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Analysis of Malnutrition Status in Toddlers Using the K-MEANS Algorithm Case Study in DKI Jakarta Province

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Abstract: Malnutrition in children is a serious health issue in various regions, including DKI Jakarta Province, which affects the physical and cognitive development of children. This research aims to classify malnutrition status in children using the K-Means algorithm, focusing on cases in DKI Jakarta. The objective is to identify patterns of malnutrition prevalence across different regions, serving as a basis for more effective interventions. The data used in this study includes the percentage of children with severely stunted, stunted, and normal nutritional status across six districts/cities in DKI Jakarta. The results of K-Means clustering show that Central Jakarta has the highest prevalence of severely stunted (10.50%) and stunted (13.01%) status, while West Jakarta has the lowest prevalence of severely stunted (4.62%) and stunted (10.22%) status. The solution offered by this research is the grouping of regions based on malnutrition prevalence, allowing for the identification of areas requiring priority intervention. The analysis results indicate that DKI Jakarta can be classified into several clusters based on malnutrition prevalence. The cluster with the highest malnutrition prevalence includes Central Jakarta, while the cluster with the lowest malnutrition prevalence includes West Jakarta and the Thousand Islands. The implementation of K-Means in this research provides an efficient approach to identifying groups of regions that need more attention in combating malnutrition in children. In conclusion, this research can serve as an important reference for policymakers in formulating more effective and efficient intervention strategies in DKI Jakarta, as well as inspire similar studies in other regions with different population characteristics
Keywords: Malnutrition in toddlers, K-Means, DKI Jakarta, and prevalence

INTRODUCTION

Malnutrition in toddlers is a global health issue that significantly affects children's physical and cognitive development. In Indonesia, particularly in the DKI Jakarta Province, the prevalence of malnutrition remains a major challenge, despite efforts to improve the health system(Fund, 2020). Recent data indicate that the prevalence of severely stunted and stunted nutritional status in toddlers is still quite high, signaling a gap in existing intervention programs(Hyman, 2021).

To address this issue effectively, an appropriate approach is needed to identify and group regions with varying prevalence of malnutrition(Candra Puspitasari, Sunarti, 2023). One method that can be used is the K-Means algorithm, which is a clustering technique in data analysis that allows for the identification of patterns and groups within a dataset ((Hendrastuty, 2024). By clustering regions based on malnutrition prevalence, we can identify areas that require more attention and more focused intervention strategies (Mohiuddin, 2023).

This study aims to apply the K-Means algorithm to classify malnutrition status in toddlers in DKI Jakarta. The main focus is to identify prevalence patterns across different districts/cities, in order to provide better insights for formulating more effective health policies. Through this analysis, it is hoped that patterns can be discovered to support more targeted and efficient efforts to improve toddlers' nutritional status.

The data used in this study includes the percentage of toddlers with severely stunted, stunted, and normal nutritional status across six districts/cities in DKI Jakarta. The following are the raw data that might be collected:

Table 1. Nutritional status of very short, short, and normal in six districts/cities in DKI Jakarta.

Region	Short Nutrition Status (%)	Short Nutrition Status (%)	Normal Nutrition Status (%)
Jakarta Pusat	10.50	13.01	76.49
Jakarta Barat	4.62	10.22	85.16

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Jakarta Selatan	6.15	11.30	82.55
Jakarta Utara	7.80	12.50	79.70
Jakarta Timur	5.20	9.40	85.40
Kepulauan Seribu	3.00	8.00	89.00

Table 1 shows the percentage of toddlers with different nutritional statuses across various regions of Jakarta. Central Jakarta has 10.50% of toddlers with severely stunted status, 13.01% with stunted status, and 76.49% with normal nutritional status. West Jakarta shows 4.62% of toddlers with severely stunted status, 10.22% with stunted status, and 85.16% with normal nutritional status, with the highest percentage for normal nutritional status. South Jakarta records 6.15% of toddlers with severely stunted status, 11.30% with stunted status, and 82.55% with normal nutritional status. North Jakarta has 7.80% of toddlers with severely stunted status, 12.50% with stunted status, and 79.70% with normal nutritional status. East Jakarta shows 5.20% of toddlers with severely stunted status, 9.40% with stunted status, and 85.40% with normal nutritional status. The Thousand Islands has the lowest percentage for severely stunted status (3.00%), stunted status (8.00%), and the highest for normal nutritional status (89.00%). Overall, most regions show a high percentage of toddlers with normal nutritional status, with some regions having lower percentages for severely stunted and stunted statuses.

