

Comparison of K-Medoids and K-Means Result for Regional Clustering of Capture Fisheries in Aceh Province

Thifal Salsabila*, Nurdin, Sujacka Retno

Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

**Corresponding author Email: thifal.210170273@mhs.unimal.ac.id*

The manuscript was received on 21 June 2024, revised on 20 October 2024, and accepted on 22 February 2025, date of publication 7 April 2025

Abstract

This research aims to develop a web-based application that can categorize areas of capture fisheries in Aceh Province. The methods used in this research are K-Means and K-Medoids. The methods used in this research are K-Means and K-Medoids, a clustering technique used to group districts/cities based on high and low catch areas. This application will use data from the Marine and Fisheries Service (KKP) of Aceh Province, covering the period 2017 to 2023. This research will analyze variables such as production (tons), number of vessels, sub-districts, villages, and fish species. The system is developed using the PHP programming language to facilitate implementation and data access by stakeholders. 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 an overview of areas with high catches and assist policymakers in designing a more strategic approach to fishing—policymakers in developing more effective strategies to increase fishing, especially in districts with low fish catch. In addition, this application also provides an interactive platform for users to analyze fisheries data quickly and efficiently.

Keywords: *Clustering, K-Means, K-Medoids, Capture Fisheries, Aceh Province.*

1. Introduction

The rapid development of information technology plays a vital role in Indonesia's fisheries sector, utilizing the great potential of a country with a vast sea area and high biodiversity. Indonesia has thousands of islands with marine resources that can be optimally managed through information technology that allows fast and accurate data access, especially regarding fishery product production, distribution, and marketing [1]. One of the provinces with great fishery potential is Aceh, with a sea area of 295,370 km², rich in fish resources and strategic access to the Indian Ocean [2]. However, fisheries management in Aceh is often not optimal, especially in data management, which does not yet have an effective grouping system. Therefore, data mining techniques, such as K-Medoids and K-Means, are expected to reveal patterns, help group areas based on fisheries catch intensity, and provide a clearer picture of areas with high, medium, and low catch potential [3]. To improve fisheries management in Aceh, a system is needed to categorize areas based on fish catch levels in various districts/cities. This system will support the Aceh Marine and Fisheries Service in monitoring fish catch patterns and provide a more substantial basis for fisheries management policies [4]. Data obtained from the official website of the Ministry of Marine Affairs and Fisheries (KKP) is expected to help understand catch patterns in Aceh. This study's K-Medoids and K-Means methods offer their respective advantages in grouping areas with different catch levels, allowing for more accurate and effective identification in determining appropriate policies [5]. A comparison of these two algorithms provides a more comprehensive understanding of the distribution of fisheries' potential, which is expected to support government efforts in planning and optimizing fisheries management in Aceh [6].



2. Literatur Review

This literature review aims to provide a theoretical basis for the clustering techniques used in this study. Key concepts such as data mining, clustering, and clustering evaluation will be discussed to understand how the K-Means and K-Medoids methods work in grouping fisheries data [7]. Data mining is extracting information from large data sets using statistical methods and artificial intelligence algorithms. One of the techniques in data mining is clustering, which aims to group data based on similar characteristics [8].

Clustering is a data grouping technique to find patterns or structures in unlabeled data. Methods frequently used in clustering are K-medoids and K-means [9]. K-Medoids are similar to K-Means but use medoids as cluster centres, which are more resistant to outliers than centroids in K-Means [10]. K-Means is a clustering method that divides data into k groups based on the Euclidean distance to the centroid, which is updated iteratively until the clustering results are stable [11]. DBI evaluates cluster quality based on the similarities and differences between clusters. The lower the DBI value, the better the clustering quality [12].

3. Research Method

This study uses a quantitative approach to analyze secondary data from the Ministry of Maritime Affairs and Fisheries (KKP) website. The data used includes the capture fisheries production (tons), number of ships, sub-districts, villages, and fish species in various regencies/cities in Aceh Province from 2017 to 2023 [13].

