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Research Article

Application of the Fuzzy C-Means Method in Grouping Heart Abnormalities Based on Electrocardiogram Medical Records

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Abstract

Heart disease is the main cause of death which can be diagnosed using an electrocardiogram. This study aims to classify heart defects using the Fuzzy C Means technique. The advantage of using Fuzzy C Means is that it is unsupervised and can reach a convergent cluster center under certain conditions. It is a clustering model that has the value of the objective function, number of iterations and completed time. In an unsupervised learning, the focus is more on exploring data such as looking for patterns in the data. Clustering itself aims to identify patterns of similar data to be grouped. It can be a solution to overcome the process of determining the risk of heart disease. The results showed that there were 10 data grouped into cluster 1 and 10 data into cluster 2. The first group (Cluster 1) consisted of patients with serial numbers 3,5,8,9,11,12,16,17,19,20, while the second group (Cluster 2) consisted of patients with serial numbers 1,2,4,6,7,10,13,14,15 and 18. Accuracy testing results in a success rate of 60%.

Keywords: Electrocardiogram; Clustering; Diagnosis; Fuzzy C-Means; Heart Disease.

Introduction

Investments to improve the quality of human resources is significantly required in the health development. Information technology is a vital sector to consider in this regard. Several computational methods have considerably contributed to the health sector. In the struggles to provide solutions to analyze heart disorders, Fuzzy C-Means technique offers approach for grouping data on patients with heart disorders. The advantages of this method is that it can perform the clustering process with many variables simultaneously. Additionally, it can also increase the rate by reducing the number of iterations as well as obtain very precise and accurate data partitions.

In addition to Fuzzy C-Means, several computational method have been used to identify cardiac abnormalities in heart disorder issues such as the use of an expert system with a certainty factor approach that is built based on a person's expertise that has been adopted into an application [1] ,[2], [3]. Also, data mining has been implemented for the various needs such as predicting heart disease [4],[5],[6], identifying the possibility of disease spread using an association rule approach [7] and supporting decisions for the diagnosis of heart disease [8]. On the other hand, Cognitive Map of Certainty (CCM) is used to assess the causality of cognitive maps using the certainty factor for heart failure[9]. Others, Fuzzy Expert System is used to diagnose Heart Disease [10], authentication method in utilizing ECG wave features [11], Cardiology expert system based on electrocardiogram data using factors with multiple rules [12], The decision tree approach is used to predict the causative factors of heart disease [13],[14],[15], classification of heart disease [16],[17],[18], and to predict a person's risk of heart attack. Everything can also be done mobile by utilizing smartphone technology [19].

Research on Fuzzy C-Means (FCM) method has been carried out by many previous researchers. It applies fuzzy grouping, where each data can be a member of several clusters with different degrees of membership in each cluster. It applies an iterative algorithm to the data clustering process. This research is expected to make a positive

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contribution to strengthening the confidence of doctors to correctly diagnose the type of heart abnormality from the results of the electrocardiogram medical record.

This study aims to provide an alternative solution to overcome the limitations of medical personnel in the field of heart disease specialists by applying cluster model approach for early diagnosis of heart disorders. Clustering is one solution that can overcome the process of determining the risk of heart disease. The results showed that there were 10 data that were grouped into cluster 1 while the other 10 data were grouped into cluster 2. The first group (Cluster 1) consisted of patients with serial numbers 3,5,8,9,11,12,16,17,19,20, while the second group (Cluster 2) consisted of patients with serial numbers 1,2, 4,6,7,10,13,14,15 and 18.

ECG COMPONENTS

There are three main components of an ECG: the P wave, which represents depolarization of the atria; the QRS complex, which represents depolarization of the ventricles; and the T wave, which represents repolarization of the ventricles. After understanding the electrical impulse system in the heart, the next step is to identify the components shown on the ECG chart. There are several important components that must be considered in the EKG results, namely, P waves, QRS complexes, T waves, and PR intervals. **Figure 1** shows the important components in the ECG result.

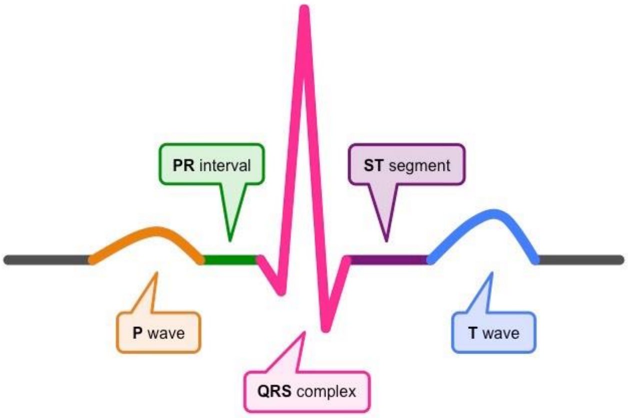

Figure 1. The important components in the ECG result.

The P wave is a small bump showing atrial depolarization with both atrial halves of the heart contracting. The QRS complex, which looks like an inverted V, shows depolarization when the heart's ventricles are contracting, while the T wave shows ventricular repolarization, when the ventricles are at rest. **Figure 2** below illustrates a normal ECG, while **Figure 3** shows an abnormal ECG.

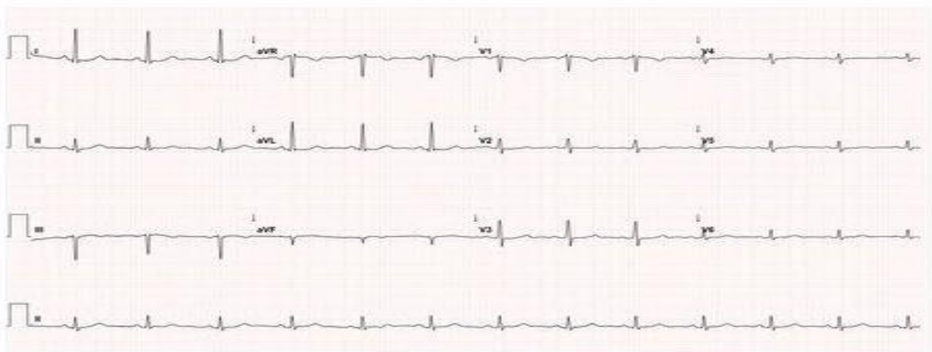

Figure 2. ECG Normal

Figure 2 shows Normal Heart Detection based on Electrocardiogram (ECG). Generally, the ECG is considered normal if it fulfills the several criteria such as: The P wave must be positive in Leads I, II, V2, V3, V4, V5 and V6; the Q wave 1 should be small squares in leads I,II,V2,V3,V4,V5,V6; the R wave rises from V1 to V4; the S wave shortens from V1 to V3; the Negative T wave should be in lead AVR; the T wave must be above leads I,II,V2,V3,V4,V5,V6; and PR intervals should be of 3-5 squares.

