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Automated Z-Score Based Nutritional Status Classification for Children Under Two Using Smart Sensor System

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Abstract

The classification of nutritional status in children under two years old is crucial for monitoring growth and early detection of nutritional problems. However, in many healthcare facilities, this classification is still performed manually, requiring relatively long processing times and being prone to human error in both measurement and data recording. The problem addressed in this study is the inefficiency and potential inaccuracy of manual nutritional status classification in toddlers. This research aims to develop an automatic and digital device capable of measuring body length and weight and classifying nutritional status in children under two years old efficiently, accurately, and in real time. The device utilizes electronic sensors integrated with a microcontroller to streamline the process and reduce measurement error. The main contribution of this study is the design and realization of a portable automation device that integrates an HC-SR04 ultrasonic sensor for measuring body length and a 50 kg full-bridge load cell sensor for measuring body weight, both controlled by an ATmega328P microcontroller. The device processes the data measurement digitally, displays the results on a 20 × 4 LCD, and provides a printed copy via a thermal printer, enhancing the data recording efficiency. The method involves the design of hardware circuits, sensor calibration, software programming using the C language in the Arduino IDE, and performance testing of the device by comparing its results to standard measuring instruments. The device's performance is evaluated based on measurement error percentage and precision level. The results demonstrate that the device achieved an error percentage of 1.26% for body length measurement and 0.98% for body weight measurement. The overall system error is recorded at 0.5%, with a precision level ranging from ±0.08 to ±0.4.

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I. Introduction

Child malnutrition remains a significant public health concern in Indonesia. Many children under two years old suffer from nutritional deficiencies that, if not addressed promptly, may lead to developmental delays and increased mortality risk. The United Nations has emphasized the importance of early nutrition monitoring to reduce long-term adverse effects on child health [1]. Nutritional assessment, particularly using anthropometric indicators, is critical in identifying growth abnormalities such as wasting, stunting, and overweight conditions [2],[3],[4]. Malnutrition is a major contributor to child morbidity and mortality and is often underdiagnosed or inadequately monitored [5],[6]. Studies [7] indicates that various factors, including maternal education, sanitation, and access to health services, contribute to a child's nutritional status [5],[8],[9]. Exclusive breastfeeding until the age of two is also essential to meet nutritional needs and support optimal neurodevelopment [10]. Therefore, consistent and accurate monitoring during this critical age range is necessary. Several studies have addressed the classification of nutritional status using anthropometric indices, typically by calculating the Z-score based on body weight and height measurements [11],[12],[13]. The classification generally follows the WHO growth standards, which define nutritional categories based on Z-score ranges: *Severely Wasted* $(Z < -3.0)$, *Wasted* $(-3.0 \leq Z \leq -2.0)$, *Normal* $(-2.0 \leq Z \leq +2.0)$, *Overweight* $(+2.0 < Z \leq +3.0)$, and *Obese* $(Z > +3.0)$. Research conducted previously [13] explored the development of anthropometric measurement tools by comparing analog and digital methods; however, the proposed devices lacked automation and required considerable time for data acquisition and interpretation [14].

Recent developments have incorporated the Internet of Things (IoT) for data collection and child growth monitoring [15]. Other implementations [16],[17] used load cell and ultrasonic sensors to record children's weight and length, displaying growth data on Android-based applications [18]. However, these studies do not perform automated classification or nutritional status

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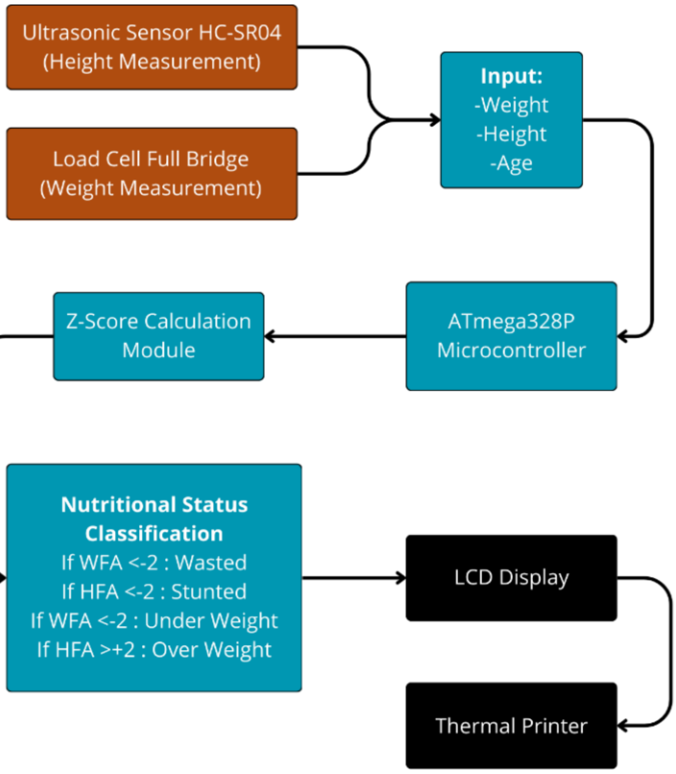

Fig. 1. Hardware Block Diagram of the Anthropometric Measurement System

assessment. Although IoT and sensor technologies have been used for monitoring child growth, most existing systems do not provide automated nutritional status classification based on standard health indices. Moreover, current tools are often not optimized for children under two years old and lack features such as gender-based differentiation, which is important due to physiological differences in growth patterns between boys and girls. This study proposed the design and implementation of a smart, automated device to assess and classify the nutritional status of children under two. The system utilizes two key sensors: the HC-SR04 ultrasonic sensor to measure body length and a full-bridge load cell to measure body weight. These parameters were processed using the ATmega328P microcontroller. The device includes a gender selection feature, which enhances assessment accuracy, and displays the output on a 20x4 LCD. Final measurement results, including date and classification, were printed using a thermal printer. The main objective of this study is to develop a low-cost, portable, and automated nutritional status monitoring device for children under two years old, integrated with IoT features to enable faster, more accurate, and accessible growth assessment. To achieve this goal, several key contributions are presented in this work:

1) The development of an automated device for classifying nutritional status based on Z-score using anthropometric data.
2) Integration of affordable sensors with ATmega328P for efficient measurement of body weight and length.
3) Implementation of gender based nutritional assessment to improve accuracy.
4) Real-time display and printout of measurement results, enhancing usability in both clinical and rural healthcare settings.

II. Materials and Methods

A. System Architecture

The complete system design is illustrated in the block diagram presented in Fig. 1 The system was organized into three primary functional units: input, processing, and output, all powered by a battery module to ensure portability and independence from external power sources. The input unit consists of three key components: 1.Ultrasonic sensor (HC-SR04), measuring the child's body length by calculating the distance between the sensor and the child's body surface; 2. Load cell (Full-Bridge Configuration), measuring the child's body weight using strain gauge-based pressure detection; and 3. Push button, which is used to input the child's gender, with a green button indicating male and a yellow button indicating female. These input signals were then transmitted to the ATmega328P microcontroller, which functions as the system's central processing unit. The microcontroller collected and processed the raw data from the sensors, computed the Z-score based on the child's age and gender, and determined the nutritional status by referencing the WHO growth standard thresholds.

