International Journal Of Artificial Intelegence Research
Vol 6, No 1, June 2022

ISSN: 2579-7298

Fuzzy subtractive clustering (FSC) with exponential membership function for heart failure disease clustering

Annisa Eka Haryati[a], Sugiyarto Surono[,a*], Toomy Tanu Wijaya[b], Goh Khang Wen[c], Aris Thobirin[a]

[a,]Mathematics, Ahmad Dahlan University, Yogyakarta, Indonesia
[b]School of Mathematical Sciences, Beijing Normal University, China
[c]INTI International and Colleges Malaysia
[1] sugiyarto@math.uad.ac.i*

ARTICLE INFO

Article history:
Received 26 May 2022
Revised 19 June 2022
Accepted 25 June 2022

Keywords:
Fuzzy clustering
Fuzzy subtractive clustering
Hamming distance
Exponential membership function

ABSTRACT

The fuzzy clustering algorithm is a partition method that assigns objects from a data set to a cluster by marking the average location. Furthermore, Fuzzy Subtractive Clustering (FSC) with hamming distance and exponential membership function is used to analyze the cluster center of a data point. The data point with the highest density will be the cluster's center. Therefore, this research aims to determine the number of collections with the best quality by comparing the Partition Coefficient (PC) values for each number produced. The data set, which is heart failure patient data, is 150 data obtained from UCI Machine Learning. The data consists of 11 variables, including age (X_1), anemia (X_2), creatinine phosphokinase (X_3), Diabetes (X_4), ejection fraction (X_5), high blood pressure (X_6), platelets (X_7), serum creatinine (X_8), serum sodium (X_9), gender (X_{10}), and smoke (X_{11}). It is simulated and processed using Fuzzy Subtractive Clustering Algorithm, Jupyter Notebook Software with Python programming language. The results showed that the most optimal number of clusters is 3, which are selected based on the most significant PC value. Based on the results, the highest PC value is in cluster 3. Therefore heart failure can be grouped into 3, namely low, moderate, and severe.

I. Introduction

Clustering is one of the unsupervised learning techniques used to divide data points into groups [1,2], while cluster analysis is used to determine patterns with high characteristics [3,4]. Cluster analysis works by grouping similar data into one cluster, thereby leading to significant differences between one collection and another [5,6].

The development of fuzzy theory has recently been used to conduct studies on fuzzy adaptive control for a class of strict feedback nonlinear systems with non-affine errors [7]. The electromechanical system also uses this method to verify the feasibility of the presented approach. Meanwhile, the Robust Fuzzy Adaptive method with a control strategy is developed to observe threshold-based event trigger signals needed to reduce the communication load. This process is carried out by applying a dynamic surface control technique to solve computational complexity problems [8]. The focus of the fuzzy application developed in this research is using a fuzzy clustering algorithm.

A fuzzy clustering algorithm is a partition method that assigns objects from a data set to clusters [9]. It determines the center by marking the average location, which is initially less accurate. However, repeatedly fixing each data point's cluster center and membership level, the cluster center moves to the correct location [1,10].

Several clustering methods exist, such as Fuzzy C-Means (FCM) and Fuzzy Subtractive Clustering (FSC). In FCM, the number of clusters is defined at the beginning using a randomly initialized membership matrix, complicating the process. Meanwhile, in FSC, the number of collections is not determined at the beginning and does not use a membership matrix. This method has more consistent results and speed than FCM [11,12].

Some research had been conducted on fuzzy clusterings, such as [13,14] a modified FCM using a combination of Minkowski and Chebyshev distances. Meanwhile, a study on FSC by [15] optimized the number of membership functions (MF) and rules using a triangular method. Furthermore, [16] also produced a fuzzy model using subtractive clustering and Fuzzy C-Means.

Another research was carried out by [17] that identified the structure of the multi-model modeling algorithm using the entropy-based subtractive fuzzy online clustering method. The result showed that the online multi-model design could be adjusted in a more precise way. In addition, [18] and [19] investigated the use of Fuzzy Subtractive Clustering to build a fuzzy personality model for image segmentation.

