BAREKENG: Journal of Mathematics and Its Applications
March 2023 Volume 17 Issue 1 Page 0295–0304
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol17iss1pp0295-0304

SUBDISTRICT CLUSTERING IN WEST JAVA PROVINCE BASED ON DISEASE INCIDENCE OF JKN PARTICIPANTS PRIMARY SERVICES

Husnun Nashir[1], **Anang Kurnia**[2*], **Anwar Fitrianto**[3]

[1,2,3]*Department of Statistics, Faculty of Mathematics and Natural Sciences, IPB University Bogor, 16680, Indonesia*

*Corresponding author's e-mail: * **anang.k@apps.ipb.ac.id***

Article History:

Received: 1st October 2022
Revised: 23rd December 2022
Accepted: 30th January 2023

Keywords:

Clustering;
Disease category;
Ensemble;
Hierarchical;
Sub-districts.

ABSTRACT

One of the efforts that can be made to optimize health services and the distribution of facilities and infrastructure efficiently in a wide scope is by profiling and clustering areas in the province of West Java to the scope of sub-districts with similar characteristics of disease category. The methods that will be compared to get the best clustering are hierarchical and ensemble. The data used as the research object is the BPJS Kesehatan capitation primary service sample data for 2017-2018. Some important variables used include primary disease diagnosis data (ICD-10) of patients at the Puskesmas (Public Health Center), service time, type of visit, and location of service sub-district. This study uses several evaluation metrics Silhouette coefficient, Dunn index, Davies-Bouldin index, and C-index, to determine the optimal number of clusters formed. In addition, descriptive analysis and visualization of the clustering results are also used as considerations in selecting the optimal cluster. Based on the evaluation results, the optimal method is hierarchical clustering with complete linkage. This method produces three clusters: Cluster 1 consists of 5 sub-districts that have a high/dominant mean value in almost all disease categories, Cluster 2 consists of 26 sub-districts that have a medium mean value, and Cluster 3 consists of 589 sub-districts that have a low mean value. Most members of Clusters 1 and 2 are sub-districts located in the districts/cities around the national capital (DKI Jakarta) and the provincial capital (Bandung), while the members of Cluster 3 are mostly sub-districts located in suburban districts/cities or far from the central government.

How to cite this article:

H. Nashir, A. Kurnia and A. Fitrianto., "SUBDISTRICT CLUSTERING IN WEST JAVA PROVINCE BASED ON DISEASE INCIDENCE OF JKN PARTICIPANTS PRIMARY SERVICES," *BAREKENG: J. Math. & App.*, vol. 17, iss. 1, pp. 0295-0304, March 2023.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article • Open Access

1. INTRODUCTION

BPJS Kesehatan is an agency in charge of administering health insurance for all Indonesian, known as JKN (Jaminan Kesehatan Nasional). This promotive and preventive program is one of the programs by BPJS Kesehatan for primary health facilities (puskesmas, clinics). One of the benefits of preventive and promotive services is direct or indirect individual health counseling. It is hoped that primary health facilities will not only be a place for treatment, but also a place for the community to get preventive health education for disease prevention. So far, health services for JKN participants are mostly in the form of curative services or health services after an illness. The costs for curative services, especially if they are carried out in hospitals, are certainly higher, so this needs to be controlled to support the sustainability of the JKN program. One of the efforts is to encourage healthy lifestyles in the community and improve the quality of services in primary health facilities.

The 2014-2018 JKN statistical report issued by the National Social Security Council (DJSN) presents an interesting condition in 2018 West Java Province became the region with the largest number of puskesmas in Indonesia, but the ratio of puskesmas per 100,000 participants was one of the smallest in Indonesia [1]. The value of this ratio describes the availability of health facilities for JKN participants, the smaller the value, the more limited the choices. This value can also be a sign that a health facility has exceeded its capacity or is not ideal. This condition resulted in less than optimal health services to participants, both curative and promotive and preventive.

Research conducted in Depok concluded that most of the puskesmas in the city of Depok with a high referral ratio did not have the complete facilities and infrastructure that must be in the puskesmas, including laboratories and emergency services [2]. One of the reasons for the referral was because some medicines were not available at the puskesmas. The referral ratio is a measure of the tendency of primary health facilities to make referrals to other health facilities. Primary health facilities, as gatekeepers, play a role in quality and cost control, screening referrals, and the patient's first point of contact so that they can serve JKN participants optimally. Low competence as a gatekeeper can affect the value of the referral ratio to be high [3].