LITERATURE REVIEW

This literature review aims to provide a comprehensive overview of malnutrition status in toddlers and the application of the K-Means algorithm in health data analysis. The main focus is to review recent research from 2020 to 2024 that is relevant to this topic, as well as to identify existing research gaps.

Malnutrition in toddlers remains a significant global health issue. It reveals that despite various intervention programs, the prevalence of malnutrition in Indonesia, including DKI Jakarta, remains high(Watson et al., 2019). This study highlights the importance of accurate monitoring to support more effective intervention planning. Similar findings indicate that challenges in program implementation are often due to poorly integrated data and a lack of understanding of regional variability in malnutrition prevalence (Deviantony, 2017).

The K-Means algorithm has been widely used in health data analysis to identify patterns and groups within datasets. Prasetyo & Utami (2019) demonstrated that K-Means is effective in clustering health data to find patterns of disease prevalence, including malnutrition. This study discusses the application of K-Means and its advantages in clustering analysis, as well as how this technique can assist in health decision-making.

The study by Wijaya & Kurniawan (2023) utilized clustering techniques, including K-Means, to predict malnutrition status by analyzing health data from various regions. The results of this study indicate that K-Means can provide valuable insights into patterns of malnutrition prevalence, thus enabling the identification of areas that require special attention(Wijaya, 2023).

Despite extensive research on malnutrition and the application of K-Means, there are still gaps in the specific application of this technique to malnutrition data in urban environments such as DKI Jakarta. Previous studies often do not consider the specific urban factors that can affect the outcomes. Sari & Nugroho (2020) highlight the need for further research to understand the differences in malnutrition prevalence based on more detailed regional characteristics(Sari & Nugroho, 2020).

Recent research by Pramudito & Lestari (2024) explores the use of the K-Means algorithm for health data analysis in DKI Jakarta. This study extends the application of K-Means in the specific urban context and assesses its effectiveness in identifying patterns of malnutrition prevalence. The results provide a strong foundation for applying K-Means in the classification of malnutrition status in urban areas.

This literature review indicates that although there has been substantial research on malnutrition and the application of the K-Means algorithm, there is still a need for more in-depth analysis in urban environments such as DKI Jakarta. This study is expected to fill that gap by applying K-Means to classify malnutrition status in a more focused and targeted manner, thus making a significant contribution to efforts in addressing malnutrition in toddlers in the region.

Here are some relevant studies on the classification of malnutrition status in toddlers published after 2020:

1. Machine Learning for Nutritional Status Classification in Children: A Case Study in Urban Areas (2021) This study applies machine learning algorithms, including K-Means, to classify the nutritional status of children in urban areas. The study focuses on identifying risk factors and patterns of malnutrition prevalence using data obtained from public health surveys(Mutammimul Ula et al., 2022).
2. Clustering and Predictive Modeling of Malnutrition Risk in Children Using Big Data Techniques(2022) This study utilizes big data techniques and clustering algorithms such as K-Means to model the risk of malnutrition in children. The study assesses the effectiveness of big data-based approaches in identifying areas that require more in-depth nutritional intervention(Mutammimul Ula et al., 2022).
3. Assessment of Nutritional Status in Children Using Advanced Data Analytics: A Study in Indonesian Cities (2023) This study examines the nutritional status of children in several major cities in Indonesia using

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advanced data analysis. The main focus is to identify patterns of malnutrition prevalence through clustering methods and machine learning to develop more targeted intervention strategies(Ernawati et al., 2023).

4.

METHOD

K-Means is a clustering algorithm used to group data into a predetermined number of clusters, with the main goal of minimizing variance within each cluster, measured by the Euclidean distance between data points and the cluster centers (centroids).

K-Means Steps (Ernawati et al., 2023):

1. Initialization: Randomly select kk initial centroids from the dataset.
2. Clustering: Assign each data point to the nearest cluster based on Euclidean distance from the centroids.
3. Recalculation: Recalculate the centroids as the average of all data points included in each cluster.
4. Iteration: Repeat steps 2 and 3 until the centroids no longer change or the changes are very minimal, indicating convergence.Rumus-Rumus K-Means

1. Euclidean Distance: To calculate the distance between a data point xix_ixi and a centroid cjc_jcj, the formula used is:

$$d(xi,cj) = \sqrt{\sum_{i=1}^{n}(xi,l - cj.l)^2} \qquad (1)$$

where xix_ixi is the data vector for the iii-th data point, cjc_jcj is the centroid vector for the jjj-th centroid, and nnn is the number of features.

