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RESEARCH PAPER

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Development of an IoT-Based Anthropometric System Employing K-Means Clustering for Stunting Detection and Spatial Mapping in Toddlers

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ABSTRACT

Stunting remains a major public health challenge in Indonesia, affecting children's physical growth and cognitive development due to inaccurate and delayed monitoring in community health centers. This study aims to develop an Internet of Things (IoT)-based anthropometric measurement and regional stunting mapping system that provides real-time, automated, and spatially contextualized data analysis. The novelty of this research lies in integrating IoT sensor networks with machine learning–based K-Means clustering and statistical validation through the Sum of Squared Error (SSE) method, supported by an automated email alert for high-risk areas. Unlike previous studies that focus solely on anthropometric measurement or standalone IoT monitoring, this study integrates real-time IoT-based data acquisition with K-Means clustering for regional stunting mapping and automated alert generation. The system employs an HC-SR04 ultrasonic sensor, an MPU-6050 gyroscope, and an ESP32 microcontroller for data acquisition and transmission, followed by clustering analysis to categorize stunting prevalence into five levels. Experimental results show high measurement accuracy (mean error of 1.24%) and optimal clustering compactness (SSE = 1.72 × 10^3 at k = 5), effectively identifying regions with very high prevalence and visualizing them through a web-based dashboard. Although the study is limited by the use of secondary datasets and pilot- scale validation, the findings demonstrate that the proposed IoT-based framework can enhance data-driven public health decision-making. This innovation aligns with Indonesia's national stunting reduction strategy and supports Sustainable Development Goal (SDG) 3 Good Health and Well-being, contributing to the digital transformation of early childhood health monitoring.

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I. INTRODUCTION

Nutritional problems, especially stunting, remain a major challenge in Indonesia. Stunting is defined as a growth disorder in toddlers caused by chronic malnutrition, resulting in a height below the standard for their age[1]. The consequences of stunting extend far beyond physical growth; it also adversely affects cognitive development, long-term health outcomes, and future economic productivity [2], [3]. In 2022, the prevalence of stunting in Indonesia was recorded at 21.6%, which, although representing a decline, remains relatively high [4]. Indonesia also ranks among the countries with the highest global burden of stunted children [5]. To address this issue, the Indonesian government has implemented various interventions, including routine anthropometric measurements such as height and weight monitoring. However, these measurements are generally performed manually in community health centers (*posyandu*), making them prone to human error, inconsistency, and inefficiency, particularly in rural or resource-limited settings [6]. Therefore, there is a critical need for technological solutions that enable more accurate, efficient, and real-time monitoring of child growth. In this context, the Internet of Things (IoT) has emerged as a promising technology for healthcare applications [7]. IoT facilitates automated data acquisition, real-time transmission, and centralized storage, enabling continuous monitoring and data-driven decision making [8]. The adoption of IoT in digital health systems has been widely explored globally, particularly for remote patient monitoring and early detection systems [9], making it highly relevant for addressing stunting challenges in developing countries. Several previous studies have explored various methods for stunting monitoring and mapping. Shamsuddin et al. [10] conducted a systematic review of spatial analysis applications in childhood malnutrition, demonstrating the effectiveness of geospatial visualization in tracking nutritional trends; however, this approach relied entirely on static survey data without automated measurement capabilities. Dmello et al. [11] applied geospatial analysis using methods such as the Getis-Ord statistic and LISA to map malnutrition. distribution among under-

