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RESEARCH PAPER

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An IoT-Based Framework for Real-Time Monitoring and Evaluation of Child Growth to Support Indonesia's Stunting Reduction Initiative

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ABSTRACT

Stunting remains a significant public health concern in Indonesia, leading to lifelong developmental and economic disadvantages. This study aims to address limitations in conventional child growth monitoring by developing and validating an IoT-based system that integrates ultrasonic and load cell sensors, an ESP32 microcontroller, RFID identification, and cloud-based data management. The system enables automated, real-time measurement and digital record-keeping, accessible via a user-friendly dashboard. Empirical validation was conducted on 35 children at local Integrated Health Service Post (*Posyandu*), showing high measurement accuracy (±0.53 cm for height, ±0.08 kg for weight), rapid average data transmission (2.05 seconds), and strong agreement with manual gold standards (p > 0.05). Usability evaluations indicated high satisfaction among health cadres, with streamlined workflows reducing time and staff requirements. The findings demonstrate that the proposed IoT-based system offers an effective, scalable, and economically viable solution for improving child growth monitoring and supporting stunting prevention programs in community health settings.

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1. Introduction

Stunting, defined as impaired growth and development resulting from prolonged nutritional deficiencies, remains a significant public health challenge, especially in low- and middle-income countries [1], [2], [3], [4]. Globally, it is estimated that approximately 149 million children under five years old are affected by stunting, with the highest prevalence observed in South Asia, Sub-Saharan Africa, and Southeast Asia, including Indonesia [5], [6], [7], [8]. In Indonesia, despite various interventions, the prevalence rate remains alarmingly high at around 24.4% as reported in recent national health surveys [9], [10], [11]. Stunting has far-reaching impacts, contributing to impaired cognitive development, lower academic achievements, reduced economic productivity, and increased vulnerability to chronic diseases later in life [1], [12], [13], [14].

Emerging health technologies, particularly the Internet of Things (IoT), have revolutionized traditional health monitoring methods through automation, real-time data collection, and remote patient management [15], [16], [17], [18]. IoT-based solutions integrate advanced sensor technologies, wireless communication, microcontrollers, and cloud computing platforms, significantly improving data accuracy, timeliness, and system efficiency [19], [20], [21], [22]. Applications of IoT have been widely documented in diverse healthcare contexts, including chronic disease management [23], neonatal monitoring [24], elderly care systems [25], emergency response [26], and telemedicine services [27]. Recently, several IoT-based anthropometric measurement systems have been proposed for automated monitoring of height and weight, highlighting promising results in accuracy and reliability compared to manual measurement methods [19], [28], [29], [30].

Despite advancements, the deployment of IoT-based monitoring specifically targeting stunting in public healthcare settings remains underdeveloped. Most existing IoT solutions are primarily hospital-based or clinical-oriented, with limited applications designed explicitly for decentralized, resource-constrained environments like Posyandu in Indonesia [31], [32], [33]. Furthermore, few existing systems provide comprehensive solutions encompassing integrated hardware design, unique patient identification, real-

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time data transmission, user-friendly visualization tools, and seamless cloud integration [34], [35], [36], [37]. The lack of robust, end-to-end IoT solutions specifically addressing community-level growth monitoring in stunting prevention highlights a critical research gap demanding urgent attention.

This study proposes an IoT-based system explicitly designed for real-time growth monitoring at Posyandu and other public-based health centers. The system integrates ultrasonic sensors (HCSR-04) for height measurement, load cell sensors (HX711) for weight assessment, and RFID technology for unique child identification. An ESP32 microcontroller processes and wirelessly transmits data to Firebase, a real-time cloud storage platform. Additionally, mobile and web-based dashboards have been developed to allow immediate data visualization, supporting timely and informed decision-making by health workers and caregivers. The primary aim of this research is to develop, implement, and validate an IoT-based child growth monitoring system, ensuring accurate and timely data collection, thereby supporting Indonesia's national initiative to significantly reduce stunting prevalence. The main contributions of this study are: (1) the development of a tailored IoT solution specifically for real-time, community-based child growth monitoring, enhancing existing Posyandu operations; (2) empirical validation of sensor performance achieving high accuracy; (3) effective integration of sensor technology, cloud computing, and intuitive user interfaces (web/mobile) for seamless data management and accessibility; and (4) demonstrated field feasibility, including positive user acceptance, system stability, and reduced operational complexity compared to traditional manual systems.