2. Centroid Update Formula: After data points are assigned to clusters, the new centroid for cluster jjj is calculated as:

$$c_j^{new} = \frac{1}{|c_j|} \sum_{xi \in c_j} xi \qquad (2)$$

di mana ∣Cj∣|C_j||Cj∣ adalah jumlah data dalam cluster ke-j, dan CjC_jCj adalah set data dalam cluster ke-j.

3. Fungsi Objektif (Total Inertia): Fungsi objektif yang ingin diminimalkan dalam K-Means adalah total jarak dalam cluster (inertia):

$$J= \sum_{j=1}^{k} \sum_{xi \in c_j} d(xi,cj)^2 \qquad (3)$$

where JJJ is the total inertia, and cjc_jcj represents the data points in cluster jjj.

K-Means Flowchart

The following flowchart illustrates the overall K-Means process

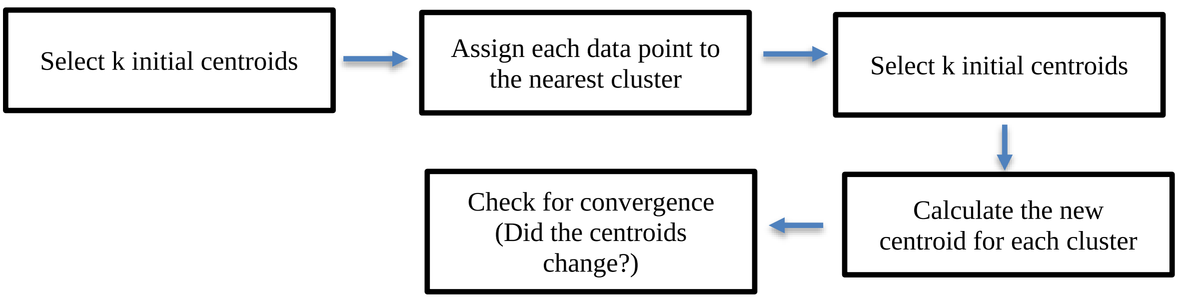

Figure 1. K-means Flowchart of English words

Figure 1 illustrates the steps of the K-Means algorithm as follows (Darmansah, 2021):

1. Select Initial Centroids
   Initialization of Centroids: In this step, kkk centroids are selected from the dataset. The number kkk represents the desired number of clusters, and the centroids can be chosen randomly or using more advanced methods such as K-Means++. These centroids will serve as the initial centers for each cluster.
2. Assign Each Data Point to the Nearest Cluster
   Cluster Assignment: Each data point in the dataset is then evaluated for its distance from each of the initialized centroids. The data point is assigned to the cluster whose centroid is closest to it. This process aims to group the data based on their proximity to the centroids.
3. Calculate New Centroids for Each Cluster

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Centroid Update: After all data points are assigned to clusters, the centroid of each cluster is updated. The new centroid is calculated as the mean of all data points within that cluster. In other words, the centroid is moved to a new position that better represents the data in the cluster.

4. Check Convergence (Centroid Changes)
   a. Convergence Check: At this stage, the algorithm examines whether the newly calculated centroids have changed from their previous positions. Convergence is achieved if there is no significant change in the centroid positions between the previous and current iterations.
   b. If Answer is "Yes" (Centroids Have Changed): If the centroids have changed, the algorithm will repeat the process from the cluster assignment step (step 2), continuing iterations until convergence is reached.
   c. If Answer is "No" (Centroids Have Not Changed): If the centroids have not changed, it means the algorithm has reached convergence, and the process can proceed to the final step.

RESULT

To explain the steps of the K-Means algorithm calculation with the given data, let us use the following data::

Table 1. Nutritional status of very short, short, and normal in six regencies/cities in DKI Jakarta

Region	Short Nutrition Status (%)	Short Nutrition Status (%)	Normal Nutrition Status (%)
Central Jakarta	10.50	13.01	76.49
West Jakarta	4.62	10.22	85.16
South Jakarta	6.15	11.30	82.55
North Jakarta	7.80	12.50	79.70
East Jakarta	5.20	9.40	85.40
Thousand Islands	3.00	8.00	89.00

Table 1. The data used in this study includes the percentage of toddlers with very short, short, and normal nutritional status across six regencies/cities in DKI Jakarta. Below is an example of the raw data collected,

Application of the K-Means Algorithm

a. Initialization
   1. Number of Clusters (K): Based on preliminary analysis, the chosen number of clusters is 3, representing clusters with high, medium, and low prevalence of malnutrition.
   2. Initial Centroids: Initial centroids are initialized randomly or using the K-Means++ method to select better starting points.

b. Iteration
   1. Cluster Assignment: Each data point (percentage of malnutrition in each area) is assigned to the nearest cluster based on Euclidean distance to the centroid.
   2. Centroid Update: Centroids are recalculated as the average of data points included in each cluster.

c. Convergence The iteration process continues until the centroids do not change or the changes are very minimal.