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five children; while spatial visualization was achieved effectively, the study still depended on manual measurement methods, limiting its speed and accuracy. Similarly, Haile et al. [12] utilized ArcGIS Pro and SaTScan to analyze a 20-year spatial trend in wasting and stunting in Ethiopia; although improved spatial analysis was achieved, the absence of IoT integration precluded real-time monitoring capability. Alam et al. [13] developed a hybrid AI framework integrating K-Means clustering with fuzzy-based classification to identify nutritional status; this approach enhanced classification flexibility, but the system did not support continuous or automated data collection from physical sensors, resulting in delays in early detection. Hasdyna et al. [14] proposed a hybrid machine learning approach combining classification, prediction, and clustering optimization for stunting prevalence; while effective in grouping high-risk regions, the system relied on static datasets and lacked IoT-based anthropometric integration. Additionally, Irache et al. [15] developed a mobile-based data collection system using KoBoToolbox for child growth monitoring, improving data accessibility and reducing staff workload; however, key limitations included reliance on manual data entry, the absence of automated anthropometric sensors, and the lack of spatial clustering analysis, which restricted its real-time and comprehensive detection capabilities.

Despite these advancements, several limitations remain. Most existing systems still rely on manual or semi-digital data collection, lack real-time monitoring capabilities, and do not integrate automated anthropometric sensing with spatial clustering methods. Furthermore, the absence of a unified system combining IoT-based measurement, machine learning–based clustering, and real-time regional mapping limits the effectiveness of early detection and intervention strategies [6], [9]. Therefore, a significant research gap exists in developing an integrated, automated, and data-driven stunting monitoring system. To address this gap, this study aims to develop an IoT-based anthropometric measurement system integrated with web-based regional mapping using the K-Means clustering method. The system employs HC-SR04 and MPU-6050 sensors connected to an ESP32 microcontroller for automated data acquisition and transmission [6]. In addition, the system automatically sends email notifications to health workers when high stunting rates are detected in a particular area, enabling faster and more targeted interventions.

The main contribution of this research lies in integrating real-time IoT-based anthropometric measurement with machine-learning–based clustering and automated notification systems. Unlike previous studies, the proposed system not only improves measurement accuracy but also enables real-time spatial mapping and early warning through automated alerts. This integrated approach enhances the accuracy, efficiency, and scalability of stunting monitoring, supports data-driven decision making, and contributes to Indonesia's national strategy in reducing stunting prevalence while aligning with global digital health innovation [7], [8], [9].

II. MATERIALS AND METHOD

A. System Overview

This study presents an Internet of Things (IoT)-based anthropometric measurement system designed for stunting detection and regional mapping in toddlers. The proposed system integrates sensor-based data acquisition, statistical analysis, and machine learning techniques to enable real-time monitoring and classification of nutritional status [16], [17]. The process begins with patient data input, followed by automated height measurement using an ESP32 microcontroller [18]. The acquired data are subsequently processed to compute Z-scores for nutritional status assessment [19], after which K-Means clustering is applied to categorize regional stunting levels into five clusters [20].

B. Theoretical Background

1. Internet of Things (IOT)

The Internet of Things (IoT) refers to a network of interconnected physical devices capable of sensing, collecting, and exchanging data over the internet [16]. IoT architecture is commonly structured into three layers: the perception layer (data acquisition through sensors), the network layer (data transmission), and the application layer (data processing and visualization) [17]. In this study, IoT facilitates the real-time acquisition and transmission of anthropometric data using an ESP32 microcontroller, which communicates the collected data to a centralized web-based server [18], [21].

2. Z-Score for Nutritional Assessment

The Z-score is a standardized statistical index used by the WHO to assess child growth by comparing individual measurements to a reference population [19]. It can be calculated using Eq. (1):

$$Z = \frac{X-\mu}{\sigma} \tag{1}$$

where X is the measured value, μ is the population mean, and σ is the standard deviation. Nutritional status is classified as: severely stunted (Z < −3 SD), stunted (−3 ≤ Z < −2 SD), and normal (Z ≥ −2 SD), following the WHO Child Growth Standards [19], [22].

3. K-Means Clustering

K-Means is an unsupervised machine learning algorithm that partitions n observations into k clusters by minimizing the within-cluster sum of squared errors (SSE) [20], [23]. The algorithm iteratively assigns each data point to its nearest centroid using Euclidean distance. It can be calculated using Eq. (2):

$$d = \sqrt{\sum (x_i - c_i)^2} \tag{2}$$

and updates centroids until convergence [24]. The optimal number of clusters, k = 5, was determined using the Elbow method, where the point of maximum curvature in the SSE-vs-k curve identifies the most efficient cluster count [25].