One of the strategic steps for the initial stage is profiling by grouping areas in West Java Province to the scope of sub-districts that have similar characteristics of disease incidence. Research on clustering in health data includes clustering in provinces in Indonesia based on Health Service Indicators in 2015 [4]. The research resulted in 5 clusters with different indicator value scales in each cluster. Research on cluster analysis was carried out by grouping provinces in Indonesia based on indicators of health services for pregnant women using the K-means cluster and ensemble cluster method [5]. The results of the study concluded that the cluster ensemble method is the most suitable method compared to the other methods. Meanwhile, research conducted on data on the ratio of health workers in disadvantaged, outermost, and leading areas (3T) in Indonesia found that the hierarchical clustering method with a single linkage produced better performance than the ensemble cluster method [6].

Based on that description, the researcher wants to examine the characteristics of areas that have a similar disease incidence in West Java from the scope to the sub-district. The methods that will be compared to get the best clustering are hierarchical clustering and ensemble clustering. The data used as the object of research is the sample data for the BPJS Kesehatan capitation primary service for the 2017-2018 period. The results of this study are expected to be reference material for relevant stakeholders in planning various policies at the puskesmas, such as promotive and preventive programs and the procurement of infrastructure for optimal health services to the JKN participants.

2. RESEARCH METHODS

2.1 Data Preparation

The data was obtained from the BPJS Kesehatan data portal, which provides sample data for primary services for JKN participants. BPJS Kesehatan sample data is a representation of all BPJS Kesehatan membership data and health services that have been standardized and extracted to maintain data quality [7]. There are five subsets of data provided in the BPJS Kesehatan sample data. The subset of data used in this study is the sample data for primary capitation services. Important variables used include primary disease diagnosis data (ICD-10) of patients at the primary health services, service time, type of visit, and sub-district location. Furthermore, based on these variables, a dataset of the incidence of disease in each sub-district will be formed.

2.2 Hierarchical Clustering

The hierarchical clustering method is the method used if the number of clusters is not known. There are two basic types used in the hierarchical method, namely, merging and division. The merging method procedure is to assume that all observations are clusters so that the two closest objects that have similarities become one cluster and then proceed to other objects. The division method procedure is the opposite of the merging method, which assumes all observations are one cluster, then different observations will come out and form a new cluster. Several measures of similarity between clusters can be seen using single linkage, complete linkage, average linkage, and Ward's method. The following is an explanation of some of the linkages in the hierarchical clustering method [8] :

a. Single linkage
This cluster analysis method uses the clustering principle based on the shortest distance between its members. The initial step of this method is to find the two closest objects and both form the first cluster, then proceed to the next object until each member has a cluster. The distance between the clusters (i, j) and k is
$$d_{(i,j)k} = \min(d_{ik}, d_{jk}) \tag{1}$$
b. Complete linkage
This cluster analysis method is the opposite of the single linkage method; this method uses the clustering principle based on the furthest distance between its members. The distance between the clusters (i, j) and k is
$$d_{(i,j)k} = \max(d_{ik}, d_{jk}) \tag{2}$$
c. Average linkage
This cluster analysis method is based on the average distance between all members of one group and all members of other clusters. The distance can be calculated by the following formula.
$$d_{(i,j)k} = \frac{n_i}{n_i+n_j} d_{(i,k)} + \frac{n_j}{n_i+n_j} d_{(j,k)} \tag{3}$$

2.3 Ensemble Clustering

Ensemble clustering is a method that combines a set of different cluster solutions from each different method into one final cluster solution. The ensemble grouping is divided into 2 (two) stages. The first stage is to cluster with several algorithms and save the results of the clustering. The second stage determines the final cluster of clusters from the results of the first stage using the consensus function [9]. Cluster ensemble combines a set of solutions regardless of the original characteristics of the data or the initial algorithm used to build the set of solutions. The advantage of this method is that it can improve the quality and robustness of the cluster solutions [10].

3. RESULTS AND DISCUSSION

3.1 Data Exploration

Before exploration, it is necessary to pre-process the sample data to form a dataset on the number of disease category events per sub-district. After the dataset is formed, missing values are still found, so it is necessary to carry out an imputation process to obtain complete data. The K-Nearest Neighbor (KNN) method has the advantage of being strong against noisy data and effective for large data training [11]. Therefore, imputation with the KNN method is used in this research.

The data imputation process resulted in a complete dataset with 16 disease category variables and 620 sub-districts. Data exploration was carried out to find out the description of the data, namely the mean value and standard deviation presented in Table 1. The results show that the average value varied with the highest mean value in the respiratory system disease category and the lowest in the neoplasms disease category.

