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Comparison of K-Means and K-Medoids Algorithms in Clustering Indonesian Provinces Using Stunting Handling Index

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Abstract: Stunting remains a major public health problem and poses a significant challenge to human resource development in Indonesia. Differences in stunting management performance across provinces indicate regional disparities that require systematic and data-driven analysis. This study aims to cluster provinces in Indonesia based on the 2022 Stunting Management Specific Index (IKPS) and to compare the performance of the K-Means and K-Medoids clustering algorithms. The study uses secondary data from the Central Statistics Agency (BPS), covering 34 provinces and ten indicators composing the IKPS. Clustering was conducted using K-Means and K-Medoids algorithms. The optimal number of clusters was determined using the Elbow Method, while clustering quality was evaluated using the Davies–Bouldin Index (DBI). The results show that the optimal number of clusters is k = 5. Furthermore, the K-Medoids algorithm produces better clustering quality, as indicated by a lower DBI value compared to the K-Means algorithm, reflecting more compact clusters and clearer separation between provinces. The clustering results reveal distinct provincial groupings with varying stunting management characteristics, ranging from provinces with relatively strong and stable performance to those facing greater challenges related to geographical constraints and limited access to health services. Overall, this study demonstrates that cluster analysis is effective for identifying regional patterns in stunting management and can support policymakers in formulating more targeted, province-based strategies to improve the effectiveness of stunting prevention and intervention programs in Indonesia.
Keywords: DBI, K-Means, K-Medoids, Provincial clustering, Stunting

Introduction

The development of a country cannot be separated from the level of welfare of its people. Welfare reflects the condition of a society that can meet material and non-material needs, including social, economic, and health aspects. The better the level of welfare of the people, the better the quality of a country's development. One important indicator in assessing the quality of human development is health, especially in vulnerable groups such as toddlers. Stunting remains a serious public health problem in Indonesia. Stunting is a condition of growth failure in children due to chronic malnutrition, which affects children's physical growth, cognitive development, and immune system (Faujia et al., 2022). Children who experience stunting are at risk of having lower intelligence, being more susceptible to disease, and having lower productivity in the future (BPS, 2023). Based on data from the Ministry of Health, the prevalence of stunting in Indonesia in 2022 reached 21.6%, a decrease of 2.8% compared to 2021. However, this figure is still far from the national target of 14% by 2024 (Ministry of Health, 2023). President Joko Widodo emphasized that achieving this target requires effective cooperation from all stakeholders.

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` As a form of the government's commitment to accelerating the reduction of stunting, Presidential Regulation of the Republic of Indonesia Number 72 of 2021 concerning the Acceleration of Stunting Reduction was issued. In support of this policy, the government developed the Special Index for Stunting Reduction (IKPS) as an instrument for evaluating the performance of local governments. The IKPS is used to monitor the achievements of stunting reduction interventions and is also part of the fulfillment of the cooperation agreement between the Government of Indonesia and the World Bank through Disbursement Linked Indicator 8 in the Investing in Nutrition and Early Years (INEY) program. The IKPS was developed by the Central Statistics Agency (BPS) and the Secretariat of the Vice President of the Republic of Indonesia (Setwapres RI) with the involvement of relevant ministries/agencies and experts to ensure the accuracy of indicator selection, methodology, and index measurement (BPS, 2023). The differences in IKPS values between provinces indicate disparities in the effectiveness of stunting prevention in Indonesia. Therefore, a data-based analytical approach is needed to group provinces based on similar characteristics to support the formulation of more targeted policies. One approach that can be used is data mining techniques, particularly clustering.

Clustering is the process of grouping data into a number of clusters with a high degree of similarity within a cluster and a low degree of similarity between clusters (Fatimah & Nuryaningsih, 2018). The clustering technique was first introduced by Lloyd in 1957 and is generally divided into hierarchical and non-hierarchical methods. Hierarchical clustering forms clusters through agglomerative or divisive processes and produces dendrograms that illustrate hierarchical relationships between objects. Although this method is effective for exploratory analysis and small datasets, recent studies note that hierarchical clustering has limitations when applied to large scale or high dimensional data due to its high computational complexity and the irreversible nature of clustering decisions(Omran et al., 2007; Xu & Tian, 2015). On the other hand, non-hierarchical clustering methods, such as K-Means and K-Medoids, are more suitable for large datasets because they are computationally efficient and allow iterative data reassignment to improve cluster quality. Given that the IKPS dataset consists of various indicators measured across provinces in Indonesia, non-hierarchical clustering provides greater flexibility in capturing similarities between provinces while maintaining computational feasibility.