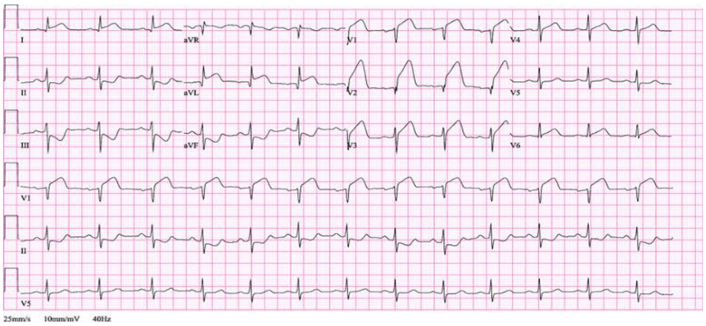

Figure 3. ECG Abnormal

Figure 3 shows the Detection of Abnormal Heart Disorders. In general, the ECG is assessed abnormal if there are several conditions appear such as: the P wave is in lead I inversion; pulmonary P wave is tapering; mitral P wave is too wide; P wave is flat; Q wave exceeds 2 small squares; R wave in V1 tends to rise; S wave exceeds 7 large squares in V1-V2; QR complex is more than a small box, V5,V6,I,II,AVL; and very long/very short QT inverted T waves.

Method

The initial stage of this study is to carry out the process of collecting data from electrocardiogram medical records. The interpretation of the type of heart abnormality from the records comes after. Next, classifying the heart disorders by applying the Fuzzy C-Means approach. The processes are continue with need analysis, system design, implementation of C-Means method, coding system, system evaluation and testing, and finally systems usage. Figure 4 below shows the stages of the research method.

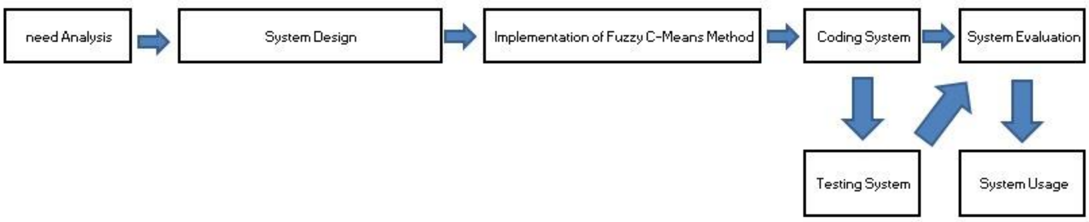

Figure 4. Stages of Research Method

The method employed in this study is the clustering technique using the Fuzzy C-Means analysis method which aims to classify normal and abnormal hearts based on electrocardiogram medical records, used as variables in this study. Firstly, the center of the cluster which is the value for each cluster as well as the degree of membership of each data point should be determined. Subsequently, the center of the cluster degree of membership will go to the right point. This research was conducted by performing manual calculations based on the Fuzzy C-Means algorithm.

Fuzzy C-Means

Fuzzy C-Means is a data clustering technique where the existence of each data point in a cluster is determined by the degree of membership. Fuzzy clustering is very useful for fuzzy modeling, especially in identifying fuzzy rules.

The stages of the Fuzzy C-Means method are as follows:

a. Input data to be clustered X, in the form of a matrix of size n x m (n = number of data samples, m = is the attribute of each data). Xij = i-th sample data (i = 1,2,….,n), jth attribute(j=1,2,…m)

b. Define:1. Number of Clusters = c;
   2. Rank = w;
   3. Maximum iteration = Maxlter;
   4. The smallest error =
   5. Initial Objective Function = P0 = 0;
   6. Initial iteration = t = 1;

Results and Discussion

Clustering Data Using Fuzzy C-Means (FCM)

Fuzzy C-Means (FCM) is a data clustering technique in which the existence of each data point in a cluster is determined by the degree of membership. Membership function of a data to a certain cluster is calculated using the following formula :

$$\frac{2}{m\ 1}$$

$$ik = \;{}^{c}_{j\ 1}\; \frac{D(x_k, v_i)}{D(x_k, v_j)}$$

where:
u ik : Membership function data k to cluster i v
i : The value of the i-th cluster centroid
m : Weighting Exponent

The membership function, u ik , has a value region of 0≤ u ik 1. Data items that have a higher probability of belonging to a group will have a membership function value to that group that is close to 1 while the other groups will be close to 0.

a. Determine the X Matrix of size n x m, where n = the number of data to be clustered; and m = number of variables (criteria).
b. Number of clusters to be formed = C(≥2)
c. Power (weight) = w (>1).
d. Maximum iterations
e. Termination criteria = (very small positive value) f. Initial iteration, t=1, and =1;
f. The form of the initial partition matrix, U0 , is as follows:

$$U = \begin{matrix} {}_{11}(x_1) & {}_{12}(x_2) & \cdots & {}_{1n}(xn) \\ {}_{21}(x_1) & {}_{22}(x_2) & \cdots & {}_{2n}(xn) \\ \vdots & \vdots & \cdots & \vdots \\ {}_{c1}(x_1) & {}_{c2}(x_2) & \cdots & {}_{cn}(xn) \end{matrix}$$

g. Calculate the Cluster Center, V, for each cluster:

$$V_{ij} = \frac{\overset{n}{\underset{k=1}{}} (\ \ _{ik})^{w} . x_{kj}}{\overset{n}{\underset{k=1}{}} (\ \ _{ik})^{w}}$$

h. Fix the degree of membership of each data in each cluster (fix the partition matrix), as follows:

$$ik = \;{}^{c}_{j=1}\; \frac{d_{ik}}{d_{jk}} \quad 2/(w\ 1) \quad 1$$

With :

$$d_{ik} = d(x_k\ \ v_i) = \overset{m}{\underset{j=1}{}} (x_{kj}\ \ v_{ij}) \quad 1/2$$

i. Determine the stopping criteria, namely the change in the partition matrix in the current iteration with the previous iteration, as follows:

$$= \| U^{1} \quad U^{1} \quad {}^{1} \|$$

j. If , then the iteration is stopped, but if > , then increase the iteration (t=t+1) and return to step 3. The search for the value of D can be carried out by taking the largest element of the absolute value of the difference between ik (t) and ik (t-1)

Table 1. Patient Data Sample

No	HR	P-R	QRS	QT	QTC	AXIS	RV6	SV1	R+S	No	HR	P-R	QRS	QT	QTC	AXIS	RV6	SV1	R+S
1	134	157	95	31s8	433	153	0,58	0,32	0,9	11	100	150	86	358	462	38	0,25	-1,12	1,66
2	106	169	99	329	439	41	2,36	1,59	3,95	12	84	92	398	470	470	26	-0,74	1	3
3	137	271	113	385	420	66	0,89	0,96	1,85	13	114	104	96	282	388	-11	2,86	- 0,424	3,77
4	140	212	99	336	412	57	1,08	0,12	1,2	14	102	140	110	340	442	43	1,633	- 0,551	0,57
5	136	158	98	390	433	17	1,1	0,5	3,32	15	115	135	84	340	471	54	1,43	0,97	2,4
6	134	136	110	272	406	40	1,19	2,13	3,32	16	66	130	98	380	398	26	2,341	- 1,904	1,65
7	118	169	100	314	441	61	2,36	1,59	3,95	17	85	136	102	365	435	-4	2,6	- 1,096	1,97
8	124	151	99	378	458	67	2,38	1,28	3,66	18	133	112	92	290	430	42	1,9	- 1,096	86
9	140	266	80	394	420	51	0,91	0,22	1,13	19	100	174	119	349	450	69	1,24	0,42	1,66
10	125	152	108	373	417	63	2,26	0,94	3,2	20	75	126	135	398	447	99	2,26	0,11	2,37

