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## USING FUZZY C-MEANS ALGORITHM TO CLUSTER HUMAN DEVELOPMENT INDEX

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**Abstract:** Human Development Index (HDI) plays an important role in the development of a modern economy, in line with proper human development will enable the production factors to be maximized. The Human Development Index (HDI) which consists of three components, consists of life expectancy, the level of education measured by a combination of the adult literacy rate and the average length of schooling and an adequate standard of living is measured by the adjusted per-capita expenditure. Long story short, this paper will examine HDI in Aceh Province, Indonesia and create clusters using fuzzy C means Manhattan distance. The results obtained are this method can form 4 clusters with an accuracy of 82.75%.

**Keywords:** human development index; fuzzy C means; clustering; development.

**2010 AMS Subject Classification:** 91B62.

### 1. INTRODUCTION

The government's echo in the effort to realize the ideals of national development is increasingly being carried out[1]. Indonesia National Development places humans as a central

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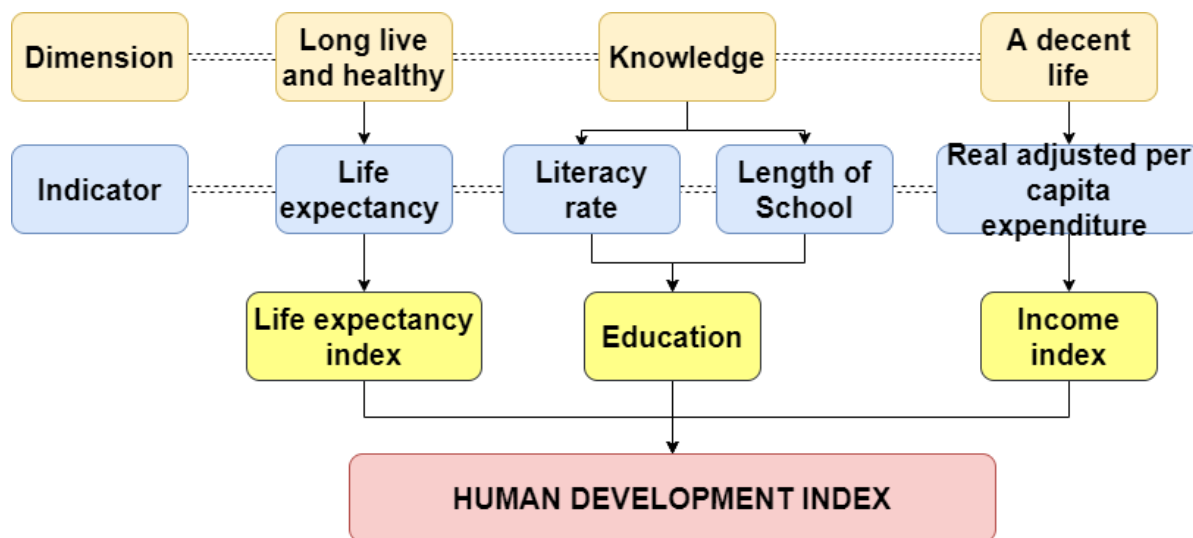
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point characterized by the people, and for the people[2]. In other words, the people are involved in the entire development process, not only as a means to achieve the final results of development, but as the ultimate goal of development itself [3][4][5]. To be able to participate in the development process, of course, Indonesian people are needed who are not only superior in terms of quantity, but also superior in terms of quality[6]. To support the economic process and it is expected to have professional human resources,[7][8] providing high quality products[9][10] and good services[11][12][13][14] with support of proper technology [15] big data[16][17] and IoT [18][19].

To survive in the challenging global market environment, supplying the human capital is the key driving force in the decisive success of a nation. Experience during the crisis shows that countries that have better quality human resources rise faster from the crisis that hit them[20]. Therefore a new concept was formulated in measuring the development of a human-oriented country. Benchmarks for the success of human development have been developed by the United Nations Development Program (UNDP) known as the Human Development Index (HDI) [21][22][23].