Data mining is discovering interesting patterns and knowledge from large amounts of data. The main goal of data mining is to obtain hidden knowledge in large data sets that can be used for better decision-making. This study uses data mining to group fishing areas based on catch intensity [14].

Clustering is a data grouping technique to find patterns in unlabeled data [15]. The methods used in this study are K-Means and K-Medoids, which can group areas based on fishing intensity [16].

K-Means is a clustering method that divides data into k groups based on the Euclidean distance to the centroid, which is updated iteratively until the clustering results are stable [17]. Next, each data using the K-Means algorithm is allocated to the nearest cluster using the Euclidean distance, with the equation:

$$D(A_n, C_x) = \sqrt{(A_n - C_x)^2 + (A_n - C_x)^2 + \dots} \quad (1)$$

K-Medoids is a clustering algorithm similar to K-Means but uses medoids as cluster centres, which are more resistant to outliers than centroids in K-Means [18]. Next, each data is allocated to the nearest cluster using the Euclidean distance, with the equation:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}; i = 1, 2, 3, \dots, n \quad (2)$$

The clustering results are evaluated using the Davies-Bouldin Index (DBI) to assess the quality of the clusters formed. DBI measures the balance between the closeness of data points within a cluster and the distance between clusters. The lower the DBI value, the better the quality of the resulting clusterization.

System scheme for clustering capture fishery areas in Aceh province with k-means and k-medoids methods:

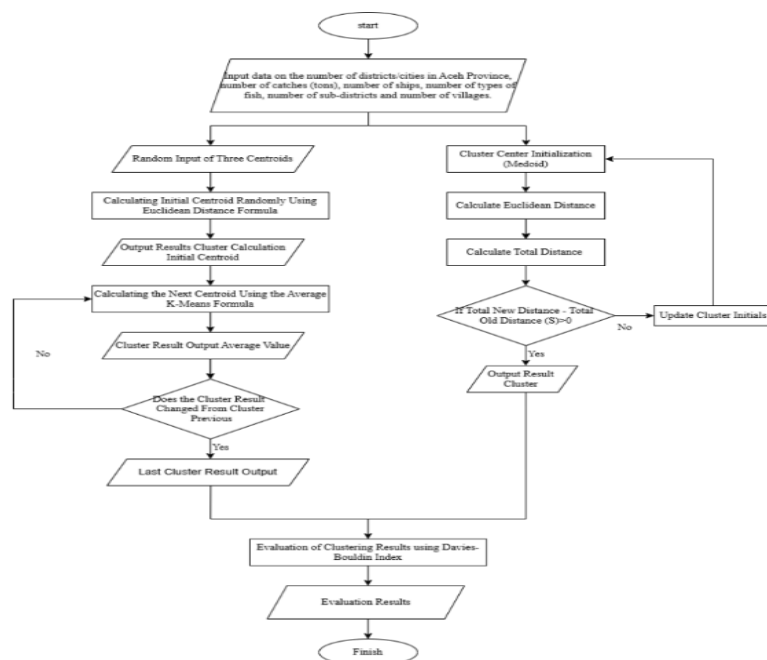


Fig 1. System Schematic

The process begins by entering data on the districts/cities in Aceh Province, including the number of catches (tons), vessels, fish species, sub-districts, and villages. In the K-Means method, three centroids are randomly selected as starting points, while in the K-Medoids

