JURNAL MATEMATIKA, STATISTIKA DAN KOMPUTASI e–ISSN: 2614–8811
Published by Departement of Mathematics, Hasanuddin University, Indonesia
https://journal.unhas.ac.id/index.php/jmsk/index
Vol. 21, No. 3, May 2025, pp. 754-762
DOI: 10.20956/j.v21i3.43339

The Fuzzy-Possibilistic Product Partition c-Means (FPPPCM) algorithm for Clustering the Welfare Levels of Regencies in East Java

Amanatullah Pandu Zenklinov[1*], Alicia Arifin[1]

[1] *Department of Statistics, Matana University*
***Email**: amanatullah.zenklinov@matanauniversity.ac.id[1],*
alicia.arifin@student.matanauniversity.ac.id[1]
**Corresponding author*
Received: 25 February 2025, revised: 9 April 2025, accepted: 15 April 2025

Abstract
Welfare is a condition where society is free from deviant behavior, poverty, ignorance, and fear, thus allowing individuals to obtain a safe and peaceful life. East Java is among the provinces in Indonesia that recorded the highest incidence of poverty from 2013 to 2022; however, it has also demonstrated a consistent decline in the number of individuals living in poverty during this period. This study aims at applying the Fuzzy-Possibilistic Product Partition c-Means (FPPPCM), which combines the probabilistic approach of Fuzzy c-Means and the possibilistic approach of Possibilistic c-Means, and is effective in handling outliers, to clustering the welfare levels of regencies and cities in East Java. The exploration is based on the data of the Badan Pusat Statistik (BPS) for 2024. Based on clustering the welfare levels, the following are the end results of the study: Cluster 1 (low population, high education/life expectancy but low labor participation and high poverty line, i.e. Kediri City) may find aid in programs that work on the issues like job creation, affordable housing, and family planning outreach to reduce inequality. Cluster 2 (medium population, low education/expenditure but high labor participation/home ownership, i.e. Pacitan) could promote vocational training, poverty reduction through SME support, and give education to the workforce. Cluster 3 (high population, low life expectancy, medium indicators but high family planning, i.e. Lamongan) should focus on improvement of the healthcare infrastructure, the health of the mother and child, and creation of industrial jobs for the local people.
Keywords: Clustering, FPPPCM, Welfare.

1. INTRODUCTION

Welfare is a condition where society is free from deviant behavior, poverty, ignorance, and fear, thus allowing individuals to obtain a safe and peaceful life [28]. In addition to having an impact on people's quality of life, this condition also shows how far a community has come socially and economically [29]. Thus, welfare becomes an important indicator in assessing the success of development in a region [23]. However, to achieve this condition, monitoring and analysis of various welfare indicators in a region are required [20].

East Java is among the provinces in Indonesia that recorded the highest incidence of poverty from 2013 to 2022; however, it has also demonstrated a consistent decline in the number of individuals living in poverty during this period [13]. This shows that local government efforts to reduce poverty rates have yielded positive results [31]. Nevertheless, welfare in East Java still shows disparities that need further examination [15]. To view the welfare mapping of regencies/cities in East Java, clustering is used [32].

The process of clustering involves putting data into groups based on shared characteristics, whereas data that don't share any commonalities will be put in separate groups [7]. Clustering is part of machine learning in statistics and is also called unsupervised learning, where it does not require label or target/response variables (y) and only uses explanatory variables (x) [12]. Clustering algorithms are those that organize data into categories based on their similarities or dissimilarities, such as distance between data points in a dataset [1]. Proximity or similarity between datums is calculated using certain distance measures. Several types of distance measures can be used, with the simplest and most widely used being the Euclidean distance [16].

Clustering aims to minimize differences within a cluster [5]. The application of clustering techniques is useful in several pattern-analysis explorations, groupings, and decision-making processes, including image segmentation, image improvement, word recognition, and medical diagnosis [16], [34]. Hierarchical and partitional clustering are the two main categories of grouping or clustering [7], [9], [11]. Each category of clustering has different principles, affecting the grouping process and producing diverse outputs [1].

Hierarchical clustering arranges clusters in a hierarchical structure or dendrogram. This method is divided into two main techniques, namely agglomerative, which merges the two closest groups at each iteration, and divisive, which splits the entire dataset into smaller clusters [8]. Its ability to eliminate the need for early input, such as the number of clusters that must be decided, is one of its benefits [4]. However, this method has disadvantages, such as difficulty in clearly determining the final cluster results [19] and higher complexity, making it less ideal for use on large datasets. On the other hand, partition algorithms are more favorable when it comes to large datasets [6].