Furthermore, research by [20] was used to classify candidate polymers according to similarities and their interactions with the chemical. The results were compared with the Fuzzy C-Means method, and it was realized that FSC is a better selection than FCM.

FSC is also applied to plan the UMTS900 Node B network placement at BTS in the Malang area. The results are compared with FCM, indicating that Node B placement planning distribution is more significant by using FSC [21].

The essence of the FSC method is to determine the data point with the highest density and make it the cluster center. The issue to be clustered is reduced in thickness [22,23], with variation between two Euclidean distances. According to [24], hamming is a well-known distance in the measurement of two fuzzy sets. Therefore, based on the explanation above, this research was conducted using the FSC method with exponential membership function and hamming distance to group the heart failure data set.

II. Methods

A. Fuzzy Subtractive Clustering (FSC)

According to [17], FSC is an unsupervised algorithm where the number of clusters is simulated at the beginning and not defined. The working procedure of this method is to select the data point with the highest density and make it the cluster center. Furthermore, the density decreases and the algorithm chooses another point until all are tested.

The FSC method has two comparison factors: accept and reject ratios in the interval of 0 to 1. Accept ratio is the lower limit where a data point is allowed to become a cluster center, while the reverse is the reject ratio. The three conditions likely to occur in an iteration are ratio > accept ratio, reject ratio < ratio ≤ accept ratio, and ratio ≤ reject ratio.

This research used the FSC method for clustering with hamming distance and exponential membership function. The quality of the resulting cluster is seen using the Partition Coefficient (PC). The following methods were used to carry out this research.

B. Exponential Membership Function

The exponential membership function is defined as follows [25,26]:

$$\mu(x) = \begin{cases} 1 & x \le a \\ \dfrac{e^{-\left(\frac{x-a}{b-a}\right)} - e^{-s}}{1 - e^{-s}} & a \le x \le b \\ 0 & x \ge b \end{cases} \tag{1}$$

Where x is the value for each data, a is the minimum data limit for each variable, and b is the maximum data limit for each variable.

C. Hamming Distance

Suppose the fuzzy sets A and B are subsets of $U = \{u_1, u_2, \ldots, u_n\}$, then the hamming distance is [24,27]:

$$d(A,B) = \sum_{i=1}^{n} |\mu_A(u_i) - \mu_B(u_i)| \quad (2)$$

$d(A,B)$ denotes the distance between fuzzy sets A and B, $\mu_A(u_i)$ is fuzzy set A and $\mu_B(u_i)$ is fuzzy set B.

D. Fuzzy Subtractive Clustering Algorithm

The following are the steps of the FSC algorithm:

- Define the value of r (radius), q (squash factor), ar (accept ratio), and rr (reject ratio).
- Convert data to fuzzy numbers using Equation 1.
- Determine the potential of each data point using Equation 3:

$$D_i = \sum_{k=1}^{n} e^{-4\left(\sum_{j=1}^{m} Dist_{ij}^2\right)} \quad (3)$$

With

$$Dist_{ij} = \left(\frac{\left|\mu_{A_j}(u_i) - \mu_{B_{ij}}(u_i)\right|}{r} \right) \quad (4)$$

Description:
D_i = potential data to the i.
$\mu_{A_j} = \mu_{B_{ij}}$; $j = 1,2,\dots,m$;
$i = 1,2,\dots,n$.
$Dist_{ij}$ = the i-th data distance on the j-th variable.

- Select the data with the most significant potential from $M = max[D_i|i = 1,2,\dots,]$ and $Z = max[D_i|i = 1,2,\dots,]$ for the first and second iterations.
- Calculate the value of the ratio (R) with Equation 5.

$$\mathrm{R} = \frac{\mathrm{Z}}{\mathrm{M}}. \quad (5)$$

For the first iteration, the value of Z is equal to the value of M.