method, the cluster centres or medoids are determined first. Next, using the Euclidean Distance formula, the K-Means method calculates the initial distance between the data and the centroid. In contrast, the K-Medoids method calculates the Euclidean distance between the data and the medoid to determine the initial cluster. The initial result of clustering using centroids in K-Means is generated. At the same time, in K-Medoids, the total distance is calculated to determine whether the medoids need to be updated. Then, in K-Means, the centroid is updated by calculating the average data points in each cluster. At the same time, if the difference between the new and old total distances is still positive in K-Medoids, the medoid is updated. A clustering result based on the average centroid in K-Means is generated, while in K-Medoids, the medoid is updated if the new total distance is greater than the previous one. The system then checks whether the clustering result changes from the prior iteration; if it does not, the process stops. If it changes, the process continues until it stabilizes. After that, the final clustering result is generated and evaluated using the Davies-Bouldin Index to determine the method that provides the best clustering quality. The evaluation results are compared between the K-Means and K-Medoids methods based on the Davies-Bouldin Index value, and finally, the process is completed. The scheme aims to compare the clustering results of the K-Means and K-Medoids methods and determine which is more accurate or appropriate for the data used.

4. Result And Discussion

4.1. Datasets

The amount of data used in the K-Means algorithm experiment is 18 Aceh Provinces. The dataset can be seen in the table below:

Table 1. Dataset For 2017

No	Regency/City	Production (ton)	Number of boats	Number of sub-districts	Number of villages	Number of fish species
1	West Aceh	2672	830	10	138	10
2	Southwest Aceh	5696	1855	9	152	12
3	Great Aceh	504	1270	23	599	12
4	Aceh Jaya	1733	1302	9	172	20
5	South Aceh	68802	2235	18	260	30
6	Aceh Singkil	1646	2475	11	116	32
...	...	...	...	...	...	...
18	Simeulue	3237	7600	10	138	45

The dataset must be normalized first using a min-max scaler to make it easier for the author to perform calculations.

Table 2. Data Normalization

No	Regency/City	Production (ton)	Number of boats	Number of sub-districts	Number of villages	Number of fish species
1	West Aceh	0.034	0.086	0.292	0.144	0.054
2	Southwest Aceh	0.078	0.224	0.250	0.161	0.108
3	Great Aceh	0.002	0.145	0.833	0.697	0.108
4	Aceh Jaya	0.020	0.149	0.250	0.185	0.324
5	South Aceh	1.000	0.275	0.625	0.290	0.595
6	Aceh Singkil	0.019	0.308	0.333	0.118	0.649
...	...	...	...	...	...	...
18	Simeulue	0.042	1.000	0.292	0.144	1.000

4.2. K-Medoids Calculation

4.2.1. Datasets

The variables used in the K-Medoids method are the Regency/City of Aceh Province, production (tons), number of ships, number of sub-districts, number of villages and number of fish species.

Table 3. Datasets for 2017

No	Regency/City	Production (ton)	Number of boats	Number of sub-districts	Number of villages	Number of fish species
1	West Aceh	0.034	0.086	0.292	0.144	0.054
2	Southwest Aceh	0.078	0.224	0.250	0.161	0.108
3	Great Aceh	0.002	0.145	0.833	0.697	0.108
4	Aceh Jaya	0.020	0.149	0.250	0.185	0.324
5	South Aceh	1.000	0.275	0.625	0.290	0.595
6	Aceh Singkil	0.019	0.308	0.333	0.118	0.649
...	...	...	...	...	...	...
18	Simeulue	0.042	1.000	0.292	0.144	1.000

4.2.2. Defining Clusters

Initialize cluster centres with as many as 2 clusters from the dataset to select each medoid. It is chosen randomly or randomly.

Table 4. Initial Medoids

Object 14	0.017	0.102	0.000	0.000	0.432
Object 17	0.046	0.000	0.208	0.245	0.135

4.2.3. Calculate Euclidean Distance

Calculating the closest distance with the Euclidean Distance equation. The next step is to calculate the Euclidean Distance to cluster each piece of data that has been obtained. Euclidean Distance. The calculation of the Euclidean Distance for each cluster with equation 2.2 is as follows:

$$d(1) = \sqrt{(0.034 - 0.017)^2 + (0.086 - 0.102)^2 + (0.292 - 0.000)^2 + (0.144 - 0.000)^2 + (0.054 - 0.432)^2} = 0.499428674$$

$$d(2) = \sqrt{(0.034 - 0.046)^2 + (0.086 - 0.000)^2 + (0.292 - 0.208)^2 + (0.144 - 0.245)^2 + (0.054 - 0.135)^2} = 0.177081902$$

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. Results of K-Medoids Algorithm Iteration 1.