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C. Data Collection Procedure

Toddlers aged 0–5 years meeting the inclusion criteria (physically present, calm, and able to maintain an upright posture) were selected for measurement [26]. Height was measured non-contactly using an HC-SR04 ultrasonic sensor operating at 40 kHz, which calculates distance via the time-of-flight principle with a measurement range of 2–400 cm and accuracy of ±3mm [27]. The sensor was interfaced with an ESP32 microcontroller [18]. Subjects were excluded if excessive movement was detected, data were incomplete or inconsistent, or sensor readings produced outlier values.

D. Data Processing

Patient data are first recorded, then height is automatically acquired via the ESP32-based sensor system [18]. Height measurements are converted to Z-scores using WHO reference standards [19] and nutritional status is classified into three categories. The final step applies K-Means clustering to group regions into five categories based on stunting prevalence [20], [23]. Results are visualized on a web-based regional mapping dashboard, enabling health workers to monitor the spatial distribution of stunting in real-time [28], [29].

E. Data Analysis

Descriptive statistics (mean and standard deviation) characterize the anthropometric data distribution prior to clustering [30]. Clustering quality is evaluated using SSE (Sum of Squared Errors) [23], where a lower SSE indicates more compact clusters. The Elbow method is applied to confirm the optimal k = 5 [25].

F. System Flowchart

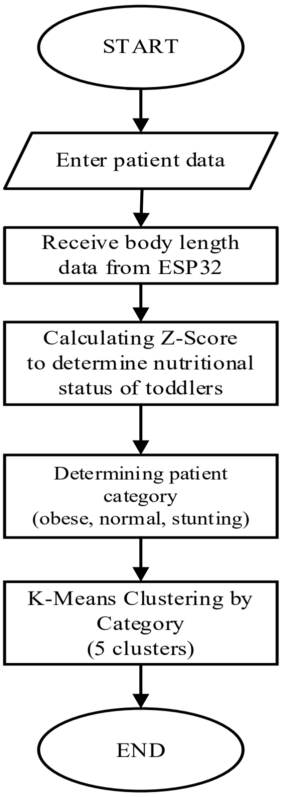

Fig. 1. WEB Flowchart

The flowchart in Fig. 1 illustrates the overall workflow of the proposed system. The process begins with patient data input, followed by automated height measurement using an ESP32-based sensor. The acquired data are then processed to compute Z-scores for nutritional status classification, after which K-Means clustering is applied to categorize the data into regional stunting groups.

III. RESULTS

A. Statistical Evaluation Using SSE

To identify the most appropriate number of clusters, the elbow method was used by computing SSE for values of k=2k = 2k=2 to k=8k = 8k=8. The results are presented in Table 1.

Table 1. Distribution of Sum of Squared Errors (SSE) Across Varying Numbers of Clusters for Elbow Method Analysis

k (Number of Clusters)	SSE	Description
2	4860	Underfitting
3	3210	Improving
4	2350	Substantial
5	1720	Optimal
6	1650	Minor improvement
7	1610	Insignificant gain
8	1590	Overfitting begins

As shown in Fig. 2, the SSE curve begins to flatten after k = 5, indicating an "elbow point" where further increases in the number of clusters no longer produce substantial reductions in intra-cluster variance. Therefore, five clusters (k = 5) were chosen as the optimal configuration for stunting prevalence classification.