The output unit includes: 1. LCD Display (20x4) to present the real-time results including body weight, height, and nutritional status; and 2. Thermal Printer to

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generate a printed report containing the child's name, date, time (synchronized via an RTC module), weight, height, and corresponding nutritional classification. All modules were powered by a dedicated battery system, making the device suitable for mobile and community-based health assessments, particularly in areas with limited access to electrical infrastructure.

B. Hardware System Design

In this study, the hardware system was designed to measure children's anthropometric parameters, specifically length and weight, and subsequently classify their nutritional status based on Z-scores [19]. The system integrates multiple sensors and electronic modules into a portable platform powered by a rechargeable battery unit, ensuring usability in field conditions. Height measurement was performed using an Ultrasonic Sensor HC-SR04 (ElecFreaks, China), which operates on the principle of emitting and receiving ultrasonic waves at a frequency of 40 kHz. The distance between the sensor and the child's body surface was calculated from the travel time of the reflected signal. This sensor operates at 5V DC, with a current consumption of 15 mA, a detection range of 2–400 cm, an accuracy of ±3 mm, and an effective angle of 15°. The sensor was mounted vertically on the upper frame of the platform to measure body length in a lying position, which complies with pediatric anthropometric measurement standards for children under two years old, who are generally unable to stand unassisted [20]. The HC-SR04 was selected because it is cost-effective, provides adequate precision for anthropometric applications, and can be easily integrated with the ESP32 microcontroller. Weight measurement was carried out using a Load Cell CZL-601 (YZC, China) in combination with the HX711 amplifier module (Avia Semiconductor, China). The sensor utilizes the strain gauge principle, where mechanical deformation generates resistance changes that are converted into proportional electrical signals. The CZL-601 has a maximum capacity of 20 kg, a sensitivity of 1.0 ± 0.1 mV/V, a nonlinearity of ±0.03% FS, and a repeatability of ±0.02% FS, making it highly precise and stable for pediatric weight measurements. The load cell was installed at the base of the platform with a circular metal plate buffer to distribute force and enhance measurement stability evenly [21]. The analog signal from the load cell was amplified and converted into digital form by the HX711 module before being transmitted to the ATmega328P microcontroller for further processing [22]. A controller box equipped with a push button allowed the operator to input the child's gender and initiate the measurement process. Once both weight and length were obtained, the microcontroller calculated the Z-score according to gender-specific growth standards and classified the child's nutritional status accordingly. The results, including the child's name, weight, length, nutritional classification, and the date and time, were displayed on an LCD screen and simultaneously printed using a thermal printer. To ensure accurate time-stamping, the printer module was synchronized with an RTC DS1302 real-time clock [23].

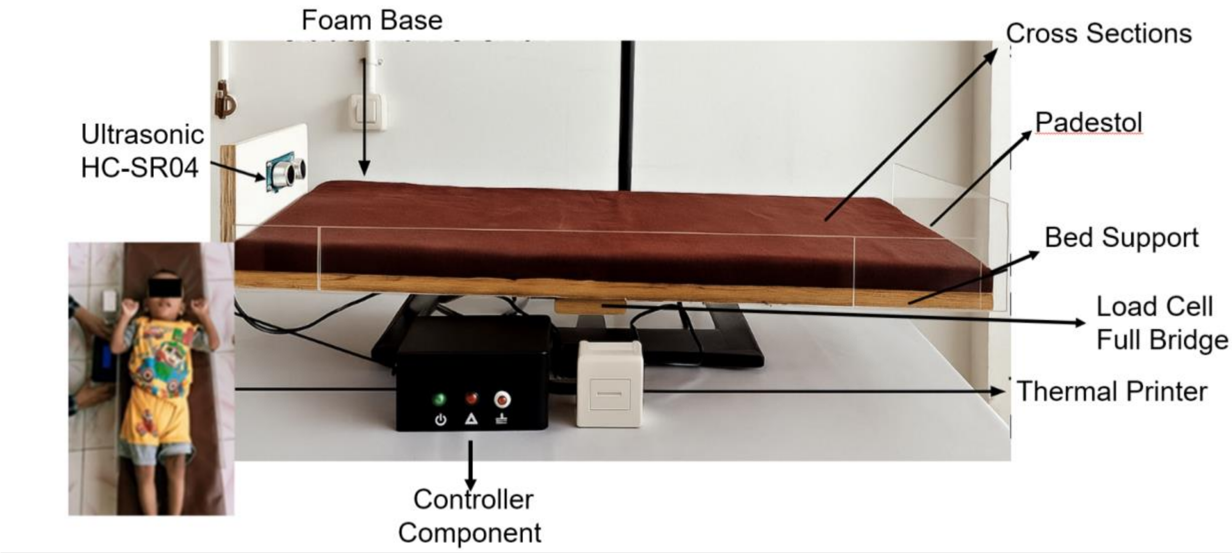

Fig. 2. Physical design of child nutritional status monitoring device based on sensor integration.

All hardware components were structurally mounted on a solid platform to ensure consistency, user safety, and ease of transport. The modular design also facilitates system maintenance and provides flexibility for future enhancements, such as data logging and wireless communication capabilities. The complete physical implementation of the system is illustrated in Fig. 2.

C. Sensor Calibration

A zero and span calibration procedure was applied for the HC-SR04 ultrasonic sensor and the full-bridge load cell. Calibration was conducted using NIST-traceable weights for weight measurement and a Harpenden stadiometer for length reference. Calibration logs were maintained and

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updated weekly in a bench test protocol, while daily field calibration was carried out before measurements [24].

D. Measurement Protocol

A standard supine position protocol was used. The child was placed on a foam-padded board with heel trackers to ensure consistent foot position. Velcro straps were placed above the knees to minimize foot movement. Each measurement was repeated twice, with a third measurement only performed if the first two measurements differed by more than 0.2 cm or 0.05 kg. Calming techniques, such as toys or parental presence, were used for uncooperative children. If a child was uncomfortable or crying, time was given so that the measurements could be repeated once the child was comfortable for more accurate results. The system was tested under varying field conditions, with ambient temperature ranging from 20 to 34°C and relative humidity between 40 and 85 %. The embedded system implemented factory-supplied temperature compensation coefficients to maintain sensor accuracy despite environmental fluctuations. These compensations ensured reliable ultrasonic and load cell sensor readings during field measurements.

E. Sensor Mounting and Integration

The HC-SR04 ultrasonic transducer was mounted 60 cm above the board at a 90° angle using a 3D-printed alignment jig to ensure a fixed distance and orientation. The 60 cm distance was selected to provide the ultrasonic sensor operated within its optimal measurement range (2–400 cm), minimizing the risk of echo interference or signal saturation. A perpendicular (90°) alignment was chosen to ensure vertical propagation of the ultrasonic wave, reducing angular error in height detection.