Continuation of **Table 1**

No	Lead II Gel P	II-III_AVF Gel T	Lead I AVL Gel T	Lead V2-V6	Lead II-III AVF Seg ST	Lead I AVL Seg ST	V2-V6 Seg ST	No	Lead II Gel P	II-III_AVF Gel T	Lead I AVL Gel T	Lead V2-V6	Lead II-III AVF Seg ST	Lead I AVL Seg ST	V2-V6 Seg ST
1	0	1	0	1	1	1	0	11	1	0	1	0	1	1	1
2	1	0	0	1	1	1	0	12	1	1	1	1	1	1	1
3	1	0	1	1	1	1	0	13	1	1	1	1	1	1	1
4	1	1	0	1	1	1	1	14	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	15	0	1	1	1	1	1	1
6	1	1	1	1	1	1	1	16	1	1	1	1	1	1	1
7	1	0	1	1	1	1	1	17	0	1	1	1	1	1	1
8	1	1	1	1	1	1	1	18	0	1	1	1	1	1	1
9	1	1	1	1	1	1	0	19	1	0	1	1	1	1	1
10	1	1	1	1	1	1	1	20	1	1	1	1	1	1	1

1) Determine Initial Value

o Number of clusters	=	c	=	2;
o Rank	=	w	=	2;
o Maximum iterations	=	MaxIter	=	100;
o Smallest error expected	=	x	=	10^{-5};
o Initial objective function	=	P_0	=	0
o Early iteration	=	t	=	1;

Table 2 Variables Used

X_1	*HR*	*X9*	*R+S*
X_2	P-R	X10	Lead II VI P Gelombang Wave
X_3	QRS	X11	II_III_AVF T Gelombang wave
X_4	QT	X12	Lead I_AVL T wave
X_5	QTC	X13	Leads V2-V6 T Gelombang wave
X_6	AXIS	X14	Lead II_III_AVF Segment ST
X_7	RV6	X15	Lead I_AVL Segment ST
X_8	SV1	X16	V2-V6 Segment ST

3) Initial Stage of Initial Partition

Table 3. Initial Partition Matrix (U)

No.	C1	C2	No.	C1	C2
1	0,393	0,607	11	0,663	0,337
2	0,479	0,521	12	0,516	0,484
3	0,540	0,460	13	0,413	0,587
4	0,464	0,536	14	0,467	0,533
5	0,640	0,360	15	0,475	0,525
6	0,324	0,676	16	0,701	0,299
7	0,354	0,646	17	0,703	0,297
8	0,571	0,429	18	0,403	0,597
9	0,552	0,448	19	0,543	0,457
10	0,494	0,506	20	0,559	0,441

4. The next step is to calculate the Cluster Center shown in **Table 4**, which is to calculate the first Cluster center

Calculating Cluster Center
Using the following equation.

$$V_{kj} = \frac{\sum_{i=1}^{n}((\mu_{ik})^{w} * X_{ij})}{(\mu_{ik})^{w}}$$

where :
(μ_ik)〗^w = Degree of membership
Xij = Sample data
Vkj = Center Cluster iteration
W = Rank
If w = 2, then the following equation can be made:

$$V_{kj} = \frac{\sum_{i=1}^{n}((\mu_{ik})^2 * X_{ij})}{(\mu_{ik})^2}$$

Looking for Cluster Center 1

So $V_{k1} = (\frac{\sum_{i=1}^{n}((\mu_{i1})^2 * x_{i1})}{(\mu_{i1})^2}) =$

Is known:

Table 4. Calculation of Cluster Center 1 iteration 1

No	Level Membership (μ_{i1})	Clustered data				$(\mu_{ik})^2$	$(\mu_{i1})^2 * x_{i1}$	$(\mu_{i1})^2 * x_{i2}$	$(\mu_{i1})^2 * x_{i3}$	$(\mu_{i1})^2 * x_{i4}$
		x_{i1}	x_{i2}	x_{i3}	x_{i4}					
1	0,39319	134	157	95	318	0,154	20,585	24,118	14,594	48,850
2	0,47924	106	169	99	329	0,237	25,110	40,034	23,452	77,936
3	0,54019	137	271	113	385	0,293	40,175	79,470	33,137	112,900
4	0,4641	140	212	99	336	0,216	30,302	45,886	21,428	72,726
5	0,63999	136	158	98	390	0,415	56,471	65,606	40,692	161,939
6	0,32433	134	136	110	272	0,104	13,913	14,121	11,421	28,241
7	0,35422	118	169	100	314	0,128	15,065	21,576	12,767	40,089
8	0,57084	124	151	99	378	0,332	41,184	50,151	32,880	125,544
9	0,55215	140	266	80	394	0,307	42,931	81,569	24,532	120,820
10	0,49397	125	152	108	373	0,246	30,740	37,380	26,559	91,728
11	0,66282	100	150	86	358	0,451	45,075	67,613	38,765	161,369
12	0,51614	84	92	398	470	0,267	22,398	24,531	106,122	125,320
13	0,41278	114	104	96	282	0,169	19,298	17,605	16,251	47,738
14	0,46687	102	140	110	340	0,228	23,251	31,913	25,075	77,504
15	0,47516	115	135	84	340	0,231	26,606	31,234	19,434	78,663
16	0,7007	66	130	98	380	0,491	32,379	63,777	48,078	186,424
17	0,70306	85	136	102	365	0,501	42,587	68,140	51,105	182,875
18	0,40266	133	112	92	290	0,162	21,498	18,103	14,870	46,874
19	0,54278	100	174	119	349	0,301	30,068	52,318	35,781	104,937
20	0,55908	75	126	135	398	0,314	23,521	39,516	42,338	124,820
$\sum(\mu_{i1}^2)$							603,157	874,661	639,281	2017,297
$\sum[(\mu_{i1}^2)*X_{ij}] / \sum(\mu_{i1}^2)$							108,7357	157,6818	115,2481	363,6735

Continued Table 4

No	Membership (μ_{i1})	Clustered data				$(\mu_{ik})^2$	$(\mu_{i1})^2 * x_{i5}$	$(\mu_{i1})^2 * x_{i6}$	$(\mu_{i1})^2 * x_{i7}$	$(\mu_{i1})^2 * x_{i8}$
		x_{i5}	x_{i6}	x_{i7}	x_{i8}					
1	0,312	433	153	0,58	0,32	0,098	42,27	14,93	0,06	0,03
2	0,087	439	41	2,36	1,59	0,008	3,35	0,31	0,02	0,01
3	0,933	420	66	0,89	0,96	0,871	365,92	57,50	0,78	0,84
4	0,558	412	57	1,08	0,12	0,312	128,44	17,77	0,34	0,04
5	0,341	433	17	1,1	0,5	0,116	50,34	1,98	0,13	0,06
6	0,204	406	40	1,19	2,13	0,042	16,94	1,67	0,05	0,09
7	0,064	441	61	2,36	1,59	0,004	1,83	0,25	0,01	0,01
8	0,197	458	67	2,38	1,28	0,039	17,69	2,59	0,09	0,05

