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Applied Machine learning for Pediatric Nutrition A K-Means Clustering Application Based on WHO Z-Scores

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***Abstract*—Nutritional status in early childhood is a key indicator of public health and serves as a basis for targeted nutritional interventions. Children's nutrional status is significantly influenced by family food adequacy and parental nutritional literacy. Nutritional problems in children can come from primary and secondary factors. Primary factors include the non-fulfillment of nutrient intake, both in quantity and quality. Meanwhile, secondary factors occur due to disturbances in the child's body in carrying out its natural functions. This study applies the K-Means Clustering algorithm to anthropometric data—including weight, height, and head circumference—to classify children's nutritional status into five categories: severely undernourished (−3 SD), moderately undernourished (−2 SD), normal, mildly overnourished (+1 SD), and moderately overnourished (+2 SD). The clustering process is based on Z-scores derived from WHO standards, namely Weight-for-Age (WAZ), Height-for-Age (HAZ), and Head Circumference-for-Age (HCAZ), which serve as input features for the clustering algorithm. The number of clusters (k = 5) is aligned with national nutritional classification guidelines. The clustering results are visualized to illustrate the data distribution across the three indicators, and evaluated using Euclidean distance to assess the proximity of each data point to its assigned cluster centroid. The results demonstrate that K-Means Clustering can effectively classify children's nutritional status in a manner consistent with manual classification based on WHO thresholds. This study highlights the potential of data mining approaches in supporting health information systems for the early and automated detection of child malnutrition.**

***Index Terms*—Nutritional Status; Anthropometry; Z-Score; K-Means Clustering**

I. Introduction

Nutritional status during early childhood forms the foundation for a child's physical growth and cognitive development. During this critical growth window (ages 0–5), any deviation—whether undernutrition or overnutrition—can have long-term consequences on a child's overall quality of life. To monitor child development objectively and in a standardized manner, the World Health Organization (WHO) recommends the use of three Z-score indicators: Weight-for-Age (WAZ), Height-for-Age (HAZ), and Head Circumference-for-Age (HCAZ) [1]. These indicators assess a child's weight, height, and head circumference relative to a healthy reference population and have become a global standard for nutritional surveillance [2].

In practice, however, nutritional classification in many healthcare facilities—especially in remote or resource-limited areas—is still performed manually. This approach is time-consuming, prone to human error, and difficult to scale efficiently within a data-driven health system. As a result, nutritional interventions are often delayed or misaligned due to the lack of rapid and reliable analysis tools [3].

With the rise of digital health technologies, data-driven methods such as machine learning have increasingly been applied in public health. One promising approach is K-Means Clustering, an unsupervised learning algorithm that can group data based on patterns or similarities in specific features [4]. Several studies have applied this method to classify children's nutritional status, used K-Means to cluster children based on weight and age, but without incorporating WHO Z-score standards [5]. Clustering to raw anthropometric values but failed to align the results with clinical thresholds [6]. In previous studies, Z-score indicator has been used, although only one or two variables were included [7].

Clustering in the context of stunting but excluded HCAZ, which is essential for assessing neurological development. Furthermore, most existing studies lack alignment with WHO nutritional cutoffs, limiting their applicability in clinical settings [8].

This highlights a clear research gap: no prior study has integrated all three Z-score indicators—WAZ, HAZ, and HCAZ—into a unified clustering model to classify children's nutritional status. The present study seeks to fill this gap by applying the K-Means Clustering algorithm to all three indicators simultaneously. Children are grouped into five categories: severely undernourished (−3 SD), moderately undernourished (−2 SD), normal, mildly overnourished (+1 SD), and moderately overnourished (+2 SD), consistent with WHO standards.

The objectives of this study are to (1) develop a data-driven nutritional classification model using K-Means Clustering with WHO-based Z-scores, and (2) evaluate its performance in comparison to conventional classification approaches. The outcomes are expected to assist healthcare providers in the early detection of growth deviations based on anthropometric data and support timely, targeted interventions.