According to UNDP, the Human Development Index (HDI) measures the achievement of human development based on a number of basic components of quality of life[24]. Moreover, the quality of life somewhat is significant in increasing job satisfaction which later improves the working atmosphere and productivity [25]. As a measure of the quality of life, HDI is built through a three-dimensional approach and describe in Figure 1. However, the long and healthy life, as measured by life expectancy at birth[26]. Knowledge, which is measured based on the average length of schooling and the literacy rate of the population aged 15 years and over. A decent life, as measured by the adjusted average real per capita expenditure. Life Expectancy Rate is the estimated average number of years that a person can take during his life. This life expectancy rate can be used as a benchmark for health indicators. The higher the Life Expectancy Rate of a community indicates the high degree of public health.

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**Figure 1.** Human Development Index Concept

Human development index (HDI) are many strategic indicators used to see effort and performance Comprehensive development program in a region. In this case, the HDI is considered as an illustration of the program results development that has been done. The progress of the development program in a period can be measured and indicated by the amount of HDI at the beginning and end of the period. HDI is a measure for see the impact of development performance an area with very large dimensions, because it shows the quality of the population, namely an area in terms of life expectancy, intellectuality and a decent standard of living.

As reported in Indonesia Statistical body, Indonesia's Human Development Index as a whole is growing. However, the growth is not followed by other provinces, such as Aceh, which is not even achieved Indonesia's index rate. This inequality may challenge Indonesia's HDI rate as an unlikable rate of a province may decrease Indonesia's status as a whole. Thus, the information about which aspects need to improve is important to discover. However, the information regarding the clustering data according to HDI's elements, especially in Aceh province is absent. Hence, a study to cluster a region accordingly is needed. Therefore, this paper will discuss HDI in Aceh Province. This study will contribute to group the regency accordingly, and later give insights to the policymaker and the government to formulate strategies to reduce the inequality.

## 2. METHODS

### A. Index Calculation

Before calculating the HDI, each component of the HDI must be calculated for the index[27].

Formula used in calculating the index of the HDI components are as follows[28][29]:

$$\text{Health Index} = \frac{\text{Life Expectancy at Birth} - \text{Life Expectancy at Birth}_{\text{minimum}}}{\text{Life Expectancy at Birth}_{\text{max}} - \text{Life Expectancy at Birth}_{\text{minimum}}} \quad (1)$$

$$\text{Length of School Index} = \frac{\text{Length of School} - \text{Length of School}_{\text{minimum}}}{\text{Length of School}_{\text{max}} - \text{Length of School}_{\text{minimum}}} \quad (2)$$

$$\text{Average of School Index} = \frac{\text{Average of School} - \text{Average of School}_{\text{minimum}}}{\text{Average of School}_{\text{max}} - \text{Average of School}_{\text{minimum}}} \quad (3)$$

$$\text{Education Index} = \frac{\text{Length of School Index} + \text{Average of School Index}}{2} \quad (4)$$

$$\text{Expenditure Index} = \frac{\ln \text{Expenditure} - \ln \text{Expenditure}_{\text{minimum}}}{\ln \text{Expenditure}_{\text{maximum}} - \ln \text{Expenditure}_{\text{minimum}}} \quad (5)$$

After getting equation (1), equation (4), and equation (5). We can calculate the HDI in equation 6.

$$\text{HDI} = \sqrt[3]{\text{Health Index} \times \text{Education Index} \times \text{Expenditure Index}} \quad (6)$$

### B. Fuzzy C-Means

Fuzzy C-Means is a data clustering technique in which the existence of each data point in a cluster is determined by the degree of membership[30]. This technique was first proposed by Dunn (1973) and later developed by Bezdek (1984)[31]. This method is a development of the non-Hierarchical C-means cluster method, because initially the number of groups or clusters to be formed is determined. The objective functions used by FCM represent in Eq(7).

$$p^t = \sum_{i=1}^n \sum_{k=1}^c (u_{ik})^m d_{ik}^2(x_i, v_k) \quad (7)$$

Where  $p^t$  represents the objective function  $t$ -th iteration,  $n$  as the number of object,  $c$  represents the cluster number.  $u_{ik}$  Represent the degree of membership with fuzzy weighted  $m \in (1, \infty)$ . Meanwhile,  $d_{ik}$  as distance from central point to cluster. Each object has a membership value in each cluster  $u_k$  which is a value that is initially formed randomly with the following conditions  $u_{ik} \in [0,1]$  and  $\sum_{k=1}^c u_k = 1$ . In addition, each group contains at least one record with a non-zero membership value, but does not contain degrees of one on all data. Cluster center is formulated as Eq(8).