No	Membership (μ_{i1})	Clustered data				$(\mu_{ik})^2$	$(\mu_{i1})^2 * x_{i5}$	$(\mu_{i1})^2 * x_{i6}$	$(\mu_{i1})^2 * x_{i7}$	$(\mu_{i1})^2 * x_{i8}$
		x_{i5}	x_{i6}	x_{i7}	x_{i8}					
9	0,929	420	51	0,91	0,22	0,864	362,82	44,06	0,79	0,19
10	0,160	417	63	2,26	0,94	0,026	10,72	1,62	0,06	0,02
11	0,66282	462	38	0,25	-1,12	0,451	208,247	17,1285	0,11269	-0,5048
12	0,51614	470	26	-0,74	1	0,267	125,32	6,93259	-0,1973	0,26664
13	0,41278	388	-11	2,86	-0,424	0,169	65,6817	-1,8621	0,48415	-0,0718
14	0,46687	442	43	1,633	-0,551	0,228	100,755	9,80196	0,37225	-0,1256
15	0,47516	471	54	1,43	0,97	0,231	108,971	12,4935	0,33085	0,22442
16	0,7007	398	26	2,341	-1,904	0,491	195,254	12,7553	1,14847	-0,9341
17	0,70306	435	-4	2,6	-1,096	0,501	217,947	-2,0041	1,30267	-0,5491
18	0,40266	430	42	1,9	-1,096	0,162	69,5034	6,7887	0,30711	-0,1772
19	0,54278	450	69	1,24	0,42	0,301	135,306	20,7469	0,37284	0,12629
20	0,55908	447	99	2,26	0,11	0,314	140,187	31,0481	0,70878	0,0345
						5,495	2367,492	256,5094	7,27251	-0,37075
$\sum[(\mu_{i1}^2)*X_{ij}] / \sum(\mu_{i1}^2)$							430,8448	498,0887	1,323478	-0,06747

Continued Table 4

No	Membership (μ_{i1})	Clustered data				$(\mu_{ik})^2$	$(\mu_{i1})^2 * x_{i9}$	$(\mu_{i1})^2 * x_{i10}$	$(\mu_{i1})^2 * x_{i11}$	$(\mu_{i1})^2 * x_{i12}$
		x_{i9}	x_{i10}	x_{i11}	x_{i12}					
1	0,312	0,9	0	0	1	0,098	0,09	0,00	0,00	0,10
2	0,087	3,95	0	1	0	0,008	0,03	0,00	0,01	0,00
3	0,933	1,85	0	1	0	0,871	1,61	0,00	0,87	0,00
4	0,558	1,2	1	1	1	0,312	0,37	0,31	0,31	0,31
5	0,341	3,32	1	1	1	0,116	0,39	0,12	0,12	0,12
6	0,204	3,32	1	1	1	0,042	0,14	0,04	0,04	0,04
7	0,064	3,95	1	0	1	0,004	0,02	0,00	0,00	0,00
8	0,197	3,66	1	1	1	0,039	0,14	0,04	0,04	0,04
9	0,929	1,13	1	1	1	0,864	0,98	0,86	0,86	0,86
10	0,160	3,2	1	1	1	0,026	0,08	0,03	0,03	0,03
11	0,663	1,66	1	0	1	0,439	0,73	0,44	0,00	0,44
12	0,516	3	1	1	1	0,266	0,80	0,27	0,27	0,27
13	0,413	3,77	1	1	1	0,170	0,64	0,17	0,17	0,17
14	0,467	0,57	1	1	1	0,218	0,12	0,22	0,22	0,22
15	0,475	2,4	0	1	1	0,226	0,54	0,00	0,23	0,23
16	0,701	1,65	1	1	1	0,491	0,81	0,49	0,49	0,49
17	0,703	1,97	0	1	1	0,494	0,97	0,00	0,49	0,49
18	0,403	86	0	1	1	0,162	13,94	0,00	0,16	0,16
19	0,543	1,66	1	0	1	0,295	0,49	0,29	0,00	0,29
20	0,559	2,37	1	1	1	0,313	0,74	0,31	0,31	0,31
$\sum(\mu_{i1}^2)$						5,454	23,63	3,59	4,62	4,57
σ							4,3326	0,658232	0,847085	0,837917

Continued Table 4

No	Membership (μ_{i1})	Clustered data				$(\mu_{ik})^2$	$(\mu_{i1})^2 * x_{i13}$	$(\mu_{i1})^2 * x_{i14}$	$(\mu_{i1})^2 * x_{i15}$	$(\mu_{i1})^2 * x_{i16}$
		x_{i13}	x_{i14}	x_{i15}	x_{i116}					
1	0,312	0	1	1	1	0,098	0	0,09761	0,09761	0,0976
2	0,087	0	1	1	1	0,008	0	0,00763	0,00763	0,0076
3	0,933	1	1	1	1	0,871	0,87123	0,87123	0,87123	0,8712
4	0,558	0	1	1	1	0,312	0	0,31174	0,31174	0,3117
5	0,341	1	1	1	1	0,116	0,11627	0,11627	0,11627	0,1163
6	0,204	1	1	1	1	0,042	0,04173	0,04173	0,04173	0,0417
7	0,064	1	1	1	1	0,004	0,00414	0,00414	0,00414	0,0041
8	0,197	1	1	1	1	0,039	0,03863	0,03863	0,03863	0,0386
9	0,929	1	1	1	0	0,864	0,86387	0,86387	0,86387	0
10	0,160	1	1	1	1	0,026	0,0257	0,0257	0,0257	0,0257
11	0,66282	0	1	1	1	0,451	0,00	0,44	0,44	0,44
12	0,51614	1	1	1	1	0,267	0,27	0,27	0,27	0,27
13	0,41278	1	1	1	1	0,169	0,17	0,17	0,17	0,17
14	0,46687	1	1	1	1	0,228	0,22	0,22	0,22	0,22
15	0,47516	1	1	1	1	0,231	0,23	0,23	0,23	0,23
16	0,7007	1	1	1	1	0,491	0,49	0,49	0,49	0,49
17	0,70306	1	1	1	1	0,501	0,49	0,49	0,49	0,49
18	0,40266	1	1	1	1	0,162	0,16	0,16	0,16	0,16
19	0,54278	1	1	1	1	0,301	0,29	0,29	0,29	0,29
20	0,55908	1	1	1	1	0,314	0,31	0,31	0,31	0,31
$\sum(\mu_{i1}^2)$						5,495	4,59157	5,44855	5,44855	4,5845
$\sum[(\mu_{i1}^2)*X_{ij}] / \sum(\mu_{i1}^2)$							0,83559 1	1,18664 2	1	0,841417

