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Clustering Analysis Of Toddler Nutritional Status Using The K-Means Method On Posyandu Data

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Abstract

The issue of toddler nutritional status remains a serious concern because it can affect children's health and development, including the risk of stunting and cognitive impairment. At the Tanjung Asri Village Health Center, nutritional status is still recorded manually, which is inefficient and prone to classification errors. This study aims to develop a system for classifying the nutritional status of infants using the K-Means Clustering method based on desktop software to simplify the classification of nutritional status into three categories: malnourished, moderately nourished, and well-nourished. This study uses a quantitative approach with primary data from 100 infants collected through observation and interviews in May and June 2025. The clustering process was performed using RapidMiner with the parameter k = 3. The test results showed that the K-Means method was able to produce accurate centroid centers consistent with manual results. In May 2025, there were 22 infants with poor nutrition, 21 infants with moderate nutrition, and 7 infants with good nutrition, while in June 2025, there were 27 infants with poor nutrition, 8 infants with moderate nutrition, and 15 infants with good nutrition. The developed system has proven effective in supporting the classification and monitoring of infant nutritional status in a more objective and efficient manner.

Keywords: Data Mining; K-Means; Clustering; Stunting

1. INTRODUCTION

Posyandu plays an important role in monitoring the growth and development of toddlers, especially in determining their nutritional status. Poor nutritional status, such as malnutrition, can cause various health problems, including stunting, cognitive development disorders, and an increased risk of infectious diseases [1]. According to data from the 2021 Indonesian Nutrition Status Survey (SSGI), Indonesia still has 24.40% of stunted toddlers, in 2022 there were 21.60% of stunted toddlers, and in 2023 there were 17.80% of stunted toddlers [2].

At the Posyandu in Tanjung Asri Village, Sei Dadap Subdistrict, Asahan Regency, data on toddlers is still recorded by writing it directly in a large folio book, similar to those used in bookkeeping [3]. The data collected includes the toddler's name, age, weight, and height. The conventional method for determining the nutritional status of infants involves matching the child's data with reference tables in the Health Card (KMS). This process has several limitations, such as taking a considerable amount of time and the possibility of errors in classifying the nutritional status of infants. Therefore, a more objective and efficient approach is needed to analyze the nutritional status of infants [4].

Nutritional status recording at the Tanjung Asri Village Health Post has been carried out monthly by officers by directly recording nutritional status using anthropometric methods, namely recording the weight and height of infants on the KMS (Health Card). Additionally, there has been no grouping of infants according to nutritional status categories, namely malnourished infants, moderately nourished infants, and well-nourished infants. Based on this, it is necessary to classify the nutritional status of toddlers so that analysis can be conducted and information provided regarding the application of nutrition for toddlers.

To address this issue, a method is needed that can classify toddlers based on their growth characteristics in a more objective manner [5]. This grouping helps in monitoring the development of toddlers over time and assessing the effectiveness of nutrition intervention programs [6]. In addition, this grouping not only helps in identifying and monitoring the nutritional status of toddlers, but also in designing and implementing more effective and efficient intervention programs [7]. With the development of technology, methods such as K-Means Clustering can be used to analyze toddler nutrition data more effectively [8]. Data clustering using K-Means enables the identification of hidden patterns that may not be visible with traditional analysis and helps detect anomalies or outliers that may indicate serious health problems [9] [10]. In addition, this grouping facilitates a better understanding of the distribution of nutritional status among toddlers, enabling the population to be segmented into more homogeneous groups [11]. This is very useful for designing more appropriate and efficient nutrition intervention programs, as well as allocating health resources more effectively [12].

Therefore, the purpose of this study is to provide information that can assist health workers in making decisions related to monitoring the nutrition of toddlers and to provide insight to the community regarding differences in child growth and development, as well as to facilitate the grouping of toddlers at the Tanjung Asri Village Health [13] Center and to identify which toddlers are classified as malnourished, moderately nourished, and well-nourished so that appropriate action can be taken [14].

Several previous studies have applied the K-Means algorithm for clustering various types of health and non-health data. Nureni [1] used K-Means for classifying newborn nutritional status, Faid and Sukron [2] applied it for





mapping stunting-prone areas, while Hasugian [3] employed K-Means to cluster students based on academic performance. These studies demonstrate the effectiveness of K-Means in grouping data according to shared characteristics.