$$v_{kj} = \frac{\sum_{i=1}^n (u_k)^m x_{ij}}{\sum_{i=1}^n (u_k)^m} \quad (8)$$

During the initial condition, the cluster center value is not accurate because it is formed from the degree of membership that is generated randomly[32]. By fixing the cluster center value and updating the membership value repeatedly, it can be seen that the cluster center value will move to the right location[33][34][35]. For  $t$ -iteration, the membership value of the  $i$ -th object in the  $k$ -th cluster is represent in Eq(9).

$$u_{ik}^t = \left[ \frac{[\sum_{j=1}^p d_{ik}^2]^{-\frac{1}{m-1}}}{\sum_{k=1}^c [\sum_{j=1}^p d_{jk}^2]^{-\frac{1}{m-1}}} \right]^{-1} \quad (9)$$

The purpose of grouping is to collect objects that have high similarities in the same cluster. One of the criteria that can be used in seeing the quality of grouping is to pay attention to the standard deviation value[36]. The average standard deviation in groups is expected to be a minimum, and the standard deviation between groups is a maximum. The average standard deviation within the group is stated in Eq(10)

$$S_W = \frac{1}{c} \sum_{k=1}^c S_k \quad (10)$$

$c$  defined as the number of clusters and  $S_k$  is the standard deviation in the  $k$ -th cluster. While the standard deviation between groups is stated as in Eq (11).

$$S_B = \left[ \frac{1}{c-1} \sum_{k=1}^c (\bar{x}_k - \bar{x})^2 \right]^{\frac{1}{2}} \quad (11)$$

Meanwhile,  $\bar{X}_k$  as average cluster ke-  $k$  dan  $\bar{X}$  is the average of all clusters.

### 3. MAIN RESULTS AND DISCUSSION

#### A. Step Construction

The complete FCM algorithm is given as follows

1. Determine the data to be in cluster  $X$ , in the form of a matrix of size  $n \times p$ .
2. Determine:
  - Number of clusters to be formed ( $C > 1$ );
  - Rank of weight ( $m > 1$ )
  - Maximum iteration = MaxIter;
  - The smallest expected error =  $\varepsilon$ ;
  - The initial objective function =  $P(0) = 0$ ;
3. Generating random numbers  $u_{ik}$ ,  $i = 1, 2, \dots, n$ ;  $k = 1, 2, \dots, c$ ; as the elements of the initial

partition matrix  $U$ , with condition  $\sum_{k=1}^c u_{ik} = 1$ .

$$U = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1c} \\ u_{21} & u_{22} & \dots & u_{2c} \\ \vdots & \vdots & \vdots & \vdots \\ u_{n1} & u_{n2} & \dots & u_{nc} \end{bmatrix}$$

4. Compute the cluster center to  $-k : v_{kj}$
5. Calculate changes to the membership matrix  $u_{ik}$ .
6. Calculates the objective function value in the  $t$ -iteration ( $P^{(t)}$ )
7. Checking the stop condition (convergent):
  - If  $|P^{(t)} - P^{(t-1)}| < \varepsilon$  or  $t > \text{MaxIter}$
  - If not, then  $t = t + 1$ , repeating back to step 4

### B. Finding Best Clustering

The distance formula with the best cluster accuracy quality is the one with the minimum  $S_W$  value and the maximum  $S_B$  value. So that the distance formula chosen is the one that gives the smallest  $S_W$  and  $S_B$  ratio value. After obtaining the best distance formula, then grouping with the distance formula is carried out with different numbers of groups. The validity of a cluster is calculated based on the ratio of compactness to separation. Density is a measure of the closeness between members in each cluster while separation is a measure of the separation between clusters from one another. The ratio of density and separation is defined as follows:

$$S = \frac{\pi}{d_{min}} \quad (12)$$

$$\pi (Compactness) = \frac{\sum_{i=1}^n \sum_{k=1}^c (u_{ik})^m d_{ik}^2(x_i, v_k)}{n} \quad (13)$$

$$d_{min} (Separation) = \min_{i \neq k} d_{ik}^2(v_i, v_k) \quad (14)$$

$d_{ik}^2(x_i, v_k)$  is the distance between the data and the cluster center  $d_{ik}^2(v_i, v_k)$  is the distance from the center of the cluster  $v_k$  to the center of the cluster  $v_i$ . The smaller the value  $S$  then the better the results of the cluster that have been done[37].

