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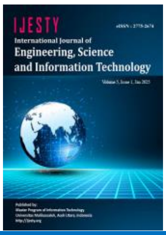

Clustering Agricultural Productivity by Type and Results Using K-Medoids Method in Districts North Aceh

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Abstract

This research aims to develop a web-based application that can cluster sub-districts in North Aceh District based on the type and yield of agricultural productivity, focusing on increasing the ease of visualization and data analysis by users. The method applied in this research is K-Medoids, a clustering technique used to group sub-districts based on high, medium, and low harvest levels. The application will use data from the North Aceh District Agriculture Office, covering 2021 to 2023, including various food crops such as rice, corn, peanuts, green beans, cassava, sweet potatoes, and soybeans. This research will analyze the sub-district name, type of agriculture, year of production, planting area, and harvest area to identify clusters of sub-districts with similar agricultural yield patterns. The system is developed using the PHP programming language to facilitate implementation and data access by stakeholders. As an evaluation tool for clustering results, the Davies-Bouldin Index (DBI) is used to measure the quality of clustering results. The results of this study are expected to provide insights into agricultural productivity in North Aceh District and assist policymakers in designing more effective strategies to increase agricultural yields, especially in low-yielding sub-districts. In addition, this application also provides an interactive platform for users to analyze agrarian data quickly and efficiently.

Keywords: *Clustering, Agricultural Productivity, K-Medoids, North Aceh District, Web Application.*

1. Introduction

Indonesia is an agrarian country where the agricultural sector is vital to the national economy. In addition to providing employment opportunities, this sector contributes significantly to the country's foreign exchange earnings. Food and plantation crop commodities, such as rice, corn, and others, are the mainstay due to their high demand and favourable selling prices [1].

Aceh Province, particularly North Aceh District, has excellent agricultural potential thanks to its fertile land and abundant natural resources. This sector is vital in poverty reduction, employment generation, and food security. The variety of agricultural output in each subdistrict is significant, covering crops such as rice, corn, beans, and fruits, reflecting broad diversification [2].

However, in 2022, North Aceh experienced heavy losses due to flooding, totalling IDR 12.2 billion, mostly from rice crop failures. In addition to natural disaster factors, the unbalanced distribution of agricultural products between sub-districts and different local policies also pose challenges. This problem is exacerbated by the lack of accurate data, which hampers strategic planning and analysis.

To overcome these problems, a comprehensive data analysis system is needed. The K-Medoids method effectively handles data with outliers and can help cluster agricultural productivity in North Aceh. Thus, production patterns and trends can be identified, enabling the formulation of more appropriate strategies to address yield imbalances and resource optimization. Next, in the study of the Application of the K-Medoids Algorithm in Clustering the Level of Crime Cases in Each Province, the results of this study with the calculation of the K-Medoids algorithm obtained high clusters in as many as 10 provinces and low clusters of as many as 24 provinces. It can be seen that the use of the K-Medoids method in clustering crime rates in each province is very appropriate [3] [4] [5].

The results of this research are expected to provide a strong basis for local government in policy evaluation and strategic planning. This will address production imbalances improve.

2. Literatur Review

This section outlines relevant previous research as a theoretical basis and reference to understand the context and methodology used in this research. Prior research provides important insights related to data clustering, analysis techniques, and the application of algorithms that support the research objectives. In addition, this discussion also aims to identify research gaps that can be used as a foothold in developing a more effective and appropriate approach. Such as research conducted [6]. This study aimed to group provinces in Indonesia based on harvest area, production, and rice productivity using the K-Medoid Clustering Analysis (PAM) method. The clusters formed are 2 clusters with an Average Silhouette of 0.86. The specification of the structure formed is strong, and all data is located in the right Cluster. Cluster 1 is a group of provinces with low productivity levels consisting of 30 provinces, and Cluster 2 is a group of provinces with high productivity levels consisting of 4 provinces. The silhouette value of each Cluster is 0.89, with the specification of the structure formed strong, and 0.66, with the specification of the structure formed well. As we can see, the k-medoids algorithm shows the best results. With the results of clustering research, there are three clusters, namely 14 districts in Cluster Zero, two districts in Cluster One, and 17 districts in Cluster Two [7] [8].

3. Research Method

Data mining is a process of automatically finding helpful information in large data stores. Data mining is used to discover knowledge models that can help make predictions. Data mining is discovering interesting patterns and knowledge from large amounts of data[9]. Data mining has several views, such as knowledge discovery or pattern recognition. The term knowledge discovery is appropriate because the primary purpose of data mining is to gain knowledge that is still hidden in chunks of data. Meanwhile, the term for pattern recognition or pattern recognition is appropriate because it finds patterns hidden in chunks of data [10] [11]. The terms data mining and knowledge discovery in database (KDD) are often used interchangeably to describe the process of extracting hidden information in an extensive database [12] [13].