However, most prior research has focused on macro-level data (e.g., district or sub-district level) or on nonclinical contexts. The research gap lies in the limited studies that specifically apply K-Means for classifying toddler nutritional status at the posyandu level using primary data collected directly in the field. Moreover, many existing studies only present clustering results conceptually, without developing a practical software application that can be directly used by community health workers.

Therefore, this study contributes novelty by integrating the K-Means algorithm into a desktop application designed to assist posyandu in automatically classifying toddler nutritional status. This approach provides not only an academic analysis but also a practical solution that enhances the accuracy and efficiency of nutritional monitoring at the community level.

2. RESEARCH METHOD

This study uses a quantitative approach using data from the May 2025 posyandu (integrated health service post) for toddlers. The stages of this study can be seen in Figure 1 below.

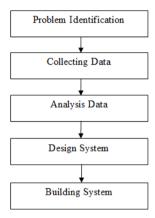


Figure 1. Research Stage

Details of the research stages in Figure 1.

2.1 Problem Identification

This stage was carried out to identify problems encountered in the field, namely the manual recording of toddler nutritional status in folio books, which made it difficult to classify nutritional status quickly and accurately. This problem prompted the need to develop a K-Means-based system to assist posyandu workers in grouping toddler data.

2.2 Collecting Data

Data was collected through direct observation and interviews at the Tanjung Asri Village Health Center. The data obtained included the age, weight, and height of toddlers recorded during health center activities. This data became the main material in the process of analyzing and classifying nutritional status [15].

2.3 Analysis Data

The collected data was analyzed to determine the characteristics and nutritional status of toddlers. This analysis also included determining patterns and similarities in the data, which formed the basis for applying the K-Means clustering method to divide toddlers into three groups: malnourished, moderately nourished, and well-nourished.

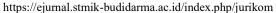
2.4 Design System

This stage includes the creation of a system design, such as ASI, UML, ERD, Flowchart, and includes the user interface, data input-output process flow, and database structure. The system design is tailored to be able to automatically group toddler data based on the K-Means Clustering algorithm [16].

2.5 Building System

After the design was completed, the system was developed using the Visual Studio 2010 programming language with a MySQL database. The system was designed to enable posyandu officers to enter data on toddlers and immediately obtain the results of nutritional status classification automatically [17].







2.6 Algorithm K-Means

The K-Means algorithm is one of the most widely used clustering methods in data mining. It partitions data into k groups (clusters) based on the distance between data points and cluster centroids. The algorithm iteratively updates the centroid positions until convergence is reached. The strengths of K-Means lie in its simplicity, computational efficiency, and its ability to handle large datasets effectively. Hasugian [3] demonstrated the effectiveness of K-Means in clustering students based on academic performance, while Faid & Sukron (2020) applied it for mapping stuntingprone areas. These studies highlight the relevance of K-Means for multivariate data classification. Nevertheless, K-Means has limitations, particularly its sensitivity to the initial choice of the number of clusters (k) and centroid initialization, which may influence the final result (Xu & Wunsch, 2009). Despite these drawbacks, K-Means is adopted in this study because the toddler nutritional status dataset shows clear grouping patterns that can be effectively analyzed using a clustering approach.

3. RESULT AND DISCUSSION

3.1 Analysis Data

Data requirements in the K-Means method system for clustering the nutritional status of toddlers. In other words, knowledge acquisition is the process of gathering information about issues directly through interviews with Posyandu officers in Tanjung Asri Village [18]. The data used is data from the May 2025 posyandu (integrated health service post) for toddlers, consisting of 100 data points, which are presented in Table 1 below.