Table 1. Descriptive Statistics

Variables	Name	Mean	Std. deviation
X1	Certain infectious and parasitic diseases	50.83	68.75
X2	Neoplasms	5.44	5.90
X3	Endocrine, nutritional and metabolic diseases	18.24	27.26
X4	Diseases of the nervous system	9.22	11.56
X5	Diseases of the eye and adnexa	20.36	27.17
X6	Diseases of the ear and mastoid process	9.39	13.45
X7	Diseases of the circulatory system	54.70	68.32
X8	Diseases of the respiratory system	188.25	268.31
X9	Diseases of the digestive system	112.22	137.10
X10	Diseases of the skin and subcutaneous tissue	34.56	43.69
X11	Diseases of the musculoskeletal system and connective tissue	59.03	65.33
X12	Diseases of the genitourinary system	11.52	15.26
X13	Pregnancy, childbirth and the puerperium	12.85	15.23
X14	Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	59.78	89.69
X15	Injury, poisoning and certain other consequences of external causes	7.50	10.65
X16	Factors influencing health status and contact with health services	35.82	54.96

3.2 Clustering Evaluation

Hierarchical clustering was carried out using the RStudio software with the 'NbClust' package. Some of the parameters that need to be set are the linkage type, the range of the number of clusters formed, the distance matrix, and the cluster goodness metric. The range of the number of clusters to be formed is determined from 2 to 5 clusters. The distance matrix used is Euclidean distance. Meanwhile, the metrics chosen to measure the goodness of a group are Silhouette, Dunn Index, Davies-Bouldin Index, and C-index. The Silhouette method is a fairly popular index used to determine the optimal number of clusters [12].

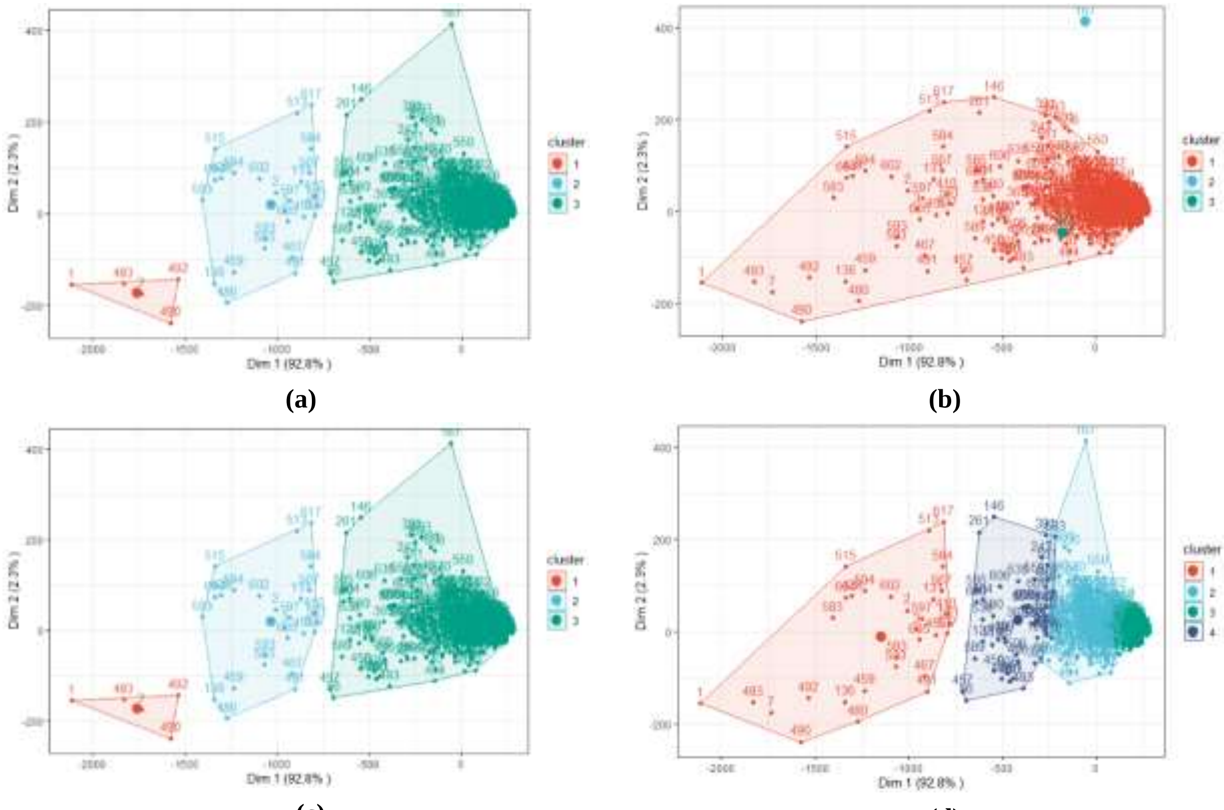
Table 2. Metrics of Hierarchical Clustering Result