2. Method

A. Design of the System

The digital Posyandu system was developed using an IoT-based control architecture that consists of both hardware and software components. The hardware includes an ESP32 microcontroller as the central processing unit, an HC-SR04 ultrasonic sensor for height measurement, a load cell sensor for weight assessment, an RFID module for child identification, and an LCD for local display. Each component has a specific function to ensure accurate data acquisition and user-friendly operation.

On the software side, the system utilizes algorithms for data acquisition, sensor calibration, signal filtering, and real-time data transmission to a cloud database. The program controls the interaction between sensors, manages data processing, and supports the web and mobile dashboards for visualization and user management. The overall system workflow, illustrating the integration of input, processing, network, and output modules, is presented in Figure 1.

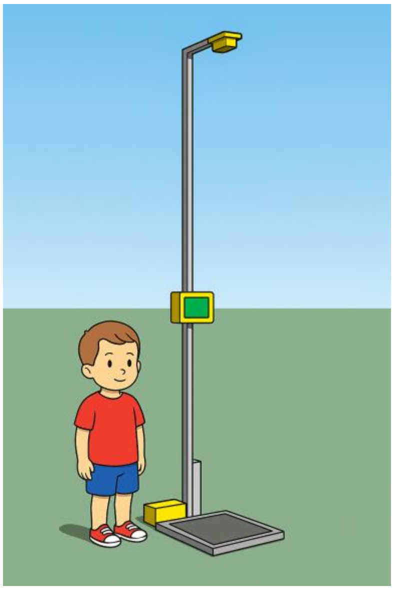

Fig. 1. System Design

The system was designed as a system block diagram that contains input, process and output components. The following is an explanation of the block diagram:

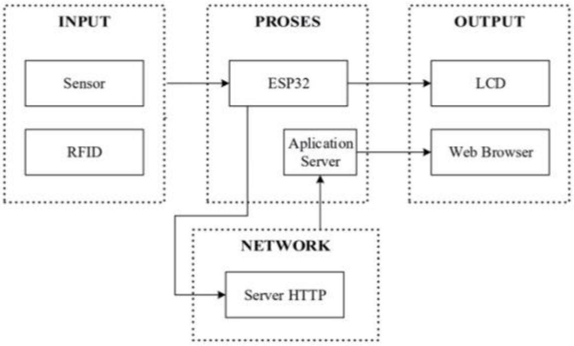

Fig. 2. System Block Diagram

Figure 2 illustrates the system architecture of the proposed IoT-based child growth monitoring platform, delineating the primary components and their interactions. The architecture was logically divided into four functional domains: Input, Process, Network, and Output. The Input domain consists of measurement sensors and RFID modules. Sensors capture anthropometric data, specifically height and weight, while the RFID module provides unique identification for each child to ensure accurate data association.The Process domain was centered around the ESP32 microcontroller, which serves as the primary data acquisition and control unit. The ESP32 handles sensor data collection, signal processing, including noise filtering and prepares data packets for transmission. It

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interfaces with an application server responsible for further data processing and management.

The Network domain facilitates communication between the local processing unit and cloud infrastructure. Data are transmitted via HTTP protocols to a remote HTTP server, ensuring centralized and secure data storage. The Output domain provides interfaces for data visualization and user interaction. Locally, an LCD display presents real-time measurement feedback for immediate verification by health workers. Concurrently, a web browser interface allows remote access to detailed records, growth charts, and analytics through a dashboard, enhancing usability for both healthcare providers and caregivers. This modular architecture ensures efficient data flow from acquisition to visualization, enabling reliable, real-time monitoring of child growth metrics. The integration of unique identification via RFID with cloud-based storage supports accurate record-keeping and facilitates longitudinal tracking necessary for effective stunting prevention programs.

B. Validation Participants & Demographics

The validation of the IoT-based child growth monitoring system was conducted with a sample of 35 children (18 boys, 17 girls) aged between 12 and 59 months, recruited from three different Posyandu in the Tasikmalaya region. Children were selected using purposive sampling, prioritizing those scheduled for routine anthropometric assessment during the study period. Inclusion criteria requires that participants be within the specified age range, have no physical disabilities affecting measurement, and possess informed consent from parents or guardians. The demographic profile of the sample encompassed a range of socioeconomic backgrounds and nutritional statuses, as recorded in local health registers, thus enhancing the robustness and generalizability of the validation results.