R = the ratio between the most significant potential in the first and subsequent iteration.

- Cluster center candidates are accepted if ratio> get ratio and rejected assuming ratio < ratio ≤ call ratio. The distances between the candidate and the previous cluster center are calculated using Equation 6.

$$\mathrm{Sd_k} = \sum_{\mathrm{j=1}}^{\mathrm{m}} \left(\frac{\mathrm{V_j\text{-}C_{kj}}}{\mathrm{r}}\right)^2. \quad (6)$$

where V_j is the candidate cluster center and C_{kj} is the k-th cluster center on the j-th variable.

The candidate cluster center is the new center, assuming the sum between the ratio and Mds (the closest distance between the prospective cluster center and the cluster center) ≥ 1. Meanwhile, it is not acceptable to assume the number between the ratio and Mds < 1. Furthermore, the iteration stops supposing the ratio ≤ reject ratio.

- After obtaining the cluster center, the initial potential data is calculated using equation 7 as follows:

$$\mathrm{D_i^t} = \mathrm{D_i^{t\text{-}1}\text{-}D_{c_{ki}}}. \quad (7)$$

Equation 8 is used to calculate $D_{c_{ki}}$, as follows:

$$D_{c_{ki}} = Z^{*} e^{-4\left[\sum_{j=1}^{m}\left(\frac{C_{kj}-x_{ij}}{r^{*}q}\right)^{2}\right]}. \quad (8)$$

D_i^t = the i-th data potential in the t-th iteration.
D_i^{t-1} = the i-th data potential in the (t-1)-th iteration.
$D_{c_{ki}}$ = the k-th data potential in the i-th iteration.
C_{kj} = the k-cluster center on the j-th variable.
x_{ij} = the i-th data on the j-th variable.
r = radius.
q = squash factor.

- Equation 9 is used to transform the cluster center to the original data as follows:

$$x = (a-b)\ln(\mu-\mu e^{-s} + e^{-s}) + a. \quad (9)$$

a = the smallest value in the data.
b = the largest value in the data.
μ = the membership value.

- Equation 10 is used to calculate the membership degree value as follows:

$$\sigma_j = \frac{r^{*}\left(X_{max_j}-X_{min_j}\right)}{\sqrt{8}}. \quad (10)$$

σ_j = the sigma on the j-th variable.
X_{max_j} = the largest value on the j-th variable.
X_{min_j} = the smallest value on the j-th variable.

- Equation 11 is used to calculate the membership degree value as follows:

$$\mu_{k_i} = e^{-\sum_{j=1}^{m}\left(\frac{x_{ij}-C_{kj}}{\sqrt{2}\sigma_j}\right)}. \quad (11)$$

μ_{k_i} = the membership value of the k-th cluster on the i-th data.
x_{ij} = the I-th data on the j-th variable.
C_{kj} = the k-cluster center on the j-th variable.
σ_j = the sigma on the jth variable.

E. Validity Index

The validity index can be found by calculating the Partition Coefficient (PC) index is used to evaluate the data membership value in each cluster. The greater the value (closer to 1), the better the quality of the cluster obtained. This index is also used to measure the amount of overlap between groups. The PC index equation by [28,29] is as follows:

$$PC = \frac{1}{N}\left(\sum_{i=1}^{N}\sum_{j=1}^{K}\mu_{ij}^{2}\right). \quad (12)$$

Where:
N = the amount of research data.
K = the number of clusters.

III. Result and Discussion

This research used 150 secondary data on heart failure patients obtained from UCI Machine Learning. The data consists of 11 variables, including age (X_1), anemia (X_2), creatinine phosphokinase (X_3), Diabetes (X_4), ejection fraction (X_5), high blood pressure (X_6), platelets (X_7), serum creatinine (X_8), serum sodium (X_9), gender (X_{10}), and smoke (X_{11}). It is simulated and processed using Fuzzy Subtractive Clustering Algorithm, Jupyter Notebook Software with Python programming language.