Weight Height Code Name of Toddler Period From (Year) (kg) (cm) A001 09/05/2025 Posyandu Dusun 1 Svafira 2 12 96 A002 Razka 09/05/2025 Posyandu Dusun 1 1 12 80 A003 Al-Kafi 09/05/2025 Posyandu Dusun 1 3,5 17 100 A004 Zakir 09/05/2025 Posyandu Dusun 1 4 17 105 A005 Zidan 09/05/2025 Posyandu Dusun 1 2 14 89 A006 Wahidah 09/05/2025 Posyandu Dusun 1 2 13 93 Muhammad A007 4 100,5 09/05/2025 Posyandu Dusun 1 16 Raihan Zailani 9,4 83 A008 Nurjanah 09/05/2025 Posyandu Dusun 1 A009 Siti Aisvah 09/05/2025 Posvandu Dusun 1 71 1 8.03 Mugiono A010 Posvandu Dusun 1 9 83 09/05/2025 1 A100 24/06/2025 Posyandu Dusun 5 2,6 12,53 91.01 Ramzi

Table 1. Data Posyandu Toddlers Mei 2025

Table 1 presents the nutritional status measurement data of toddlers collected from posyandu activities in May 2025. The data include the toddler's identification code, name, measurement date, posyandu location, age, weight, and height. This information serves as the basis for the analysis and application of the K-Means Clustering method to classify toddlers into malnourished, moderately nourished, and well-nourished categories.

3.2 Determining the Centroid

Next, determine the centroid centers for May 2025 and June 2025. This is done to test the analysis of the given data, with the aim of identifying the centers of groups or clusters that are formed. This test aims to obtain accurate and reliable results in the process of classifying or grouping more complex data [19]:

Table 2 shows the centroid centers obtained from the K-Means Clustering process on toddler nutritional status data for May and June 2025. Each centroid represents the midpoint of a cluster derived from age, weight, and height parameters. This information is used to identify malnourished, moderately nourished, and well-nourished categories for each period.

Period May 2025 Period June 2025 **Pusat Centroid Pusat Centroid** Status Data Ke Status Data Ke No Gizi Kurang Gizi Kurang 1 C1A002 C1 A002 C2C22 Gizi Sedang A001 Gizi Sedang A009 A009 C3 Gizi Baik C3 Gizi Baik A001

Table 2. Centroid Center May and June 2025

Based on trials conducted with RapidMiner to determine the centroid centers for the period of May and June 2025, it can be concluded that the data clustering process successfully produced accurate centroid centers [20]. The selection of three clusters was based on the categories of poor nutrition, moderate nutrition, and good nutrition. The test





results show that in May 2025, four centroid centers were formed with codes A002, A001, and A009, as shown in Table 2, while in June 2025, four centroid centers with the same codes were also formed, as shown in Table 2.

3.3 Output Data

This output data is used for further analysis based on nutritional standards and can be seen in Table 3.

Table 3. Output Data

	Age (Year)	Weight (Kg)			
Data Flow		Malnutrition	Moderate Nutrition	Good Nutrition	Height (cm)
Nutritional Status Group for Toddlers	1 year	< 8.0 kg	8.0-8.9 kg	9.0-11.0 kg	76.0 cm
	1,5 year	< 8.5 kg	8.5-9.3 kg	9.4-12.0 kg	82.0 cm
	2 year	< 8.5 kg	8.5-9.5 kg	9.6-13.9 kg	85.0 cm
	2,5 year	< 9.0 kg	9.0-10.0 kg	10.1-14.2 kg	88.0 cm
	3 year	< 9.5 kg	9.5-10.8 kg	10.9-15.0 kg	95.0 cm
	3,5 year	< 10.0 kg	10.0-11.4 kg	11.5-15.6 kg	98.0 cm
	4 year	< 10.5 kg	10.5-11.9 kg	12.0-16.5 kg	102.0 cm
	4,5 year	< 11.0 kg	11.0-12.4 kg	12.5-17.0 kg	105.0 cm
	5 year	< 11.5 kg	11.5-13.0 kg	13.1-18.2 kg	108.0 cm

Table 3 presents the classification standards for toddler nutritional status based on age group, body weight, and height. Each category malnourished, moderately nourished, and well-nourished is determined by specific weight ranges appropriate for each age group. This information serves as a reference for interpreting the clustering results obtained through the K-Means method.