Table 5. Calculation of Cluster Center 2 iteration 1

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{1i}$	$(\mu_{i1})^2 * x_{i2}$	$(\mu_{i1})^2 * x_{i3}$	$(\mu_{i1})^2 * x_{i4}$
		x_{i1}	x_{i2}	x_{i3}	x_{i4}					
1	0,688	134	157	95	318	0,473	63,349	74,223	44,912	150,336
2	0,913	106	169	99	329	0,833	88,296	140,774	82,465	274,051
3	0,067	137	271	113	385	0,004	0,608	1,202	0,501	1,708
4	0,442	140	212	99	336	0,195	27,310	41,355	19,312	65,543
5	0,659	136	158	98	390	0,434	59,065	68,620	42,562	169,379
6	0,796	134	136	110	272	0,633	84,845	86,112	69,649	172,223
7	0,936	118	169	100	314	0,875	103,304	147,953	87,546	274,894
8	0,803	124	151	99	378	0,646	80,047	97,476	63,908	244,013
9	0,071	140	266	80	394	0,005	0,697	1,324	0,398	1,961
10	0,840	125	152	108	373	0,705	88,133	107,170	76,147	262,988
11	0,337	100	150	86	358	0,11	11,37	17,05	9,78	40,70
12	0,484	84	92	398	470	0,23	19,67	21,54	93,18	110,04
13	0,587	114	104	96	282	0,34	39,31	35,86	33,10	97,24

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i1}$	$(\mu_{i1})^2 * x_{i2}$	$(\mu_{i1})^2 * x_{i3}$	$(\mu_{i1})^2 * x_{i4}$
		x_{i1}	x_{i2}	x_{i3}	x_{i4}					
14	0,533	102	140	110	340	0,28	28,99	39,79	31,27	96,64
15	0,525	115	135	84	340	0,28	31,68	37,19	23,14	93,66
16	0,299	66	130	98	380	0,09	5,91	11,65	8,78	34,04
17	0,297	85	136	102	365	0,09	7,49	11,99	8,99	32,18
18	0,597	133	112	92	290	0,36	47,46	39,96	32,83	103,48
19	0,457	100	174	119	349	0,21	20,90	36,37	24,88	72,96
20	0,441	75	126	135	398	0,19	14,58	24,50	26,25	77,38
$\sum (\mu_{i1}^2)$						6,983	823,014	1042,109	779,6	2375,416
$\sum [(\mu_{i1}^2)*X_{ij}] / \sum (\mu_{i1}^2)$							117,8597	1,266211	0,748098	3,046968

Continued **Table 5** Calculation of Cluster Center 2 iteration 1

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i5}$	$(\mu_{i1})^2 * x_{i6}$	$(\mu_{i1})^2 * x_{i7}$	$(\mu_{i1})^2 * x_{i8}$
		x_{i5}	x_{i6}	x_{i7}	x_{i8}					
1	0,688	433	153	0,58	0,32	0,473	204,70	72,33	0,27	0,15
2	0,913	439	41	2,36	1,59	0,833	365,68	34,15	1,97	1,32
3	0,067	420	66	0,89	0,96	0,004	1,86	0,29	0,00	0,00
4	0,442	412	57	1,08	0,12	0,195	80,37	11,12	0,21	0,02
5	0,659	433	17	1,1	0,5	0,434	188,05	7,38	0,48	0,22
6	0,796	406	40	1,19	2,13	0,633	257,07	25,33	0,75	1,35
7	0,936	441	61	2,36	1,59	0,875	386,08	53,40	2,07	1,39
8	0,803	458	67	2,38	1,28	0,646	295,66	43,25	1,54	0,83
9	0,071	420	51	0,91	0,22	0,005	2,09	0,25	0,00	0,00
10	0,840	417	63	2,26	0,94	0,705	294,01	44,42	1,59	0,66
11	0,337	462	38	0,25	-1,12	0,11	52,52	4,32	0,03	-0,13
12	0,484	470	26	-0,74	1	0,23	110,04	6,09	-0,17	0,23
13	0,587	388	-11	2,86	-0,424	0,34	133,79	-3,79	0,99	-0,15
14	0,533	442	43	1,633	-0,551	0,28	125,63	12,22	0,46	-0,16
15	0,525	471	54	1,43	0,97	0,28	129,74	14,87	0,39	0,27
16	0,299	66	130	98	380	0,09	35,65	2,33	0,21	-0,17
17	0,297	85	136	102	365	0,09	38,36	-0,35	0,23	-0,10
18	0,597	133	112	92	290	0,36	153,43	14,99	0,68	-0,39
19	0,457	100	174	119	349	0,21	94,07	14,42	0,26	0,09
20	0,441	75	126	135	398	0,19	86,90	19,25	0,44	0,02
$\sum (\mu_{i1}^2)$						6,983	3035,7	376,27	12,4	5,45
$\sum [(\mu_{i1}^2)*X_{ij}] / \sum (\mu_{i1}^2)$							434,72 72	53,88372	1,775741	0,780467

Continued **Table 5** Calculation of Cluster Center 2 iteration 1

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i9}$	$(\mu_{i1})^2 * x_{i10}$	$(\mu_{i1})^2 * x_{i11}$	$(\mu_{i1})^2 * x_{i12}$
		x_{i9}	x_{i10}	x_{i11}	x_{i12}					
1	0,688	0,9	0	0	1	0,473	0,43	0,00	0,00	0,47
2	0,913	3,95	0	1	0	0,833	3,29	0,00	0,83	0,00
3	0,067	1,85	0	1	0	0,004	0,01	0,00	0,00	0,00
4	0,442	1,2	1	1	1	0,195	0,23	0,20	0,20	0,20

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i9}$	$(\mu_{i1})^2 * x_{i10}$	$(\mu_{i1})^2 * x_{i11}$	$(\mu_{i1})^2 * x_{i12}$
		x_{i9}	x_{i10}	x_{i11}	x_{i12}					
5	0,659	3,32	1	1	1	0,434	1,44	0,43	0,43	0,43
6	0,796	3,32	1	1	1	0,633	2,10	0,63	0,63	0,63
7	0,936	3,95	1	0	1	0,875	3,46	0,88	0,00	0,88
8	0,803	3,66	1	1	1	0,646	2,36	0,65	0,65	0,65
9	0,071	1,13	1	1	1	0,005	0,01	0,00	0,00	0,00
10	0,840	3,2	1	1	1	0,705	2,26	0,71	0,71	0,71
11	0,337	1,66	1	0	1	0,11	0,19	0,11	0,00	0,11
12	0,484	3	1	1	1	0,23	0,70	0,23	0,23	0,23
13	0,587	3,77	1	1	1	0,34	1,30	0,34	0,34	0,34
14	0,533	0,57	1	1	1	0,28	0,16	0,28	0,28	0,28
15	0,525	2,4	0	1	1	0,28	0,66	0,00	0,28	0,28
16	0,299	1,65	1	1	1	0,09	0,15	0,09	0,09	0,09
17	0,297	1,97	0	1	1	0,09	0,17	0,00	0,09	0,09
18	0,597	86	0	1	1	0,36	30,69	0,00	0,36	0,36
19	0,457	1,66	1	0	1	0,21	0,35	0,21	0,00	0,21
20	0,441	2,37	1	1	1	0,19	0,46	0,19	0,19	0,19
$\sum (\mu_{i1}{}^2)$						6,983	50,42	4,95	5,31	6,15
$\sum [(\mu_{i1}{}^2)^* X_{ij}] / \sum (\mu_{i1}{}^2)$							7,2203 92	0,7088 64	0,760418	0,88071