No	Regency/City	C1	C2	proximity	nearest cluster
1	West Aceh	0.499428674	0.177081902	0.177081902	2
2	Southwest Aceh	0.460436749	0.246473122	0.246473122	2
3	Great Aceh	1.134349153	0.786523363	0.786523363	2
4	Aceh Jaya	0.332576307	0.252907098	0.252907098	2
5	South Aceh	1.223728728	1.171859633	1.171859633	2
6	Aceh Singkil	0.462970841	0.625733969	0.462970841	1
...	...	...	...	...	...
18	Simeulue	1.111599298	1.328720437	1.111599298	1
total proximity				9.925241061	

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 6. New Medoids

New Medoids					
Object 3	0.002	0.145	0.833	0.697	0.108
Object 7	0.004	0.127	0.375	0.234	0.514

4.2.4. Calculate Euclidean Distance

The same calculation is still done for all data. After doing the calculation to all data and attributes, it will get the closest distance of each data in each cluster

Table 7. Iteration 2 Calculation Results for the Year 2017

No	Regency/City	C1	C2	proximity	nearest cluster
1	West Aceh	0.778402852	0.478717035	0.478717035	2
2	Southwest Aceh	0.799501094	0.447967633	0.447967633	2
3	Great Aceh	0	0.767656824	0	1
4	Aceh Jaya	0.805623361	0.234234925	0.234234925	2
5	South Aceh	1.207884928	1.042169372	1.042169372	2
6	Aceh Singkil	0.951199243	0.257742119	0.257742119	2
...	...	...	...	...	...
18	Simeulue	1.458348038	1.007351974	1.007351974	2
total proximity				8.538990666	

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 8. New Medoids

New Medoids					
Object 1	0.034	0.086	0.292	0.144	0.054
Object 2	0.078	0.224	0.25	0.161	0.108

4.2.5. Calculate Euclidean Distance

The same calculation is still done for all data. After doing the calculation to all data and attributes, it will get the closest distance of each data in each cluster

Table 9. Iteration 3 Calculation Results for the Year 2017

No	Regency/City	C1	C2	proximity	nearest cluster
1	West Aceh	0	0.161086933	0	1
2	Southwest Aceh	0.161086933	0	0	2
3	Great Aceh	0.778402852	0.799501094	0.778402852	1
4	Aceh Jaya	0.283742841	0.237109679	0.237109679	2
5	South Aceh	1.180577401	1.116745271	1.116745271	2
6	Aceh Singkil	0.637095754	0.558530214	0.558530214	2
...	...	...	...	...	...
18	Simeulue	1.31543757	1.183718294	1.183718294	2
total proximity				10.35478021	

4.2.6. Standard Deviation (Total Deviations)

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.