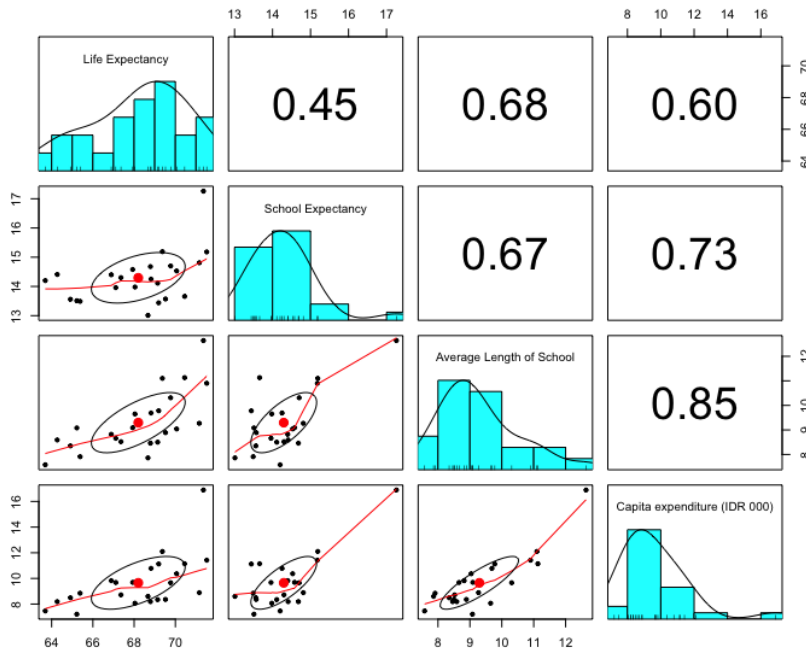
This paper uses variable life expectancy, school expectancy, average length of school and capital expenditure at Aceh Province Indonesia in 2019 covering 23 regions. Figure 2 explains that there is a fairly high relationship between average length of school and capital expenditure. According to Official Statistics report, Human development in Aceh Province has experienced significant developments with the increase in the Human Development Index (HDI). In 2019, the HDI of Aceh Province reached 71.90. Also increased by 0.71 points compared to 2018 which amounted to 71.19. Meanwhile, start From 2016 to 2019, human development in Aceh Province has classify as a “high” status valued at 70.00 or more. The HDI of Aceh Province in 2019 grew by 1.00 percent compared to 2018. The components forming the HDI have also increased. In 2019, newborns had the chance to live up to 69.87 years, an increase of 0.23 years compared to the previous year. Children aged 7 years have the opportunity to attend school for 14.30 years in 2019, an increase of 0.03 years compared to 2018. Meanwhile, the population aged 25 years and over has

on average studied 9.18 years, increasing 0.09 years compared to the previous year. Per capita expenditure (constant 2012 prices) of the public has reached Rp. 9,603 million rupiah in 2019, an increase of Rp. 417 thousand rupiah compared to the previous year.

**Table 1** Descriptive Statistics of the Aceh Province Human Development Index 2019 Indicators

Statistics	Life Expectancy	School Expectancy Average	Length of School	Capital Expenditure	IPM %
Min	63.69	13.01	7.58	7.21	0.69
1st Qu	68	13.62	8.51	8.355	1.02
Median	68.79	14.25	9.04	8.889	1.15
Mean	68.2	14.29	9.297	9.654	1.163
3rd Qu	69.64	14.63	9.735	10.573	1.34
Max	71.52	17.26	12.64	16.892	1.54

Based on Table 1, it is known that the highest life expectancy value in Aceh Province is 71.52 years, including Lhokseumawe. Meanwhile, the lowest life expectancy was 63.69 years at Sabulussalam. The average Life Expectancy in Aceh Province is 68.22 years and there are 10 regions with Life Expectancy below the average in Aceh Province