The load cell was embedded beneath an aluminum baseplate covered with a non-slip mat to ensure weight stability. The non-slip surface minimized child movement-induced variability, and the platform was designed to distribute load evenly for accurate readings. A circular pressure buffer plate was also used to avoid point loads. Repeated weight testing under static conditions validated the embedded load cell for consistent output post-mounting. In addition, all sensor positions were tested before data collection to confirm that the mechanical integration did not introduce significant measurement drift or error. The mounting setup ensures reproducible sensor alignment, essential for longitudinal field measurements and comparisons.

F. Signal Processing

Raw signals from the load cell were processed using a five-sample median filter followed by a first-order IIR low-pass filter with a 10 Hz cutoff frequency. To reduce signal noise for the ultrasonic sensor, an amplitude threshold and echo-timeout rejection were applied. These filtering techniques were implemented to suppress transient noise, eliminate outliers, and enhance the reliability of real-time measurements. The median filter is particularly effective for rejecting spike noise caused by mechanical vibration or electrical interference during weight measurement. The IIR low-pass filter further smoothens the signal to capture the true trend of the load signal while discarding high-frequency fluctuations. For the ultrasonic sensor, amplitude threshold was used to discard low-amplitude echoes that soft objects or ambient disturbances might cause. At the same time, echo-timeout rejection ensures that only valid reflection signals within an expected range are accepted. These signal conditioning strategies improve the system's measurement stability and enable accurate Z-score calculation, particularly under real-world field conditions.

G. Nutritional Status Classification Using Z-Score

Assessing a child's nutritional status typically involves analyzing anthropometric indicators, particularly body weight and height. These parameters are evaluated using the Z-score method, which quantifies the number of standard deviations a child's measurement deviates from the median of a reference population. This standardized statistical approach enables objective classification into nutritional categories such as undernourished, normal, overweight, or obese [25]. In this study, the Z-score method was implemented to process real-time anthropometric data, allowing for precise identification of deviations from WHO growth references. The system calculates Z-scores based on age and sex specific medians and standard deviations, ensuring accurate assessment of nutritional conditions [26]. This framework facilitates early detection of nutritional imbalances and supports timely intervention. The Z-score was calculated using the Eq. (1) as follows [27]:

$$Zscore = \frac{X}{\sigma} \quad (1)$$

where X represents the observed anthropometric measurement, μ denotes the reference median for the corresponding age and sex, and σ refers to the standard deviation from the reference population. According to the WHO growth standards, the Z-score is calculated using the LMS method Eq. (2) and Eq. (3) [28]:

If $L \neq 0$:

$$Z = \frac{\left(\frac{y^L}{M}\right) - 1}{L \times S} \quad (2)$$

If $L \neq 0$:

$$Z = \ln\left(\frac{y}{M}\right)/S \quad (3)$$

where y is the observed weight or length measurement, M is the median, L is the Box-Cox exponent to account for skewness, and S is the coefficient of variation. These parameters are published by WHO for each age or height. The Z-score indicates how far and in which direction a child's measurements deviate from the WHO reference median in terms of standard deviations. Each Z-score range corresponds to a specific nutritional condition, as shown in Table 1. These categories are implemented in the system's algorithm to determine child nutritional outcomes based on real-time input data. The Z-score computed from real-time anthropometric inputs was

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directly mapped to the corresponding category, enabling automated, consistent, and reproducible interpretation. The final result is displayed on an LCD interface and printed via a thermal printer for documentation.

Table 1. Nutritional Status Classification Based on Z-Score [20]

Z-score Range	Nutritional Status	Interpretation
$Z < -3.0$	Severely Wasted	Severe malnutrition
$-3.0\ \delta - 2.0$	Wasted	Moderate malnutrition
$+2.0\ \delta\ Z < +2.0$	Normal	Normal growth range according to WHO standards
$+2.0 < Z\ \delta + 3.0$	Overweight	Risk Overweight
$Z > +3.0$	Obese	Obesity (requires medical attention)

H. Software Implementation and Output

The software flowchart for the nutritional status monitoring system is presented in Fig. 3. It illustrates the sequential logic of operations performed by the microcontroller to manage data acquisition, user input, and Z-score processing. The program began with a power check, verifying whether the system was properly connected to the battery. If no power is detected, the system remains idle in a standby loop until a stable power connection is established.

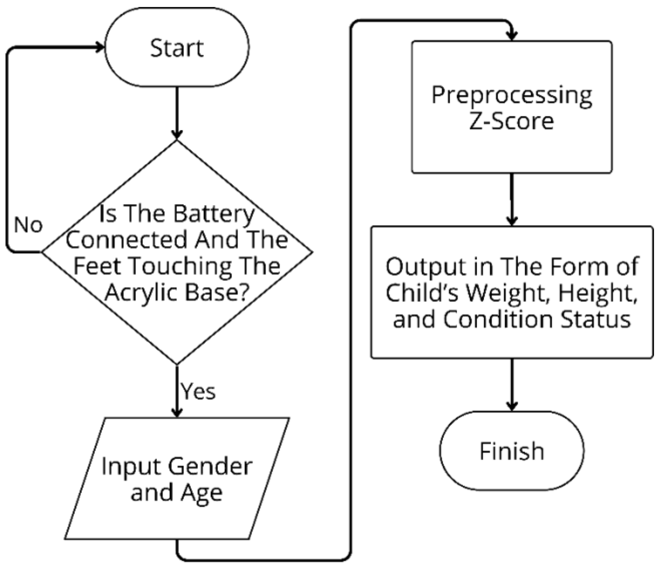

Fig. 3. Software Flowchart of the Nutritional Status Monitoring System.

Once the battery connection was confirmed, the system proceeded to the input stage, where the user was prompted to provide two key parameters, namely gender and age. Gender is selected using a push button, with green indicating male and yellow indicating female, while age is entered either through a predefined interface or manually configured in the code. These parameters are critical for the Z-score calculation because the reference median and standard deviation vary according to age and sex, following the WHO growth standards. After both inputs are received, the system advanced to the Z-score processing block, in which the body weight and body length data obtained from sensors were combined with age and gender information to calculate the Z-score using the previously described Z-score formula.

To ensure data reliability, the algorithm first verifies that the input sensor values fall within biologically plausible ranges, such as weight between 2–30 kg and length between 40–100 cm. If out-of-range values are detected, the system triggers an automatic prompt for remeasurement. After validation, the system applies classification rules based on WHO growth reference thresholds, in which a Z-score below –3 indicates severe malnutrition, values between –3 and –2 indicate moderate malnutrition, scores between –2 and +2 are considered normal, and values above +2 indicate overweight or at risk. User inputs are handled through a physical keypad, enabling entry of a unique child ID, along with gender and age. These entries are stored together with measurement data in both EEPROM and a microSD card, ensuring persistent storage. Each dataset is encoded using a CRC16 checksum to maintain data integrity. For cloud integration, the system supports TLS-encrypted data transmission to the "Puskesmas Baitussalam" platform, enabling secure syncing with national health systems. Additionally, all sessions were timestamped using a real-time clock (RTC) for traceable records. The final result including weight, length, Z-score, and nutritional status, was displayed on a 20×4 LCD screen and printed using a thermal printer, with output time-stamped via RTC synchronization. This automated and structured approach improves consistency, minimizes user error, and supports scalable, efficient, and field-deployable pediatric nutritional assessments.