The two most used non-hierarchical algorithms are K-Means and K-Medoids. K-Means groups data based on proximity to the cluster mean (centroid), giving it advantages in computational efficiency and speed , which has been widely reported as effective for large public health and socio economic datasets (Arora et al., 2016), but it is sensitive to outliers (Mohemad et al., 2022; Nirmal, 2019). In contrast, K-Medoids uses actual objects as cluster centers (medoids), making it more robust against noise and outliers, a characteristic that is particularly important in regional health data where extreme values may occur, although it requires longer computation time. The combined use of K-Means and K-Medoids allows this study to compare efficiency oriented and robustness-oriented clustering results, thereby increasing the reliability of provincial groupings used as the basis for targeted stunting prevention policies.

Several previous studies have compared the performance of the K-Means and K-Medoids algorithms. Nirmal (2019) showed that K-Medoids is superior in handling data containing outliers and is more stable on large-scale datasets. Meanwhile, Mohemad et al. (2022) found that K-Means provided the best results in document clustering with an accuracy rate of 78% and performed better in evaluating the average distance within clusters. The differences in the results of these studies show that there is no consistent conclusion regarding the most optimal non-hierarchical clustering algorithm. In addition, most previous clustering studies have been applied to socioeconomic, global health, or text data, and have not specifically examined regional clustering in Indonesia based on the Special Index for Stunting Management. Research that integrates IKPS data with a non-hierarchical clustering approach to identify patterns of similarity between provinces is still very limited. This condition indicates a research gap related to the use of clustering algorithms in evaluating stunting handling policies based on composite indices.

Based on this research gap, this study has the novelty of applying and comparing the K-Means and K-Medoids algorithms in clustering provinces in Indonesia based on the 2022 Special Index for Stunting Handling (IKPS). Additionally, this study evaluates cluster quality using the Davies Bouldin Index (DBI) method to determine the best algorithm in the context of IKPS data. The results of this study are expected to provide an overview of provincial clustering patterns in stunting management and serve as a basis for more strategic and data-driven decision-making and policy formulation.

Method

The research method used in this study is a descriptive quantitative approach. This approach aims to describe and analyze the grouping patterns of provinces in Indonesia based on the 2022 Special Index for Stunting Management (IKPS) through a comparison of the K-Means and K-Medoids algorithms. The analysis process was carried out using statistical, mathematical, and computational methods. The data used is secondary data in the form of the 2022 Provincial Stunting Handling Index (IKPS) in Indonesia, obtained from the official website of the Central Statistics Agency (BPS). The research objects consist of 34 provinces in Indonesia, with each province represented by the indicators that make up the IKPS.

Table 1. Research Variables for 2022 Province IKPS Data

Variable	Description
X1	Immunization
X2	Childbirth assistance by health workers in health facilities
X3	Modern family planning
X4	Exclusive breastfeeding
X5	Complementary feeding
X6	Safe drinking water
X7	Adequate sanitation
X8	Food consumption
X9	Early childhood education
X10	JKN/Jamkesda Ownership

The clustering process was carried out using non-hierarchical algorithms, namely K-Means and K-Medoids, to group provinces in Indonesia based on the similarity of IKPS indicator values. The optimal number of clusters (k) is determined using the Elbow method, which evaluates the relationship between the number of clusters and the sum of squares within clusters (WCSS). The optimal k value is identified at the point where the decrease in WCSS begins to stabilize, forming an elbow that indicates a balance between model complexity and clustering effectiveness (Herdiana et al., 2025). The clustering results from the two algorithms were then evaluated using the Davies Bouldin Index (DBI) method to assess the quality of the clusters formed. Algorithmsithm with the lowest DBI value is considered to produce the best cluster structure and is further analyzed to interpret the characteristics of each cluster. The research variables used in this study are the indicators that make up the 2022 Special Index for Stunting Management (IKPS), which are presented in table 1.