Cluster	Complete				Single			
	S	D	DB	CI	S	D	DB	CI
2	0.778	0.135	0.499	0.165	0.579	0.222	0.517	0.136
3	0.749	0.192	0.621	0.235	0.523	0.185	0.572	0.136
4	0.586	0.064	0.763	0.154	0.521	0.206	0.454	0.151
5	0.590	0.072	0.671	0.175	0.523	0.164	0.389	0.156
Cluster	**Average**				**Ward**			
	S	D	DB	CI	S	D	DB	CI
2	0.778	0.135	0.499	0.165	0.709	0.039	0.758	0.088
3	0.749	0.192	0.621	0.235	0.446	0.018	0.909	0.060
4	0.658	0.192	0.542	0.236	0.464	0.026	0.874	0.074
5	0.615	0.192	0.504	0.235	0.422	0.026	1.222	0.059

Notes: S = Silhouette index, D = Dunn index, DB = Davies-Bouldin index, CI = C-index

Table 2 shows the results of the index value of the cluster goodness metric for each type of hierarchical clustering linkage. The Silhouette and Dunn index are optimal at the largest value, while the Davies-Bouldin index and C-index are optimal at the smallest values. In addition to looking at these values, it is also necessary to pay attention to the trend of rising and falling index values as the number of clusters increases. It can also be considered to select the optimal number of clusters. With the help of a simple line plot, it can be determined that the optimal number of clusters is complete linkage: 3 clusters, single linkage: 3 clusters, average linkage: 3 clusters, and ward linkage: 4 clusters.

The goodness of clustering results can also be seen with two-dimensional visualization. In order to display the visualization, the many variables must be reduced to only two important variables. Variable reduction can be done by principal component analysis (PCA) [13]. Dimensional reduction can also remove irrelevant features and reduce noise from the data [14]. Figure 1 shows a visualization of the clustering results at each linkage. From these results, it can be seen that the complete linkage and average linkage of the clustering results are quite good because each cluster is almost completely separated. Meanwhile, the Ward method still has clusters that appear to be intersecting and the single linkage forms clusters with only one member.

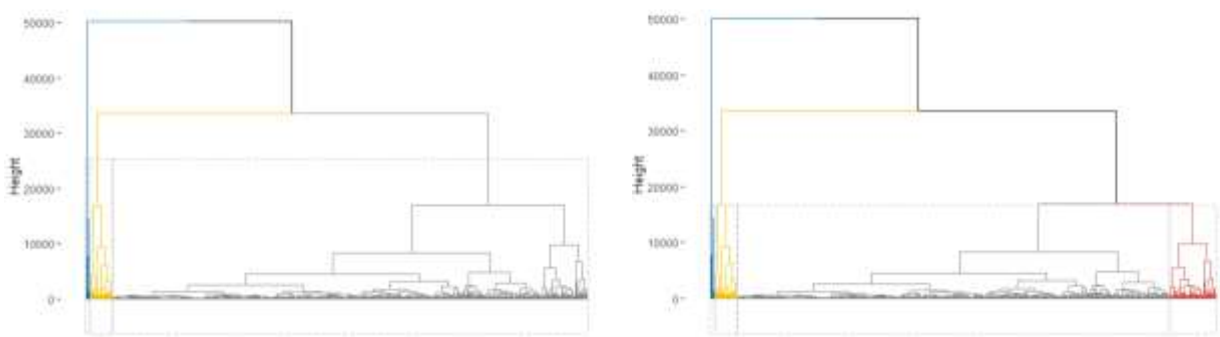


(a) (b)

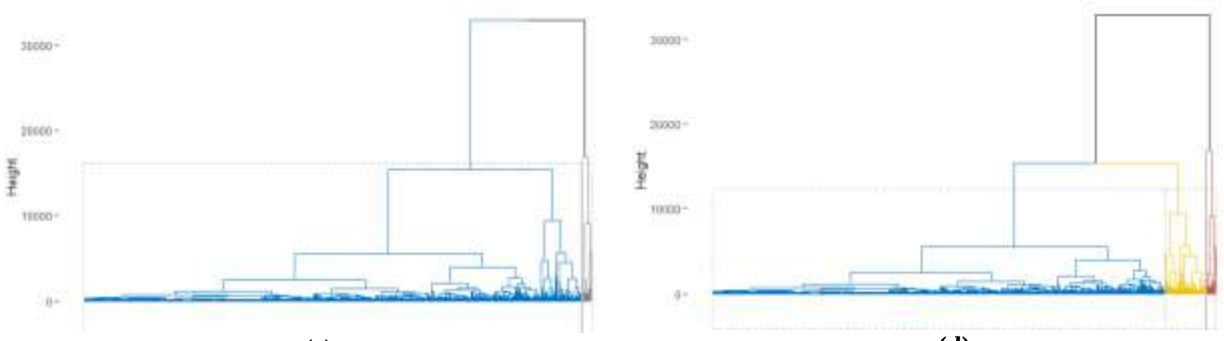
(c) (d)