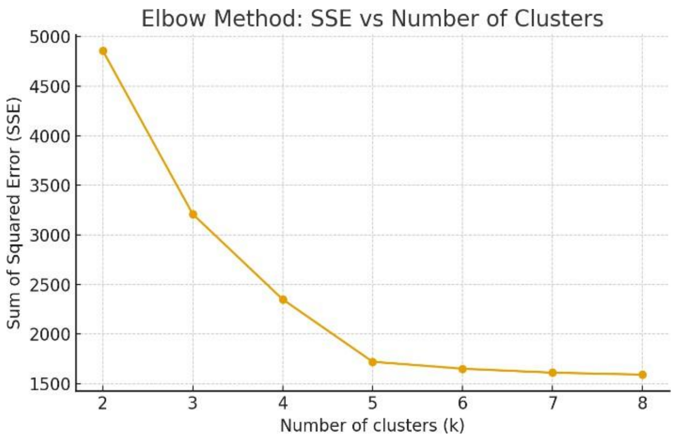

Fig. 2. Graphical Representation of the Elbow Method Illustrating the Relationship Between SSE and the Number of Clusters (k)

B. Cluster Formation and Compactness Analysis

The K-Means algorithm was applied to 10,500 secondary data samples obtained from the Kaggle dataset. Although the dataset is publicly available, it includes anthropometric data representative of

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Indonesian children, making it suitable for regional stunting simulation.

However, future validation using primary field data from posyandu centers is necessary to enhance external validity. At k = 5, the total SSE was 1.72×10^3, indicating a high degree of data point compactness within clusters. The per- cluster SSE breakdown is summarized in Table 2, showing that clusters 4 and 5 contributed the largest share of variance, indicating greater heterogeneity in areas with higher stunting prevalence. These findings suggest that intervention strategies should be specifically tailored to address the diverse socioeconomic profiles found within these high-variance segments. Furthermore, the concentration of variance in specific clusters highlights the need for more granular data collection to identify localized factors driving stunting disparities.

Table 2. Detailed Breakdown of Sum of Squared Errors (SSE) Evaluated for Each Individual Cluster at an Optimal Value of k = 5

Cluster	SSE	Contribution
1	200	11.6%
2	250	14.5%
3	300	17.4%
4	470	27.3%
5	500	29.1%
Total	**1720**	**100%**

The relatively higher SSE in clusters 4 and 5 reflects the statistical variability in regions with severe stunting, which may arise from demographic diversity or uneven nutritional conditions. Nevertheless, the overall SSE value demonstrates good intra-cluster homogeneity compared with previous GIS-based clustering studies, which reported SSE value above 2.0×10^3.