II. Literatur Review

Nutritional status during early childhood forms the foundation for a child's physical growth, cognitive development, and long-term quality of life. In this critical growth window (ages 0–5), both undernutrition and overnutrition can lead to persistent deficits in health, learning capacity, and productivity later in life. To monitor child development objectively and in a standardized manner, the World Health Organization (WHO) recommends the use of three Z-score indicators—Weight-for-Age (WAZ), Height-for-Age (HAZ), and Head Circumference-for-Age (HCAZ)—which compare a child's weight, height, and head circumference against a healthy reference population [9]. These indicators have become the global standard for nutritional surveillance and early detection of growth deviations.

In many healthcare facilities, particularly in remote or resource-limited settings, nutritional classification is still performed manually. Health workers often rely on manual plotting or basic spreadsheets to interpret WHO growth charts, which is time-consuming, prone to human error, and difficult to scale in a data-driven health system [10]. As the volume of routine anthropometric data increases, this manual process can delay the identification of children at risk and contribute to interventions that are either late or poorly targeted [11].

With the rise of digital health technologies, data-driven methods such as machine learning have increasingly been applied in public health to address these challenges. One promising approach is K-Means clustering, an unsupervised learning algorithm that groups data based on similarities in selected features [12]. Several studies have used K-Means to classify children's nutritional status or to explore patterns of malnutrition, generally using weight, height, or age as input variables [13]. Some studies have clustered children based on raw anthropometric values or on one or two Z-score indicators, yet their cluster definitions are not always aligned with WHO cut-off points, which limits their direct applicability in clinical decision-making[14]. Other works have demonstrated that simple anthropometric features can also be used in supervised models, such as K-Nearest Neighbours, to support early detection of stunting and abnormal nutritional status [15] .

Despite these advances, important gaps remain. Most existing clustering studies do not integrate all three WHO Z-score indicators—WAZ, HAZ, and HCAZ—into a single model, even though head circumference is closely related to brain growth and is a sensitive marker of early neurodevelopmental risk [16]. In many cases, HCAZ is either ignored or analysed separately, and the resulting clusters do not map directly to the five WHO nutritional categories. This misalignment makes the outputs harder to interpret in routine practice and reduces their usefulness for front-line health workers [17].

These limitations highlight a clear research gap: there is a need for an integrated clustering model that simultaneously uses WAZ, HAZ, and HCAZ and produces clusters that are consistent with WHO nutritional cutoffs. To address this gap, the present study applies the K-Means clustering algorithm to all three Z-score indicators at once. Children are grouped into five categories—severely undernourished (≤ −3 SD), moderately undernourished (≤ −2 SD), normal, mildly overnourished (≥ +1 SD), and moderately overnourished (≥ +2 SD)—in accordance with WHO standards. The objectives of this study are to (1) develop a data-driven nutritional classification model using K-Means clustering with WHO-based Z-scores and (2) evaluate its performance in comparison with conventional classification approaches. The expected outcome is a more systematic and scalable way to detect growth deviations based on anthropometric data, thereby supporting healthcare providers in delivering timely and targeted interventions.

Assessing the nutritional status of children through anthropometric data is a foundational practice in global child health monitoring. The World Health Organization (WHO) recommends the use of standardized growth indicators such as Weight-for-Age Z-score (WAZ), Height-for-Age Z-score (HAZ), and Head Circumference-for-Age Z-score (HCAZ). These indicators quantify the deviation of a child's anthropometric measurements from the median values of a healthy reference population, adjusted for age and sex, and provide a common framework for comparing nutritional status across populations and over time.

Each indicator captures a specific dimension of growth. WAZ reflects a child's general weight status and is used to detect underweight conditions [18]. HAZ identifies stunting, which indicates chronic malnutrition or long-term growth restriction and has been associated with adverse health and educational outcomes [19]. HCAZ reflects head growth and serves as an early indicator of neurological development and brain growth, especially in the first two years of life, when rapid brain development occurs [20]. Evidence shows that low head circumference-for-age is associated with increased risk of suboptimal neurodevelopment, making HCAZ an important complementary indicator alongside WAZ and HAZ. In this study, these Z-scores are categorized into five clinical groups: severely undernourished ($Z < -3$ SD), moderately undernourished (-3 SD $\leq Z < -2$ SD), normal (-2 SD $\leq Z \leq +1$ SD), mildly overnourished ($+1$ SD $< Z \leq +2$ SD), and moderately overnourished ($Z > +2$ SD), consistent with WHO recommendations[21].