By identifying the centroids of each cluster, partitional clustering organizes clusters with the goal of reducing the distance between the data and each cluster's centroid [1], [7], [12]. A distinctive feature of partitioning is its capability to handle very large data sets, that this property gives it an edge over hierarchical clustering techniques, for it takes long to compute visitations necessary to create a dendrogram in hierarchical clustering [23]. The basic idea behind the method is to minimize the distance between the data points and the centroid of the cluster in either fuzzy c-means (FCM) or k-means algorithm [26].

When dealing with overlap, the FCM method has shown itself to be more stable than hierarchical clusters and self-organizing maps (SOM) [20]. The FCM method also produces clusters of higher quality than the k-means technique [27]. This algorithm also has good capabilities in detecting clusters and accurately placing cluster centers [25]. However, FCM is not without drawbacks; the most significant being its sensitivity to outliers [33]. Data points that deviate significantly from the bulk of other data points are known as outliers [2].

The issue of FCM ' sensitivity to noise and outliers can be resolved by the possibilistic c-means algorithm (PCM) [17]. The main aim of any possibilistic approach is to assign membership values relating to the typicality typical to the given data point for a specific cluster or in some cases evaluate whether the point really belongs to that cluster. The most significant distinction between PCM and FCM is the use of parameter estimation Ω related to an M-estimator [14]. The PCM approach, on the other hand, may prove disadvantageous in that it leads to coincidental clusters where the data distinctions are not so readily evident [22].

Szilágyi introduced the fuzzy-possibilistic product partition c-means (FPPPCM) algorithm, which applies blind speaker clustering. This method involves analyzing audio data (e.g., speech signals) to group speakers into clusters without prior knowledge of speaker identities or labels. These approaches identify patterns in speaker characteristics (e.g., pitch, spectral features, or prosody) by assigning data points to clusters based on similarity, where membership degrees are determined as the product of probabilistic and possibilistic frameworks [30]. This innovative method can preserve or even increase accuracy in data without outliers by removing the impact of distant outliers [10]. Therefore, this study uses the FPPPCM for clustering the welfare of regencies/cities in East Java in 2023.

2. FPPPCM

An approach called FPPPCM was created to remove outliers' impact on fuzzy and possibilistic clustering techniques. This program uses a multiplicative strategy to integrate probabilistic and possibilistic approaches [30].

The objective function of the FPPPCM algorithm, as suggested by Szilágyi, is expressed as follows. Fuzzy and possibilistic elements are included in the algorithm's objective function to enhance clustering outcomes. One way to formulate the objective function is:

$$J_{FPPPCM}(\mathbf{X};\mathbf{V},\mathbf{U},\mathbf{T})=\sum_{j=1}^{k}\sum_{i=1}^{n}u_{ij}^{m}\left[t_{ij}^{n}d^{2}(\overrightarrow{x_{\iota}},\overrightarrow{v_{j}}+\Omega_{j}(1-t_{ij})^{\eta}\right]. \tag{2.1}$$

with:

- u_{ij} is the degree of data membership against x_i to cluster $c_j$in the fuzzy partition U.
- t_{ij} is the possibilistic typicality value of data x_i to cluster c_j in the possibilistic partition U.
- m is the exponential weight of the fuzzy partition, usually $m=2$
- η is the exponential weight of the possibilistic partition, usually $\eta\ =2$
- $\|x_i-v_j\|$ is the Euclidean distance between data x_i and centroid v_j.
- v_j is the centroid of c_j.
- k is the number of clusters.
- n is the number of data in the dataset.

The parameter m is a key indicator of the degree of fuzziness of the partition, where a higher parameter m (for instance m>2) will lead to more overlap of the clusters which suit the case of datasets with overlapping clusters inherent in the data, whereas a low value (e.g., $m\approx$1.5) gives clear clusters for well-separated data [17], [25]. Conversely, the possibilistic parameter η that affects the cluster compactness positively will make the cluster more compact, i.e., smaller values of η (e.g., η <2) lead to the elimination of the deviation element, by means of the emphasis on zero membership probabilities so that the robustness becomes more evident in noisy datasets [10], [33].