Continued **Table 5** Calculation of Cluster Center 2 iteration 1

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i13}$	$(\mu_{i1})^2 * x_{i14}$	$(\mu_{i1})^2 * x_{15}$	$(\mu_{i1})^2 * x_{i16}$
		x_{i13}	x_{i14}	x_{i15}	x_{i16}					
1	0,688	0	1	1	1	0,473	0	0,47276	0,47276	0,4728
2	0,913	0	1	1	1	0,833	0	0,83298	0,83298	0,833
3	0,067	1	1	1	1	0,004	0,00444	0,00444	0,00444	0,0044
4	0,442	0	1	1	1	0,195	0	0,19507	0,19507	0,1951
5	0,659	1	1	1	1	0,434	0,4343	0,4343	0,4343	0,4343
6	0,796	1	1	1	1	0,633	0,63317	0,63317	0,63317	0,6332
7	0,936	1	1	1	1	0,875	0,87546	0,87546	0,87546	0,8755
8	0,803	1	1	1	1	0,646	0,64554	0,64554	0,64554	0,6455
9	0,071	1	1	1	0	0,005	0,00498	0,00498	0,00498	0
10	0,840	1	1	1	1	0,705	0,70506	0,70506	0,70506	0,7051
11	0,337	100	150	86	358	0,11	11,37	17,05	9,78	40,70
12	0,484	84	92	398	470	0,23	19,67	21,54	93,18	110,04
13	0,587	114	104	96	282	0,34	39,31	35,86	33,10	97,24
14	0,533	102	140	110	340	0,28	28,99	39,79	31,27	96,64
15	0,525	115	135	84	340	0,28	31,68	37,19	23,14	93,66
16	0,299	66	130	98	380	0,09	5,91	11,65	8,78	34,04
17	0,297	85	136	102	365	0,09	7,49	11,99	8,99	32,18
18	0,597	133	112	92	290	0,36	47,46	39,96	32,83	103,48
19	0,457	100	174	119	349	0,21	20,90	36,37	24,88	72,96
20	0,441	75	126	135	398	0,19	14,58	24,50	26,25	77,38

No	Membership (μ_{i2})	Clustered data				$(\mu_{i2})^2$	$(\mu_{i1})^2 * x_{i13}$	$(\mu_{i1})^2 * x_{i14}$	$(\mu_{i1})^2 * x_{15}$	$(\mu_{i1})^2 * x_{i16}$
		x_{i13}	x_{i14}	x_{i15}	x_{i16}					
$\sum(\mu_{i1}^2)$							230,663	280,7038	297,0038	763,1189
$\sum[(\mu_{i1}^2)*X_{ij}] / \sum(\mu_{i1}^2)$							40,19816	42,5324	109,2824	40,19816

The results from calculation of the cluster center can be calculated using the formula for each variable:

Table 6. Results of the 1st Iteration Cluster Center

$\sum[(\mu_{i1}^2)*X_{ij}] / \sum(\mu_{i1}^2)$	$\sum[(\mu_{i2}^2)*X_{ij}] / \sum(\mu_{i2}^2)$
90,028	107,615
149,902	137,021
102,081	103,722
366,583	337,932
423,925	411,961
40,5009	58,02
1,36	1,382
0,507	0,484
2,979	4,816
0,819	0,823
0,693	0,757
0,894	0,857
0,843	0,839
0,984	0,975
1	1
0,973	0,988

5. The next step is to calculate the objective function (Pt)

To calculate the objective function, the following formula is applied:

$$P_t = \sum_{i=1}^{n} \sum_{k=1}^{c} \left(\left[\sum_{j=1}^{m} (X_{ij} - V_{kj})^2 \right] (\mu_{ik})^2 \right)$$

where :
(μ_ik)〗^w = Degree of membership
X_ij = Sample data
V_kj = Center Cluster iteration
W = Rank
P_t = Total Objective Function 2 Cluster

Table 7. Objective Function Results

No	Squared Degree of membership data i		$\left[\sum_{j=1}^{m}(X_{ij} - V_{kj})^2\right](\mu_{ik})^w$	$\left[\sum_{j=1}^{m}(X_{ij} - V_{kj})^2\right](\mu_{ik})^w$	Lt= L1+L2
	$(\mu_{i1})^2$	$(\mu_{i2})^2$	*L1*	*L2*	
1	0,153673706	0,369648946	2633,90821	4084,781127	6718,689337
2	0,236357545	0,264025204	537,6463127	568,4934532	1106,139766
3	0,293180816	0,210257336	5276,726175	4468,855709	9745,581884

No	Squared Degree of membership data i		$\left[\sum_{j=1}^{m}(X_{ij}-V_{kj})^2\right](\mu_{ik})^w$	$\left[\sum_{j=1}^{m}(X_{ij}-V_{kj})^2\right](\mu_{ik})^w$	Lt= L1+L2
	$(\mu_{i1})^2$	$(\mu_{i2})^2$	*L1*	*L2*	
4	0,216369051	0,286059316	1669,670206	1919,952693	3589,622898
5	0,414899232	0,126645791	1401,92278	774,7287642	2176,651544
6	0,103856679	0,459320632	1190,199664	2502,854698	3693,054362
7	0,127479161	0,413394682	590,4723743	1063,562264	1654,034638
8	0,331772564	0,179778529	1048,625136	772,1207732	1820,745909
9	0,306562314	0,19920092	5317,475597	4286,69345	9604,169047
10	0,245876905	0,254157378	457,080935	464,7372781	921,8182132
11	0,450016409	0,108351162	852,5809261	418,5620583	1271,142984
12	0,266633504	0,233902166	27727,11959	25969,69179	53696,81138
13	0,169296887	0,346382829	2339,666626	3346,540021	5686,206648
14	0,227239769	0,273846316	306,9713688	337,1882582	644,1596271
15	0,230962679	0,269791146	988,2731284	1068,479195	2056,752323
16	0,490694881	0,089702545	1011,435174	432,4201584	1443,855333
17	0,500595871	0,085539871	1166,386897	482,2960029	1648,6829
18	0,161625497	0,357572024	2615,947909	3890,962889	6506,910797
19	0,300325572	0,204286208	831,8830528	686,2867338	1518,169787
20	0,313624397	0,193580832	2140,137251	1681,399207	3821,536458
Fungsi Objektif (P1)					119324,74

Calculating Matrix Changes (μ_ik). The change in the matrix is calculated using the following formula:

$$\mu_{ik} = \frac{\left[\sum_{j=1}^{m}(x_{ij}-v_{kj})^2\right]^{\frac{-1}{w-1}}}{\sum_{k=1}^{c}\left[\sum_{j=1}^{m}(x_{ij}-v_{kj})^2\right]^{\frac{-1}{w-1}}} = \frac{(Lt/\ \mu\_ik^2)}{\sum(Lt/\ \mu\_ik^2)}$$

The calculation of the new membership degrees collected in the Partition Matrix is shown in Table 8.