Based on [30], the values of q (squash factor), ar (accept ratio), and rr (reject ratio) are 1.25, 0.7, and 0.3, respectively. The best radius (r) simulations for 2, 3, and 4 clusters are 1.97, 2.45, and 2.5. The data for FSC calculations were converted into fuzzy numbers using Equation 1 to obtain the following results:

Table 1. Membership value of each variable

X_1	X_2	X_3	X_4	$\cdots$	X_{11}
0.2609	1	0.8911	1	$\cdots$	1
0.6387	1	0	1	$\cdots$	1
0.4324	1	0.9754	1	$\cdots$	0
0.7571	0	0.9823	1	$\cdots$	1
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
0.5308	1	0.6071	1	$\cdots$	1

The analysis with $r = 1.97$, 2.45, and 2.5 results in 4, 3, and 2 clusters, respectively. The results of the cluster center obtained are as follows:

$$C_{1.97} = \begin{bmatrix} 0.6387 & 1 & 0.8602 & 1 & 0.4071 & 1 & 0.6269 & 0.8790 & 0.2036 & 0 & 1 \\ 0.4324 & 0 & 0.9789 & 0 & 0.6594 & 0 & 0.5768 & 0.8301 & 0.2302 & 1 & 1 \\ 0.3775 & 0 & 0.9607 & 1 & 0.5689 & 0 & 0.5884 & 0.9470 & 0.1289 & 0 & 0 \\ 0.2427 & 1 & 0.9913 & 0 & 0.4071 & 1 & 0.6482 & 0.9645 & 0.2302 & 0 & 0 \end{bmatrix}$$

The first, second, third, and fourth row in matrix C shows the respective cluster center in the 107th, 22nd, 23^{rd,} and 91st data.

$$C_{2.45} = \begin{bmatrix} 0.6387 & 1 & 0.8602 & 1 & 0.4071 & 1 & 0.6269 & 0.8790 & 0.2036 & 0 & 1 \\ 0.4324 & 0 & 0.9789 & 0 & 0.6594 & 0 & 0.5768 & 0.8301 & 0.2302 & 1 & 1 \\ 0.3775 & 0 & 0.9607 & 1 & 0.5689 & 0 & 0.5884 & 0.9470 & 0.1289 & 0 & 0 \end{bmatrix}$$

The first, second, and third rows in the C matrix above show the respective cluster center in the 107th, 22^{nd,} and 68th data.

$$C_{2.5} = \begin{bmatrix} 0.6378 & 1 & 0.8602 & 1 & 0.4071 & 1 & 0.6269 & 0.8790 & 0.2036 & 0 & 1 \\ 0.4324 & 0 & 0.9789 & 0 & 0.6594 & 0 & 0.5768 & 0.8301 & 0.2302 & 1 & 1 \end{bmatrix}$$

The first and second rows in the C matrix above show the respective cluster center in the 107th and 22nd data with the sigma value i calculated using equation 2.10 and the results shown in Table II.

Table 2. Sigma value of cluster

r	X_1	X_2	X_3	$\cdots$	X_{11}
1.97	37.6110	0.6965	5459.1684	$\cdots$	0.6965
2.45	46.7751	0.8662	6789.3211	$\cdots$	0.8662
2.5	47.7297	0.8839	6927.8787	$\cdots$	0.8839

The membership degree value is calculated using Equation 11 to obtain the following results in Table III.

Table 3. Membership value $r = 1.97$

The value of μ in the cluster			
1	2	3	4
0.2513	0.0408	0.1041	0.0365
0.4223	0.0056	0.0157	0.0419
0.2699	0.0052	0.1018	0.2839
⋮	⋮	⋮	⋮
0.3306	0.0409	0.1133	0.0395

Based on Table III, the first data is in cluster 1 due to the presence of the most significant membership degree. Furthermore, the second data is in cluster 1 because the highest membership degree is located in cluster 3 until the 150th data. The cluster results from Table III are shown in Figure 1.