Clustering is a method to categorize data into groups, where data in one group is more similar than data in another group. This process helps identify patterns or structures in data without using existing labels so that it can be used for various data analysis and machine learning applications [14] [15].

K-Medoids is an algorithm used to find medoids in a cluster. The basic strategy of this algorithm is to find k clusters on n objects first, which is done randomly. Each object is grouped with the most similar medoid. The K-Medoids algorithm is a representative object as a representative point in taking the average value of objects in each Cluster [16] [17] [18].

Calculating the K-Medoids algorithm begins with determining the initial centre (medoids) of as many as k clusters. Next, each data is allocated to the nearest Cluster using the Euclidean distance, with the equation:

…………………………………………………………………..………………(1)

$$d_{ij} = \sqrt{\sum_{a=1}^{p}(x_{ia} - x_{ja})^2} = \sqrt{(x_i - x_j)'(x_i - x_j)}$$

After that, objects in each Cluster are randomly selected as new candidate medoids, and the distance of each object in the Cluster is calculated concerning the candidate. The change in the total distance between the new candidate medoids and the previous medoids is calculated. If there is a reduction in the total distance, the medoids are replaced with new candidates. This process is repeated until the medoids stabilize and there is no further change, thus forming clusters and their members[19].

Davies Bouldin Index (DBI) is one of the methods used to measure the validity or the most optimal number of clusters in a clustering method, defined as the sum of the cohesion of the proximity of the data to the cluster centre point of the Cluster followed[20].

The scheme of the agricultural productivity grouping system based on type and yield using the k medoids method :

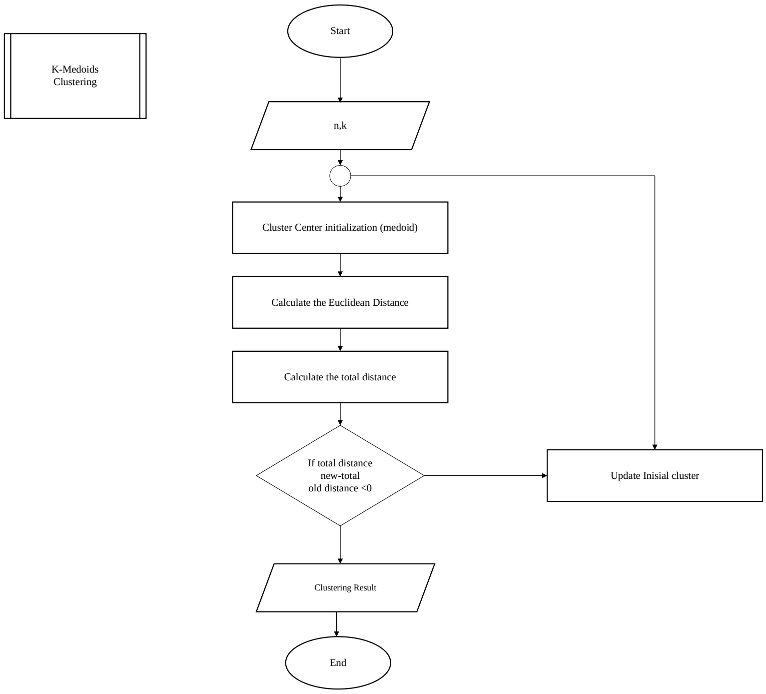

Fig. 1 System Schematic

The calculation process in the K-Medoids method starts with data normalization, followed by random cluster centre initialization. The distance between the data and the cluster centre is calculated using Euclidean Distance, and the total distance within the Cluster is calculated. After that, the cluster centres are updated, and the distance is calculated again. The difference between the total distance between the old and new is calculated. After obtaining the final Cluster, the average dissimilarity (ai) value is calculated for evaluation using the silhouette coefficient, followed by the calculation of the lowest average dissimilarity (bi) and the silhouette coefficient (si) value to assess the cluster quality.

4. Result and Discussion

Researchers collected rice productivity data from the Agriculture Office to ensure the system runs as expected. The data used covers the period from 2021 to 2023. However, the dataset that will be displayed in this section is the 2023 paddy data.

4.1. Datasets

The variables used in the K-Medoids method are the name of the sub-district, type of agriculture, year of production, planting area, and harvest area. The types of crops to be analyzed include rice, corn, peanuts, green beans, cassava, sweet potatoes, and soybeans. These crops are selected based on their relevance and contribution to the local economy and the availability of adequate data for each crop type.