In recent years, machine learning—particularly clustering techniques—has been adopted to enhance the efficiency and objectivity of nutritional classification. Clustering is an unsupervised learning approach that groups data based on similarity across multiple features without requiring labeled training data. Among various clustering methods, K-Means clustering is one of the most widely used due to its conceptual simplicity and computational efficiency. It partitions data into k clusters by iteratively assigning observations to the nearest centroid and updating centroids to minimize within-cluster variance. This makes K-Means suitable for exploring patterns in large anthropometric datasets and for segmenting children into risk-based groups.

Several studies have demonstrated the applicability of K-Means clustering in child nutrition classification. Improved upon these early efforts by using Z-score indicators in their models; however, they typically restricted the analysis to one or two dimensions (for example, only WAZ or HAZ), which reduces the ability of the model to capture the multidimensional nature of child growth [22].

More recent work has expanded the use of K-Means to different datasets and levels of aggregation. Several studies have used K-Means to cluster toddlers based on combinations of anthropometric indicators and related variables for the purpose of identifying malnutrition or stunting risk at the individual level. Other studies have applied K-Means to classify districts or cities based on stunting prevalence or malnutrition indicators, providing a basis for spatial targeting and program prioritization [23]. In parallel, supervised learning methods such as K-Nearest Neighbours (KNN) have been developed to classify toddlers' nutritional status and support early detection of stunting using simple anthropometric inputs. Together, these studies show that routine growth data can be transformed into decision-support tools that assist health workers in identifying children and areas at higher risk.

However, several important limitations are evident across the existing literature. First, many clustering studies operate on raw anthropometric values or on a limited subset of indicators (e.g., only WAZ or HAZ) and do not integrate all three WHO growth indicators—WAZ, HAZ, and HCAZ—within a single model. Second, head circumference is frequently omitted, even though HCAZ is a sensitive marker of early brain development and can provide additional insight into neurodevelopmental risk. Third, not all studies explicitly align the resulting clusters with WHO nutritional cut-offs, which weakens their clinical relevance and makes it difficult for practitioners to directly use the outputs in routine child health services. These limitations reduce the extent to which existing models can be integrated into digital health applications or standard growth monitoring workflows.

To date, and to the best of our knowledge, there is no documented study that simultaneously incorporates WAZ, HAZ, and HCAZ into a unified K-Means clustering model for individual-level nutritional classification. This gap presents an opportunity to develop a more holistic, data-driven framework that captures both physical growth and early neurodevelopmental indicators while remaining aligned with WHO clinical categories.

The present study seeks to address this gap by applying the K-Means clustering algorithm to all three Z-scores—WAZ, HAZ, and HCAZ—simultaneously. The aim is to classify children's nutritional status into clinically relevant groups that are consistent with WHO cut-offs and to enable early detection of deviations from normal growth. This approach is expected to provide a more comprehensive and interpretable classification than models based on a single indicator, while also offering a scalable analytic component for digital health applications in early childhood nutrition monitoring.

III. Methodology

This study implements the K-Means Clustering algorithm to classify children's nutritional status using three anthropometric indicators standardized by the World Health Organization (WHO): Weight-for-Age Z-score (WAZ), Height-for-Age Z-score (HAZ), and Head Circumference-for-Age Z-score (HCAZ). The methodological process consists of four main stages: (1) data preparation, (2) Z-score calculation, (3) clustering using K-Means, and (4) system implementation and visualization.

A. Data Preparition

The dataset consists of 77 records of children aged 0 to 60 months, collected from a local pediatric clinic. Each record includes the child's sex, age (in months), weight (kg), height (cm), and head circumference (cm). The sex and age of each child are used to select the appropriate WHO reference data during Z-score computation.