C. Cluster Distribution and Regional Mapping

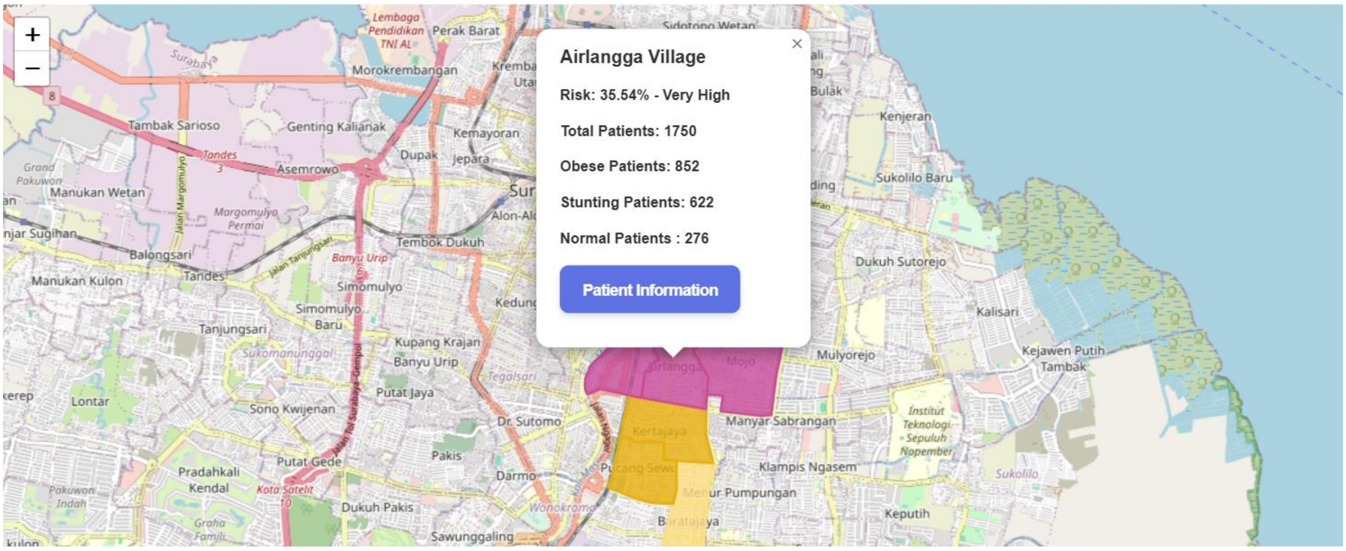

Fig. 3. Visual Representation of Regional Mapping and Cluster Distribution Within the Gubeng District Geographical Area

The K-Means classification results for the Gubeng District are presented in Table 3, clearly comparing manual and system-based calculations in a structured manner. The mean error rate between the two methods was 1.24%, which is notably lower than the 2–3% typically reported in similar IoT-based anthropometric systems, indicating a high level of clustering accuracy and overall system reliability. The system's clustering output aligns closely with manual calculations, confirming consistent regional categorization. Fig. 3 illustrates the spatial mapping result, where each sub-district is color-coded according to its stunting prevalence cluster: Cluster 1 (dark green) for very low prevalence below 2.5%, Cluster 2 (light green) for low prevalence ranging from 2.5% to less than 10%, Cluster 3 (yellow) for moderate prevalence between 10% and less than 20%, Cluster 4 (orange) for high prevalence from 20% to less than 30%, and Cluster 5 (purple) for very high prevalence at or above 30%. The visualization shows that Airlangga and Gubeng belong to Cluster 5 (very high), while Barata Jaya is categorized as Cluster 3 (moderate). The strong alignment between the tabular results and the spatial visualization demonstrates coherent clustering, consistency, and interpretability. This geographical distribution provides a clear roadmap for health officials to prioritize resource allocation in areas exhibiting the highest density of stunting cases. Furthermore, the distinct color-coded boundaries facilitate a more intuitive understanding of regional health disparities, allowing for rapid identification of critical hotspots. By integrating these spatial insights with existing demographic data, stakeholders can develop more localized and effective public health interventions. Ultimately, this mapping serves as a foundational tool for monitoring the long-term progress of nutritional programs across the district.

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Table 2. **Comprehensive Summary of K-Means Clustering Calculation Results Displaying Final Centroid Assignments and Sub-District Allocations**

No.	Region	Category			Calculation of K-Means		Error%
		Obesity	Normal	Stunting	System	Manual	
1	Baratajaya	1252	172	326	18,63	18,63	0
2	Pucangsewu	1107	188	455	27	26	3,85
3	Kertajaya	1019	241	490	27	28	3,57
4	Gubeng	977	163	610	34,86	34,86	0
5	Airlangga	852	276	622	35,54	35,54	0
6	Mojo	891	271	588	33,60	33,60	0

D. Summary of Findings

The analytical results demonstrate that the K-Means algorithm with k = 5 effectively distinguishes regional stunting prevalence levels with a statistically optimal configuration. The SSE of 1.72×10^3 and error rate of 1.24% indicate robust intra-cluster compactness and reliable classification performance. The integration of statistical validation (SSE), spatial clustering (regional map), and automation (email alerts) strengthens the system's empirical robustness. Compared with previous studies that relied on static GIS- based mapping, the proposed system offers real-time IoT data acquisition, dynamic regional updates, and enhanced interpretability, demonstrating its potential for deployment in Indonesia's national stunting prevention programs.