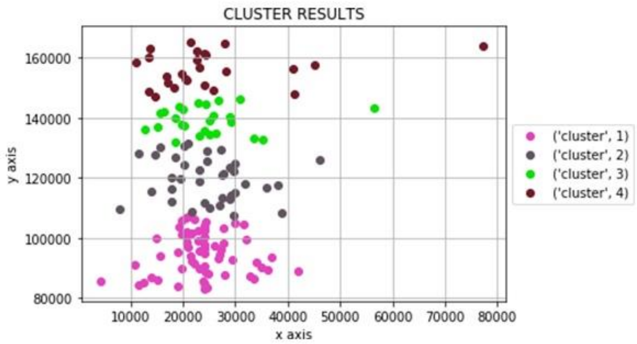

Fig. 1. Results of 4 clusters.

Table 4. Membership value $r = 2.45$

The value of μ in the cluster		
1	2	3
0.4094	0.1264	0.2315
0.5727	0.0351	0.0682
0.4288	0.0333	0.2283
⋮	⋮	⋮
0.4889	0.1265	0.2446

Table 4 shows that the first, second to the 150th data are in cluster 1 due to the presence of the highest memberships shown in Figure 2.

Fig. 2. Results of 3 clusters.

Table 5. Membership value $\boldsymbol{r} = \mathbf{2.5}$

The value of μ in the cluster	
1	2
0.4241	0.1372
0.5855	0.0401
0.4435	0.0381
⋮	⋮
0.5030	0.1373

Table 5 shows that the first, second, and 150th data are in cluster 1 due to the largest memberships shown in Figure 3.

Fig. 3. Results of 2 clusters.

Table 6. Partition coefficient value and number of iterations

Number of clusters	Partition coefficient value	Number of iterations
2	0.5447	3
3	0.7393	4
4	0.5681	5

Based on table 6, the PC values for the number of 2, 3, and 4 clusters are 0.5447, 0.7393, and 0.5681 with 3, 4, and 5 iterations, respectively. Figure 4 is a graph of the PC value and the number of iterations.

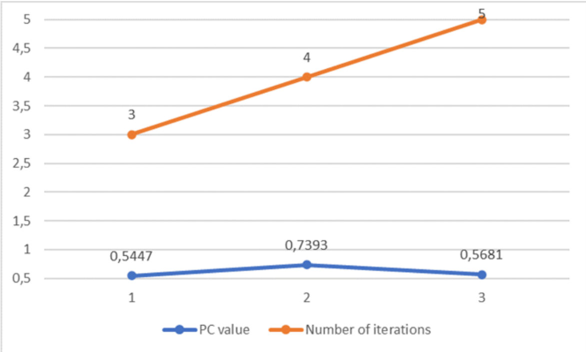

Fig. 4. PC value and number of iterations

IV. Conclusion

This research uses fuzzy subtractive clustering with Hamming distance and exponential membership functions to determine the most optimal heart failure group by examining the Partition Coefficient (PC) value. Based on the proposed method, the optimal cluster is 3, with a PC value of 0.7393. Furthermore, other topics used for further research include comparing the results of Fuzzy Subtractive Clustering using different membership functions or on additional data.

Acknowledgment

The authors thank the Department of Mathematics, Faculty of Applied Science and Technology, for supporting this research.