B. Z-Score Calculation

Three nutritional indices are calculated based on WHO child growth standards:

- **WAZ (Weight-for-Age Z-score)**: Indicates overall underweight status.
- **HAZ (Height-for-Age Z-score)**: Identifies stunting or linear growth delay.
- **HCAZ (Head Circumference-for-Age Z-score)**: Serves as a proxy for brain development.

The Z-score for each indicator is calculated using the following general formula:

(1)

Where:

- XXX is the child's measured value (e.g., weight, height, head circumference),
- μ\muμ is the median value for the same age and sex from WHO growth standards,
- σ\sigmaσ is the standard deviation for that measurement.
- Separate computations are performed for male and female children based on WHO growth charts.

C. K-Means Clustering

The calculated WAZ, HAZ, and HCAZ scores are used as input features for the K-Means Clustering algorithm. The algorithm performs the following steps:

1. **Initialize centroids**: Five initial centroids are chosen, representing the five nutritional categories:
   - Cluster 1: Severely undernourished (Z < −3 SD)
   - Cluster 2: Moderately undernourished (−3 SD ≤ Z < −2 SD)
   - Cluster 3: Normal (−2 SD ≤ Z ≤ +1 SD)
   - Cluster 4: Mildly overnourished (+1 SD < Z ≤ +2 SD)
   - Cluster 5: Moderately overnourished (Z > +2 SD)
2. **Distance calculation**: Each data point is assigned to the nearest centroid using the Euclidean distance:

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

Where xxx is the Z-score vector of a child and yyy is the centroid vector.

3. **Centroid update**: New centroids are calculated by averaging the members of each cluster:

$$\mu j = \frac{1}{n_j}\sum_{i=1}^{n_j} xi \quad (3)$$

Where njn_jnj is the number of data points in cluster jjj.

4. **Iteration**: Steps 2 and 3 are repeated until convergence is reached, i.e., no significant changes in centroid positions.

D. System Implementation and Visualization

To support practical deployment, a prototype system with a simple graphical user interface (GUI) was developed. The system provides the following functionalities:

- Input form for anthropometric data
- Automatic computation of WAZ, HAZ, and HCAZ using WHO reference values
- Clustering of new data points based on trained K-Means model
- Display of results including assigned cluster and nutritional category
- Visualization using scatter plots for WAZ, HAZ, and HCAZ distributions across clusters
- Summary statistics for each cluster (count, percentage)

This system can assist healthcare workers in performing rapid assessments and identifying children at risk for growth deviations or abnormal development.

IV. Results and Discussion

This section presents the results of the Z-score computations, K-Means clustering process, system implementation, and visualization of classification outcomes. The discussion highlights the effectiveness of the proposed approach in identifying growth deviations and its alignment with WHO-based nutritional categories.

A. Z-Score Computation Results

The first step involved calculating WAZ, HAZ, and HCAZ for each of the 77 children in the dataset using WHO reference data. Separate computations were performed for male and female children to account for sex-specific growth standards.

Table I shows a sample of the computed Z-scores for five children:

TABLE I Sample Z-Score Calculation (WAZ, HAZ, HCAZ)

ID	Gender	Age	WAZ	HAZ	HCAZ
M1	Female	44	-1,21	-1,05	0,29
M2	Female	24	-0,38	0,09	-0,14
M3	Male	38	0,26	-0,37	-0,79
M4	Female	60	-1,58	-2	-0,64

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M5	Male	40	-1,53	-2,72	-0,5
M6	Male	39	-0,41	-0,79	0,5
ID	**Gender**	**Age**	**WAZ**	**HAZ**	**HCAZ**
M7	Female	31	-0,6	-1,26	-0,71
M8	Male	53	-1,57	-3,2	-1,43
M9	Male	24	-0,93	0,13	-0,36
M10	Male	59	-1,04	-1,17	0,33
…	…	…	…	…	…
M77	Female	27	0,19	0,5	-0,43

The complete Z-score data served as the input for clustering.

B. K-Means Clustering Results

The K-Means algorithm was applied with k = 5 to reflect the five clinical nutrition categories defined by WHO. Initial centroids were selected based on representative values from the Z-score ranges for each group.