Figure 1. Visualization of hierarchical clustering result,
(a) Complete linkage, (b) Single linkage, (c) Average linkage, (d) Ward's method

Cluster analysis can also be done by looking at the dendrogram plot. The number of clusters and their cluster members is obtained from dendrogram cutting at the largest difference in the merging distance [15]. Figure 2 shows a comparison of the single linkage and average linkage dendrogram plots with the number of clusters 3 and 4, it can be concluded that clustering with k=4 is still possible. However, if mapped in a two-dimensional visualization, the results of clustering with k=4 are not better than k=3.



(a) (b)



(c) (d)

Figure 2. Dendrogram plot of average and complete linkage,
(a) Complete linkage k=3, (b) Complete linkage k=4, (c) Average linkage, k=3, (d) Average linkage, k=4

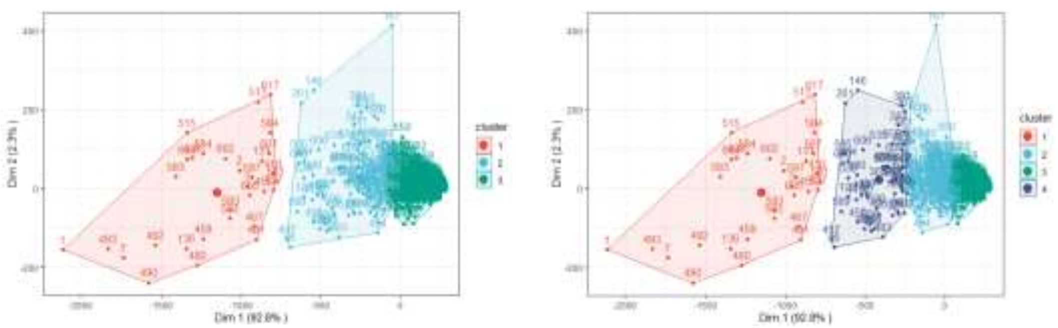
Ensemble clusters form a group of results obtained from various different methods as members of the ensemble. The clustering using the ensemble method was carried out using the RStudio software with the 'diceR' package. Some important parameters that need to be set are the clustering algorithm and the consensus function to be used. The clustering algorithm used is K-Means and hierarchical clustering with complete and average linkage. Meanwhile, the consensus functions chosen are CSPA (Cluster-based Similarity Partitioning Algorithm) and LCE (Link-based Cluster Ensemble).

Table 3. Metrics of Ensemble Clustering Result

Cluster	Ensemble (CSPA)				Ensemble (LCE)			
	S	D	DB	CI	S	D	DB	CI
3	0.469	0.036	0.687	0.032	0.470	0.037	0.685	0.029
4	0.380	0.023	0.808	0.030	0.379	0.023	0.808	0.030

Notes: S = Silhouette index, D = Dunn index, DB = Davies-Bouldin index, CI = C-index

Table 3 shows the results of cluster goodness metric index values of ensemble clustering. By looking at these values, it appears that the ensemble cluster is not better than hierarchical clustering. To see more clearly, the results of the clustering are mapped in a two-dimensional visualization.



(a) (b)

Figure 3. Visualization of ensemble clustering result,
(a) Ensemble cluster k=3, (b) Ensemble cluster k=4

Figure 3 shows the results of clustering using the ensemble method. The figure shows that there are still clusters that intersect with each other at k=3 and k=4. Therefore, the hierarchical clustering method with complete linkage and the number of clusters 3 was chosen as the optimal method.

3.3 Interpretation of Clustering Results

The optimal clustering method chosen is hierarchical clustering with complete linkage. The average linkage is a linkage in the hierarchical clustering method that collects variables based on similarity or the furthest distance (as opposed to single linkage), so that each variable that have the least similarity will be included in the first cluster and so on [16]. This method produces more robust and dense clusters than single linkage [17].