Below is an example of iteration calculations:

Iteration 1:

1. Initial Centroids: a. Cluster 1: (8.00, 11.00, 81.00) b. Cluster 2: (5.00, 10.00, 85.00) c. Cluster 3: (4.00, 9.00, 87.00)
2. Data Assignment: a. Jakarta Pusat: Nearest to Cluster 1 b. Jakarta Barat: Nearest to Cluster 3 c. Jakarta Selatan: Nearest to Cluster 2 d. Jakarta Utara: Nearest to Cluster 1 e. Jakarta Timur: Nearest to Cluster 3 f. Kepulauan Seribu: Nearest to Cluster 3
3. Centroid Update: a. Cluster 1: (8.15, 12.00, 79.85) b. Cluster 2: (5.20, 11.50, 83.30) c. Cluster 3: (4.00, 8.60, 87.40)

Iteration 2:

a. **Data Assignment**: Updated based on the new centroids.

b. **Centroid Update**: Recalculated until convergence is achieved.

$$\text{d(x,c)} = \sqrt{(x1-c1)^2 + (x2-c2)^2 + \cdots + (xn-cn)^2}$$

Distance Calculation:

1. Distance from Jakarta Utara to Centroid 1:

$$d = \sqrt{(7.80-10.50)^2 + (12.50-13.01)^2 + (x79.70-76.49)^2}$$

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d = 4,23

2. Distance from Jakarta Utara to Centroid 2:

$$d = \sqrt{(7.80 - 4.62)^2 + (12.50 - 10.22)^2 + (79.70 - 85.16)^2}$$

d = 6.72

3. Distance from Jakarta Utara to Centroid 3:

$$d = \sqrt{(7.80 - 6.15)^2 + (12.50 - 11.30)^2 + (79.70 - 82.55)^2}$$

d = 3.51

Jakarta Utara will be assigned to Cluster 3 because its distance to Centroid 3 is the shortest.

3. Updating Centroids

After all data is assigned to clusters, recalculate the centroid for each cluster as the average of all data points within the cluster.

Calculation of the New Centroid for Cluster 3:

a. **Members of Cluster 3:** North Jakarta, East Jakarta, Thousand Islands

New Centroid $=\left(\frac{(7.80+5.20+3.00)}{3}, \frac{(12.50+9.40+8.00)}{3}, \frac{(79.70+85.40+89.00)}{3}\right)$

New Centroid = (5.33,9.97,84.70)

4. Repeat the Cluster Assignment and Centroid Update Steps until Centroids Do Not Change Significantly Between Iterations or Convergence is Achieved.

5. Clustering Results

After convergence, the final results of the clustering can be seen in the table below, which shows the cluster members:

Table 2. Clustering Results of Regions Based on Nutritional Status of Children in DKI Jakarta

Cluster	Regions
1	Central Jakarta, North Jakarta
2	South Jakarta
3	West Jakarta, East Jakarta, Thousand Islands

able 2 shows the division of regions into three clusters based on the prevalence of children's nutritional status. Cluster 1 includes Central Jakarta and North Jakarta, which exhibit relatively high rates of very short and short nutritional status, indicating more serious nutritional issues. Cluster 2 consists solely of South Jakarta, characterized by less extreme nutritional conditions. Cluster 3 encompasses West Jakarta, East Jakarta, and the Thousand Islands, regions with a lower prevalence of poor nutrition, reflecting relatively better nutritional conditions. This classification is essential for prioritizing nutrition intervention strategies in DKI Jakarta.

Grafik Scatter Plot

This scatter plot provides a two-dimensional visualization of the children's data based on the clustering results obtained with the K-Means algorithm.