1. *Clutering*

Clustering is one of the approaches in unsupervised learning that is widely used in data mining to find hidden patterns in unlabeled data (Rahman & Wijayanto, 2021). Clustering aims to group data objects into several clusters based on a certain level of similarity, so that objects in one cluster have a high level of similarity, while clusters have a low level of similarity (Dewi et al., 2021). This technique is widely used in multivariate data analysis because it provides a natural representation of the data structure.

In this study, the clustering results were interpreted by comparing the average values of the IKPS indicators in each group to identify distinguishing characteristics and the level of stunting management performance at the provincial level. This interpretation formed the basis for drawing substantial conclusions from the clustering results.

2. *K-Means*

The K-Means algorithm is a non-hierarchical clustering method that is iterative and used to partition data into a predetermined number of clusters. This algorithm works by grouping data based on proximity to the cluster center (centroid), so that data with similar characteristics are in the same cluster, while data with different characteristics are grouped into other clusters (Syukron et al., 2022). The data analysis procedure using K-Means consists of the following steps:

1) Randomly initializing k centroids.
2) Calculating the distance between each data point and the centroids using Euclidean Distance.
3) Assigning data points to the nearest centroid.
4) Updating centroids based on the mean of cluster members.

These steps are repeated iteratively until convergence is achieved, indicated by no change in cluster membership or centroid positions (Abbas et al., 2020).

In the K-Means algorithm, the cluster centers are determined randomly at the initial stage. The clustering process is greatly influenced by the distance measurement method used. Some commonly used distance metrics include Euclidean Distance, Manhattan Distance, and Chebyshev Distance. However, Euclidean Distance is more commonly used because it has a high level of computational efficiency and is easy to interpret (Alam et al., 2019).

3. *K-Medoids*

K-Medoids is a clustering method like K-Means, but uses actual objects in the dataset as cluster centers (medoids) (Madbouly et al., 2022). This approach makes K-Medoids more resistant to noise and outliers than K-Means. The K-Medoids analysis procedure includes:

1) Selecting k initial medoids randomly from the dataset.
2) Assigning each data point to the nearest medoid based on Euclidean Distance.
3) Evaluating possible swaps between medoids and non-medoids by calculating changes in the cost function.
4) Updating medoids if a swap reduces the total clustering cost.

This process is repeated iteratively until no further improvement is obtained (Abbas et al., 2020).

The K-Medoids algorithm attempts to minimize the total distance between data points in a cluster and the medoid that represents it (Prahara et al., 2020). The cost function is defined as:

$$Cost = \sum_{M_i} \sum_{Pi \in mi} d(P_i, M_i) \quad (1)$$

4. Euclidean Distance

Euclidean Distance is one of the most commonly used distance metrics in clustering analysis to measure the proximity between two objects in a multidimensional space (Cabitza et al., 2022). In distribution-based data representation, Euclidean distance is defined as the geometric distance between two data vectors. In the clustering process, this metric is used to calculate the distance between each data point and the cluster center to determine cluster membership (Luchia et al., 2022). The use of Euclidean distance in this study is justified due to its suitability for continuous numerical data measured on the same scale. Since all IKPS indicators are index values that have been normalized by the data provider and expressed on a comparable scale, data normalization is not necessary. The absence of normalization does not affect the distance calculation, as no variable dominates the clustering process due to scale differences.

$$d(x_i, x_j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{in} - x_{jn})^2} \quad (2)$$

5. Davies-Bouldin Index

The Davies-Bouldin Index (DBI) was introduced by David L. Davies and Donald W. Bouldin as an internal evaluation method for assessing the quality of clustering results (Mughnyanti et al., 2020). This index measures the ratio between the average intra-cluster distance and the inter-cluster distance, thereby describing the level of cluster compactness and separation between clusters (Agbaje et al., 2019). In this study, DBI is used as the primary criterion for drawing conclusions regarding clustering performance. A lower DBI value indicates more compact clusters and greater separation between clusters, suggesting superior clustering quality. The clustering method that produces the smallest DBI value is considered the most appropriate for interpreting provincial IKPS patterns (Brito Da Silva et al., 2020).

$$DB = \frac{1}{k} \sum_{i=0}^{k} R_i \quad (3)$$

Result and Disscusion

Determination of the Optimal Number of Clusters

Before applying the K-Means and K-Medoids algorithms, the optimal number of clusters is first determined using the Elbow Method. This method works by calculating the Within-Cluster Sum of Squares (WCSS) value for various numbers of clusters (K). The WCSS value describes the level of data variation within each cluster, the smaller the value, the more homogeneous the clusters are.