The degree of membership of the probabilistic fuzzy part of the objective function J_{FPPPCM} is updated with the equation:

$$u_{ij}=\frac{\left[t_{ij}^{n}d^{2}\left(\overrightarrow{x_{\iota}},\overrightarrow{v_{j}}\right)+\Omega_{j}(1-t_{ij})^{\eta}\right]^{-1/(m-1)}}{\left[\sum_{l=1}^{k}t_{il}^{n}\,d^{2}\left(\overrightarrow{x_{\iota}},\overrightarrow{v_{j}}\right)+\Omega_{j}(1-t_{ij})^{\eta}\right]^{-1/(m-1)}};1\leq i\leq n,1\leq j\leq k \tag{2.2}$$

The typicality degree in the possibilistic part of the objective function J_{FPPPCM} is calculated as follows:

$$t_{ij} = \left[1 + \left(\frac{d^2(\overrightarrow{x_i}, \overrightarrow{v_j})}{\Omega_j}\right)^{1/(\eta-1)}\right]^{-1} ; 1 \leq i \leq n, 1 \leq j \leq k \tag{2.3}$$

$\overrightarrow{\Omega}$ is called the possibilistic penalty term, which functions to control the variance of the clusters [10].

$$\overrightarrow{\Omega} = K \frac{\sum_{i=1}^{n} u_{ij}^{m} \, d^2(\overrightarrow{x_i}, \overrightarrow{v_j})}{\sum_{i=1}^{n} u_{ij}^{m}} ; 1 \leq j \leq k \tag{2.4}$$

where K is a coefficient, $K \in (0, \infty)$, usually chosen the number 1.

The update equation for cluster prototypes is as follows:

$$\vec{v}_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} \, t_{ij}^{\eta} \, \vec{x}_i}{\sum_{i=1}^{n} u_{ij}^{m} \, t_{ij}^{\eta}} ; 1 \leq j \leq k \tag{2.5}$$

3. RESEARCH METHODS

3.1 Data and Variables

Badan Pusat Statistik (BPS) provided the secondary data used in this study. The information was extracted from the "Jawa Timur dalam Angka 2024" BPS publications [3]. This research utilizes data from 38 regencies using 8 variables as the basis for grouping regencies/cities according to welfare indicators. The 8 variables were selected based on the publication by BPS on the indicators of people's welfare in East Java. **Table 3.1** lists these Variables.

Table 3.1. Research Variables

Variable	Indicator	Scale
X_1	Population Size (thousand people)	Ratio
X_2	Life Expectancy (Years)	Ratio
X_3	Expected Years of Schooling (Years)	Ratio
X_4	Labor Force Participation Rate (%)	Ratio
X_5	Adjusted Real Per Capita Expenditure (thousand rupiah)	Ratio
X_6	Household Ownership Distribution (own)	Ratio
X_7	Poverty Line (rupiah/capita/month)	Ratio
X_8	Number of Active Family Planning Participants	Ratio

The type of data to be processed is called a data structure. Cluster analysis is the data structure that is employed. **Table 3.2** displays the entire data structure.

Table 3.2. Data Structure

i	X_1	X_2	$\cdots$	X_8
Pacitan ($i = 1$)	588,6	72,86	$\cdots$	68.517
Ponorogo ($i = 2$)	962,9	73,55	$\cdots$	92.659
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Batu City ($i = 38$)	222,7	73,29	$\cdots$	23.541

3.2 Analysis Stages

The following stages were employed in this study:

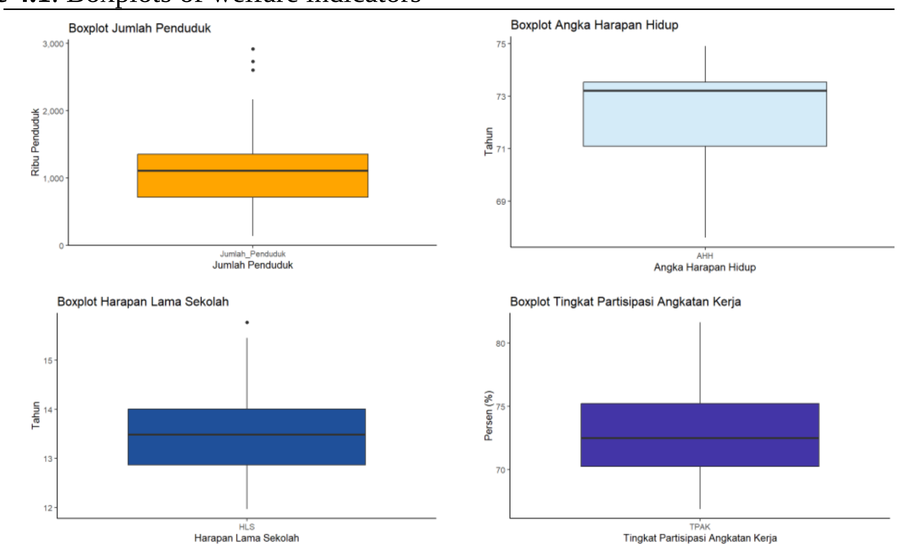
1. Perform a descriptive analysis of the East Java province's welfare indicators in 2023.

2. Perform cluster analysis using the FPPPCM algorithm with Euclidean distance, parameters $m = 2$, $\eta = 2$, $K = 1$, and the number of clusters is 3, to cluster regencies/cities. The reason for specifying the number of clusters as 3 has been that the cost was significantly reduced by that number due to the inertia (a measure of within-cluster variance) which was rapidly decreasing up to 3 clusters, hence signifying that the grouping of regencies/cities into clusters by welfare indicators in East Java was effective. As the cost continued to decrease in smaller amounts with the addition of clusters, it meant that the new clusters would only increase the model complexity but not with equivalent gains in interpretability or result quality [18].
3. Using the clustering results, describe the features of the East Javan regencies' and cities' welfare clusters.

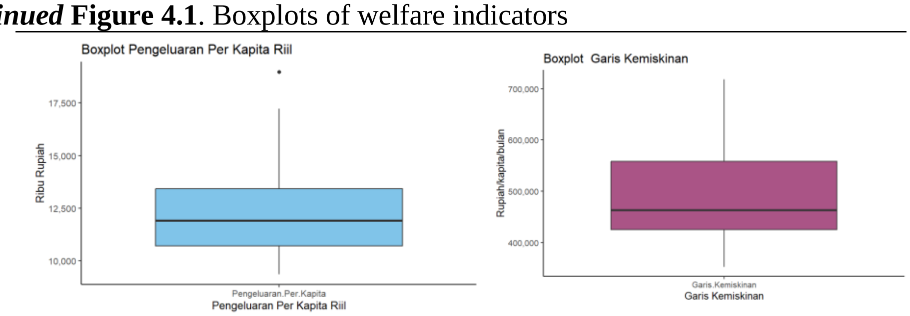
4. RESULTS AND DISCUSSION

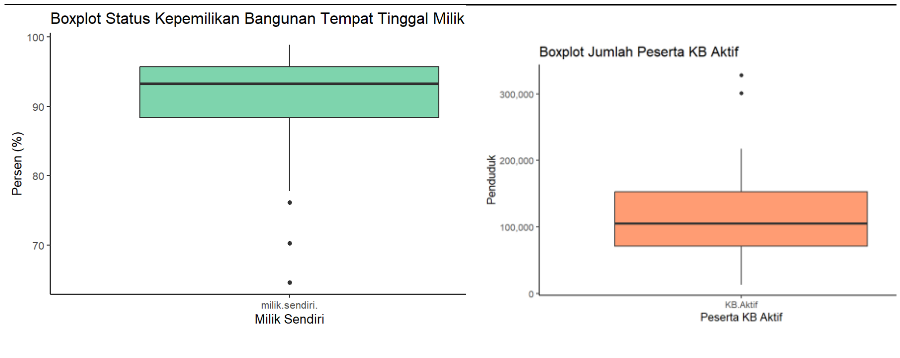
Community welfare reflects the success of regional development. To obtain an overview of community welfare, boxplot visualization is used to facilitate identification of patterns and outliers for each indicator in East Java. **Figure 4.1** displays the welfare indicators boxplot.