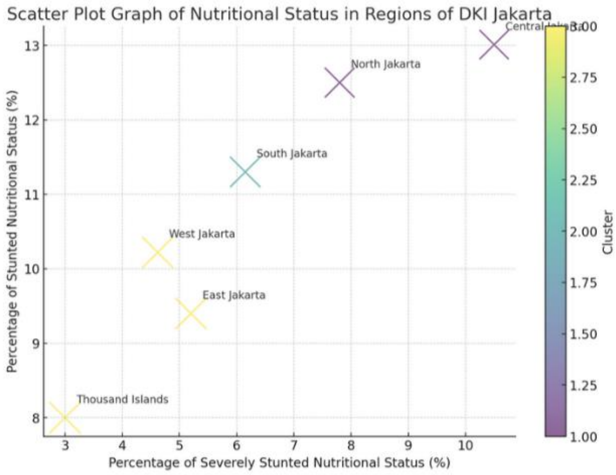

Figure 1. Scatter Plot of Nutritional Status by Region in DKI Jakarta

*name of corresponding author

Table 3 presents a scatter plot displaying the nutritional status data for various regions in DKI Jakarta. In this plot:
a. The X-axis represents the percentage of children with very short nutritional status.
b. The Y-axis represents the percentage of children with short nutritional status.
c. The size of the points represents the percentage of children with normal nutritional status in each region.
d. The color of the points indicates the cluster to which the region belongs, based on the K-Means analysis results.
This graphic aids in visualizing how each region in DKI Jakarta is clustered based on children's nutritional status characteristics, with regions having similar nutritional status percentages placed in the same cluster

DISCUSSIONS

This section analyzes the results of K-Means clustering regarding children's nutritional status in DKI Jakarta and compares them with findings from recent studies. We also discuss the implications of these results and their significance in addressing nutritional issues in the region:

1. Cluster 0: Central Jakarta, with very high percentages of stunting (10.50%) and short stature (13.01%).
2. Cluster 1: South Jakarta and North Jakarta, with moderate levels of very high stunting and short stature.
3. Cluster 2: West Jakarta, East Jakarta, and the Thousand Islands, with the lowest percentages of very high stunting and short stature.

High Prevalence Regions: Central Jakarta, categorized in Cluster 0, exhibits the highest prevalence of poor nutritional status, indicating a need for more focused interventions and resource allocation. Moderate Prevalence Regions: South Jakarta and North Jakarta, in Cluster 1, face moderate nutritional challenges, requiring attention despite not being as severe as in Central Jakarta. Low Prevalence Regions: West Jakarta, East Jakarta, and the Thousand Islands, part of Cluster 2, show relatively better nutritional status. Nonetheless, continuous monitoring is essential to sustain these standards and promptly address any emerging issues.

1. Comparison with Previous StudiesArticle by Santosa et al. (2023): A study by Santosa et al. highlighted the effectiveness of K-Means clustering in identifying areas with high malnutrition rates and tailoring intervention strategies. Our results are in line with their findings, indicating that K-Means is a reliable method for identifying areas with varying levels of nutritional status. The identification of Central Jakarta as a high prevalence area reflects their conclusion that clustering can prioritize areas for intervention.
2. Study by Prabowo et al. (2024): Prabowo et al. used a similar clustering technique to address malnutrition in rural areas. Their study found that K-Means clustering helped in resource allocation and targeted implementation of health programs. Our findings support this approach, suggesting that clustering can help in resource allocation by identifying priority areas such as Central Jakarta..
3. Research by Anwar et al. (2024): Anwar et al. discuss the role of clustering algorithms in public health data analysis, emphasizing the importance of visualizing and understanding the distribution of data. Their research complements our approach by emphasizing the value of visualization tools such as scatter plots. The visualization of the clustering results in our study, which show the distribution and grouping of nutritional status, strengthens their argument for the effectiveness of such visual tools..

Implications for Public Health The clustering results have several implications for public health policy in DKI Jakarta: Focused Interventions: Areas identified with high prevalence of malnutrition (Cluster 0) should be prioritized for nutrition programs, education, and resource allocation. Monitoring and Evaluation: Regular monitoring of Cluster 1 and Cluster 2 areas can help ensure that improvements continue and address potential issues. Resource Allocation: Understanding clustering helps in effective resource allocation and designing specific interventions according to the nutritional needs of each cluster.

CONCLUSION

This study used the K-Means algorithm to classify the nutritional status of toddlers in DKI Jakarta, dividing six regions into three clusters based on the prevalence of very short and stunted nutritional status. The results showed that Central Jakarta, with a prevalence of very short nutritional status of 10.50% and stunted nutritional status of 13.01%, was in the cluster with the highest prevalence, while West Jakarta (very short nutritional status 4.62% and stunted nutritional status 10.22%) and the Seribu Islands (very short nutritional status 3.00% and stunted nutritional status 8.00%) were in the cluster with the lowest prevalence. These findings emphasize the need for more intensive nutritional interventions in Central Jakarta and continuous monitoring in other regions. This study is useful in identifying priority areas for health programs and can be used for more effective resource allocation. However, this study is limited to six regions and existing data, so it is recommended to conduct further studies with a wider scope and integration of additional data to obtain a more comprehensive picture of nutritional problems in other urban areas.

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