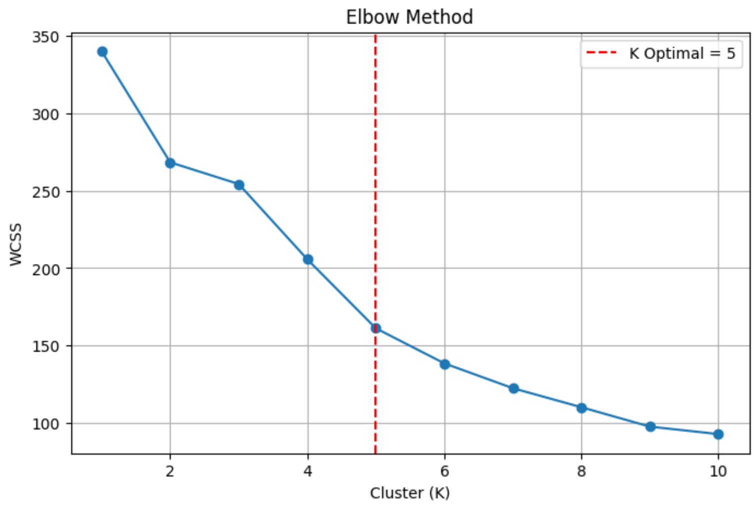

Figure 1. Elbow Method

Based on the Elbow Method graph (figure 1), the WCSS value decreases sharply from k = 1 to k = 5. After k = 5, the decline in WCSS tends to level off and does not show significant changes. This pattern forms an elbow at k= 5, which indicates that adding more clusters after that value no longer provides a significant improvement in cluster quality.

Therefore, the optimal number of clusters selected is k = 5. This value is considered to provide a balance between model complexity and data clustering quality. The results of determining the number of clusters are then used as the basis for applying the K-Means and K-Medoids algorithm in the next stage.

K-Means Clustering

Using k = 5, the K-Means algorithm was applied to cluster the provinces based on the IKPS indicators. The clustering process resulted in five distinct clusters, as presented in table 2.

Table 2. K-Means Clustering Result

Cluster	Province
1	Aceh, Papua. West Java, West Nusa Tenggara,
2	Riau, West Sumatra, South Sumatra, Bengkulu, Jambi, Lampung, South Kalimantan, Central Kalimantan, West Java, West Kalimantan.
3	Bangka Belitung Islands, Riau Islands, DKI Jakarta, Central Java, Yogyakarta, East Java, Bali, East Nusa Tenggara, East Kalimantan, North Kalimantan, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi
4	North Sumatra, Banten, West Nusa Tenggara, North Sulawesi, Central Sulawesi
5	Maluku, North Maluku, West Papua

To determine the characteristics and differences between clusters formed by the K-Means algorithm, an analysis was conducted on the average of each variable in each cluster. The results of the variable average calculations are presented in table 3.

Table 3. Average Value of the Variable using K-Means

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Immunization	38.15	64.2	79.64	66.32	61.43
Childbirth assistance by health workers in health facilities	82.45	85.5	94.06	89.28	62.1
Modern family planning	36.55	73.62	60.76	67.64	45.2
Exclusive breastfeeding	87.55	87.64	87.86	84.38	79.23
Complementary feeding	86.35	89.94	82.11	79.66	77.57
Safe drinking water	77.55	82.21	91.4	92.2	87.27
Adequate sanitation	58.9	78.31	86.71	81.9	76.47
Food consumption	60.7	81.42	78.2	89.48	49
Early childhood education	24.15	32.71	42.85	35.76	34.6
JKN/Jamkesda Ownership	90.5	61.25	76.21	66.3	65.8

The results indicate that Cluster 3 has the highest average values for most indicators, while Cluster 1 records the lowest averages for several indicators. Cluster 4 shows relatively high values in access to safe drinking water and food consumption, whereas Cluster 5 has lower averages in food consumption and childbirth assistance in health facilities. Cluster 2 demonstrates moderate values across most indicators.