Details of the calculation of matrix changes can be seen in the following table:

Table 8 Results of Matrix Changes in Iteration 14

No	$\left[\sum_{j=1}^{16}(X_{ij}-V_1)^2\right]^{-1}$	$\left[\sum_{j=1}^{16}(X_{ij}-V_2)^2\right]^{-1}$	$\sum_{k=1}^{3}\left[\sum_{j=1}^{16}(X_{ij}-V_{ij})^2\right]^{-1}$	(μ_{i1})	(μ_{i2})
	L1	*L2*	*Lt = L1 + L2*	*L1/LT*	*L2/LT*
1	5,83444E-05	9,04942E-05	0,000149	0,391998	0,608002
2	0,000439615	0,00046443	0,000904	0,486276	0,513724
3	5,55611E-05	4,70495E-05	0,000103	0,541475	0,458525
4	0,000129588	0,000148993	0,000279	0,465172	0,534828
5	0,00029595	0,000163471	0,000459	0,64418	0,35582
6	8,72599E-05	0,000183519	0,000271	0,322255	0,677745
7	0,000215894	0,000388689	0,000605	0,357095	0,642905
8	0,000316388	0,000232837	0,000549	0,576062	0,423938
9	5,76519E-05	4,64696E-05	0,000104	0,553698	0,446302

No	$\left[\sum_{j=1}^{16}(X_{ij}-V_1)^2\right]^{-1}$	$\left[\sum_{j=1}^{16}(X_{ij}-V_2)^2\right]^{-1}$	$\sum_{k=1}^{3}\left[\sum_{j=1}^{16}(X_{ij}-V_{ij})^2\right]^{-1}$	(μ_{i1})	(μ_{i2})
	L1	***L2***	***Lt = L1 + L2***	***L1/LT***	***L2/LT***
10	0,000537929	0,000546884	0,001085	0,495872	0,504128
11	0,000527828	0,000258865	0,000787	0,670945	0,329055
12	9,61634E-06	9,00674E-06	1,86E-05	0,516367	0,483633
13	7,23594E-05	0,000103505	0,000176	0,411451	0,588549
14	0,000740264	0,000812147	0,001552	0,476848	0,523152
15	0,000233703	0,0002525	0,000486	0,48067	0,51933
16	0,000485147	0,000207443	0,000693	0,700482	0,299518
17	0,000429185	0,00017736	0,000607	0,70759	0,29241
18	6,17847E-05	9,18981E-05	0,000154	0,402027	0,597973
19	0,000361019	0,000297669	0,000659	0,548088	0,451912
20	0,000146544	0,000115131	0,000262	0,560023	0,439977

7. Check stop condition

If (|Pt - (Pt-1)| <) or t > Maxlter then stop

Is known :

Pt = 22787,89785

P t-1 = 0

= 10〗^(-5)

Then: (604057,484 – 0) < (〖10〗^(-5)) = false, then continue on the 2nd iteration

And so on, until |Pt- Pt-1|< or t>MaxIter.

In this case, the new process stopped at the 14th iteration which resulted in the 14th Cluster Center as follows:

Table 9. The 14th Cluster Center

V1	137.8	246.8	97.25	377.7
	420.54	60.03	0.964	0.565
	1.607	0.58	0.959	0.62
	0.838	1	1	0.627

V2	124.1	159.7	101.5	336.9
	432	60.71	1.844	1.23
	3.233	0.73	0.723	0.828
	0.686	1	1	0.999

4. The next stage is the process of calculating the Objective Function (Pt)

To calculate the objective function, the following formula is applied.

$$P_t = \sum_{i=1}^{n}\sum_{k=1}^{c}\left(\left[\sum_{j=1}^{m}(X_{ij}-V_{kj})^2\right](\mu_{ik})^w\right)$$

Table 10. Results of Iteration 14 Objective Function

No	Squared Degree of membership data i		$\left[\sum_{j=1}^{m}(X_{ij}-V_{kj})^2\right](\mu_{ik})^w$	$\left[\sum_{j=1}^{m}(X_{ij}-V_{kj})^2\right](\mu_{ik})^w$	Lt= L1+L2
	$(\mu_{i1})^2$	$(\mu_{i2})^2$	***L1***	***L2***	
1	0,15361232	0,369744168	2633,064228	4085,057623	6718,121851
2	0,236935272	0,263415324	538,6751276	567,9881544	1106,663282
3	0,293251839	0,210197198	5277,821263	4468,361338	9746,182602
4	0,216452371	0,28596353	1670,225737	1919,774831	3590,000568
5	0,415255994	0,126448803	1402,6674	774,0288581	2176,696259
6	0,103828422	0,459380063	1189,863212	2502,794128	3692,65734
7	0,127689323	0,413016466	591,3150311	1063,479433	1654,794464
8	0,332153369	0,179498401	1049,525051	771,5373368	1821,062388
9	0,306657221	0,19912443	5318,779623	4285,96303	9604,742653
10	0,245918257	0,254115339	457,3115494	464,8704959	922,1820453
11	0,450812984	0,107960819	853,271891	417,5701323	1270,842023
12	0,266637877	0,23389807	27728,01553	25969,95277	53697,9683
13	0,169284143	0,346401058	2339,471012	3346,566722	5686,037734
14	0,228015788	0,272995813	307,842509	336,8473874	644,6898963
15	0,231395436	0,269323846	989,6834636	1067,729591	2057,413055
16	0,49057748	0,089752752	1011,749766	432,7547316	1444,504498
17	0,5010644	0,085346349	1166,845695	481,5745317	1648,420227
18	0,161638313	0,357552962	2616,046932	3890,846401	6506,893333
19	0,300707753	0,203971225	832,726686	685,8324121	1518,559098
20	0,313613558	0,193589348	2140,455504	1681,701464	3822,156968
Objective Function (P2)					119330,6

The next stage is the process of calculating the Matrix Change (μ_ik) using the following formula.

$$\mu_{ik} = \frac{\left[\sum_{j=1}^{m}(x_{ij} - V_{kj})^2\right]^{\frac{-1}{w-1}}}{\sum_{k=1}^{c}\left[\sum_{j=1}^{m}(x_{ij} - V_{kj})^2\right]^{\frac{-1}{w-1}}}$$

Details of the calculation of matrix changes can be seen as follows:

Table 11. Results of Matrix Changes in Iteration 14

No	$\left[\sum_{j=1}^{16}(X_{ij}-V_1)^2\right]^{-1}$	$\left[\sum_{j=1}^{16}(X_{ij}-V_2)^2\right]^{-1}$	$\sum_{k=1}^{3}\left[\sum_{j=1}^{16}(X_{ij}-V_{ij})^2\right]^{-1}$	(μ_{i1})	(μ_{i2})
	L1	***L2***	***Lt = L1 + L2***	***L1/LT***	***L2/LT***
1	5,83398E-05	9,05114E-05	0,000149	0,391934	0,608066
2	0,000439848	0,000463769	0,000904	0,486764	0,513236
3	5,5563E-05	4,70412E-05	0,000103	0,541528	0,458472
4	0,000129595	0,000148957	0,000279	0,465245	0,534755
5	0,000296047	0,000163364	0,000459	0,644405	0,355595
6	8,72608E-05	0,000183547	0,000271	0,322224	0,677776
7	0,000215941	0,000388363	0,000604	0,357338	0,642662

No	$\left[\sum_{j=1}^{16}(X_{ij}-V_1)^2\right]^{-1}$	$\left[\sum_{j=1}^{16}(X_{ij}-V_2)^2\right]^{-1}$	$\sum_{k=1}^{3}\left[\sum_{j=1}^{16}(X_{ij}-V_{ij})^2\right]^{-1}$	(μ_{i1})	(μ_{i2})
	L1	***L2***	***Lt = L1 + L2***	***L1/LT***	***L2/LT***
8	0,00031648	0,00023265	0,000549	0,576329	0,423671
9	5,76556E-05	4,64597E-05	0,000104	0,553767	0,446233
10	0,000537748	0,000546637	0,001084	0,495901	0,504099
11	0,000528335	0,000258545	0,000787	0,67143	0,32857
12	9,61619E-06	9,00649E-06	1,86E-05	0,51637	0,48363
13	7,236E-05	0,000103509	0,000176	0,411442	0,588558
14	0,00074069	0,000810444	0,001551	0,477515	0,522485
15	0,000233808	0,00025224	0,000486	0,481039	0,518961
16	0,00048488	0,000207399	0,000692	0,700412	0,299588
17	0,000429418	0,000177224	0,000607	0,707861	0,292139
18	6,17872E-05	9,18959E-05	0,000154	0,402043	0,597957
19	0,000361112	0,000297407	0,000659	0,54837	0,45163
20	0,000146517	0,000115115	0,000262	0,560012	0,439988

7. Check stop condition

If (|Pt - (Pt-1)| <) or t > Maxlter, Stop noted that :

P1	22781.3956
P0	22781.39561
P1-P0	-0.0000075

Data ke -	Derajat Keanggotaan		Cluster c1/c2
	1	*2*	

In the 14th iteration, it stops because the results already show the smallest error. From the process of changing the matrix, information about the tendency of patients to be grouped in which cluster can be obtained. The highest degree of membership indicates the highest tendency to become a member of the group.

Table 12. Degrees of Membership of Each Data In Each Last Iteration Cluster

Data ke -	**Derajat Keanggotaan**		**Cluster c1/c2**
	1	***2***	
1	0,391934	0,608066	C2
2	0,486764	0,513236	C2
3	0,541528	0,458472	CI
4	0,465245	0,534755	C2
5	0,644405	0,355595	CI
6	0,322224	0,677776	C2
7	0,357338	0,642662	C2
8	0,576329	0,423671	CI
9	0,553767	0,446233	CI

10	0,495901	0,504099	C2
11	0,67143	0,32857	CI
12	0,51637	0,48363	CI
13	0,411442	0,588558	C2
14	0,477515	0,522485	C2
15	0,481039	0,518961	C2
16	0,700412	0,299588	CI
17	0,707861	0,292139	CI
18	0,402043	0,597957	C2
19	0,54837	0,45163	CI
20	0,560012	0,439988	CI

Based on the results of the degree of membership of each data in each of the last iteration clusters, ten data are grouped in cluster 1 and the other ten data are included in cluster 2. While the former consists of patient data numbers 3, 5, 8, 9,11,12,16,17,19 and 20, the latter consists of patient data numbers 1,2,4,6,7,10,13,14,15, and 18.

Measurement of Accuracy Level

Measurement of accuracy applies both the success rate method and kappa statistics. The results of accuracy using the success rate method is presented as follows.

Success Rate

To determine the level of accuracy, a comparison table is made in advance between the results of experts and the results of calculations that have been carried out. Below is the results of test data from RSUD dr. Dradjat Prawiranegara Serang City and the system.

Table 13. Accuracy test results using the Success Rate Method

Data to -	**Membership Degree**		**System Fuzzy C-Means Diagnostics C1/c2 . clusters C1= Normal C2= Abnormal**	**Doctor's diagnosis**
	1	*2*		
1	0,391934	0,608066	C2	Abnormal
2	0,486764	0,513236	C2	Abnormal
3	0,541528	0,458472	CI	Abnormal
4	0,465245	0,534755	C2	Abnormal
5	0,644405	0,355595	CI	Abnormal
6	0,322224	0,677776	C2	Abnormal
7	0,357338	0,642662	C2	Abnormal
8	0,576329	0,423671	CI	Abnormal
9	0,553767	0,446233	CI	Abnormal
10	0,495901	0,504099	C2	Abnormal
11	0,67143	0,32857	CI	Normal
12	0,51637	0,48363	CI	Normal
13	0,411442	0,588558	C2	Normal
14	0,477515	0,522485	C2	Normal
15	0,481039	0,518961	C2	Normal
16	0,700412	0,299588	CI	Normal
17	0,707861	0,292139	CI	Normal
18	0,402043	0,597957	C2	Normal

Data to -	Membership Degree		System Fuzzy C-Means Diagnostics C1/c2 . clusters C1= Normal C2= Abnormal	Doctor's diagnosis
	1	*2*		
19	0,54837	0,45163	CI	Normal
20	0,560012	0,439988	CI	Normal

To measure the SR value, the confusion matrix approach is applied as follows:

		Predicated Class	
		Normal	***Abnormal***
Actual Class	***Normal***	(TP) 6	(FN) 4
	Abnormal	(FP) 4	(TN) 6

True Positive rate =TP/(TP+FN)
= 6/10 = 0,6
False Positive Rate = FP/ (FP+TN) 4/ (4+6)
= 4/10 =0,4

Success rate = (TP+TN)/(TP+TN+FP+FN)
= (6+6)/(6+6+4+4) = 12/ 20 = 0,60
Error rate = 1 – Success Rate.
= 1-0,60= 0,40

Conclusion

Based on the analysis of 20 data of patients with heart problems using the Fuzzy C-Means approach, detection of heart abnormalities can be carried out using electrocardiogram medical records which consists of interval values for HR, PR, PRS, QT, QTC, Axis, RV6, SV1, R +S variable. Therefore, Clustering technique could be considered as one solution to overcome the process of determining the risk of heart disease. Detection of heart defects using the Fuzzy C-Means approach offers measurement accuracy of 60%. The results showed that there were 10 data grouped into cluster 1 and 10 data into cluster 2. The first group (Cluster 1) consisted of patients with serial number 3 ,5,8,9,11,12,16,17,19,20, while the second group (Cluster 2) consisted of patients with serial numbers 1,2, 4,6,7,10,13,14,15 and 18.

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