References

[1] I. Sangadji, Y. Arvio, and Indrianto, "Dynamic segmentation of behavior patterns based on quantity value movement using fuzzy subtractive clustering method," *J. Phys. Conf. Ser.*, vol. 974, no. 1, pp. 0–7, 2018, doi: 10.1088/1742-6596/974/1/012009.
[2] C. Gu and K. F. Kim, "Fuzzy clustering algorithm of interactive multi-sensor probabilistic data," *J. Intell. Fuzzy Syst.*, vol. 35, no. 4, pp. 4267–4275, 2018, doi: 10.3233/JIFS-169747.
[3] A. C. Rencher, *Methods of multivariate analysis*, Second edi., vol. 4, no. 1. United States of America: John wiley & sons, inc., 2016
[4] C. C. Aggarwal, *An Introduction to Cluster Analysis*, 1 st. 2014.
[5] Rahmawati, Wartono, and A. Y. Putri, "Pengklasteran tingkat pendidikan pegawai menggunakan metode fuzzy substractive clustering (studi kasus : badan kepegawaian dan pelatihan daerah provinsi Riau)," vol. 5, no. 1, pp. 79–89, 2019.
[6] R. Sharma and K. Verma, "Fuzzy shared nearest neighbor clustering," *Int. J. Fuzzy Syst.*, vol. 21, no. 8, pp. 2667–2678, 2019, doi: 10.1007/s40815-019-00699-7.
[7] K. Sun, L. Liu, J. Qiu, and G. Feng, "Fuzzy Adaptive Finite-Time Fault-Tolerant Control for Strict-Feedback Nonlinear Systems," *IEEE Trans. Fuzzy Syst.*, vol. PP, no. c, pp. 1–10, 2020, doi:

10.1109/tfuzz.2020.2965890.
[8] S. Kangkang, Q. Jianbin, H. R. Karimi, and Y. Fu, "Event-Triggered Robust Fuzzy Adaptive Finite-Time Control of Nonlinear Systems with Prescribed Performance," *IEEE Trans. Fuzzy Syst.*, vol. 6706, no. c, pp. 1–12, 2020, doi: 10.1109/tfuzz.2020.2979129.
[9] E. Mehdizadeh, S. Nezhad, Sadi, S, and R. Moghhaddam, Tavakkoli, "Optimization of fuzzy clustering criteria by a hybrid pso and fuzzy c-means clustering algorithm," vol. 5, no. 3, pp. 1–14, 2008.
[10] S. Surono, A. E. Haryati, and J. Eliyanto, *An Optimization of Several Distance Function on Fuzzy Subtractive Clustering*. IOS Press, 2021.
[11] Y. Syahra and M. Syahril, "Implementasi data mining dengan menggunakan algoritma fuzzy subtractive clustering dalam pengelompokan nilai untuk menentukan minat belajar siswa smp primbana Medan," vol. 17, no. 1, pp. 54–63, 2018.
[12] A. E. Haryati and Sugiyarto, "Clustering with Principal Component Analysis and Fuzzy Subtractive Clustering Using Membership Function Exponential and Hamming Distance," in *IOP Conference Series: Materials Science and Engineering*, 2021, vol. 1077, no. 1, p. 012019, doi: 10.1088/1757-899x/1077/1/012019.
[13] S. Surono and R. D. A. Putri, "Optimization of fuzzy c-means clustering algorithm with combination of minkowski and chebyshev distance using principal component analysis," *Int. J. Fuzzy Syst.*, vol. 23, no. 1, pp. 139–144, 2020, doi: 10.1007/s40815-020-00997-5.
[14] O. Rodrigues, "Combining minkowski and cheyshev: new distance proposal and survey of distance metrics using k-nearest neighbours classifier," *Pattern Recognit. Lett.*, vol. 110, pp. 66–71, 2018, doi: 10.1016/j.patrec.2018.03.021.
[15] H. Hosseini, B. Tousi, and N. Razmjooy, "Application of fuzzy subtractive clustering for optimal transient performance of automatic generation control in restructured power system," *J. Intell. Fuzzy Syst.*, vol. 26, no. 3, pp. 1155–1166, 2014, doi: 10.3233/IFS-130802.
[16] L. M. Goyal, M. Mittal, and J. K. Sethi, "Fuzzy model generation using subtractive and fuzzy c-means clustering," *CSI Trans. ICT*, vol. 4, no. 2–4, pp. 129–133, 2016, doi: 10.1007/s40012-016-0090-3.
[17] X. Zhao and G. Yang, "An entropy-based online multi-model identification algorithm and generalized predictive control," *J. Intell. Fuzzy Syst.*, vol. 32, no. 3, pp. 2339–2349, 2017, doi: 10.3233/JIFS-16317.
[18] L. G. Martínez, J. R. Castro, G. Licea, A. Rodríguez-Díaz, and R. Salas, "Implementing fuzzy subtractive clustering to build a personality fuzzy model based on big five patterns for engineers," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 8266 LNAI, no. PART 2, pp. 497–508, 2013, doi: 10.1007/978-3-642-45111-9_43.
[19] L. T. Ngo and B. H. Pham, "Approach to image segmentation based on interval type-2 fuzzy subtractive clustering," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 7197 LNAI, no. PART 2, pp. 1–10, 2012, doi: 10.1007/978-3-642-28490-8_1.
[20] T. Sonamani Singh, P. Verma, and R. D. S. Yadava, "Fuzzy subtractive clustering for polymer data mining for saw sensor array based electronic nose," *Adv. Intell. Syst. Comput.*, vol. 546, pp. 245–253, 2017, doi: 10.1007/978-981-10-3322-3_23.
[21] S. Anggraini, M. Kusumawardani, and H. Darmono, "Perbandingan penempatan node b umts900 pada bts existing menggunakan fuzzy c-means dan fuzzy subtractive clustering," *J. JARTEL*, vol. 4, no. 1, pp. 170–177, 2017.
[22] S. Kusumadewi and H. Purnomo, *Aplikasi logika fuzzy untuk pendukung keputusan*. Yogyakarta: Graha Ilmu, 2010.
[23] E. S. Abdolkarimi and M. R. Mosavi, "Wavelet-adaptive neural subtractive clustering fuzzy inference system to enhance low-cost and high-speed INS/GPS navigation system," *GPS Solut.*, vol. 24, no. 2, pp. 1–17, 2020, doi: 10.1007/s10291-020-0951-y.
[24] K. Rezaei and H. Rezaei, "New distance and similarity measures for hesitant fuzzy sets and their application in hierarchical clustering," *J. Intell. Fuzzy Syst.*, vol. 39, no. 3, pp. 4349–4360, 2020, doi: 10.3233/JIFS-200364.
[25] S. Mahajan and S. K. Gupta, "On fully intuitionistic fuzzy multiobjective transportation problems using different membership functions," *Ann. Oper. Res.*, pp. 1–31, 2019, doi: 10.1007/s10479-019-03318-8.
[26] I. P. Debnath and S. K. Gupta, "Exponential membership function and duality gaps for i-fuzzy linear programming problems," *Iran. J. Fuzzy Syst.*, vol. 16, no. 2, pp. 147–163, 2019, doi: 10.22111/ijfs.2019.4549.
[27] K. Rezaei and H. Rezaei, "New distance and dimilarity measures for hesitant fuzzy soft sets," vol. 16, no. 6, pp. 159–176, 2019.
[28] J. C. Bezdek, *Pattern recognition with fuzzy objective function algorithms*. New York: Plenum Press, 1981.
[29] P. L. S. Cahyaningrum and N. Irsalinda, "Indonesian community welfare levels clustering using the fuzzy subtractive clustering (FCM) method," *J. Phys. Conf. Ser.*, vol. 1373, no. 1, 2019, doi: 10.1088/1742-6596/1373/1/012036.
[30] N. Azizah, D. Yuniarti, and R. Goejantoro, "Penerapan Metode Fuzzy Subtractive Clustering (Studi Kasus: Pengelompokkan Kecamatan di Provinsi Kalimantan Timur Berdasarkan Luas Daerah dan Jumlah Penduduk Tahun 2015)," *J. EKSPONENSIAL*, vol. 9, no. 2, pp. 197–206, 2018.