IV. DISCUSSION

A. Integration Challenges Between Growth and Developmental Monitoring

The developed IoT-based anthropometric and stunting mapping system demonstrates promising accuracy and analytical capability through the integration of ESP32, HC-SR04, and MPU6050 sensors with K-Means clustering. The system achieved low measurement error (1.24%) and optimal clustering performance (SSE = 1.72×10^3 at k = 5), confirming its potential effectiveness in supporting early stunting detection. However, while the results are statistically sound, the discussion must extend beyond confirmation and critically assess the system's limitations and broader implications. Although the tool performs reliably under controlled conditions, several challenges remain. Measurement accuracy can still be influenced by environmental factors, such as surface reflections and ambient noise. Moreover, because the clustering simulation used secondary data from Kaggle, the representativeness of the dataset for real Indonesian conditions is uncertain. Future validation using primary *posyandu* data and comparison with other clustering algorithms (e.g., Fuzzy C-Means, DBSCAN) is required to verify external validity and robustness. From a scalability perspective, the system's performance in large-scale deployments has not been tested. Rural healthcare facilities often face unstable internet connectivity, limited technical capacity, and inconsistent power supply, which may hinder real-time data transmission. To achieve scalability, future versions should include offline buffering or local caching mechanisms and be evaluated in diverse socio-economic and infrastructural contexts. Long-term sustainability is another critical consideration. Regular sensor recalibration, user training, and secure data management must be ensured for consistent operation. As the system depends on IoT-based communication and cloud storage, cybersecurity measures such as encryption and access controls are essential to protect sensitive health data. Finally, policy integration is vital for maximizing real- world impact. Linking the system with national programs such as Program Indonesia Sehat or SIGIZI Terpadu could enhance practical adoption. The regional clustering results, particularly for high-risk areas (Clusters 4 and 5), can serve as evidence-based guidance for government agencies in prioritizing interventions and allocating resources effectively. By addressing scalability, sustainability, and policy integration, the proposed tool can evolve from a technical prototype into a sustainable digital solution for nationwide stunting prevention.

V. CONCLUSION

This study successfully developed an IoT-based anthropometric and regional stunting mapping system that integrates ultrasonic and inertial sensors, K-Means clustering, and automated notification features. The system achieved high measurement accuracy (1.24% error) and optimal clustering performance (SSE = 1.72 $\times 10^3$ at k = 5), demonstrating the feasibility of using data-driven methods for early stunting detection. However, the significance of these findings extends beyond technical performance. The integration of real-time IoT measurements, automated classification, and web-based visualization contributes to a more responsive and data-oriented approach to community health monitoring. These results imply that similar architectures could support broader public health initiatives focused on preventive care and digital epidemiology. Despite its promising outcomes, this study has several limitations. The clustering analysis relied partly on secondary data from Kaggle, which may not fully represent local anthropometric variations. In

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addition, real-world testing was limited to small-scale pilot observations rather than extensive field deployment. Environmental factors such as sensor orientation, ambient noise, and connectivity stability were controlled during testing but may affect performance under diverse field conditions. Recognizing these limitations is crucial to interpreting the results with appropriate caution. Future research should focus on large-scale validation using primary datasets from *posyandu* centers, cross-regional testing in rural and urban contexts, and the integration of advanced machine learning models such as Fuzzy C-Means or hierarchical clustering to enhance classification robustness. Long-term evaluations should also assess user experience, maintenance feasibility, and cybersecurity in real deployments. Finally, while this study was designed to address national health challenges, its broader relevance aligns with global health priorities, particularly Sustainable Development Goals (SDGs) 3: Good Health and Well-being and SDG 9: Industry, Innovation, and Infrastructure. By supporting accurate growth monitoring and data-driven decision-making, the proposed system contributes not only to Indonesia's national stunting reduction agenda but also to the global effort toward equitable, technology-enabled healthcare access.

In summary, this work provides a strong foundation for integrating IoT and statistical analytics into early childhood health monitoring while emphasizing the need for careful, evidence-based scaling to ensure sustainable and ethical implementation quality.