I. Validation Protocol

The system's accuracy was validated through direct comparison with standard manual anthropometric instruments, namely the SECA 874 digital weighing scale and a Harpenden infant stadiometer. Measurements were taken sequentially for each child, first using the smart monitoring system and then with manual tools, under consistent conditions. Acceptance criteria for measurement deviations were set at a maximum of 0.5 cm for length and 0.1 kg for weight, ensuring precision in anthropometric assessments. Several statistical analyses were used to evaluate the agreement and reliability between the intelligent monitoring system and the manual measurement method. Bland-Altman plots were used to visualize the agreement level and detect systematic bias between the two measurement techniques. Furthermore, Pearson correlation coefficients were calculated to

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measure the strength and direction of the linear relationship between the readings of the innovative system and those obtained through manual measurements. Furthermore, Kappa statistics were applied to assess the agreement level in nutritional status classification, based on Z-score thresholds, by comparing the results from the intelligent system with the manual reference standard. This comprehensive validation protocol ensures that the proposed system meets clinical requirements for accuracy and diagnostic relevance in pediatric nutritional assessments.

J. Statistical Analysis

To evaluate the performance and agreement of the developed system with conventional manual measurements, several statistical metrics were used. The Mean Absolute Error (MAE) and Standard Deviation (SD) were computed to quantify average deviation and variability in measurements. A 95% Confidence Interval (CI) was calculated for each measurement set to determine the expected range of error with statistical confidence. Paired t-tests were conducted to compare differences between the prototype and manual tools, assessing statistical significance. Furthermore, Bland–Altman analysis was employed to examine the agreement between the two measurement methods. Finally, the Intraclass Correlation Coefficient (ICC), using a two-way random effects model with absolute agreement, was used to assess the consistency and reliability of repeated measurements across methods.

III. Result

The performance evaluation of the proposed smart nutrition monitoring system was conducted through a series of tests focusing on two primary sensors: the HC-4 full bridge load cell sensor for measuring body weight. Each sensor was individually assessed for both accuracy and precision, followed by analysis of its integration within the overall system. The accuracy test aimed to evaluate how close the sensor readings were to the true reference values, while the precision test examined the consistency of repeated measurements under identical conditions. The following subsections present the experimental results for each sensor. Table 1 shows that the average measurement error was 0.20 cm (SD=1.03 cm, 95% CI: -0.54 to 0.94 cm) for length and 0.04 kg (SD=0.089 kg, 95% CI: -0.02 to 0.10 kg) for weight. These values were reported consistently across subjects, and all tables and figures in this section include the appropriate units, statistical indicators, and percentage of measurement error.

IV. Discussion

A. Sensor Accuracy and Precision

The ultrasonic sensor (HC-SR04) was evaluated for accuracy by measuring 10 length samples five times each, and the results were compared with standard measuring tape references. The average error was 0.49%, indicating high accuracy Fig. 4 and Fig. 5 show that repeated measurements under the same conditions exhibit minimal variation, within ±0.4 cm, confirming acceptable precision for field use.

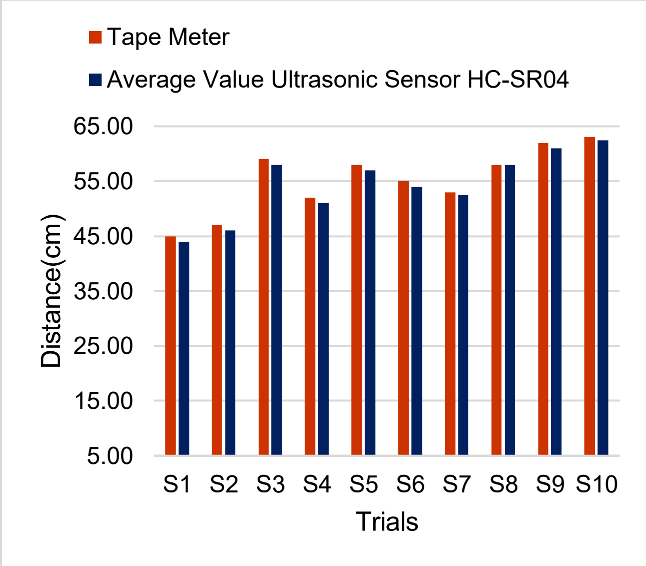

Fig. 4. Accuracy Comparison of the Ultrasonic Sensor HC-SR04 Against Tape Meter.

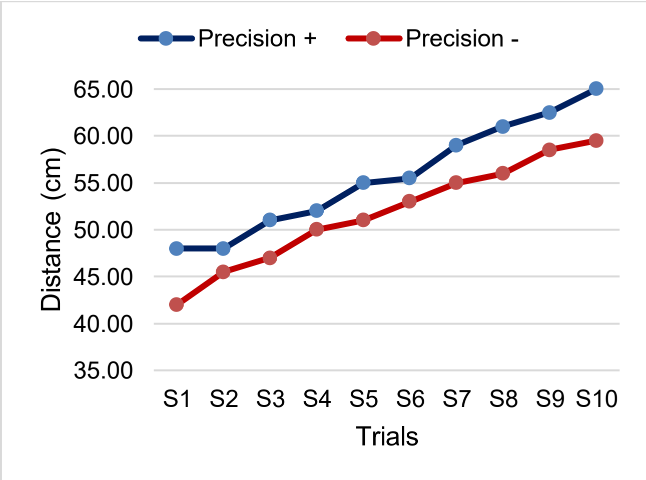

Fig. 5. Precision Analysis of the Ultrasonic Sensor HC-SR04 Measurements.

Fig. 6 and Fig. 7 present the evaluation results of the load cell sensor, in which weights ranging from 0.5 to 5 kg were measured five times each [23]. The average error was 0.98%, and repeated testing demonstrated minimal deviation, confirming both accuracy and consistency. Owing to its mechanical stability, the load cell is also less sensitive to environmental noise compared to the ultrasonic sensor. Minor discrepancies between system and manual measurements may arise due to subject movement, sensor alignment tolerance, or variations in supine posture. For instance, slight head tilts or leg motions can influence height readings, while uneven weight distribution may affect scale accuracy.