Figure 4.1. Boxplots of welfare indicators



***Continued* Figure 4.1**. Boxplots of welfare indicators





Based on the collection of boxplots in **Figure 4.1**, East Java has a population range of 137,400 to 2,922,000 people, with an average of 1,100,380 people. The population has 3 regencies/cities with outliers above the maximum value. Life expectancy ranges from 67.6 to 74.91 years, with an average of 72.42 years. Expected years of schooling range from 11.97 to 15.77 years, with an average of 13.52 years. Expected years of schooling have one outlier regency/city above the maximum value. The labor force participation rate ranges from 66.89% to 81.64%, with an average of 73.16%. Adjusted real per capita expenditure ranges from Rp 9,363,000 to Rp 18,977,000, with an average expenditure of Rp 12,287,050. Adjusted real per capita expenditure has one outlier regency/city above the maximum value. The percentage of home ownership ranges from 64.64% to 98.89%, with an average of 90.49%. The poverty line ranges from Rp 352,606 to Rp 718,370 per month per capita, with an average of Rp 487,879.08 per month per capita. The poverty line has 3 regencies/cities with outliers below the minimum value. The number of active family planning participants ranges from 12,879 to 328,452 people, with an average of 118,063.16 people. The number of active family planning participants has 2 outlier regencies/cities above the maximum value.

Based on their shared characteristics, areas are grouped into multiple clusters using descriptive analysis. **Table 4.1** shows how the FPPPCM algorithm was used to group welfare in East Java regencies.

Table 4.1. Welfare Clustering of East Java Regencies/Cities

***Cluster* 1**	***Cluster* 2**	***Cluster* 3**	
Kediri City	Pacitan	Kediri	Pasuruan
Blitar City	Ponorogo	Malang	Sidoarjo
Malang City	Trenggalek	Bojonegoro	Mojokerto
Probolinggo City	Tulungagung	Tuban	Jombang

***Continued* Table 4.1**. Welfare Clustering of East Java Regencies/Cities

***Cluster* 1**	***Cluster* 2**	***Cluster* 3**	
Pasuruan City	Blitar	Lamongan	Nganjuk
Mojokerto City	Lumajang	Gresik	City of Surabaya
Madiun City	Madiun	Bangkalan	
Batu City	Magetan	Sumenep	
	Ngawi	Jember	
	Sampang	Banyuwangi	
	Pamekasan	Bondowoso	
	Situbondo	Probolinggo	

Cluster characteristics are distinctive features or properties that describe a cluster. The characteristics of the FPPPCM clusters can be seen in **Table 4.2**.

Table 4.2. Characteristics of *East* Java Regency/City cluster

Cluster	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
1	410,58	**73,47**	**14,50**	72,15	**14.615,97**	80,66	**600.964,27**	36.270,99
2	985,37	72,30	13,13	**74,76**	10.918,59	**94,70**	417.992,46	105.254,89
3	**1.491,97**	71,95	13,28	72,48	12.201,17	92,86	483.131,95	**171.941,84**

Based on **Table 4.2**, it was found that Cluster 1 has a low population, high life expectancy, high expected years of schooling, low labor force participation rate, high adjusted real per capita expenditure, low percentage of home ownership, high poverty line, and low number of active family planning participants. Cluster 2 has a medium population, medium life expectancy, low expected years of schooling, high labor force participation rate, low adjusted real per capita expenditure, high percentage of home ownership, low poverty line, and medium number of active family planning participants. Cluster 3 has a high population, low life expectancy, medium expected years of schooling, medium labor force participation rate, medium adjusted real per capita expenditure, medium percentage of home ownership, medium poverty line, and high number of active family planning participants.

5. CONCLUSION

1. There are 3 indicators that do not have outliers, namely Life Expectancy, Labor Force Participation Rate, and Poverty Line. The remaining 5 indicators that have outliers include Population Size, Expected Years of Schooling, Adjusted Real Per Capita Expenditure, Home Ownership Status, and Number of Active Family Planning Participants.
2. There are 8 cities that belong to Cluster 1, 12 regencies that belong to Cluster 2, and the remaining 18 regencies/cities fall into Cluster 3. Cluster 1 has the highest values for Life Expectancy, Expected Years of Schooling, Adjusted Real Per Capita Expenditure, and Poverty Line indicators. Cluster 2 has the highest values for Labor Force Participation Rate and Percentage of Home Ownership indicators. Finally, Cluster 3 has the highest values for Population Size and Number of Active Family Planning Participants indicators.
3. From the findings of the clusters, the local authorities can make use of them to prepare policies based on the need of the people. Cluster 1 (low population, high education/life expectancy but low labor participation and high poverty line) may find aid in programs that work on the issues like job creation, affordable housing, and family planning outreach to reduce inequality. Cluster 2 (medium population, low education/expenditure but high labor participation/home ownership) could promote vocational training, poverty reduction through SME support, and give education to the workforce. Cluster 3 (high population, low life expectancy, medium indicators but high family planning) should focus on improvement of the healthcare infrastructure, the health of the mother and child, and creation of industrial jobs for the local people. This will help them in reducing the overcrowding and improving the living standards. This kind of approach ensures that resources are distributed efficiently and allows for the realization of different economic ends in each cluster.