**Figure 2.** Variable Correlation towards Variables

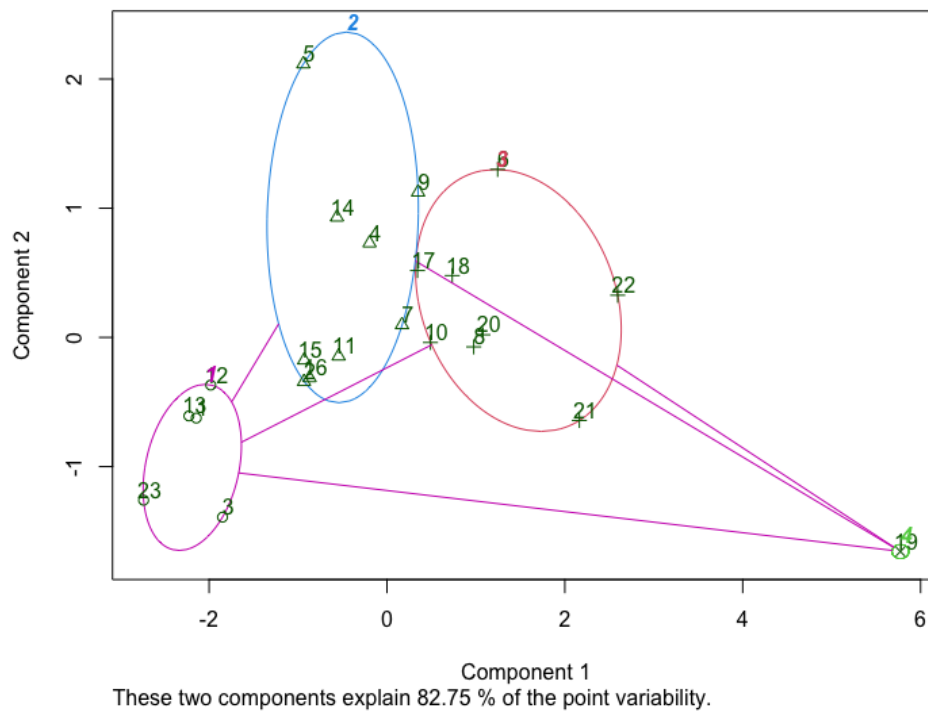


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During the clustering we set the number of clusters with clusters 4. First, the data preparing standardized HDI indicator data Determining the initial parameter values: fuzzifier ( $m$ )=2, maximum iteration = 1000, smallest error =  $10^{-5}$  the initial objective function  $P(0) = 0$  and the results are obtained in Table 2 and Appendix section. Figure 3 represents based on cluster analysis with Fuzzy C Means, it was found that of the 23 regions in Aceh Province, the Banda Aceh region had very significant differences compared to other region and can be explained by 82.75%.

**Table 2** Fuzzy c-means clustering with 4 clusters

Cluster centers:	Life Expectancy School	Expectancy Average	Length of School	Capital expenditure (IDR 000)	IPM%	Location
1	69.90835	14.39806	10.186195	10.743835	1.0601007	Aceh Singkil(2), Aceh Tenggara(4), Aceh Timur(5), Aceh Barat(7), Pidie(9), Aceh Utara(11), Aceh Tamiang(14), Nagan Raya(15) ,Aceh Jaya(16)
2	68.43083	14.09812	8.761255	8.767689	1.1462269	Banda Aceh(19)
3	64.80405	13.85978	8.328618	8.133034	1.4501584	Simeulue(1), Aceh Selatan(3),Aceh Barat Daya(12), Gayo Lues(13), Sabulussalam(23)
4	71.33630	17.21324	12.598834	16.779061	0.8338279	Aceh Tengah (6), Aceh Besar(7), Bireuen (10), Bener Meriah (17),Pidie Jaya(18), Sabang,(20) Langsa(21), Lhokseumawe (22).