Table 1. Rice Dataset For 2023

No.	Sub-district	Paddy 2023			
		Planted Area (Ha)	Harvested Area (Ha)	Productivity (Kw/Ha)	Production (Ton)
1	010 Sawang	4.628	5.585	60,60	33845,10
2	020 Nisam	3.514	3.534	60,13	21249,35
3	021 Nisam Antara	0	0	0,00	0
4	022 Banda Baro	1.130	890	60,00	5.340,00
5	030 Kuta Makmur	3.284	3.268	59,90	19.575,32
…	…	…	…	…	…
27	170 Dewantara	711	466	55,00	2.563,00

4.2. Defining Clusters

Initialize cluster centres with as many as 3 clusters from the dataset to select each medoid. It is chosen randomly or randomly.

Table 2. Initial Medoids

Object 5	0,427826993	0,585138765	0,983579639	0,578379736
Object 15	0,261334028	0,179588183	0,986863711	0,178106432
Object 25	0,061750912	0,107072516	0,9408867	0,101241834

4.3. Calculate Euclidean Distance

Calculating the closest distance with the Euclidiance Distance equation. To cluster each piece of data that has been obtained, the next step is to calculate the Euclidiance Distance. Euclidian Distance. The calculation of the Euclidean Distance for each Cluster with equation 2.1 is as follows as follows:

$$d_1 = \sqrt{(0{,}427 - 0{,}602)^2 + (0{,}585 - 1)^2 + (0{,}983 - 0{,}995)^2 + (0{,}578 - 1)^2} = 0{,}616$$

$$d_2 = \sqrt{(0{,}261 - 0{,}602)^2 + (0{,}179 - 1)^2 + (0{,}986 - 0{,}995)^2 + (0{,}178 - 1)^2} = 1{,}210$$

$$d_3 = \sqrt{(0{,}061 - 0{,}602)^2 + (0{,}107 - 1)^2 + (0{,}940 - 0{,}995)^2 + (0{,}101 - 1)^2} = 1{,}378$$

The same calculation is still done for all data. After calculating all data and attributes, the closest distance for each data in each Cluster will be obtained.

Table 3. Results of K-Medoids Algorithm Iteration 1.

No.	Sub-district	**C1**	**C2**	**C3**	**proximity**	**nearest Cluster**
1	010 Sawang	0,616978554	1,210508873	1,3787255	0,616978554	1
2	020 Nisam	0,075011309	0,668002409	0,84419499	0,075011309	1
3	021 Nisam Antara	1,351804474	1,051745822	0,954356007	0,954356007	3
4	022 Banda Baro	0,661018157	0,11768236	0,123284232	0,11768236	2
5	030 Kuta Makmur	0	0,593650305	0,76944285	0	1
…	…	…	…	…	…	…
27	170 Dewantara	0,789427973	0,234950379	0,05991007	0,05991007	3
		total proximity			6,102715724	

Determining the value of new Medoids by selecting new medoids randomly or randomly with the provision that each medoid that has been chosen is not used again. Random with the provision that any medoids that have been selected cannot be used again as new medoids. As new medoids.

Table 4. New Medoids

New Medoids				
Object 2	0,457790516	0,632766338	0,987328815	0,627841253
Object 12	0,129233976	0,16347359	0,939683499	0,154373898
Object 22	0,097055758	0,144673232	0,929392447	0,135123844

4.4. Calculate Euclidean Distance of Iteration Two

The same calculation is still done for all data. After calculating all data and attributes, the closest distance for each data in each Cluster will be obtained.

Table 5. Iteration 2 Paddy Calculation Results for Year 2023

No.	Sub-district	**C1**	**C2**	**C3**	**Proximity**	**Cluster**
1	010 Sawang	0,542664465	1,281524392	1,319016867	0,542664465	1
2	020 Nisam	0	0,7447325	0,783895092	0	1
3	021 Nisam Antara	1,406758055	0,974813528	0,955185289	0,955185289	3
4	022 Banda Baro	0,735894762	0,049249191	0,079757892	0,049249191	2
5	030 Kuta Makmur	0,075011309	0,669826195	0,709106151	0,075011309	1
…	…	…	…	…	…	…
27	170 Dewantara	0,864307596	0,12356385	0,089373324	0,089373324	3
		The Number of Proximities			6,27352295	

4.1 Standard Deviation

After receiving the distance value between the first and second iterations, the next step is to calculate the total deviation (S) by subtracting the new total cost (number of closeness) from the old total cost (number of closeness). If the value of S is smaller than 0, then the process continues by swapping objects and determining a new medoid. However, if the value of S is greater than 0, the calculation is stopped or considered complete.