REFERENCES

[1] Aggarwal, C. C., 2015. Data Mining: The Text Book. In *Springer International Publishing Switzerland*. Springer. https://doi.org/10.1007/978-3-319-14142-8 ISBN

[2] Aggarwal, C. C., & Zhai, C., 2012. *Mining Text Data*. Springer. https://doi.org/10.1007/978-1-4614-3223-4

[3] Badan Pusat Statistik, 2024. *Provinsi Jawa Timur dalam Angka 2024*.
[4] Basu, T., & Murthy, C. A., 2015. A similarity assessment technique for effective grouping of documents. *Information Sciences*, *311*, 149–162. https://doi.org/10.1016/j.ins.2015.03.038
[5] Berkhin, P., 2009. Survey of Clustering Data Mining Techniques, 1–56.
[6] Celebi, M. E., Kingravi, H. A., & Vela, P. A., 2013. Expert Systems with Applications A comparative study of efficient initialization methods for the k-means clustering algorithm. *Expert Systems With Applications*, *40*(1), 200–210. https://doi.org/10.1016/j.eswa.2012.07.021
[7] Cios, K. J., Swiniarski, R. W., Pedrycz, W., & Kurgan, L. A., 2007. *Data Mining : A Knowledge Discovery Approach*. Springer. https://doi.org/10.1007/978-0-387-36795-8
[8] Dean, J., 2014. *Big Data, Data Mining, and Machine Learning - Value Creation for Business Leaders and Practitioners* (J. Wiley (ed.)). John Wiley & Sons, Inc.
[9] Gorunescu, F., 2011. *Data Mining: Concepts, Models, and Techniques* (J. Kacprzyk & L. C. Jain (eds.); 12th ed.). Springer. https://doi.org/10.1007/978-3-642-19721-5
[10] Gosztolya, G., & Szilágyi, L., 2015. Application of Fuzzy and Possibilistic c-Means Clustering Models in Blind Speaker Clustering. *Acta Polytechnica Hungarica*, *12*(7), 41–56. https://doi.org/10.12700/aph.12.7.2015.7.3
[11] Han, J., Kamber, M., & Pei, J., 2012. *Data Mining: Concepts and Techniques* (3rd ed.). Elsevier.
[12] Harrington, P., 2012. *Machine Learning in Action* (T. Hoffman & A. Ott (eds.)). Manning Publications Co.
[13] Hilmy Abdullah, & Ismadiyanti Purwaning Astuti, 2023. Indeks Pembangunan Manusia, Pertumbuhan Ekonomi, Jumlah Penduduk Terhadap Kemiskinan Jawa Timur 2013-2022. *Jurnal Ekobistek*, *12*(3), 687–692. https://doi.org/10.35134/ekobistek.v12i3.628
[14] Huber, P. J., 1981. *Robust Statistics*. John Wiley & Sons, Inc.
[15] Husniatul, H., Jumiati, A., Priyono, T. H., Adenan, M., Lilis, Y., & Qori'ah, C. G., 2024. Analisis Kemiskinan Jawa Timur. *Jurnal Perencanaan Wilayah Dan Pembangunan*, *2*(1), 40–48. https://jurnal.unej.ac.id/index.php/JPWP/article/view/47928
[16] Jain, A. K., Murty, M. N., & Flynn, P. J., 1999. Data Clustering: A Review. *ACM Computing Surveys (CSUR)*, *31*(3), 264–323. https://doi.org/10.1145/331499.331504
[17] Krishnapuram, R., & Keller, J. M., 1996. The Possibilistic C-Means Algorithm: Insights and Recommendations. *IEEE Transactions on Fuzzy Systems*, *4*(3), 385–393.
[18] Koni, M. R., Djakaria, I., & Yahya, N. I., 2023. Pengelompokkan Kabupaten/Kota Provinsi Jawa Timur Berdasarkan Indikator Kesejahteraan Rakyat Menggunakan Metode Elbow dan Algoritma K-Prototype. *Jurnal Estimasi*, 4(1), 10-19. DOI: 10.20956/ejsa.vi.24837
[19] Mann, A. K., & Kaur, N., 2013. Survey Paper on Clustering Techniques. *International Journal of Science, Engineering and Technology Research (IJSTER)*, *2*(4), 803–806.
[20] Mawardi, R. A., 2023. Dilema Pembangunan di Indonesia: Analisis Mengenai Dampak dan Implikasi Kebijakan Pembangunan Era Presiden Joko Widodo. *Jurnal Mengkaji Indonesia*, *2*(1), 39–62. https://doi.org/10.59066/jmi.v2i1.246
[21] Mingoti, S. A., & Lima, J. O., 2006. Comparing SOM neural network with Fuzzy c-means, K-means and traditional hierarchical clustering algorithms. *European Journal of Operational Research*, *174*, 1742–1759. https://doi.org/10.1016/j.ejor.2005.03.039
[22] Pal, N. R., Pal, K., & Bezdek, J. C., 1997. A Mixed c-Means Clustering Model. *IEEE Procedings of 6th International Fuzzy Systems Conference*, *1*, 11–21.
[23] Pimentel, B. A., & Souza, R. M. C. R. De., 2013. A Multivariate Fuzzy C-Means Method. *Applied Soft Computing Journal*, *13*(4), 1592–1607. https://doi.org/10.1016/j.asoc.2012.12.024
[24] Rahman, A., Syafii, M., & Hakim, S. H., 2021. *Kesejahteraan dan Indikator Kunci*