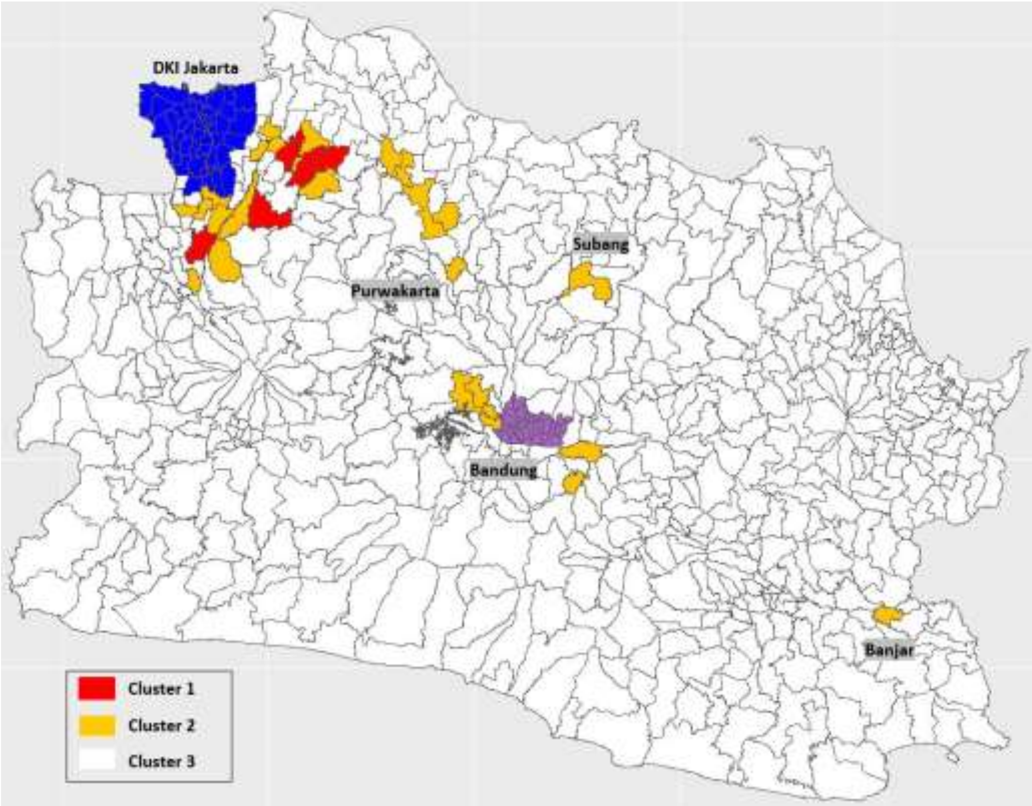


Figure 4. Sub-district clustering result mapping

The results of the clustering using the hierarchical and complete linkage method formed three clusters with sub-districts in groups, as shown in Figure 4. Based on the mapping, it can be concluded that cluster 1 consists of 5 sub-districts and cluster 2 consists of 26 sub-districts. Meanwhile, cluster 3 is the largest cluster with 589 sub-district members. Most of the members of clusters 1 and 2 are sub-districts located around of national capital (DKI Jakarta) and the provincial capital (Bandung), only Subang, Purwakarta, and Banjar, which are relatively far from both. While the members of cluster 3 are mostly sub-districts located in suburban districts/cities or far from the center of government.

The clustering of districts/cities in West Java based on community indicators concluded that Kabupaten Bekasi, Bekasi City, Sukabumi City, Cirebon City, Bogor City, Depok City, Bandung City, and Cimahi City are included in cluster 1 [18]. This cluster has characteristics of high scores on the variables of population density, population growth rate, labor force, life expectancy, real expenditure per capita, and the average length of schooling. The grouping carried out in the sub-districts in Surabaya based on the factors causing the occurrence of tuberculosis resulted in 4 clusters [19]. The clusters with the most vulnerable characteristics and very high population density are Tambak Sari and Sawahan sub-districts. These two sub-districts are directly adjacent to the Central Surabaya area. Both of these reference studies can show that areas around the center of government with high population density can affect the quality of health.