3.4 K-Means Method Analysis with Rapid Miner

In determining the centroid through RapidMiner for the period of May 2025, the selection of 3 clusters (k:3) was based on the predetermined output, namely malnutrition, good nutrition, and moderate nutrition. Figure 2 displays the clustering model of toddler nutritional status data for May 2025 using the K-Means method with k = 3. Each cluster represents the categories of malnourished, moderately nourished, and well-nourished based on age, weight, and height

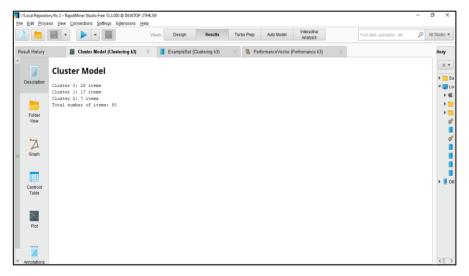


Figure 2. Cluster Grouping Model for May 2025

In the RapidMiner calculation of the nutritional status of toddlers at the Tanjung Asri Village Health Center in May 2025, it was found that there were three outputs, namely 22 cases of malnutrition, 21 cases of moderate nutrition, and 7 cases of good nutrition. From these results, it can be concluded that manual calculations and calculations using RapidMiner yield similar results, indicating that the use of RapidMiner in the clustering process produces consistent results with manual calculations despite utilizing artificial intelligence for data processing. For the June 2025 period, it was found that in determining the centroid center in selecting the number of 3 clusters (k:3), it was based on the predefined outputs, namely poor nutrition, good nutrition, and moderate nutrition.

Figure 3 presents the clustering model of toddler nutritional status data for June 2025 using the K-Means method. The comparison with the previous period is used to assess changes in the distribution of malnourished, moderately nourished, and well-nourished categories.







Figure 3. Cluster Grouping Model for June 2025

In the RapidMiner calculation of the nutritional status of toddlers at the Tanjung Asri Village Health Center in June 2025, it was found that there were three outputs, including 27 cases of malnutrition, 8 cases of moderate nutrition, and 15 cases of good nutrition. From these results, it can be concluded that manual calculations and calculations using RapidMiner yield similar outcomes, indicating that the use of RapidMiner in the clustering process produces results consistent with manual calculations despite employing artificial intelligence for data processing.

3.5 Output Data

In May 2025, there were 3 outputs based on the nutritional status of toddlers at the Tanjung Asri Village Health Center, including 22 with poor nutrition, 21 with moderate nutrition, and 7 with good nutrition. Meanwhile, in June 2025, there were 3 outcomes based on the nutritional status of infants at the Tanjung Asri Village Health Post, including 27 cases of malnutrition, 8 cases of moderate nutrition, and 15 cases of good nutrition. After obtaining the data on the nutritional status of infants for the periods of May 2025 and June 2025, a pie chart can also be used to illustrate the nutritional status of infants for each output obtained. From the pie chart, the number of children with good, moderate, and poor nutritional status can be seen, providing an overview of the nutritional condition at the Tanjung Asri Village Health Post. This is crucial for further evaluation of efforts to improve the nutritional status of children in the area, as shown in Figure 4.



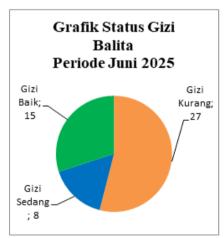


Figure 4. Graph Comparing the Nutritional Status of Toddlers in May and June 2025

Figure 4 shows a comparison graph of toddler nutritional status between May and June 2025. This visualization highlights the number of toddlers in each nutritional category, enabling the identification of trends in improvement or decline in nutritional status. Based on a comparison of the nutritional status graphs for toddlers in May and June 2025, there are several noticeable differences. In the May 2025 graph, the majority of toddlers at the Tanjung Asri Village Health Center showed moderate nutritional status, with 21 children. Poor nutritional status was also quite significant, with 22 children, while only 7 children showed good nutritional status. This indicates that the majority of toddlers are malnourished, requiring more attention. Meanwhile, in the June 2025 chart, the nutritional status of toddlers showed a slight improvement. Although the number of children with good nutritional status increased to 15, the number of children with poor nutritional status remained high at 27, which was the highest among the other categories. Meanwhile, the number of children with moderate nutritional status decreased to only 8 children. The conclusion from comparing the two graphs is that although there was an improvement in the nutritional status of infants in June 2025





compared to May 2025, there are still a significant number of children with poor nutritional status. This indicates the need for further efforts to improve children's nutrition, particularly to enhance awareness and take appropriate actions to prevent poor nutritional status.