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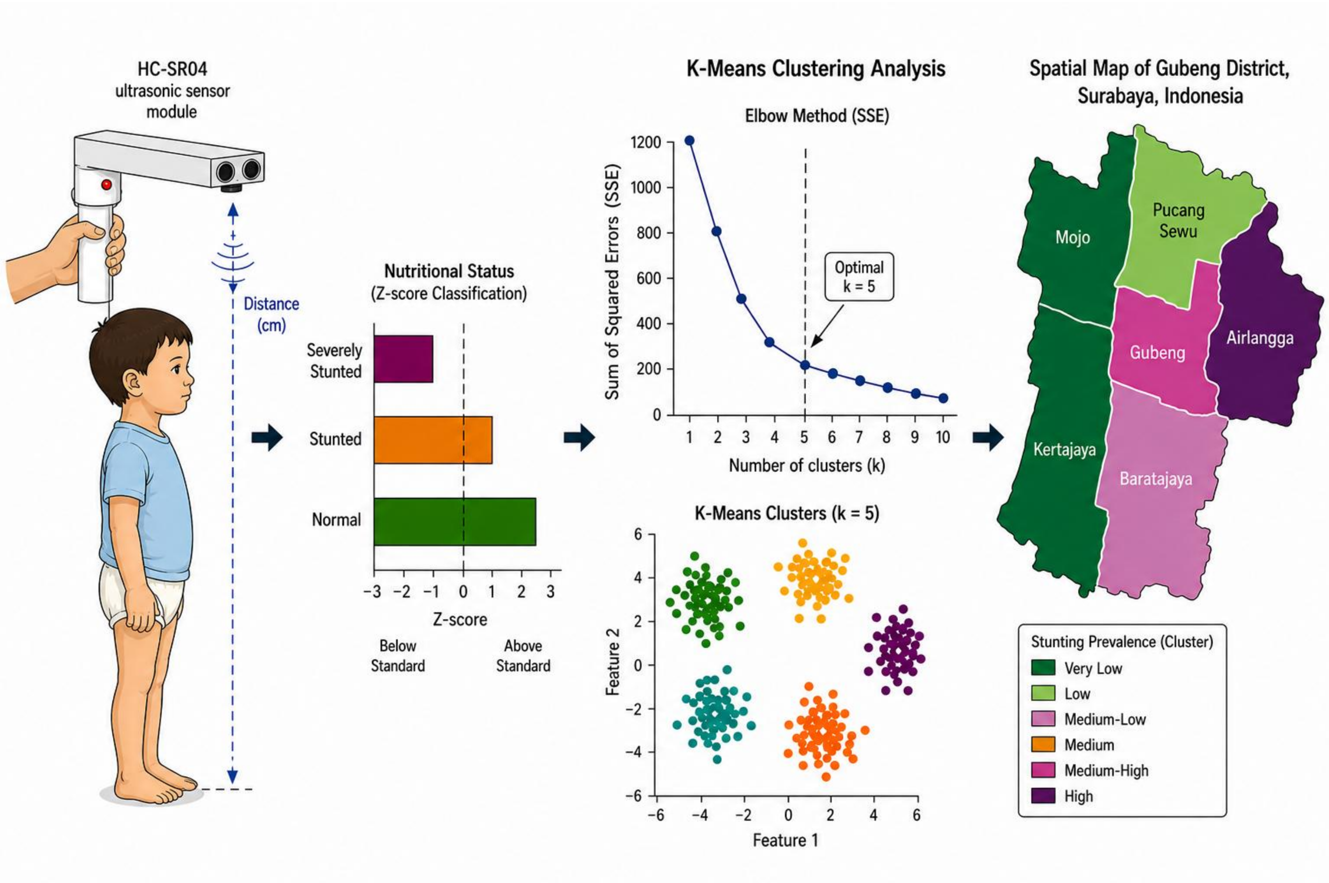

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