The algorithm converged after three iterations, producing five clusters that correspond to the intended nutritional classifications. Table II summarizes the final centroid values for each cluster:

TABLE II FINAL CLUSTER CENTROIDS (WAZ, HAZ, HCAZ)

Kode	Category	WAZ	HAZ	HCAZ
C1	Saverely Undernourished	-4,3	-7,105	-5
C2	Moderately Undernourished	-1,47189	-2,08242	-0,87014
C3	Normal	-0,29039	-0,39824	-0,01824
C4	Mildly Overnourished	2,59	0,98	-0,43
C5	Moderately Overnourished	2,605	3,07	1,605

The cluster distribution is summarized in Table III.

TABLE III CLUSTER DISTRIBUTION AND PERCENTAGE

Cluster	Category	Children	Percentage
C1	Saverely Undernourished	2	2,60%
C2	Moderately Undernourished	22	28,57%
C3	Normal	49	63,64%
C4	Mildly Overnourished	2	2,60%
C5	Moderately Overnourished	2	2,60%

The results show that the majority of children (63.64%) fall within the normal category, while a significant portion (28.57%) are moderately undernourished, highlighting the importance of early identification and intervention.

C. Visualization of Cluster Results

To enhance interpretability, a 3D scatter plot was generated using WAZ, HAZ, and HCAZ as axes. Each cluster is represented with a distinct color (e.g., red for severely undernourished, blue for normal).

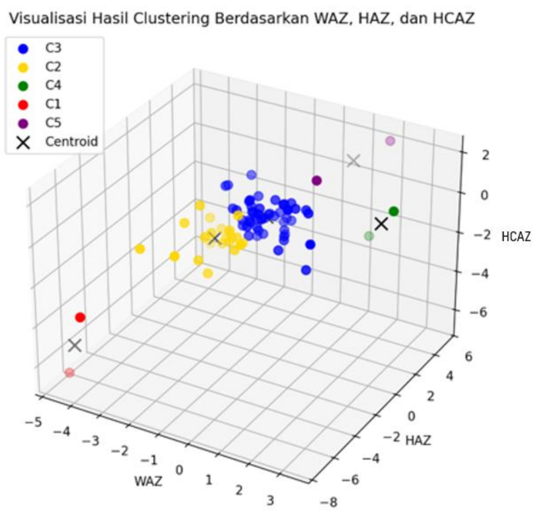

Fig. 1. Scatter Plot of Cluster Based on Z-Scores

The plot demonstrates clear group separation, with distinct boundaries between malnourished and normal children. Outliers were successfully captured in extreme clusters (C1 and C5), validating the effectiveness of the distance-based grouping.

D. System Implementation and Use Case

To bridge the gap between algorithmic output and real-world application, a simple yet functional interface was developed as part of this study. Health workers can enter basic anthropometric information—such as age, sex, weight, height, and head circumference—into the system. The system then automatically calculates the Z-scores (WAZ, HAZ, and HCAZ), performs clustering, and returns the child's nutritional classification based on the nearest cluster.

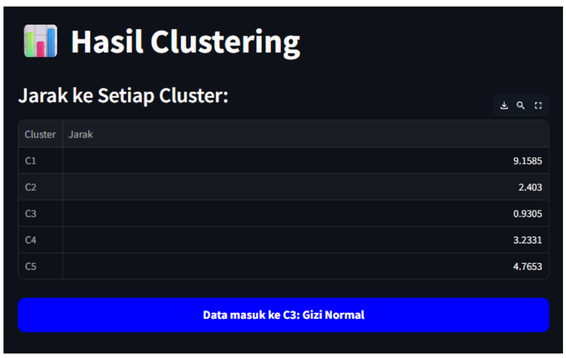

Fig. 2 GUI Interface and Nutritional Classification Results

The system was designed with usability in mind, especially for field settings or primary healthcare clinics where time and resources are limited. By providing quick, standardized feedback based on WHO guidelines, it helps frontline health staff make faster, data-informed decisions—without the need for advanced technical knowledge.