S = new total cost – old total cost

= 6,273 – 6,102 = 0,171

4.2 Cluster Result

Table 6. Final result of paddy calculation 2023

No.	Sub-district	Cluster
1	010 Sawang	High
2	020 Nisam	High
3	021 Nisam Antara	Low
4	022 Banda Baro	Medium
5	030 Kuta Makmur	High
…	…	…
27	170 Dewantara	Low

4.3 Clustering Chart 2023, 2022 Dan 2021

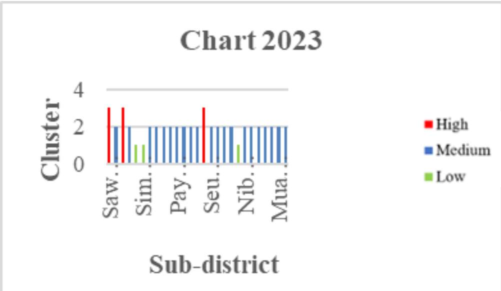

Fig. 2 Graphical results for 2023

4.4 Davies Building Index (DBI)

DBI measures a clustering result based on cohesion and separation values. The cohesion clustering result is the sum of the proximity of data to a centre point (centroid) of a clustering result, and grouping result separation is based on the distance between the Cluster's centroid [21]. Method DBI evaluation method has advantages in terms of measuring cluster evaluation on a method clustering method due to the cohesion and separation values that it produces[22]. We will continue the clustering calculation by combining data from different crop types throughout 2023. The calculated data includes :

X1 = Paddy, X2 = Corn, X3 = Soybean, X4 = Groundnut, X5 = Mung Bean**,** X6 = Cassava, X7 = Sweet Potato.

Table 7. Agricultural Dataset for the Year 2023

No	X1	X2	X3	X4	X5	X6	X7
1	0.616978554	1.310415091	0.281421423	0.212034941	0	0.112622978	0
2	0.075011309	0	0	0.120352647	0.833030772	0.085250955	0.1
3	0.954356007	0.326189021	0.651659005	0.164238349	0.23309411	0.084094998	0.1
4	0.11768236	0.195342917	0	0.129306455	0.833030772	0	0.1
5	0	1.062203249	0.421131721	0	0.833030772	0	0.1
…	…	…	…	…	…	…	…
27	0.05991007	0.182356081	0	0.022488079	0.833030772	0	0.1

Table 8. Initial Medoids

Object 6	0.088970983	1.45989751	0.539900009	1.252631344	0.773995116	0.122943934	0.1
Object 13	0.101256267	0.540907547	0.245658219	0	0.833030772	0.106539598	0.151860353
Object 15	0	0.882514568	0.471556266	0	0.210450363	0	0.1

1. Calculating SSW (Sum Of Square Within Cluster)
   The sum of squares within a Cluster (SSW) is the cohesion matrix within a cluster [23].

Table 9. Members of Cluster 1 (Low Category)

No	Paddy	Corn	Soybean	Groundnut	Mung Bean	Cassava	Sweet Potato
5	0	1.062203249	0.421131721	0	0.833030772	0	0.1
6	0.088970983	1.45989751	0.539900009	1.252631344	0.773995116	0.122943934	0.1
20	0.317878376	0.976473876	0.072039082	0.248902777	0.833030772	0.701901806	0.1

Table 10. Members of Cluster 1 (Low Category)

Members of Cluster 1 (Low Category)								
X1	X2	X3	X4	X5	X6	X7	Distance	SSW
							1.329612038	
0.088970983	1.45989751	0.539900009	1.252631344	0.773995116	0.122943934	0.1	1.38778E-17	0.896725948
							1.360565806	

Table 11. Members of Cluster 2 (Medium)