$$S = \text{new total cost} - \text{old total cost}$$

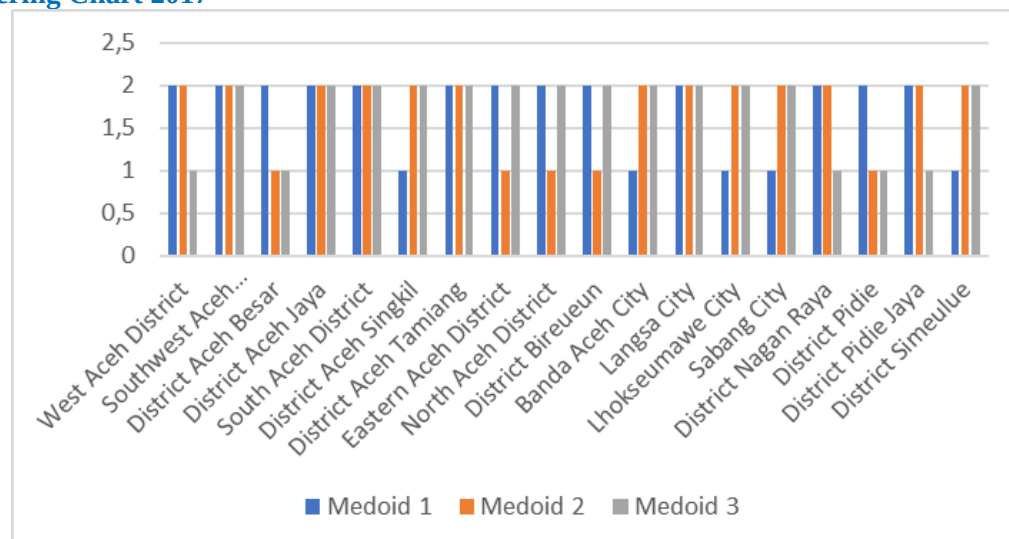
$$= 10.35478021 - 8.538990666$$

4.2.7. Cluster Result

Table 10. The final result of the calculation 2017

No	Regency/City	Result
1	West Aceh	Low
2	Southwest Aceh	High
3	Great Aceh	Low
4	Aceh Jaya	High
5	South Aceh	High
6	Aceh Singkil	High
...	...	...
18	Simeulue	High

4.2.7. Clustering Chart 2017

**Fig. 2** Graphical Result K-Medoids

4.3. K-Means Calculation

4.3.1. Datasets

The variables used in the K-Medoids method are the Regency/City of Aceh Province, production (tons), number of ships, number of sub-districts, number of villages and number of fish species.

Table 11. Datasets for 2017

No	Regency/City	Production (ton)	Number of boats	Number of sub-districts	Number of villages	Number of fish species
1	West Aceh	0.034	0.086	0.292	0.144	0.054
2	Southwest Aceh	0.078	0.224	0.250	0.161	0.108
3	Great Aceh	0.002	0.145	0.833	0.697	0.108
4	Aceh Jaya	0.020	0.149	0.250	0.185	0.324
5	South Aceh	1.000	0.275	0.625	0.290	0.595
6	Aceh Singkil	0.019	0.308	0.333	0.118	0.649
...	...	...	...	...	...	...
18	Simeulue	0.042	1.000	0.292	0.144	1.000

4.3.2. Defining Clusters

In the k-means algorithm, the first step is determining the number of clusters to use. This system will use 2 clusters, namely:

C1 = Low catchment area

C2 = High catchment area

4.3.3. Determining the Cluster Center Point Value (Centroid)

The centre point value for the initial centroid is taken randomly or randomly from the data. The following is the initial centroid selected:

Table 12. Initial Centroid

C1	0.002	0.145	0.833	0.697	0.108
C2	0.004	0.127	0.375	0.234	0.514

4.3.4. Cluster Center Distance Calculation

Then, the distance from each data set to the existing cluster centre will be calculated using the Euclidean distance formula in equation (2).

$$d(1) = \sqrt{(0.034 - 0.002)^2 + (0.086 - 0.145)^2 + (0.292 - 0.833)^2 + (0.144 - 0.697)^2 + (0.054 - 0.108)^2} = 0.778402855$$

$$d(2) = \sqrt{(0.034 - 0.004)^2 + (0.086 - 0.127)^2 + (0.292 - 0.375)^2 + (0.144 - 0.234)^2 + (0.054 - 0.514)^2} = 0.470717035$$

This calculation is performed on all data so that the closest distance of each data to the cluster in the first iteration is obtained as in the following table:

Table 13. Results of K-Means Algorithm Iteration 1

No	Regency/City	C1	C2	Closest Distance	Cluster
1	West Aceh	0.778402852	0.478717035	0.478717035	C2
2	Southwest Aceh	0.799501094	0.447967633	0.447967633	C2
3	Great Aceh	0	0.767656824	0	C1
4	Aceh Jaya	0.805623361	0.234234925	0.234234925	C2
5	South Aceh	1.207884928	1.042169372	1.042169372	C2
6	Aceh Singkil	0.951199243	0.257742119	0.257742119	C2
...	...	...	...	...	...
18	Simeulue	1.458348038	1.007351974	1.007351974	C2