E. Discussion

The results of this study reinforce the potential of machine learning—particularly K-Means Clustering—as a practical tool for early childhood growth monitoring. By using three key anthropometric indicators (WAZ, HAZ, and HCAZ) in combination, this model offers a more holistic view of a child's health status compared to single-indicator methods.

1. Comparison with Previous Studies

Earlier work by Kumar et al. [4] focused on clustering children based on weight and age but did not use Z-scores or reference growth standards, which limited the clinical interpretability of their results. In contrast, our model is rooted in WHO-standardized indicators, making the clusters directly relevant to real-world classifications of undernutrition and overnutrition.

Huang et al. [5] and Ranjawali et al. [5] also explored clustering based on raw anthropometric data, but again, without mapping their output to WHO-defined thresholds. Dewi et al. f and Muhammad et al. improved on this by introducing WAZ and HAZ scores—but stopped short of incorporating HCAZ, an important signal for early brain development. By including all three indicators, our approach captures a more complete picture of a child's nutritional and developmental status.

Another key differentiator of this study is its emphasis on practical usability. While most prior studies ended at the algorithmic or analytical stage, this work goes a step further by developing a working system that can be used by practitioners. The interface is intuitive and requires minimal training, making it accessible even in lower-resource environments.

2. Key Contributions

In summary, this study contributes to the field in three important ways:

- It integrates all three WHO-recommended Z-score indicators into the clustering process, offering a richer and more reliable classification.
- It aligns cluster groupings with clinically accepted nutritional categories, making the results immediately useful in healthcare settings.
- It provides a ready-to-use digital tool for real-time classification, empowering health workers with faster, data-based insights.

3. Limitations and Future Directions

Despite these strengths, the study does have limitations. The dataset is relatively small (77 records), which may affect the generalizability of the model. In future work, the model should be trained and tested on larger, more diverse datasets across multiple regions to increase robustness.

Other clustering methods—such as DBSCAN or Gaussian Mixture Models—could also be explored for comparison, especially in handling outliers or non-spherical data. Additionally, integrating this model into national electronic health record systems could extend its impact by enabling large-scale, automated nutritional screening.

V. Conclusion

This study examined the application of the K-Means Clustering algorithm to classify children's nutritional status using three WHO-standard anthropometric indicators: Weight-for-Age Z-score (WAZ), Height-for-Age Z-score (HAZ), and Head Circumference-for-Age Z-score (HCAZ). By integrating all three indicators into one model, the study offers a more comprehensive and clinically meaningful approach to identifying nutritional deviations during early childhood. The clustering process successfully grouped children into five categories consistent with WHO growth standards. Most children were classified as having normal nutritional status, while a significant proportion were found to be moderately undernourished. This confirms that using multiple Z-score indicators provides a clearer and more accurate picture of a child's growth pattern.

A key contribution of this work lies in the development of a functional system that enables health workers to input basic anthropometric data and instantly receive a nutritional classification. This tool supports early detection and timely intervention, especially in low-resource settings where manual classification may be impractical or inconsistent. Compared to previous studies that relied on limited indicators or remained at the modeling stage, this study not only improves classification accuracy but also bridges the gap between data analysis and practical application. The inclusion of HCAZ as a developmental metric adds further value, especially for assessing brain growth in younger children.

An important strength of the clustering approach used in this research is its ability to quantify how far each group deviates from the standard growth curve. The model revealed that 36.36% of children fell outside the WHO-defined normal nutritional range—either as undernourished or overnourished—while 63.64% were classified within normal limits. Among those outside the normal range, the majority belonged to the moderately undernourished group, indicating early signs of growth faltering. This method not only categorizes but also provides measurable insight into the severity and distribution of growth deviations. It enables a more targeted and data-informed nutritional intervention strategy, especially in contexts where time, accuracy, and simplicity are critical.

Although the dataset used in this study was relatively small, the findings are promising. Future work should involve larger and more diverse datasets, as well as comparisons with other clustering algorithms to evaluate robustness and scalability. Integrating this model into national health systems or mobile health platforms could further amplify its practical impact, making machine learning a valuable tool in improving child health outcomes.

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