K-Medoids Clustering

Following the K-Means analysis, the K-Medoids algorithm was applied using the same number of clusters (k = 5). The resulting cluster memberships are shown in table 4.

Table 4. K-Medoids Clustering Result

Cluster	Province
1	Aceh
2	West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, West Java, West Kalimantan, Central Kalimantan, South Kalimantan
3	Bangka Belitung Islands, Riau Islands, DKI Jakarta, Central Java, Yogyakarta Special Region, East Java, Bali, East Nusa Tenggara, East Kalimantan, North Kalimantan, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi
4	North Sumatra, Banten, West Nusa Tenggara, North Sulawesi
5	Maluku, North Maluku, West Papua, Papua

Similar to the K-Means analysis, cluster characteristics were examined by calculating the average value of each IKPS indicator within each cluster. These results are presented in table 5.

Table 5. Average Value of the Variable using K-Medoids

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Immunization	25	64.2	79.37	64	58.9
Childbirth assistance by health workers in health facilities	92.4	85.5	93.55	90.03	64.7
Modern family planning	53.4	73.62	61.17	67.8	38.83
Exclusive breastfeeding	82.4	87.64	87.49	84.9	82.6

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Complementary feeding	95.9	89.94	81.76	80.35	77.38
Safe drinking water	89.7	82.21	91.09	93.58	81.8
Adequate sanitation	77.5	78.31	85.93	83.63	67.43
Food consumption	81.7	81.42	78.33	91.83	46.68
Early childhood education	34.2	32.71	42.75	34.35	29.48
JKN/Jamkesda Ownership	97	61.25	75.87	65.13	70.35

The results indicate that Cluster 3 shows consistently high average values across most indicators, while Cluster 5 records the lowest averages for several key variables, particularly food consumption and modern family planning. Cluster 1 is characterized by high JKN/Jamkesda ownership and childbirth assistance but low immunization coverage. Cluster 4 shows relatively high averages for access to safe drinking water and food consumption, while Cluster 2 displays moderate indicator values.

Cluster Validity Comparison

To evaluate the quality of the clustering results obtained from the K-Means and K-Medoids algorithms, the Davies–Bouldin Index (DBI) method was used. This index measures the degree of similarity between clusters by considering the ratio between intra-cluster distance and inter-cluster distance. A smaller DBI value indicates better cluster quality, as it signifies more compact clusters with clearer separation. The Davies–Bouldin Index values for each clustering method are presented in table 6.

Table 6. Davies–Bouldin Index Result

Method	Davies–Bouldin Index
K-Means	1.80791772
K-Medoids	1.50359777

The results show that the K-Medoids method yields a lower DBI value (1.5036) compared to the K-Means method (1.8079), indicating better cluster compactness and separation.

The clustering results show significant heterogeneity among provinces in Indonesia in terms of stunting management performance. Based on the K-Medoids clustering method, which was chosen as the primary method due to its lower Davies–Bouldin Index value, Cluster 3 consistently represents provinces with relatively high performance on most IKPS indicators, including immunization coverage, births attended by trained health personnel, sanitation, and early childhood education. This pattern reflects a more established health system and stronger supporting infrastructure in these provinces. On the other hand, Cluster 5 emerged as the most vulnerable group, characterized by low food consumption, limited access to maternal health services, and weaker early childhood education indicators. These conditions indicate a higher risk of malnutrition and maternal and child health problems, highlighting the need for prioritized and intensive policy interventions.

Cluster 2 represents provinces with moderate performance across most indicators, particularly showing relatively strong results in modern family planning and basic health services, but lower coverage of health insurance and early childhood education. This suggests that provinces in this cluster could benefit from targeted improvements in social protection and human development support to improve overall stunting management outcomes. An interesting pattern is seen in Cluster 1, which shows high JKN/Jamkesda coverage but low preventive health indicators, particularly immunization coverage. This indicates a strong reliance on curative health services rather than preventive health behaviors. Meanwhile, Cluster 4 shows relatively strong access to clean water and food consumption, indicating better environmental resilience despite moderate performance on other health indicators.