No	X1	X2	X3	X4	X5	X6	X7
2	0.075011309	0	0	0.120352647	0.833030772	0.085250955	0.1
4	0.11768236	0.195342917	0	0.129306455	0.833030772	0	0.1
7	0.340409706	0	0	0	1.068242323	0.24742748	0.029945057
8	0.093020078	0.239832136	0.039665993	0	0.833030772	0	0.1
9	0.139789634	0.230677904	0	0.095574336	0.50019292	0.155324519	0.1
10	0.27660643	0	0	0	0.833030772	0.144613344	0.1
11	0.288361529	0.128077433	0.148460138	0	0.833030772	0	0.1
12	0.102759471	0	0	0.089952317	0	0.098452333	0
13	0.101256267	0.540907547	0.245658219	0	0.833030772	0.106539598	0.151860353
14	0.344587159	0.045796946	0.359195937	0.15823856	0.81165511	0.57842421	0.585505139
16	0.182958646	0	0	0	0.833030772	0.268804719	0.785558947
17	0.657978296	0.19333011	0	0.095574336	0.072081013	0.102339145	0.028447804
18	0.254457882	0.225233673	0	0.089952317	0	0.096769976	0.101155218
19	0.56632783	0.106714239	0.398473108	0.129066674	0.833030772	0.079104962	0.1
21	0.071947333	0.174842444	0.19300356	0.067464237	0.833030772	0.192637071	0.1
22	0.062772243	0	0	0.101196356	0.833030772	0.128754311	1.441107055
23	0.043506926	0	0	0	0.833030772	0.123265594	0.1
24	0.065976677	0	0	0	0.833030772	0.122654252	0
25	0	0.223411949	0	0	0.833030772	0	0.11431963
26	0.279211955	0.178558799	0	0.089952317	0.013105639	0	0.1
27	0.05991007	0.182356081	0	0.022488079	0.833030772	0	0.1

Table 12. Members of Cluster 2 (Medium)

X1	X2	X3	X4	X5	X6	X7	Distance	SSW
							0.609298938	
							0.459122023	
							0.70722027	
							0.383649862	
							0.53203399	
							0.622748522	
							0.478460794	
0.10125627	0.540907547	0.245658219	0	0.83303077	0.1065396	0.15186	1.038311058	0.672016263
							0	
							0.868017564	
							0.887416527	
							1.046195366	
							0.942426036	
							0.669528296	
							0.39024208	

							1.42383328	
							0.59936064	
							0.614406082	
							0.429143611	
							0.957977885	
							0.452948693	

Table 13. Members of Cluster 3 (High Category)

No	X1	X2	X3	X4	X5	X6	X7
1	0.616978554	1.310415091	0.281421423	0.212034941	0	0.112622978	0
3	0.954356007	0.326189021	0.651659005	0.164238349	0.23309411	0.084094998	0.1
15	0	0.882514568	0.471556266	0	0.210450363	0	0.1

Table 14. Members of Cluster 3 (High Category)

Members of Cluster 3 (High Category)								
X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**Distance**	**SSW**
0	0.882514568	0.471556266	0	0.21045036	0	0.1	0.843708929	0.659432238
							1.134587786	
							0	

2. Calculating SSB (Sum Of Square Between Clusters)
The sum of Square Between Clusters (SSB) is a separation matrix that measures the distance between clusters. or proximity between one Cluster and another by calculating the distance between cluster centroids.[23]

Table 15. Calculating SSB (Sum Of Square Between Clusters)

		Medoids to		
	SSB	**1**	**2**	**3**
Medoids to	**1**	0	1.583287972	1.499246793
	2	1.583287972	0	0.761330851
	3	1.499246793	0.761330851	0

3. Calculating the Ratio

Table 16. Calculating the Ratio

		Medoids to			
	SSB	**1**	**2**	**3**	R MAX
Medoids to	**1**	0	0.99081294	1.03795999	1.03795999
	2	0.99081294	0	1.748843488	1.748843488
	3	1.03795999	1.748843488	0	1.748843488
Calkulating DBI					1.511882322

Table 17. DBI Evaluation and Medoid Selection for 2021-2023

Year	Number of Iterations	Selected Medoid	Deviation	DBI
2021	2	4,26,12	3.655078492	1.497382531
2022	2	7,14,20	10.95584415	1.292713279
2023	2	6,13,15	7.739442965	1.511882322
DBI MIN				1.292713279

5. Conclusion

This research successfully developed a web-based application that can categorize sub-districts in North Aceh Regency based on the type and results of agricultural productivity using the K-Medoids method. This application facilitates the process of visualizing and analyzing agricultural data, including information on crop types, production yields, planting areas, and harvest areas in each sub-district from 2021 to 2023. Using data from the North Aceh District Agriculture Office, the application generates sub-district clusters based on yield levels divided into high, medium and low categories. In 2023, the distribution of sub-districts in North Aceh District shows that most sub-districts (73.08%) fall into the medium Cluster. A total of 15.38% of sub-districts are in the high Cluster, while 11.54% of sub-districts are in the low Cluster. This shows that although some sub-districts have good agricultural yields (high Cluster), most sub-districts are still at a medium yield level, and only a few show low agricultural yields.

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