3.6 Design System

3.6.1 Use Case Diagram

Figure 5 presents the Use Case Diagram of the developed toddler nutritional status classification system. This diagram illustrates the interaction between the main actor, namely the posyandu staff, and the system. It shows that the staff can input toddler data (age, weight, and height), perform the classification process using the K-Means algorithm, and view the clustering results into three categories: malnourished, moderately nourished, and well-nourished. Thus, the Use Case Diagram provides a comprehensive overview of the system's main functionalities and the user's role within the classification workflow.

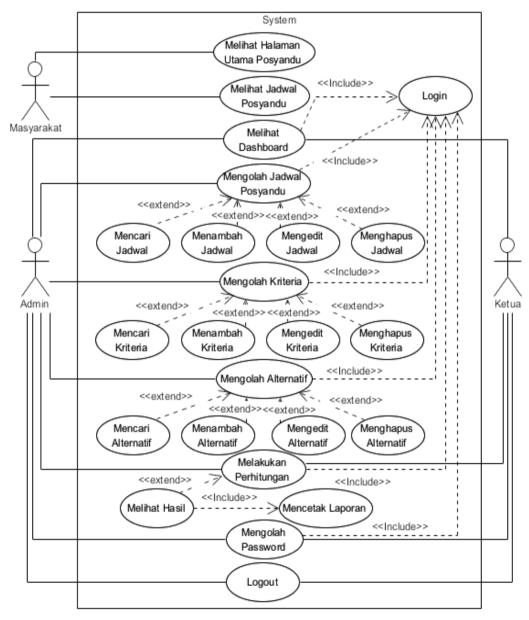
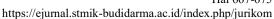


Figure 5. Use Case Diagram

3.7 Building System

3.7.1 Dashboard

Figure 6 shows the Dashboard of the toddler nutritional status classification system. This page provides access to the main menus for managing toddler data, performing classification using the K-Means algorithm, and viewing a summary of classification results. The dashboard is designed to be simple and intuitive, enabling posyandu staff to easily record and analyze toddler nutrition data.





POSYANDU ■ Jadwal Posyandu ■ Kriteria ♣ Alternatif ■ Perhitungan ♣ Password ← Logout ♣ Admin (Posyandu Dusun 1)

POS PELAYANAN TERPADU (POSYANDU) DESA TANJUNG ASRI



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Figure 6. Dashboard System

3.7.2 Calculation Result Page

Figure 7 illustrates the Calculation Result Page, which displays the output of the classification process using the K-Means algorithm. This page allows users to view the clustering results of toddlers into malnourished, moderately nourished, and well-nourished categories based on age, weight, and height data. This feature helps users directly evaluate the nutritional status of each toddler.

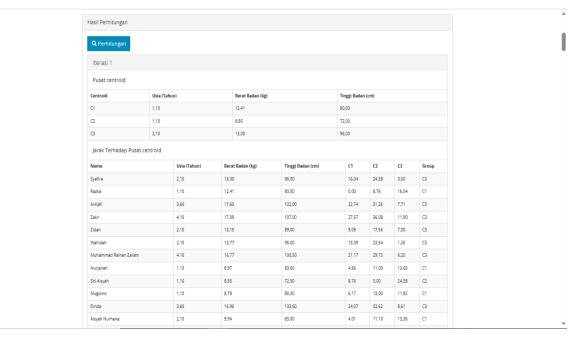


Figure 7. Calculation Result Page

3.7.3 Calculation Report

Figure 8 presents the Calculation Report page, which provides the classification results in a structured report format. The report includes a summary of the number of toddlers in each nutritional category along with supporting data details. This feature enables posyandu staff to print or store the classification results as official documentation for monitoring and health reporting purposes.