**Figure 3.** Cluster Plot Fuzzy C Means

### CONCLUDING REMARKS

Based on the quality of the accuracy of grouping using the standard deviation ratio in clusters and between clusters, the grouping of districts or cities in Aceh Province based on the HDI indicator uses more FCM with a Manhattan distance of 82.75%. The achievement of human development is measured by paying attention to three essential aspects, including a long and healthy life, knowledge, and a decent standard of living. Therefore, the increase in HDI achievement cannot be separated from the increase in each of its components. Along with the increase in HDI figures, the index for each HDI component also showed an increase of year to year. Meanwhile, the dimension of knowledge in the HDI is formed by two indicators, including the School Expectations and Average Length of School.

Besides, it is noteworthy to mention that this attempt has contributed to augmenting the body of knowledge of Human Capital Development in Aceh Province, Indonesia. The implementation of clustering will be prone to helping the policy-maker in building its society. This study also seizes the importance of healthier life, more educated civilizations, and a better place to live to boost a country's HDI. Thus, it will help the government (i.e., Aceh) to distinguish the appropriate

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approach executed, as well as forecasted to the endowment allocations.

This study is not without limitation. The clustered resulted from this study was based on the secondary data obtained from the Statistical Body in Indonesia. However, the data may be outdated prone to this study accomplished and may no longer relevant. Therefore, the future research needs to look into more updated data which may offer different result, increase its validation, more reliable results, and reduce the possible bias. Moreover, indeed, the clustering resulted from this study was based on the prominent aspects of the Human development index. However, this indexing's usefulness is not apparent yet. Therefore, it is prosperous to investigate the effectiveness of HDI model in improving society's quality of life in future research. Nevertheless, as the human development index is considered as a multi-dimensional construct, we inspire upcoming research to investigate its possible antecedents, such as quality of work-life, and outcomes, such as job satisfaction, employee commitment and performance.

**APPENDIX (Manhattan Distance)**

<b>Location</b>	<b>C1</b>	<b>C2</b>	<b>C3</b>	<b>C4</b>	<b>Final Cluster</b>
Simeulue	0.108574835	0.009284	0.842763	0.039378	3
Aceh Singkil	0.777693798	0.00934	0.139272	0.073695	1
Aceh Selatan	0.034919094	0.004219	0.945644	0.015218	3
Aceh Tenggara	0.791120555	0.010969	0.093426	0.104485	1
Aceh Timur	0.762600146	0.014495	0.100471	0.122434	1
Aceh Tengah	0.216075989	0.019238	0.044535	0.720152	4
Aceh Barat	0.736260702	0.013187	0.079524	0.171029	1
Aceh Besar	0.186610341	0.015423	0.031479	0.766488	4
Pidie	0.550995464	0.023129	0.251138	0.174738	1

Bireuen	0.376326372	0.039099	0.072473	0.512102	4
Aceh Utara	0.872185634	0.007599	0.04756	0.072656	1
Aceh Barat Daya	0.017843502	0.001635	0.973755	0.006766	3
Gayo Lues	0.094687597	0.007403	0.865003	0.032905	3
Aceh Tamiang	0.775582774	0.012608	0.05603	0.155779	1
Nagan Raya	0.878587711	0.006991	0.037896	0.076526	1
Aceh Jaya	0.627838393	0.017529	0.211075	0.143557	1
Bener Meriah	0.17492465	0.022581	0.043507	0.758988	4
Pidie Jaya	0.203901701	0.017817	0.033118	0.745163	4
Banda Aceh	0.000172488	0.999395	0.000114	0.000318	2
Sabang	0.103248118	0.033774	0.032841	0.830137	4
Langsa	0.139273387	0.080743	0.056249	0.723734	4
Lhokseumawe	0.137039743	0.085801	0.047516	0.729643	4
Sabulussalam	0.080392513	0.011494	0.871486	0.036627	3

## CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

## REFERENCES

- [1] L. Martini, J. H. Tjakraatmadja, Y. Anggoro, A. Pritasari, L. Hutapea, Triple Helix Collaboration to Develop Economic Corridors as Knowledge Hub in Indonesia, *Procedia - Soc. Behav. Sci.* 52 (2012), 130–139.
- [2] S. Thomas, M. Richter, W. Lestari, S. Prabawaningtyas, Y. Anggoro, I. Kuntoadji, Transdisciplinary research methods in community energy development and governance in Indonesia: Insights for sustainability science,

