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

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## ABSTRACT

Fuzzy clustering algorithm is a partition method used to assign 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 center of the cluster. Therefore, the purpose of this research is to determine the number of clusters 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 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 largest PC value. Based on the results obtained, the highest PC value is in cluster 3, therefore heart failure can be grouped into 3, namely low, moderate, severe.

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## 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 cluster 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 in reducing 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 used to assign objects from a data set to clusters [9]. It determines the center by marking the average location, which is initially less accurate. However, by fixing the cluster center and membership level of each data point repeatedly, the cluster center moves to the right location [1,10].

There are several types of clustering methods, 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, which makes the process complicated. Meanwhile, in FSC,

the number of clusters is not defined at the beginning and does not use a membership matrix. This method has more consistent results and better speed compared to FCM [11,12].

Some researches had been conducted on fuzzy clusterings, such as [13,14] a modified FCM using a combination of Minkowski and Chebyshev distances. Meanwhile, research on FSC was conducted 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] 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 structure can 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 some similarities and in relation to 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 greater 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 point to be clustered is reduced in density [22,23], with variation between two Euclidean distances. According to [24], a well-known distance in the measurement of two fuzzy sets is hamming. 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 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 choose another point until all are tested.

The FSC method has 2 comparison factors, namely 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 3 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]:

$$\mu(x) = \begin{cases} 1 & x \leq a \\ e^{-\frac{(x-a)}{(b-a)} - e^{-s}} & a \leq x \leq b \\ 0 & x \geq b \end{cases} \quad (1)$$

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  $U = \{u_1, u_2, \dots, u_n\}$ , 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:

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

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

With

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

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.

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

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

where for the first iteration, the value of  $Z$  is equal to the value of  $M$ .

$R$  = the ratio between the largest potential in the first and subsequent iteration.

- 6. Cluster center candidates are accepted if  $ratio > accept\ ratio$  and rejected assuming  $ratio < accept\ ratio$ . The distances between the candidate and the previous cluster center is calculated using Equation 6.

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

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 accepted as the new center assuming the sum between the ratio and  $Mds$  (the closest distance between the prospective cluster center and the cluster center)  $\geq 1$ . Meanwhile, it is not accepted assuming the number between the ratio and  $Mds < 1$ . Furthermore, the iteration stops supposing the  $ratio \leq reject\ ratio$ .

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

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

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

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

- $D_i^t$  = 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.
- $\mu$  = the membership value.

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

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

- $\sigma_j$  = 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:

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

- $\mu_{ki}$  = 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.
- $\sigma_j$  = 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 was carried out using 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 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

$X_1$	$X_2$	$X_3$	$X_4$	...	$X_{11}$
0.2609	1	0.8911	1	...	1
0.6387	1	0	1	...	1
0.4324	1	0.9754	1	...	0
0.7571	0	0.9823	1	...	1
⋮	⋮	⋮	⋮	⋮	⋮
0.5308	1	0.6071	1	...	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 107<sup>th</sup>, 22<sup>nd</sup>, 23<sup>rd</sup> and 91<sup>st</sup> 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 row in the C matrix above shows the respective cluster center in the 107<sup>th</sup>, 22<sup>nd</sup> and 68<sup>th</sup> 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 shows the respective cluster center in the 107<sup>th</sup> and 22<sup>nd</sup> data with the sigma value  $\sigma$  calculated using equation 2.10 and the results shown in Table II.

Table 2. Sigma value of cluster

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

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

**6**  
 Table 3. Membership value  $r = 1.97$

The value of $\mu$ 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 **6** in cluster 1 due to the presence of the largest membership degree. Furthermore, the second data is in cluster 1 because the highest membership degree is located in cluster 3 until the 150<sup>th</sup> data. The cluster results from Table III are shown in Figure 1.

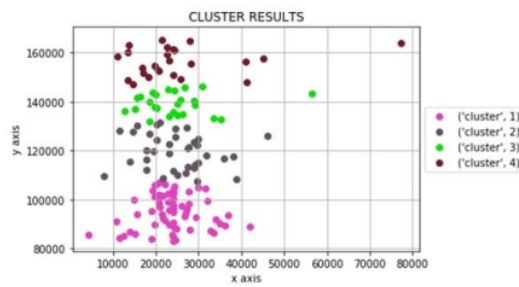


Fig. 1. Results of 4 clusters.

Table 4. Membership value  $r = 2.45$

The value of $\mu$ 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 150<sup>th</sup> 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  $r = 2.5$

The value of $\mu$ 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 150<sup>th</sup> 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.

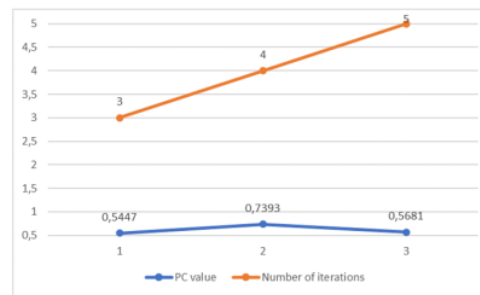


Fig. 4. PC value and number of iterations

#### IV. Conclusion

This research shows the use of 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 most 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 different data.

#### 23 Acknowledgment

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