PEMERINTAH KABUPATEN ASAHAN KECAMATAN SEI DADAP DESA TANJUNG ASRI Sekretariat : Jl. Perjuangan Kp.21272

LAPORAN HASIL STATUS GIZI BALITA

Kode	Nama	Periode	Asal	Cluster	Status Gizi
A051	Syafira	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A052	Razka	2025-06-24	Posyandu Dusun 1	C1	Gizi Kurang
A053	Al-Kafi	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A054	Zakir	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A055	Zidan	2025-06-24	Posyandu Dusun 1	C1	Gizi Kurang
A056	Wahidah	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A057	Muhammad Raihan Zailani	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A058	Nurjanah	2025-06-24	Posyandu Dusun 1	C1	Gizi Kurang
A059	Siti Aisyah	2025-06-24	Posyandu Dusun 1	C3	Gizi Baik
A060	Mugiono	2025-06-24	Posyandu Dusun 1	C1	Gizi Kurang
A061	Dinda	2025-06-24	Posyandu Dusun 1	C2	Gizi Sedang
A062	Aisyah Nurhana	2025-06-24	Posyandu Dusun 1	C1 Activa	ie Wind Gizi/Kurang
A063	Sopian	2025-06-24	Posyandu Dusun 1	c1 Go to Se	ttings to a ctivate Wi ndows.
A064	Amelia Putri	2025-06-24	Posyandu Dusun 1	C1	Gizi Kurang

Figure 8. Calculation Report

4. CONCLUSION

Based on the research conducted, the following conclusions can be drawn, the K-Means Clustering method can effectively classify toddler nutritional status into three categories malnourished, moderately nourished, and wellnourished using age, weight, and height parameters. The analysis results indicate consistency between manual calculations and data processing using RapidMiner software with k = 3, demonstrating the accuracy of this method. In May 2025, 22 toddlers were malnourished, 21 moderately nourished, and 7 well-nourished; in June 2025, there were 27 malnourished, 8 moderately nourished, and 15 well-nourished. The developed system is effective in assisting health workers to classify and monitor nutritional status more objectively, quickly, and efficiently. Future research is recommended to integrate this system with an online database to facilitate continuous monitoring and enable long-term trend analysis.

REFERENCES

- T. R. Nureni, "Analisis Klasterisasi K-Means untuk Klasifikasi Status Gizi dan Kondisi Bayi Baru Lahir Berdasarkan Kecamatan di Kabupaten Probolinggo 2023," Digit. POLICY INSIGHTS Adv. Data Min. Digit. Gov., vol. 1, no. 1, pp. 14–26,
- M. Faid and M. Sukron, "Pemetaan Daerah Rawan Stunting dengan Algoritma K-Means dan Analisis Demografis di Kabupaten Probolinggo," JOKI J. Comput. Informatics, vol. 2, no. 1, pp. 16–25, 2025.
- [3] J. R. S. Penda Sudarto Hasugian, "Penerapan Data Mining Untuk Pengelompokan Siswa Berdasarkan Nilai Akademik dengan Algoritma K-Means," KLIK Kaji. Ilm. Inform. dan Komput., vol. 3, no. 3, pp. 262-268, 2022, [Online]. Available: https://djournals.com/klik
- [4] A. Y. Simanjuntak, I. S. S. Simatupang, and Anita, "Implementasi Data Mining Menggunakan Metode Naïve Bayes Classifier Untuk Data Kenaikan Pangkat Dinas," J. Sci. Soc. Res., vol. 4307, no. 1, pp. 85-91, 2022.
- A. Yahya and R. Kurniawan, "Implementasi Algoritma K-Means untuk Pengelompokan Data Penjualan Berdasarkan Pola Penjualan," MALCOM Indones. J. Mach. Learn. Comput. Sci. J., vol. 5, no. January, pp. 350-358, 2025.
- R. Rahmawati, W. Prihartono, and K. Cirebon, "Optimasi Stok Dengan Clustering Data Transaksi Penjualan Menggunakan Algoritma K-Means di Konter Agung Cell," JITET (Jurnal Inform. dan Tek. Elektro Ter., vol. 13, no. 2, 2025.
- [7] A. Alawiyah, N. Aghnia, and F. F. Abdalah, "Implementasi Clustering Algoritma K-Means Pada Penjualan Beras Di CV Tangguh Bumi Perkasa," J. Komisi (Jurnal Komput. dan Sist. Informasi), vol. 2, no. 2, pp. 17-23, 2025.
- N. Hendrastuty, "Penerapan Data Mining Menggunakan Algoritma K-Means Clustering Dalam Evaluasi Hasil Pembelajaran Siswa," J. Ilm. Inform. Dan Ilmu Komput., vol. 3, no. 1, pp. 46-56, 2024, [Online]. Available: https://doi.org/10.58602/jimailkom.v3i1.26
- R. Farismana, "Penerapan K-Means Clustering Untuk Pemetaan Produktivitas Padi Dan Prediksi Panen Di Kabupaten Indramayu," J. Inf. Syst. Applied, Manag. Account. Res., vol. 8, no. 3, p. 589, 2024, doi: 10.52362/jisamar.v8i3.1572.
- [10] M. Syahran, "Membangun Kepercayaan Data dalam Penelitian Kualitatif," Prim. Educ. J., vol. 4, no. 2, pp. 19–23, 2020, doi: 10.30631/pej.v4i2.72.
- [11] N. Bili, R. T. Abineno, and A. Aha Pekuwali, "Penerapan Algoritma K-Means Clustering Untuk Pengelompokkan Peforma Siswa Pada Pembelajaran Bahasa Indonesia (Studi Kasus: SD Inpress Waingapu 3)," SATI Sustain. Agric. Technol. Innov., pp.
- [12] W. P. Priyadi, J. D. Irawan, and A. Faisol, "Penerapan Data Mining Untuk Clustering Wilayah Produksi Pada Menggunakan Metode K-Means (Studi Kasus: Wilayah Jawa Timur)," JATI (Jurnal Mhs. Tek. Inform., vol. 8, no. 5, pp. 8381–8388, 2024.