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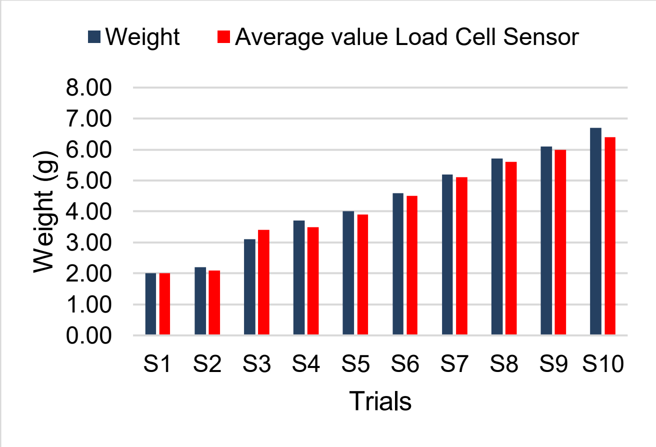

Fig. 6. Accuracy Comparison of the Full Bridge Load Cell Sensor Against Analog Scale.

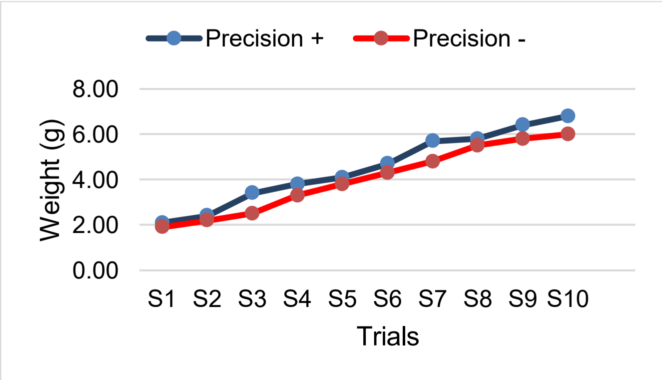

Fig. 7. Precision Analysis of the Full Bridge Load Cell Sensor Measurements.

B. System Implementation on Children

The complete system was implemented in a field trial involving 10 children (five boys and five girls) aged between 8 and 22 months. These participants were selected from both rural and peri-urban areas in the Baitussalam District, Aceh Province, Indonesia. This small but diverse group was intended to capture a range of sociodemographic backgrounds, including varying household income levels and access to healthcare services. Children were measured while lying on a foam padded platform to minimize movement, and gender input was registered via a push-button interface (green for boys, yellow for girls), which was connected to the microcontroller for subsequent Z-score computation based on WHO growth standards. Results were displayed on a 20x4 LCD and printed with timestamps using a thermal printer (Fig. 8).

Table 2 summarizes the comparison between prototype and manual measurements. The mean error is 1.26% for body length and 0.98% for weight, both values are within clinically acceptable limits (<2%), supporting use in early screening and field conditions. The observed margin of error (length: 1.26%, weight: 0.98%) is within clinically acceptable thresholds for pediatric anthropometry. According to WHO guidelines, deviations below 0.5 cm and 0.1 kg are not expected to significantly alter nutritional classification results. The observed mean error rates (1.41% for length and 0.99% for weight) remain within the generally accepted clinical threshold of <2% for anthropometric measurements in field-based pediatric applications. According to WHO standards, absolute deviations below 0.5 cm for length and 0.1 kg for weight are unlikely to affect the nutritional classification outcome based on Z-scores. The system demonstrated a mean absolute error of 0.47 cm (SD = 0.21 cm, 95% CI: 0.35–0.59 cm) for length and 0.082 kg (SD = 0.04 kg, 95% CI:

Table 2. Comparative Measurement Data: Prototype vs. Manual Anthropometry

No.	Child ID	Body Length (cm)		Weight (Kg)		Error (%)	
		Manual	Prototype	Manual	Prototype	Length	Weight
1.	S01	70.00	71.00	7.00	7.08	1.42	1.14
2.	S02	64.00	65.00	6.70	6.66	1.56	0.6
3.	S03	75.00	76.00	7.50	7.57	1.33	0.93
4.	S04	65.00	64.00	5.80	5.81	1.53	0.17
5.	S05	74.00	73.00	7.20	7.32	1.35	1.66
6.	S06	83.00	82.00	11.00	11.19	1.20	1.72
7.	S07	73.00	74.00	8.30	8.2	1.36	1.2
8.	S08	77.00	76.00	8.50	8.44	1.29	0.7
9.	S09	68.00	69.00	7.10	7.19	1.47	1.26
10.	S10	67.00	68.00	7.80	7.84	1.49	0.51
Average						**1.26**	**0.98**

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0.06–0.10 kg) for weight. These values indicate that the smart system provides sufficient precision for practical use in early screening and growth monitoring, even under field conditions. Consequently, the error margins observed are clinically acceptable and do not significantly impact classification results, making the system viable for community-level implementation.

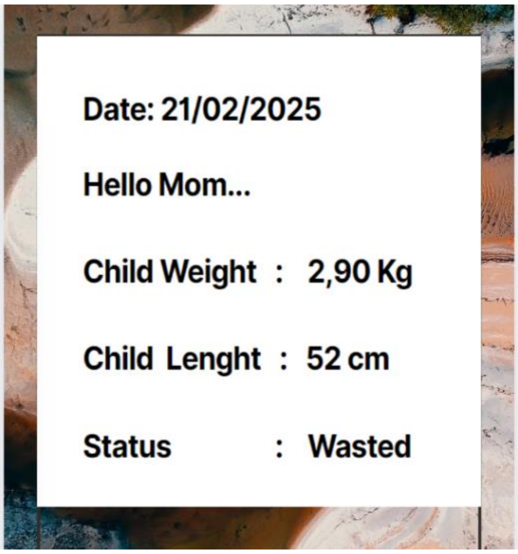

Fig. 8. Thermal printer output for children's nutritional status.

Repeatability was tested by performing triplicate measurements for each subject. The intra-subject coefficient of variation was 0.41% for weight and 0.62% for length. Measurements were also repeated by two different operators, yielding an inter-operator ICC of 0.96, indicating high reproducibility.

Table 3. Summary Statistic of Error Rates (n=10 children)

No.	Weight (kg)	Length (cm)	Z-Score	Nutritional Status
1.	7.08	71	-2.6	Wasted
2.	6.66	65	-1.06	Normal
3.	7.57	76	-2.7	Wasted
4.	5.81	64	-2.38	Wasted
5.	7.32	73	-2.54	Wasted
6.	11.19	82	0.48	Normal
7.	8.2	74	-1.57	Normal
8.	8.44	76	-1.57	Normal
9.	7.19	69	-1.68	Normal
10.	7.84	68	0.22	Normal

C. Nutritional Status Classification Performance

Prior analyses in Table 2 and Table 3Table 3. **Summary Statistic of Error Rates (n=10 children)**

No.	Weight (kg)	Length (cm)	Z-Score	Nutritional Status
1.	7.08	71	-2.6	Wasted
2.	6.66	65	-1.06	Normal
3.	7.57	76	-2.7	Wasted
4.	5.81	64	-2.38	Wasted
5.	7.32	73	-2.54	Wasted
6.	11.19	82	0.48	Normal
7.	8.2	74	-1.57	Normal
8.	8.44	76	-1.57	Normal
9.	7.19	69	-1.68	Normal
10.	7.84	68	0.22	Normal

demonstrated strong agreement between the prototype and manual tools, with error margins for length and weight remaining below 2%, a threshold widely regarded as clinically acceptable for pediatric anthropometry. Moreover, the stable classification output observed in Table 4, despite minor sensor deviations, underscores the robustness of the system in real-world conditions. This supports its application in early childhood growth monitoring and screening programs.