Based on the calculations above, a new centroid is produced for the next iteration calculation, namely as follows:

Table 14. New Centroid

C1	0.2344	0.2596	0.8248	0.7708	0.346
C2	0.168230769	0.201076923	0.256384615	0.154615385	0.382538462

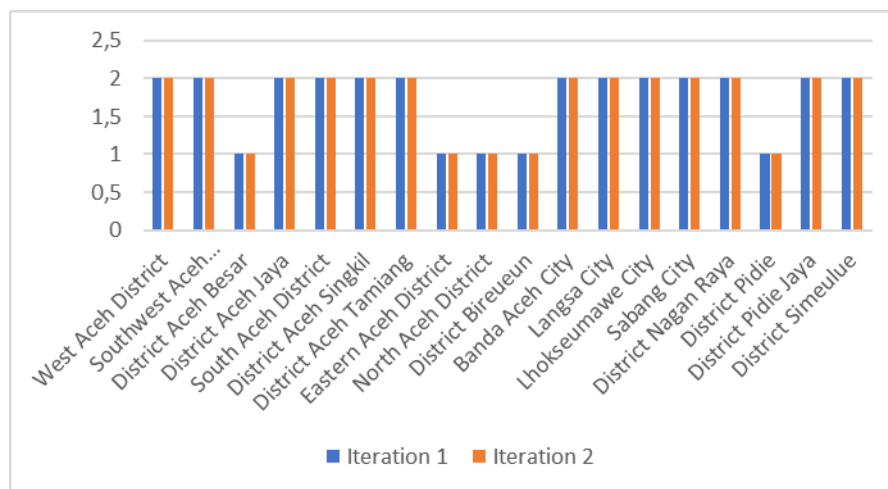
After the new centroid is calculated, the next step is to compare it with the initial centroid. If the value is the same, then the calculation process is stopped, but if the result is different, the process continues until the same centroid result is obtained.

Table 15. Result of K-Means Algorithm Iteration 2

No	Regency/City	C1	C2	Closest Distance	Cluster
1	West Aceh	0.912313104	0.374939009	0.374939009	C2
2	Southwest Aceh	0.885789704	0.290034399	0.290034399	C2
3	Great Aceh	0.359583926	0.856046161	0.359583926	C1
4	Aceh Jaya	0.855710465	0.170514241	0.170514241	C2
5	South Aceh	0.958890088	0.946916509	0.946916509	C2
6	Aceh Singkil	0.899201757	0.334536578	0.334536578	C2
...	...	...	...	...	...
18	Simeulue	1.299876917	1.018259389	1.018259389	C2

After checking the last iteration, the second iteration, this iteration is the same as the first iteration, which means the calculation is stopped at the second iteration.

4.3.5. Clustering Chart 2017

**Fig. 3** Graphic Result K-Means

4.4. DBI Calculation Result

Evaluation of clustering results using the Davies-Bouldin Index (DBI) aims to assess the quality of clusters formed after applying the K-Means and K-Medoids clustering algorithms [19]. DBI measures the balance between the proximity of data points in a cluster and the distance between clusters. The lower the DBI value, the better the quality of the clustering [20].

The evaluation results using the Davies-Bouldin Index (DBI) for both clustering methods, K-Means and K-Medoids, show different results in terms of clustering quality. The following are the results of the DBI calculation after applying the two algorithms:

Table 16. Evaluation Results of K-means and K-Medoids Data

Evaluation DBI K-Means		Evaluation Result DBI K-Medoids	
2017	1.10397052	2017	3.335783782
2018	1.48692805	2018	2.328071538
2019	1.44460567	2019	1.849306262
2020	1.52331559	2020	1.510445158
2021	1.17139495	2021	3.119186813
2022	1.08787101	2022	1.801656597
2023	1.16390357	2023	1.797282903
Results	1.283141337	Results	2.248819008

After calculating using DBI, the best clustering result was obtained by K-Means. This can be seen clearly from the average DBI value, where K-Means has an average DBI of 1.283141337, much lower than K-Medoids, which reaches 2.248819008. The lower DBI value indicates that the K-Means cluster is better than the K-Medoids.

