency	2	2	1	1	2
24	Kendal Regency	2	2	1	1	6
25	Batang Regency	2	2	1	1	6
26	Pekalongan Regency	2	2	1	1	2
27	Pemalang Regency	2	2	1	5	5
28	Tegal Regency	1	3	3	3	3
29	Brebes Regency	1	3	3	3	3
30	Magelang City	1	1	2	2	1
31	Surakarta City	1	1	2	2	1
32	Salatiga City	1	1	2	2	1
33	Semarang City	1	1	4	4	4
34	Pekalongan City	1	1	2	2	1
35	Tegal City	1	1	2	2	1

Next, to determine the best scenario for the number of clusters, the silhouette coefficient values presented in Table 5 are considered.

Table 5. Silhouette Coefficient Calculation Results

Number of Clusters	Silhouette Coefficient
2	0.224969
3	0.245022
4	0.237987
5	0.220860
6	0.249042

Based on Table 5, the silhouette coefficient value for using 6 clusters is 0.249042, which is higher than that for the other numbers of clusters. Therefore, 6 clusters are used. Based on the best grouping, the characteristics of the attributes in each group can be described as presented in Table 6.

Table 6. Average characteristics of people's welfare in Central Java by district/city in 2022

Cluster	Average value				
	Unemployment Rate	Economically Active Participation Rate	Poverty	Human Development Index	Regional Minimum Wage
1	5.109231	68.788462	9.040769	77.043077	2082888.409231
2	3.310000	73.302500	11.103750	71.410000	1921782.871250
3	9.580000	65.733333	11.656667	69.183333	2028065.743333
4	7.600000	70.960000	4.250000	84.080000	2835021.290000
5	5.834000	72.334000	15.628000	69.004000	1919121.538000
6	5.736000	75.768000	9.328000	72.626000	2175241.586000

Based on Table 6, the characteristics of each cluster can be interpreted by Cluster 1, consisting of Banyumas Regency, Klaten Regency, Sukoharjo Regency, Karanganyar Regency, Sragen Regency, Kudus Regency, Jepara Regency, Demak Regency, Magelang City, Surakarta City, Salatiga City, Pekalongan City, and Tegal City, has the following average characteristics: Unemployment Rate of 5.109231%, Economically Active Participation Rate of 68.788462%, Poverty rate of 9.040769%, Human Development Index of 77.043077%, and Regional Minimum Wage of IDR. 2,082,888.409231. Cluster 2, consisting of Purworejo Regency, Wonogiri Regency, Grobogan Regency, Blora Regency, Rembang Regency, Pati Regency, Temanggung Regency, and Pekalongan Regency, has the following average characteristics: Unemployment Rate of 3.31%, Economically Active Participation Rate of 73.302500%, the Poverty rate of 11.103750%, Human Development Index of 71.41%, and Regional Minimum Wage of IDR. 1,921,782.871250. Cluster 3, consisting of Cilacap Regency, Tegal Regency, and Brebes Regency, has the following average characteristics: Unemployment Rate of 9.58%, Economically Active Participation Rate of 65.733333%, Poverty rate of 11.656667%, Human Development Index of 69.183333%, and Regional Minimum Wage of IDR. 2,028,065.743333.

Cluster 4, consisting of Semarang City, has the following average characteristics: Unemployment Rate of 7.6%, Economically Active Participation Rate of 70.96%, Poverty rate of 4.25%, Human Development Index of 84.08%, and Regional Minimum Wage of Rp. 2,835,021.29. Cluster 5, consisting of Purbalingga Regency, Banjarnegara Regency, Kebumen Regency, Wonosobo Regency, and Pemalang Regency, has the following average characteristics: Unemployment Rate of 5.834%, Economically Active Participation Rate of 72.334%, Poverty rate of 15.628%, Human Development Index of 69.004%, and Regional Minimum Wage of IDR. 1,919,121.538. Cluster 6, consisting of Magelang Regency, Boyolali Regency, Semarang Regency, Kendal Regency, and Batang Regency, has the following average characteristics: Unemployment Rate of 5.736%,

Economically Active Participation Rate of 75.768%, Poverty rate of 9.328%, Human Development Index of 72.626%, and Regional Minimum Wage of IDR. 2,175,241.586.

4. CONCLUSION

Based on our research, grouping regencies and cities in Central Java Province into six clusters is optimal, achieving the highest silhouette coefficient of 0.249042. This segmentation provides a robust statistical basis and offers actionable insights for policy development. For instance, Cluster 1 includes regions such as Banyumas, Klaten, Sukoharjo, Karanganyar, Sragen, Kudus, Jepara, Demak, Magelang City, Surakarta, Salatiga, Pekalongan City, and Tegal City; Cluster 2 comprises Purworejo, Wonogiri, Grobogan, Blora, Rembang, Pati, Temanggung, and Pekalongan Regency; Cluster 3 consists of Cilacap, Tegal Regency, and Brebes; Cluster 4 includes only Semarang City; Cluster 5 covers Purbalingga, Banjarnegara, Kebumen, Wonosobo, and Pemalang; and Cluster 6 comprises Magelang, Boyolali, Semarang, Kendal, and Batang. These clearly defined clusters enable policymakers to tailor regional strategies—optimizing resource allocation and public services to the unique characteristics of each cluster.

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