Table 4. Z-score Calculation Results for Child Nutritional Status

Measurement	Mean (%)	Standard Deviation	95% CI Lower	95% CI Upper
Length Error	1.41	0.11	1.33	1.48
Weight Error	0.99	0.50	0.68	1.31

Based on the calculated Z-scores, the system automatically classified each child's nutritional status in accordance with WHO child growth standards [28]. Table 4 presents the classification outcomes, where four out of ten children were categorized as “wasted” (Z-score < -2.0), and six were identified as having normal nutritional status. These results reflect the system’s ability not only to obtain accurate anthropometric measurements, but also to interpret and classify nutritional status reliably. The classification was fully consistent with standard clinical guidelines, suggesting that even small deviations in measurement did not significantly alter the diagnostic outcomes.

Table 5. Summary of Nutritional Status Distribution

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Nutritional Status	Number of Children	Proportional (%)
Normal	6	60.0 %
Wasted	4	40.0 %

Table 6. **Comparative Measurement Data: Prototype vs. Manual Anthropometry**

No.	Ref	Population/ Age Focus	Measurement Performance	WHO Z Classification/ Decision Metrics
1.	This work	< 2 y (infants)	Length err 1.26% (MAE 0.47 cm); Weight err 0.98% (MAE 0.082 kg); ICC = 0.96	Automated WHO Z; stable under small deviations
2.	[22]	Infants (general)	NR vs clinical reference (device capture)	Not implemented (no WHO Z)
3.	[29]	Infants (general)	NR (IoT feasibility; dual sensors)	Not reported (fuzzy, no WHO Z accuracy)
4.	[30]	Children (general)	NR (framework-level)	Not reported (no infant WHO Z validation)
5.	[31]	2–5 y	Weight-only; NR vs standard	Threshold-based (non–WHO Z), non–sex-specific
6.	[32]	Clinical (general)	Measurement reported for 3D scan; no WHO Z	Not applicable (measurement study)
7.	[33]	Maternal (adults)	Manual anthropometry; NR for devices	ML accuracy reported (different task, not infant WHO Z)

Table 5 provides a summarized distribution of the nutritional status classifications generated by the system. Out of the 10 children assessed, 60% were identified as having normal nutritional status, while 40% were categorized as wasted. This proportional analysis reinforces the diagnostic capability of the system, as the results align with expected population trends in at-risk communities. Presenting the classification outcome in aggregate form offers a clearer epidemiological picture, facilitating potential use in public health reporting, early intervention planning, and targeted nutritional support programs.

D. Limitations and Reproducibility

The acceptance criteria for measurement deviation were defined as: Length ≤ 0.5 cm and Weight ≤ 0.1 kg. To evaluate agreement and reliability between the prototype and the reference method, we conducted correlation analysis (Pearson's r), error-based metrics (RMSE and MAE), and Bland–Altman analysis to estimate bias and limits of agreement.

Several limitations should be acknowledged. First, the relatively small sample size (n = 10) restricts statistical generalizability. Second, manual entry of gender and age may introduce input errors, and the absence of formal inter-operator or inter-session repeatability tests limits robustness. Third, inconsistent child postures and motion artifacts, together with environmental variations (e.g., temperature), can affect measurement accuracy—particularly for the ultrasonic sensor. Although heel locks and calming techniques were employed to mitigate movement-related noise, complete elimination was not feasible in real-world settings. These limitations highlight the need for larger, demographically diverse cohorts and controlled repeatability studies under varied conditions.

E. Deployment Potential and Future Work

The developed device demonstrates strong potential for real-world applications due to its low cost, portability, and battery-powered operation, ideal features for use in public health settings such as Integrated Health Posts (Posyandu) and Community Health Centers (Puskesmas). Further development will enhance the system's functionality and user experience through several enhancements. It includes the implementation of automatic gender and age recognition to minimize manual input errors, as well as integration with mobile applications and cloud platforms to facilitate data accessibility and management. Furthermore, the addition of real-time wireless communication capabilities such as Wi-Fi or Bluetooth will enable seamless data transmission. Expansion of the training dataset is also planned to improve the accuracy of the classification model. Finally, efforts will be directed toward developing environmental calibration techniques and a guided child positioning mechanism to reduce measurement variability and improve overall system reliability. These improvements enhance robustness, usability, and impact in public health monitoring. A limitation of this study is the relatively small sample size (n=10), which may restrict the generalizability of the results. Future studies will include larger, more diverse populations to enhance statistical power and better reflect the variability across regions and age groups. The system was also tested under varying

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environmental conditions (20–34°C; 40–85% RH). Sensor readings remained consistent thanks to the embedded temperature compensation algorithm. However, high humidity and child movement can still cause temporary interference, which was mitigated through signal filtering and repeated measurements. For real-world implementation, the device will be piloted in selected Puskesmas centers with healthcare workers trained on its use. Planned upgrades include wireless data sync with national databases and multilingual interfaces. Integration with digital health records and mass-screening campaigns is also being explored for future deployment.

F. Comparative Performance with Similar Studies

Recent device-oriented works highlight the feasibility of low-cost sensing and IoT integration for pediatric anthropometry; however, most do not report end-to-end, WHO Z-score–based classification accuracy in infants under two years or sex-specific modeling. Sujiwa et al. combine ultrasonic and load-cell sensing on Arduino to capture length/weight, but do not implement automated WHO Z-score classification nor decision-level agreement metrics [22]. Fajrian et al. propose an IoT device with dual sensors and fuzzy logic for infant assessment; the emphasis is on system integration, with no quantitative accuracy for WHO category assignment [29]. Mannolkar et al. describe an assistive IoT framework for malnutrition monitoring, without infant-specific validation against clinical references or sex-stratified Z-score outputs [30]. Tsani et al. target overweight detection in children aged 2–5 years using weight-only measurements; this differs from our under-two use case and applies a single-threshold decision rather than multidimensional WHO Z-score categories [31]. Beyond sensing/IoT, Wang et al. demonstrate that digital anthropometry/3D scanning attains accurate measurements in clinical practice, yet no real-time WHO Z-score computation for infants is provided [32]. Kurnianingtyas et al. report machine-learning accuracy for maternal nutritional classification using manually collected anthropometry—a different population and data pathway from our sensor-driven infant pipeline [33].