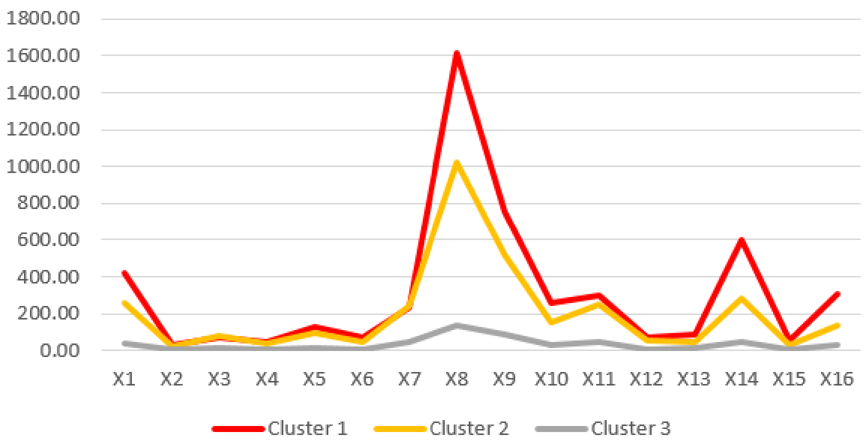


Figure 5. **Mean value of variables plot**

The characteristics of a cluster that is formed can also be seen from the mean value of the variables from each cluster member [20]. Figure 5 shows a plot of the mean value of the variables from each cluster. The clustering results can be said to be quite good because the mean value pattern is uniform and each cluster is divided into different levels of the mean value. From the plots presented, it can be concluded that cluster 1 has a high/dominant mean value for each variable except X3 (endocrine, nutritional, and metabolic disorders) and X7 (diseases in the circulatory system). Cluster 2 has a medium mean value of each variable except X3 and X7, which are higher. While cluster 3 has a low mean value on all variables.

The dominant disease category in cluster 1 is X8 (Diseases of the respiratory system). Respiratory disorders can occur in a work environment that contains industrial dust, especially at high levels [21]. Included in cluster 1 are Cileungsi, Cikarang, and parts of Tambun sub-districts are industrial areas, which are quite dense. It is also confirmed that the pattern of most diseases in the Bekasi district health center is mostly diseased due to respiratory disorders and a small proportion are intestinal infections, hypertension, and myalgia [22].

4. CONCLUSIONS

The appropriate clustering method for clustering sub-districts in West Java province based on the frequency of disease incidence is a hierarchical method with complete linkage. This is because this method can produce clusters with strong structure and independence as well as a better evaluation metric measure than other clustering methods (single linkage, Ward's method, ensemble cluster). The cluster results form three clusters with details: Cluster 1 consists of 5 sub-districts that have a high/dominant mean value in each disease category except X3 (endocrine, nutritional, and metabolic disorders) and X7 (diseases in the circulation system); Cluster 2 consists of 26 sub-districts that have medium mean value in each disease category except X3 and X7 are high; and Cluster 3 consists of 589 sub-districts that have low mean value in all disease categories. Most of the members of Clusters 1 and 2 are sub-districts located in the districts/cities around the national capital (DKI Jakarta) and the provincial capital (Bandung), while the members of Cluster 3 are mostly sub-districts located in suburban districts/cities or far from the center of government.

REFERENCES

[1] Dewan Jaminan Sosial Nasional, "Statistik JKN 2014-2018," 2020.
[2] I. Nurlinawati, R. Rosita, and S. Werni, "Gambaran Faktor Penyebab Rujukan di Puskesmas Kota Depok," *Bul. Penelit. Sist. Kesehat.*, vol. 22, no. 3, pp. 176–183, 2019, doi: 10.22435/hsr.v22i3.512.
[3] W. Budiarto and O. Oktarina, "Analysis of First Level Health Care Facility (FKTP) Readiness as 'Gatekeeper' on The JKN Implementation in East Kalimantan and Central Java Year 2014," *Bul. Penelit. Sist. Kesehat.*, vol. 19, no. 1, pp. 11–19, 2016, doi: 10.22435/hsr.v19i1.4985.11-19.
[4] A. S. Hamur, B. Susetyo, and Indahwati, "Comparing K-Means and Fuzzy C-Means Clustering (Case : Clustering of Provinces in Indonesia Based on the Indicator of the Health Service in 2015)," *Int. J. Eng. Manag. Res.*, vol. 7, no. 3, pp. 387–390, 2017.
[5] C. Suhaeni, A. Kurnia, and R. Ristiyanti, "Perbandingan Hasil Pengelompokan menggunakan Analisis Cluster Berhirarki, K-Means Cluster, dan Cluster Ensemble (Studi Kasus Data Indikator Pelayanan Kesehatan Ibu Hamil)," *J. Media Infotama*, vol.

14, no. 1, pp. 31–38, 2018, doi: 10.37676/jmi.v14i1.469.

[6] K. Millati, C. Suhaeni, and B. Susetyo, "Penggerombolan Daerah 3T di Indonesia Berdasarkan Rasio Tenaga Kesehatan dengan Metode Penggerombolan Berhierarki dan Cluster Ensemble," *Xplore J. Stat.*, vol. 10, no. 2, pp. 197–213, 2021, doi: 10.29244/xplore.v10i2.744.