Overall, the lower DBI value confirms that K-Medoids provides a more robust and reliable representation of provincial inequalities in stunting management compared to K-Means. The use of medoids as cluster centers allows for better handling of extreme regional characteristics and reduces sensitivity to outliers, which is particularly relevant for provincial-level health data. These findings provide an evidence-based foundation for designing cluster-specific and more targeted stunting prevention policies, in line with the unique characteristics of each provincial group.

In the context of national stunting reduction programs, these findings reinforce the importance of differentiated policy approaches rather than uniform interventions across provinces. Provinces grouped within the same cluster tend to share similar structural and service-related challenges, indicating that cluster-based policy design may improve the efficiency and effectiveness of resource allocation. Furthermore, the consistency of high- and low-performing clusters across methods strengthens the robustness of the identified patterns. This supports the practical applicability of clustering analysis as a decision-support tool in public health planning.

Conclusion

This study demonstrates that cluster analysis is an effective approach for identifying patterns of stunting management performance across provinces in Indonesia based on the 2022 Stunting Management Index (IKPS). The evaluation of cluster validity using the Davies–Bouldin Index indicates that the K-Medoids algorithm outperforms K-Means, as reflected by its lower DBI value, signifying more compact clusters and clearer separation. Using the Elbow Method, the optimal number of clusters was determined to be five, resulting in distinct provincial groupings that reflect varying levels of stunting management performance. Some clusters represent provinces with relatively strong and stable performance that may serve as benchmarks, while others highlight provinces with unique vulnerabilities and more complex challenges, underscoring the need for targeted, cluster-specific policy interventions. Despite these findings, this study is limited by the use of provincial-level secondary data and a restricted set of indicators. Future research is therefore recommended to employ more granular data at the district or city level, incorporate additional socioeconomic and health system variables, and compare K-Medoids with other clustering techniques to further enhance the robustness and applicability of clustering results in supporting stunting prevention policies.

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Author Contribution

All authors played an active role in conducting the research, from data collection to manuscript preparation. The first and second authors made major contributions to data processing and analysis, as well as drafting and revising the manuscript.

References

Abbas, S. A., Aslam, A., Rehman, A. U., Abbasi, W. A., Arif, S., & Kazmi, S. Z. H. (2020). K-Means and K-Medoids: Cluster Analysis on Birth Data Collected in City Muzaffarabad, Kashmir. *IEEE Access*, *8*, 151847–151855. https://doi.org/10.1109/ACCESS.2020.3014021

Agbaje, M. B., Ezugwu, A. E., & Els, R. (2019). Automatic data clustering using hybrid firefly particle swarm optimization algorithm. *IEEE Access*, *7*, 184963–184984. https://doi.org/10.1109/ACCESS.2019.2960925

Alam, M. S., Rahman, M. M., Hossain, M. A., Islam, M. K., Ahmed, K. M., Ahmed, K. T., Singh, B. C., & Miah, M. S. (2019). Automatic human brain tumor detection in mri image using template-based k means and improved fuzzy c means clustering algorithm. *Big Data and Cognitive Computing*, *3*(2), 1–18. https://doi.org/10.3390/bdcc3020027

Arora, P., Deepali, & Varshney, S. (2016). Analysis of K-Means and K-Medoids Algorithm for Big Data. *Physics Procedia*, *78*(December 2015), 507–512. https://doi.org/10.1016/j.procs.2016.02.095

BPS. 2023. Laporan Indeks Khusus Penanganan Stunting.

Brito Da Silva, L. E., Melton, N. M., & Wunsch, D. C. (2020). Incremental Cluster Validity Indices for Online Learning of Hard Partitions: Extensions and Comparative Study. *IEEE Access*, *8*, 22025-22047. https://doi.org/10.1109/ACCESS.2020.2969849

Cabitza, F., Campagner, A., & Mattioli, M. (2022). The unbearable (technical) unreliability of automated facial emotion recognition. *Big Data and Society*, *9*(2). https://doi.org/10.1177/20539517221129549

Dewi, S., Defit, S., & Yuhandri, Y. (2021). Akurasi Pemetaan Kelompok Belajar Siswa Menuju Prestasi Menggunakan Metode K-Means. *Jurnal Sistim Informasi Dan Teknologi*, *3*, 28–33. https://doi.org/10.37034/jsisfotek.v3i1.40

Fatimah, & Nuryaningsih. (2018). Buku Ajar Buku Ajar.