In contrast, this work couples instrumented measurement with automated, sex-specific WHO Z-score classification and reports performance at both the measurement level (mean errors 1.26% length; 0.98% weight; MAE 0.47 cm, 0.082 kg) and the decision level (stable category assignments under small deviations) [34]. Similarities across prior device studies include low-cost sensors and connected platforms [29], [30], [31]. The principal contrasts/contradictions are: (i) absence of automated WHO Z-score classification, (ii) age focus (≥ 2 y vs. < 2 y), (iii) lack of sex-specific modeling, and (iv) missing quantitative agreement with clinical references. These differences explain why systems that only capture measurements or target older cohorts are not directly comparable on classification accuracy, whereas our evaluation is aligned to WHO standards for infants under two years. As summarized in Table 6, related device/IoT studies demonstrate feasibility of low-cost sensing but rarely report decision-level performance for WHO Z-score classification in infants. Sujiwa et al. [22], Fajrian et al. [29], and Mannolkar et al. [30] provide device capture or framework feasibility but do not report WHO category accuracy; Tsani et al. [31] targets children aged 2–5 years using a weight-only threshold (non–WHO Z) and is therefore not directly comparable. Wang et al. [32] report measurement agreement for 3D scanning without real-time WHO Z, while Kurnianingtyas et al. [33] reports ML accuracy in a different population (maternal) with manually entered anthropometry. In contrast, our prototype reports both measurement-level errors (length 1.26%, MAE 0.47 cm; weight 0.98%, MAE 0.082 kg; ICC = 0.96) and decision-level robustness (stable WHO Z categories under small deviations). Similarities across prior works include low-cost sensors and connected platforms; the principal contradictions are the absence of automated WHO Z-score classification, lack of sex-specific modeling, different age focus, and missing quantitative agreement with clinical references.

V. Conclusion

This study aims to develop a portable, automated device for classifying the nutritional status of children under two years of age by digitally measuring body length and weight. The system integrates an HC-SR04 ultrasonic sensor for length measurement and a full-bridge 50 kg load cell sensor for weight, all controlled by an ATmega328P microcontroller. Testing results demonstrate strong performance, with average error rates of 1.26% for body length and 0.98% for body weight. The overall system error is recorded at 0.5%, with a precision level ranging from ±0.08 to ±0.4**.** These results confirm the reliability and accuracy of the system for anthropometric assessments in non-clinical settings. For future work, the system can be enhanced by integrating automatic gender and age detection, wireless data transmission (with Bluetooth or Wi-Fi), and cloud-based data logging for longitudinal monitoring. These improvements would further optimize usability in remote areas and support broader adoption in public health programs.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request via email (yunidar@usk.ac.id).

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Author Contribution

Yunidar Yunidar conceptualized and designed the study, set the validation criteria/protocol, interpreted findings, supervised the work, and served as corresponding author. Melinda Melinda designed the hardware–firmware integration, implemented signal conditioning and calibration, and oversaw device validation. Rina Ridara built the prototype, led field data collection, and performed statistical analyses (Pearson, MAE/RMSE, Bland–Altman) and figure/table preparation. Nurlida Basir provided methodological guidance, literature review, and critical manuscript revisions. All authors approved the final manuscript and accept responsibility for its integrity and accuracy.

Declarations

Ethical Approval

No formal ethics committee approval was obtained. Measurements were non-invasive and limited to comparing the prototype with standard instruments during routine service at Puskesmas Baitussalam; all data were anonymized with no personal identifiers.

Consent for Publication Participants.

Consent for publication was given by all participants.

Competing Interests

The authors declare no competing interests.

REFERENCES

[1] H. Andriani, E. Friska, M. Arsyi, A. E. Sutrisno, A. Waits, and N. D. Rahmawati, “A multilevel analysis of the triple burden of malnutrition in Indonesia: trends and determinants from repeated cross-sectional surveys,” *BMC Public Health*, vol. 23, no. 1, Dec. 2023, doi: 10.1186/s12889-023-16728-y.

[2] N. I. L. Gusnedi Gusnedi, Ricvan Dana Nindrea, Idral Purnakarya, Hermita Bus Umar, Andrafikar, Syafrawati, Asrawati, Andi Susilowati, Novianti, Masrul, “Risk factors associated with childhood stunting in Indonesia: A systematic review and meta-analysis,” *Asia Pac J Clin Nutr*, vol. 32, no. 2, pp. 184– 195, 2023, doi: 10.6133/apjcn.202306_32(2).0001.

[3] Y. Ayukarningsih, H. Sa’adah, M. A. Kusmayadi, and M. Z. Ramadhan, “Stunting: Early Detection with Anthropometric Measurements and Management (Stunting: Deteksi Dini Dengan Pengukuran Antropometri Dan Penatalaksanaannya),” *Journal of Health and Dental Sciences*, vol. 04, no. 01, pp. 91–104, 2024, doi: 10.54052/jhds.Article.

[4] P. Piqueras, A. Ballester, J. V Durá-gil, and S. Martinez-hervas, “Anthropometric Indicators as a Tool for Diagnosis of Obesity and Other Health Risk Factors: A Literature Review,” vol. 12, no. July, 2021, doi: 10.3389/fpsyg.2021.631179.

[5] N. E. Soboksa, S. R. Gari, A. B. Hailu, and B. M. Alemu, “Childhood Malnutrition and the Association with Diarrhea, Water supply, Sanitation, and Hygiene Practices in Kersa and Omo Nada Districts of Jimma Zone, Ethiopia,” vol. 15, p. 1178630221999635, 2021, doi: 10.1177/1178630221999635.

[6] Y. F. Djoumessi, “The impact of malnutrition on infant mortality and life expectancy in Africa,” *Nutrition*, vol. 103, p. 111760, 2022, doi: 10.1016/j.nut.2022.111760.

[7] N. Gaffan, A. Kpozehouen, C. Degbey, and Y. G. Ahanhanzo, “Effects of the level of household access to water, sanitation and hygiene on the nutritional status of children under five, Benin,” *BMC Nutr*, vol. 9, no. 1, p. 95, 2023, doi: 10.1186/s40795-023-00751-8.

[8] J. Lin and X. L. Feng, “Exploring the impact of water, sanitation and hygiene (WASH), early adequate feeding and access to health care on urban – rural disparities of child malnutrition in China,” *Matern Child Nutr*, vol. 19, no. 4, p. e13542, 2023, doi: 10.1111/mcn.13542.

[9] R. Saheed *et al.*, “Impact of Drinking Water Source and Sanitation Facility on Malnutrition Prevalence in Children under Three: A Gender-Disaggregated Analysis Using PDHS 2017–18,” *Children*, vol. 9, no. 11, p. 1674, 2022, doi: 10.3390/children9111674.

[10] E. S. Chade *et al.*, “The Influence of Nutritional Status on Brain Development: Benefits of Exclusive Breastfeeding,” *Pediatr Rep*, vol. 16, no. 3, pp. 724–735, 2024, doi: 10.3390/pediatric16030061.

[11] A. Kansu and M. Ays, “The significance of MUAC z-scores in diagnosing pediatric with special emphasis on neurologically discable children,” *Front Pediatr*, vol. 11, p. 1081139, 2023, doi: 10.3389/fped.2023.1081139.

[12] A. Ahmed, J. Hoddinott, and S. Roy, “Food Transfers, Cash Transfers, Behavior Change Communication and Child Nutrition: Evidence from Bangladesh,” *World Bank Econ Rev*, vol. 39, no. 2, pp. 439–472, 2025, doi: 10.1093/wber/lhae023.