## USING FUZZY C-MEANS ALGORITHM TO CLUSTER HUMAN DEVELOPMENT INDEX

- Energy Res. Soc. Sci. 45 (2018), 184–194.
- [3] T. Dartanto, Nurkholis, The determinants of poverty dynamics in Indonesia: evidence from panel data, *Bull. Indones. Econ. Stud.* 49 (2013), 61–84.
- [4] R.E. Caraka, Y. Lee, R. Kurniawan, et al. Impact of COVID-19 large scale restriction on environment and economy in Indonesia, *Glob. J. Environ. Sci. Manag.* 6 (Spec. Iss.) (2020), 65–82.
- [5] R. Kurniawan, T. H. Siagian, B. Yuniarto, B. I. Nasution, R. E. Caraka, Construction of social vulnerability index in Indonesia using partial least squares structural equation modeling, *Int. J. Eng. Technol.* 7(4) (2018), 6131–6136.
- [6] T. Dartanto, S. Otsubo, Measurements and Determinants of Multifaceted Poverty: Absolute, Relative, and Subjective Poverty in Indonesia, Working Papers 54, JICA Research Institute, 2013.
- [7] M.F. Ahammad, K.W. Glaister, E. Gomes, Strategic agility and human resource management, *Human Resource Manage. Rev.* 30 (2020), 100700.
- [8] N.Y. Ansari, M. Farrukh, A. Raza, Green human resource management and employees pro - environmental behaviours: Examining the underlying mechanism, *Corp. Soc. Responsib. Environ. Manag.* (2020), <https://doi.org/10.1002/csr.2044>.
- [9] C.W. Zhang, R. Pan, T.N. Goh, Reliability assessment of high-Quality new products with data scarcity, *Int. J. Product. Res.* (2020). <https://doi.org/10.1080/00207543.2020.1758355>.
- [10] A. Widarjono, M. B. H. Anto, F. Fakhrunnas, Financing risk in Indonesian Islamic rural banks: Do financing products matter? *J. Asian Financ. Econ. Bus.* 7(9) (2020), 305-314.
- [11] M. Ibrahim, Y. Yusra, Work-Family Conflict and Job Satisfaction: The Mediating Role of Person-Organization Fit Study on Employees of The BRI Aceh Region, *South East Asian J. Manag.* 10(2) (2016), 173–182.
- [12] Y. Yusra, A. Agus, The influence of Perceived Service Quality towards Customer Satisfaction and Loyalty in Airasia Self Check-in System, *J. Soc. Sci. Res.* 2(Spec. Iss.) (2018), 766–775.
- [13] Y. Yusra, A. Agus, The influence of online food delivery service quality on customer satisfaction and customer loyalty: the role of personal innovativeness, *J. Environ. Treat. Tech.* 8(1) (2020), 6–12.
- [14] Y. Yusra, R. E. Caraka, A. Agus, P. U. G. Ahmad Azmi Mohd Ariffin, R. C. Chen, Y. Lee, An investigation of online food aggregator (OFA) service: Do online and offline service quality distinct? *Serbian J. Manag.* 15(2) (2020), 277–294.
- [15] F. A. Hudaefi, How does Islamic fintech promote the SDGs? Qualitative evidence from Indonesia, *Qual. Res. Financ. Mark.* 12(4) (2020), 353-366.