Faujia, R. A., Setianingsih, E. S., & Pratiwi, H. (2022). Analisis Klaster K-Means Dan Agglomerative Nesting Pada Indikator Stunting Balita Di Indonesia. *Seminar Nasional Official Statistics*, *2022*(1), 1249–1258. https://doi.org/10.34123/semnasoffstat.v2022i1.1511

Frayudi, F., Bahri, S., & Bakar, N. N. (2019). Menentukan Akar Persamaan Nonlinier Dengan Metode Approksimasi Lingkaran. *Jurnal Matematika UNAND*, *4*(2), 38-45. https://doi.org/10.25077/jmu.4.2.38-45.2015

Herdiana, I., Kamal, M. A., Triyani, E., N, M., & Renny. (2025). A More Precise Elbow Method for Optimum K-means Clustering. 1–22. http://arxiv.org/abs/2502.00851

Luchia, N. T., Handayani, H., Hamdi, F. S., Erlangga, D., & Octavia, S. F. (2022). Perbandingan K-Means dan K-Medoids Pada Pengelompokan Data Miskin di Indonesia. *Malcom: Indonesian Journal of Machine Learning and Computer Science*, *2*(2), 35-41. https://doi.org/10.57152/malcom.v2i2.422

Madbouly, M. M., Darwish, S. M., Bagi, N. A., & Osman, M. A. (2022). Clustering Big Data Based on Distributed Fuzzy K-Medoids: An Application to Geospatial Informatics. *IEEE Access*, *10*, 20926–20936. https://doi.org/10.1109/ACCESS.2022.3149548

Mohemad, R., Mohd Muhait, N. N., Mohamad Noor, N. M., & Othman, Z. A. (2022). Performance analysis in text clustering using k-means and k-medoids algorithms for Malay crime documents. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(5). https://doi.org/10.11591/ijece.v12i5.pp5014-5026

Mughnyanti, M., Efendi, S., & Zarlis, M. (2020). Analysis of determining centroid clustering x-means algorithm with davies-bouldin index evaluation. *IOP Conference Series: Materials Science and Engineering*, *725*(1). https://doi.org/10.1088/1757-899X/725/1/012128

Nirmal, S. (2019). Comparative study between k-means and k-medoids clustering algorithms. *International Research Journal of Engineering and Technology*, *839*, 839–844. https://www.irjet.net/archives/V6/i3/IRJET-V6I3154.pdf

Omran, M. G. H., Engelbrecht, A. P., & Salman, A. (2007). An overview of clustering methods. *Intelligent Data Analysis*, *11*(6), 583–605. https://doi.org/10.3233/ida-2007-11602

Prahara, A., Ismi, D. P., & Azhari, A. (2020). Parallelization of Partitioning Around Medoids (PAM) in K-Medoids Clustering on GPU. *Knowledge Engineering and Data Science*, *3*(1), 40–49. https://doi.org/10.17977/um018v3i12020p40-49

Rahman, R. R. A., & Wijayanto, A. W. (2021). Pengelompokan Data Gempa Bumi Menggunakan Algoritma Dbscan. *Jurnal Meteorologi Dan Geofisika*, *22*(1), 31. https://doi.org/10.31172/jmg.v22i1.738

Syukron, H., Fauzi Fayyad, M., Junita Fauzan, F., Ikhsani, Y., & Rizkya Gurning, U. (2022). Perbandingan K-Means K-Medoids dan Fuzzy C-Means untuk Pengelompokan Data Pelanggan dengan Model LRFM. *Malcom: Indonesian Journal of Machine Learning and Computer Science*, *2*(2), 76-83. https://doi.org/10.57152/malcom.v2i2.442

Xu, D., & Tian, Y. (2015). A Comprehensive Survey of Clustering Algorithms. *Annals of Data Science*, *2*(2), 165–193. https://doi.org/10.1007/s40745-015-0040-1