[13] D. B. Abitew, A. W. Yalew, A. M. Bezabih, and A. N. Bazzano, “Comparison of Mid-Upper-Arm Circumference and Weight-For-Height Z -Score in Identifying Severe Acute Malnutrition among Children Aged 6 – 59 Months in South Gondar Zone , Ethiopia,” *J Nutr Metab*, vol. 2021, pp. 1–10, 2021, doi: 10.1155/2021/8830494.

[14] N. Kelly, J. Shepherd, and S. B. Heymsfield, “Digital Anthropometric Evaluation of Young Children:

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DOI: https://doi.org/10.35882/ijeeemi.v6i3.407

Comparison to Results Acquired with Conventional Anthropometry," *Eur J Clin Nutr*, vol. 76, no. 2, pp. 251–260, 2022, doi: 10.1038/s41430-021-00938-x.Digital.

[15] C. Li, J. Wang, S. Wang, and Y. Zhang, "A review of IoT applications in healthcare," *Neurocomputing*, vol. 565, p. 127017, 2024, doi: 10.1016/j.neucom.2023.127017.

[16] P. T. N. An, Pham Duc, "Controlling Board Prototype for a Smart Weighting Device Using Ultrasonics and Loadcell Sensors," *Proceedings of the International Conference on Advanced Mechanical Engineering, Automation, and Sustainable Development 2021 (AMAS2021)*, pp. 872–876, 2022, doi: 10.1007/978-3-030-99666-6_127.

[17] A. H. Angguh Gubawa, Tomy Abuzairi, "Electronic system design for clinical applications of stunting case," in AIP Conference Proceedings, AIP Publishing. Accessed: Jun. 17, 2025. [Online]. Available: https://pubs.aip.org/aip/acp/article-abstract/2344/1/050004/748853/Electronic-system-design-for-clinical-applications

[18] B. M. Carvalho, "Baby Date: a mobile application for teaching nursing care to newborns in primary care," *Rev Lat Am Enfermagem*, vol. 32, p. e4164, 2024, doi: 10.1590/1518-8345.7022.4164.

[19] K. Widatama and P. Wahyu Setyaningsih, "The Using of Information Systems to Calculate Z-Score and to Determination of Stunting Categories In Toddlers," *bit-Tech*, vol. 6, no. 2, pp. 152–160, 2023, doi: 10.32877/bt.v6i2.1013.

[20] A. Lan, "A microcontroller-based system for body mass index," *Journal of Innovation Science and Technology*, vol. 2, no. 1, 2025.

[21] P. E. Mensah, "Design and Implementation of a Load Sensor in a Bearing Adapter Assembly for Freight Railcar Applications," *Master's Thesis, The University of Texas Rio Grande Valley*, 2023.

[22] A. Sujiwa, S. H. Prajitno, and B. T. Marta, "Baby Weight and Length Based on Arduino Uno with Combination of Ultrasonic Sensor Hc-Sr04 and Weight Sensor (Load Cell)," *Journal of Applied Electrical & Science Technology*, vol. 6, no. 1, pp. 7–13, 2024, doi: 10.36456/best.vol6.no1.8822.

[23] C. L. Mills, "The Design and Implementation of a LowCost High-Precision 3D-Printed Translation Stage Using an Optimized PID Controller for Optical Applications," The Pennsylvania State University, 2022.

[24] T. Ewetumo, K. D. Adedayo, Y. B. Lawal, A. T. Edun, and J. E. Orokhe, "Development of an Automatic Body Mass Index Measurement Machine," *FUOYE Journal of Engineering and Technology*, vol. 4, no. 2, 2020, doi: 10.46792/fuoyejet.v4i2.373.

[25] Y. Nurwati, Y. Nurwati, S. A. Marliyanti, B. I. Santoso, and D. Anggraini, "Effects of Maternal Anthropometry on Infant Anthropometry: A Cross-sectional Study at Public Hospital X in Ternate, Indonesia," *Jurnal Kesehatan Masyarakat Nasional*, vol. 19, no. 1, pp. 59–66, 2024, doi: 10.21109/kesmas.v19i1.7336.

[26] S. A. Thurstans, "Sex Differences in Risk and Outcomes from Severe Malnutrition: Implications for Management," *PhD Thesis, London School of Hygiene & Tropical Medicine*, 2024. doi: https://doi.org/10.17037/PUBS.04672595.

[27] N. T. Simorangkir, ""Optimization of a Decision Support System for Monitoring Growth and Development Using the Z-Score Method at Cempaka Health Post," *Proceedings of the Multidisciplinary Research Community*, vol. 1, no. 1, pp. 176–182, 2024.

[28] A. M. El Shafie *et al.*, "Development of LMS and Z Score Growth References for Egyptian Children from Birth Up to 5 Years," *Front Pediatr*, vol. 8, no. January, pp. 1–15, 2021, doi: 10.3389/fped.2020.598499.

[29] A. H. Fajrian, R. R. Nurmalasari, L. Kamelia, and P. D. Fitriani, "ANTIS: Automatic and Anthropometric Measurement and Weight IoT-Monitoring for Enhanced Infant Nutrition Assessment Using Dual Sensor and Fuzzy Logic," in *2024 10th International Conference on Wireless and Telematics (ICWT)*, 2024, pp. 1–6. doi: 10.1109/ICWT62080.2024.10674673.

[30] S. Mannolkar, S. M. George, M. R, N. P, and D. P. Bharathi, "Assistive System for Monitoring Malnutrition in Children," in *2025 10th International Conference on Signal Processing and Communication (ICSC)*, 2025, pp. 761–766. doi: 10.1109/ICSC64553.2025.10968423.

[31] N. F. Tsani, D. Marfuah, I. Prasojo, and S. Aprilia, "Detection of overweight based on body weight in children aged 2-5 years based on Arduino Uno," *AIP Conf Proc*, vol. 3142, no. 1, p. 020120, Mar. 2025, doi: 10.1063/5.0262367.

[32] M. Wang, Y. Song, X. Zhao, Y. Wang, and M. Zhang, "Utilizing Anthropometric Measurements and 3D Scanning for Health Assessment in Clinical Practice," 2024, *Ubiquity Press*. doi: 10.5334/paah.379.

[33] D. Kurnianingtyas, N. Daud, A. W. Widodo, and T. Herawan, "Performance Evaluation of Different Classification Algorithms Applied for Identifying Maternal Nutritional Status by Anthropometric Measurements," *International Journal of Integrated Engineering*, vol. 17, no. 1, pp. 463–475, 2025, doi: 10.30880/ijie.2025.17.01.037.

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DOI: https://doi.org/10.35882/ijeeemi.v6i3.407

[34] E. Borghi and H. S. Sachdev, "Should a single growth standard be used to judge the nutritional status of children under age 5 years globally: Yes," *Am J Clin Nutr*, vol. 120, no. 4, pp. 764–768, 2024, doi: https://doi.org/10.1016/j.ajcnut.2024.04.019.

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