[7] BPJS Kesehatan, "Data Sampel BPJS Kesehatan Tahun 2015-2018," 2020.

[8] R. A. Johnson and D. W. Wichern, *Applied Multivariate Statistical Analysis*, 5th ed. New Jersey: Prentice Hall, 2002.

[9] R. Ghaemi, N. Sulaiman, H. Ibrahim, and N. Mustapha, "A survey: Clustering ensembles techniques," *World Acad. Sci. Eng. Technol.*, vol. 38, pp. 644–653, Feb. 2009.

[10] A. Strehl and J. Ghosh, "Cluster Ensembles - A Knowledge Reuse Framework for Combining Multiple Partitions," *J. Mach. Learn. Res.*, vol. 3, pp. 583–617, Jan. 2002, doi: 10.1162/153244303321897735.

[11] K. Saxena, Z. Khan, and S. Singh, "Diagnosis of Diabetes Mellitus using K Nearest Neighbor Algorithm," *Int. J. Comput. Sci. Trends Technol.*, vol. 2, no. 4, pp. 36–43, 2014.

[12] C. L. Clayman, S. M. Srinivasan, and R. S. Sangwan, "K-means clustering and principal components analysis of microarray data of L1000 landmark genes," *Procedia Comput. Sci.*, vol. 168, pp. 97–104, Jan. 2020, doi: 10.1016/j.procs.2020.02.265.

[13] G. Rahayu and Mustakim, "Principal Component Analysis Untuk Dimensi Reduksi Data Clustering Sebagai Pemetaan Persentase Sertifikasi Guru Di Indonesia," in *Seminar Nasional Teknologi Informasi Komunikasi dan Industri*, 2017, pp. 201–208. [Online]. Available: http://ejournal.uin-suska.ac.id/index.php/SNTIKI/article/view/3265

[14] A. Izzuddin, "Optimasi Cluster pada Algoritma K-Means dengan Reduksi Dimensi Dataset Menggunakan Principal Component Analysis untuk Pemetaan Kinerja Dosen," *J. ENERGY*, vol. 5, no. 2, pp. 41–46, 2015.

[15] E. Fitriani Rafikasari, "Pengelompokan Kabupaten/Kota di Jawa Timur Berdasarkan Indikator Pendidikan Tahun 2013 Menggunakan Analisis Hierarchial Cluster," *J. Din. Penelit.*, vol. 16, no. 2, pp. 247–262, 2016, doi: 10.21274/dinamika.2016.16.2.247-262.

[16] D. Rachmatin, "Aplikasi Metode-Metode Agglomerative dalam Analisis Klaster pada Data Tingkat Polusi Udara," *Infin. J.*, vol. 3, no. 2, p. 133, 2014, doi: 10.22460/infinity.v3i2.59.

[17] P. Govender and V. Sivakumar, "Application of k-means and hierarchical clustering techniques for analysis of air pollution: A review (1980–2019)," *Atmos. Pollut. Res.*, vol. 11, no. 1, pp. 40–56, 2020, doi: 10.1016/j.apr.2019.09.009.

[18] Soemartini and E. Supartini, "Analisis K-Means Cluster Untuk Pengelompokan Kabupaten / Kota Di Jawabarat Berdasarkan Indikator Masyarakat," in *Konferensi Nasional Penelitian Matematika dan Pembelajarannya II (KNPMP II)*, 2017, no. Knpmp Ii, pp. 144–154.

[19] N. Suherni and Maduratna, "Analisis Pengelompokan Kecamatan di Kota Surabaya Berdasarkan Faktor Penyebab Terjadinya Penyakit Tuberkulosis," *J. Sains dan Seni ITS*, vol. 2, no. 1, pp. 2337–3520, 2013, [Online]. Available: http://ejurnal2.its.ac.id/index.php/sains_seni/article/view/3083

[20] N. Thamrin and A. W. Wijayanto, "Comparison of Soft and Hard Clustering: A Case Study on Welfare Level in Cities on Java Island," *Indones. J. Stat. Its Appl.*, vol. 5, no. 1, pp. 141–160, 2021, doi: 10.29244/ijsa.v5i1p141-160.

[21] A. Darmawan, "Penyakit Sistem Respirasi Akibat Kerja," *Jambi Med. J.*, vol. 1, no. 1, pp. 68–83, 2013, doi: 10.22437/jmj.v1i1.2691.

[22] Dinas Kesehatan Kabupaten Bekasi, "Profil Kesehatan Kabupaten Bekasi 2020," 2021.