Pembangunan (1st ed.).

[25] Scitovski, R., Vidovi, I., & Bajer, D., 2016. A New Fast Fuzzy Partitioning Algorithm. *Expert Systems With Applications*. https://doi.org/10.1016/j.eswa.2015.12.034

[26] Simhachalam, B., & Ganesan, G., 2016. Performance Comparison of Fuzzy and Non-Fuzzy Classification Methods. *Egyptian Informatics Journal*, *17*(2), 183–188. https://doi.org/10.1016/J.EIJ.2015.10.004

[27] Sivarathri, S., & Govardhan, A., 2014. Experniments on Hypothesis "Fuzzy K-Means is Better than K-Means for Clustering." *International Journal of Data Mining & Knowledge Process (IJDKP)*, *4*(5), 21–34.

[28] Sukmasari, D., 2020. Konsep Kesejahteraan Masyarakat Dalam Perspektif Al-Quran. *Journal of Qur'an and Hadis Studies*, *3*(1), 1–16.

[29] Sultan, Rahayu, H. C., & Purwiyanta, 2023. Analisis Pengaruh Kesejahteraan Masyarakat Terhadap Pertumbuhan Ekonomi di Indonesia. *Jurnal Informatika Ekonomi Bisnis*, *5*, 75–83. https://doi.org/10.37034/infeb.v5i1.198

[30] Szilágyi, L., 2011. Fuzzy-Possibilistic Product Partition: A Novel Robust Approach to c-Means Clustering. *Lecture Notes in Computer Science*, *6820*, 150–161. https://doi.org/10.1007/978-3-642-22589-5_15

[31] Umami, U., 2013. Cara Pandang dan Upaya Pemerintah dalam Mengurangi Kemiskinan. *Jurnal Pembangunan Wilayah & Kota*, *9*(4), 343. https://doi.org/10.14710/pwk.v9i4.6673

[32] Wahyuni, I., & Wulandari, S. P., 2022. Pemetaan Kabupaten/Kota di Jawa Timur Berdasarkan Indikator Kesejahteraan Rakyat Menggunakan Analisis Cluster Hierarki. *Jurnal Sains Dan Seni*, *11*(1), D70–D75.

[33] Yu, H., & Fan, J., 2017. Cutset-type Possibilistic C-Means Clustering Algorithm. *Applied Soft Computing Journal*. https://doi.org/10.1016/j.asoc.2017.12.024

[34] Yu, H., Fan, J., & La, R., 2019. Suppressed Possibilistic C-Means Clustering Algorithm. *Applied Soft Computing Journal*. https://doi.org/10.1016/j.asoc.2019.02.027