- [16] R. C. Chen, C. Dewi, S. W. Huang, R. E. Caraka, Selecting critical features for data classification based on machine learning methods, *J. Big Data*, 7 (2020), 52.
- [17] E. Peters, T. Klieštík, H. Musa, P. Durana, Product Decision-Making Information Systems, Real-Time Big Data Analytics, and Deep Learning-enabled Smart Process Planning in Sustainable Industry 4.0, *J. Self-Governance Manag. Econ.* 8(3) (2020), 16–22.
- [18] H. Cai, L. Da Xu, B. Xu, C. Xie, S. Qin, L. Jiang, IoT-Based configurable information service platform for product lifecycle management, *IEEE Trans. Ind. Inform.* 10(2) (2014), 1558–1567.
- [19] C. Yang, S. Lan, W. Shen, G. Q. Huang, X. Wang, T. Lin, Towards product customization and personalization in IoT-enabled cloud manufacturing, *Cluster Comput.* 20(2) (2017), 1717–1730.
- [20] T. Dartanto, Nurkholis, Income Shocks and Consumption Smoothing Strategies: An Empirical Investigation of Maize Farmer's Behavior in Kebumen, Central Java, Indonesia, *Mod. Econ.* 1(3) (2010), 149-155.
- [21] D. Rodrik, The Global Governance of Trade As If Development Really Mattered, Report submitted to United Nations Development Programme (UNDP), 2001.
- [22] H. Jin, X. Qian, T. Chin, H. Zhang, A global assessment of sustainable development based on modification of the human development index via the entropy method, *Sustainability*, 12(8) (2020), 3251.
- [23] R. L. do Carvalhal Monteiro, V. Pereira, H. G. Costa, Dependence Analysis Between Childhood Social Indicators and Human Development Index Through Canonical Correlation Analysis, *Child Indic. Res.* 13(1) (2020), 337–362.
- [24] M. McGillivray, The human development index: Yet another redundant composite development indicator? *World Develop.* 19(10) (1991), 1461–1468.
- [25] A. Agus, R. Selvaraj, The mediating role of employee commitment in the relationship between quality of work life and the intention to stay, *Employ. Relat.* 42 (2020), 1231–1248.
- [26] R. E. Caraka, H. Yasin, *Spatial Data Panel*, 1st ed. Wade Group, Jawa Timur, 2018.
- [27] A. G. Dijkstra, L. C. Hanmer, Measuring socio-economic gender inequality: Toward an alternative to the UNDP gender-related development index, *Feminist Econ.* 6(2) (2000), 41–75.
- [28] Suparmi, N. Kusumawardani, D. Nambiar, Trihono, A. R. Hosseinpoor, Subnational regional inequality in the public health development index in Indonesia, *Glob. Health Action*, 11(Sup1) (2018), 41–53.
- [29] M. Ragdad Cani, Human Development Disparities and Convergence across Districts of Indonesia: A Spatial Econometric Approach, MPRA Paper No. 102453, 2020, <https://mpra.ub.uni-muenchen.de/102453/>.

## USING FUZZY C-MEANS ALGORITHM TO CLUSTER HUMAN DEVELOPMENT INDEX

- [30] J. C. Bezdek, R. Ehrlich, W. Full, FCM: The fuzzy c-means clustering algorithm, *Comput. Geosci.* 10(2–3) (1984), 191–203.
- [31] J. C. Dunn, Well-Separated Clusters and Optimal Fuzzy Partitions, *J. Cybern.* 4 (1974), 95–104.
- [32] B. I. Nasution, R. Kurniawan, T. H. Siagian, A. Fudholi, Revisiting social vulnerability analysis in Indonesia: An optimized spatial fuzzy clustering approach, *Int. J. Disaster Risk Reduct.* 51 (2020), 101801.
- [33] P. A. Kaban, R. Kurniawan, R. E. Caraka, B. Pardamean, B. Yuniarto, Sukim, Biclustering method to capture the spatial pattern and to identify the causes of social vulnerability in Indonesia: A new recommendation for disaster mitigation policy, *Procedia Comput. Sci.* 157 (2019), 31–37.
- [34] R.E. Caraka, Y. Lee, Cluster Around Latent Variable for Vulnerability Towards Natural Hazards, Non-Natural Hazards, Social Hazards in West Papua, *IEEE Access.* (2020), <https://doi.org/10.1109/ACCESS.2020.3038883>.
- [35] A. Budiarto, B. Mahesworo, J. Baurley, T. Suparyanto, B. Pardamean, Fast and effective clustering method for ancestry estimation, *Procedia Comput. Sci.* 157 (2019), 306–312.
- [36] B. I. Nasution, R. Kurniawan, Robustness of classical fuzzy C-means (FCM), in: 2018 International Conference on Information and Communications Technology (ICOIACT), IEEE, Yogyakarta, 2018: pp. 321–325.
- [37] R. E. Caraka and H. Yasin, *Geographically Weighted Regression (GWR) Sebuah Pendekatan Regresi Geografis*, 1st ed. Mobius, Yogyakarta, 2017.