5. Conclusion

K-Means and K-Medoids algorithms were successfully applied to categorize capture fisheries catchment areas in Aceh Province into two groups: high catchment areas and low catchment areas. Based on data from 2017 to 2023 using the K-Medoids method, the average high

and low catchment areas ranged from, year 2017 C1:28%, C2:72%, year 2018 C1:72%, C2:28%, year 2019 C1:83%, C2:17%, year 2020 C1:83%, C2:17%, year 2021 C1:83%, C2:17%, year 2022 C1:33%, C2:67%, year 2023 C1:33%, C2:67%. These results reflect the dynamics of fisheries in Aceh, which continue to change yearly. Based on calculations from 2017 to 2023 using the K-Means method, high and low catch areas ranged from, the year 2017 C1:28%, C2:72%, year 2018 C1:72%, C2:28%, year 2019 C1:61%, C2:39%, year 2020 C1:56%, C2:44%, year 2021 C1:67%, C2:33%, year 2022 C1:61%, C2:39%, year 2023 C1:67%, C2:33%.

References

- [1] M. Y. Matdoan, N. A. Purnamasari, and N. S. Laamena, "Application of the K-Means Algorithm for Clustering Production of Capture Fisheries in Maluku Province," *Pattimura Int. J. Math.*, vol. 2, no. 2, pp. 63–70, 2023, doi: 10.30598/pijmathvol2iss2pp63-70.
- [2] Nurdin, Bustami, R. Meiyanti, and A. Fahada, "Clustering Types of Capture Fisheries Products Using the K-Means Clustering Algorithm," *J. Theor. Appl. Inf. Technol.*, vol. 102, no. 17, pp. 6482–6492, 2024.
- [3] Q. Shang, Y. Yu, and T. Xie, "A Hybrid Method for Traffic State Classification Using K-Medoids Clustering and Self-Tuning Spectral Clustering," *Sustain.*, vol. 14, no. 17, 2022, doi: 10.3390/su141711068.
- [4] S. Mousavi, F. Z. Boroujeni, and S. Aryanmehr, "Improving customer clustering by optimal selection of cluster centroids in K-means and K-medoids algorithms," *J. Theor. Appl. Inf. Technol.*, vol. 8, no. 10, pp. 3807–3814, 2020.
- [5] X. Ran, X. Zhou, M. Lei, W. Tepsan, and W. Deng, "A Novel K-Means Clustering Algorithm With A Noise Algorithm For Capturing Urban Hotspots," *Appl. Sci.*, vol. 11, no. 23, 2021, doi: 10.3390/app112311202.
- [6] N. Nurdin, F. Fajriana, M. Maryana, and A. Zanati, "Information System for Predicting Fisheries Outcomes Using Regression Algorithm Multiple Linear," *J. Informatics Telecommun. Eng.*, vol. 5, no. 2, pp. 247–258, 2022, doi: 10.31289/jite.v5i2.6023.
- [7] Nurdin, M. Zarlis, Tulus, and S. Efendi, "Data Driven Optimization Approach to Fish Resources Supply Chain Planning in Aceh Province," *J. Phys. Conf. Ser.*, vol. 1255, no. 1, 2019, doi: 10.1088/1742-6596/1255/1/012081.
- [8] Z. A. Muchlisin, "Analisis Kebijakan Introduksi Spesies Ikan Asing Di Perairan Umum Daratan Provinsi Aceh," vol. 1, no. 1, pp. 79–89, 2020.