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Hal 667-675

https://ejurnal.stmik-budidarma.ac.id/index.php/jurikom

- [13] S. Wijayanto and M. Yoka Fathoni, "Pengelompokkan Produktivitas Tanaman Padi di Jawa Tengah Menggunakan Metode Clustering K-Means," *Jupiter*, vol. 13, no. 2, pp. 212–219, 2021.
- [14] I. Ibrahim and W. Usino, "Klasterisasi Tingkat Kelayakan Provinsi Dalam Pembangunan Kawasan Industri Menggunakan Algoritma K-Means," SENAFTI (Semiinar Nas. Mhs. Fak. Teknol. Informasi), vol. 3, no. September, pp. 324–333, 2024.
- [15] W. W. Kristianto, "Penerapan Data Mining Pada Penjualan Produk Menggunakan Metode K-Means Clustering (Studi Kasus Toko Sepatu Kakikaki)," *J. Pendidik. Teknol. Inf.*, vol. 5, no. 2, pp. 90–98, 2022, doi: 10.37792/jukanti.v5i2.547.
- [16] D. D. Susilo, S. S. Hilabi, B. Priyatna, and E. Novalia, "Implementasi Data Mining dalam Pengelompokan Data Pembelian Menggunakan Algoritma K-Means Pada PT.Otomotif 1," *Jutisi J. Ilm. Tek. Inform. dan Sist. Inf.*, vol. 13, no. 1, p. 476, 2024, doi: 10.35889/jutisi.v13i1.1836.
- [17] J. Multidisiplin Saintek, Y. Candra Pratama, and Z. Reno Saputra, "Sistem Informasi Desa Delta Upang Berbasis Web," *J. Sains dan Teknol.*, vol. 2, no. 12, pp. 86–96, 2024, [Online]. Available: https://ejournal.warunayama.org/index.php/kohesi/article/download/2788/2634
- [18] A. E. Febriyanti, S. Z. Harahap, and M. Masrial, "Penerapan Data Mining Untuk Evaluasi Data Penjualan Menggunakan Metode Clustering dan Algoritma Hirarki Divisive Studi Kasus Toko Sembako Pujo," *INFORMATIKA*, vol. 15, no. 1, pp. 72–86, 2024, doi: 10.25130/sc.24.1.6.
- [19] M. Adelina Bui and A. Bahtiar, "Implementasi Metode Algoritma K-Means Clustering Untuk Mengelompokkan Transaksi Penjualan Barang Di Toko Arino," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 2, pp. 1451–1456, 2024, doi: 10.36040/jati.v8i2.8975.
- [20] A. Y. Sari and E. Supriatna, "Penerapan Data Mining Menggunakan Metode Algoritma Naive Bayes Classifier untuk Mendukung Strategi Promosi," *J. Dimamu*, vol. 3, no. 1, pp. 18–28, 2023, doi: 10.32627/dimamu.v3i1.837.