- [9] M. Anwar, M. Shafira, and S. Sunarto, "Harmonisasi Kewenangan Pengelolaan Sumber Daya Perikanan Di Era Otonomi Daerah Berbasis Pancasila," *Pancasila Law Rev.*, vol. 1, no. 1, p. 54, 2020.
- [10] S. A. Abbas, A. Aslam, A. U. Rehman, W. A. Abbasi, S. Arif, and S. Z. H. Kazmi, "K-Means and K-Medoids: Cluster Analysis on Birth Data Collected in City Muzaffarabad, Kashmir," *IEEE Access*, vol. 8, pp. 151847–151855, 2020, doi: 10.1109/ACCESS.2020.3014021.
- [11] M. Nurdin, Bustami, Rini Meiyanti, Amalia Fahada, "Application of the K-Means Method for Clustering Capture Fisheries Products in North Aceh with A Data Mining Approach," *J. Adv. Zool.*, vol. 44, no. 04, pp. 1770–1780, 2023.
- [12] A. Maulana and N. Nur Akbar, Khahari, "Penerapan Clustering Menggunakan Algoritma K-Means Sebagai Analisis Produksi Komoditas Perikanan Provinsi di Indonesia," *EJECTS E-Journal Comput. Technol. Informations Syst.*, vol. 01, no. 01, pp. 34–39, 2021.
- [13] N. Istiqomah, M. A. Ridla, and N. Azise, "Data Mining: Tingkat Penghuni Kamar Hotel Di Aceh Dari Tahun 2018-2022 Menggunakan Aplikasi Zaitun," *Gudang J. Multidisiplin Ilmu*, vol. 2, no. 8, pp. 9–12, 2024, [Online]. Available: <https://gudangjurnal.com/index.php/gjmi/article/view/671>
- [14] Nayla Azkia, Rizky Feliana Devi, Fajar Hartanto Siswanto, and Jerry Heikal, "Application of K-Means Clustering To Analyze Insurance Data At Pt Axa Insurance Indonesia," *J. Soc. Econ. Res.*, vol. 6, no. 1, pp. 1136–1144, 2024, doi: 10.54783/jsr.v6i1.482.
- [15] S. Darma, Y. Yusman, and J. Hendrawan, "Analisis Data Tingkat Kehadiran Pegawai dengan Menggunakan Clustering K-Means Pada Dinas Pekerjaan Umum dan Penataan Ruang Kabupaten Langkat," *J. Minfo Polgan*, vol. 13, no. 1, pp. 1105–1116, 2024, doi: 10.33395/jmp.v13i1.13958.
- [16] F. Fajriana, "Analisis Algoritma K-Medoids pada Sistem Klasterisasi Produksi Perikanan Tangkap Kabupaten Aceh Utara," *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 2, p. 263, 2021, doi: 10.26418/jp.v7i2.47795.
- [17] R. Putri, F. Riana, and B. Wulandari, "Implementasi K-Medoids Dalam Pengelompokan Fasilitas Pelayanan Kesehatan Pada Kasus Tuberculosis," *J. Inform.*, vol. 11, no. 1, pp. 17–24, 2024, doi: 10.31294/inf.v11i1.20044.
- [18] S. Hajar, A. A. Novany, A. P. Windarto, A. Wanto, and E. Irawan, "Penerapan K-Means Clustering Pada Ekspor Minyak Kelapa Sawit Menurut Negara Tujuan," *Semin. Nas. Teknol. Komput. Sains* 2020, pp. 314–318, 2020.
- [19] N. L. Anggreini, "Teknik Clustering Dengan Algoritma K-Medoids Untuk Menangani Strategi Promosi Di Politeknik Tedc Bandung," *J. Teknol. Inf. dan Pendidik.*, vol. 12, no. 2, pp. 1–7, 2019, doi: 10.24036/tip.v12i2.215.
- [20] E. Sabna, U. Hang, and T. Pekanbaru, "Analysis Of K-Mean Clustering In Grouping Child Mortality," no. x, pp. 1–5, 2024.