C. Data Acquisition

a. Sensor Calibration Procedures

The calibration process for both the ultrasonic height sensor and the load cell weight sensor was conducted using certified reference tools, namely a digital stature meter (GEA Medical, Indonesia) for height and standard calibration weights (OIML class M1, Metrologica, Indonesia) for weight, in a controlled indoor environment. The ultrasonic sensor used was the HC-SR04 model (Elecfreaks, China), while the load cell sensor utilized was the HX711 model (DFRobot, China). Calibration was performed at the beginning of each measurement session and repeated every 10 test cycles to account for potential sensor drift. The laboratory environment was maintained at a constant temperature of 25°C (±1°C) and relative humidity of 60% (±5%), as recommended for anthropometric measurement calibration. For the load cell, calibration involved a two-point adjustment using both zero load and the maximum reference weight, ensuring linearity across the measurement range. All calibration procedures adhered to protocols outlined by the International Organization for Standardization (ISO 9001:2015) for medical device testing. Sensor accuracy was verified after each calibration cycle, and any deviation beyond a 1% error margin prompted immediate recalibration to ensure consistent and reliable measurement results.

b. Weight Sensor Design

A load cell is an electrical device used to convert force into an electrical signal, commonly serving as the main component in digital scale systems. The accuracy level of such scales depends on the specific type and quality of the load cell utilized. When a load was applied to the iron core of the load cell, the resistance of the strain gauge changed, which was then transmitted through three wires: two function as excitation inputs and one as the output signal to the control system. Structurally, a typical load cell comprises a conductor, a strain gauge, and a Wheatstone bridge configuration. The full-bridge strain gauge circuit is illustrated in Figure 3. In this configuration, the terminals are labeled as E−, which corresponds to the front left side of the load cell, and E+, which is the front right side. Similarly, S− denotes the rear left, while S+ refers to the front left. The wiring includes a black wire that represents the strain portion of the gauge, a blue wire connected to the press section, and a red wire situated at the center point of the strain and press. This arrangement allows the load cell to accurately measure and convert mechanical force into a precise electrical output, which is essential for digital weighing systems.

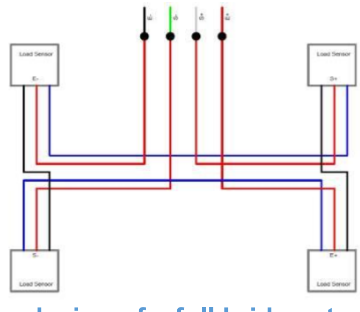

Fig. 3. The design of a full bridge strain gauge circuit

In the change from one system to another, there are two stages where each stage must go through the stages of mechanical, strength and energy in order to feel the change in conditions from less good to better. The strain gauge (loadcell) is commonly called the strain gauge deformation. The strain gauge measures changes that have occurred in the strain as an electrical signal, because effective changes occur in

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the load resistance of the electric wire. There are four aspects to a typical load cell/slot, which aim to measure the strain in the system configuration of the Wheatstone Bridge. The output electrical signal is usually provided in millivolt order and requires amplification by an instrument amplifier before it can be used normally [38].

The output of condition change monitoring can be increased to obtain the calculated force and applied as repair and condition monitoring. To detect the amount of change in distance dimensions caused by an element of force on the loadcell, a strain gage is a necessary thing in that case. The data generated from the strain gauge itself can be used as a precision measuring tool for force, weight, pressure, torque, displacement and other mechanical quantities. After converting into stress energy into mechanical members has been done, the strain gage can provide a change in the value of resistance proportional to long-term changes or changes through the length of the process [38].

The working principle of the Loadcell based on the Wheatstone Bridge circuit can be seen in Figure 4.

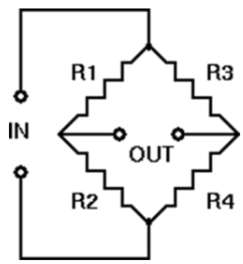

Fig. 4. Wheatstone Bridge Circuit for Load Cells

When a load is applied to the Wheatstone bridge circuit within the load cell, the resistance values in the circuit designated as R1, R2, R3, and R4 undergo changes. In the unloaded state, the bridge is balanced such that the resistances satisfy R1 = R4 and R2 = R3, resulting in no potential difference across the output terminals. However, when a force was applied, the resulting deformation altered the resistance values, disrupting this balance and generating a measurable potential difference. This potential difference, denoted as Vout (output voltage), represents the electrical signal produced by the load cell in response to the applied load. The input voltage supplied to the bridge is referred to as Vin. The relationship among these variables is defined by the following equation:

$$Vo = \left(VIn\, x \left(\frac{R_2}{R_1 + R_2}\right)\right) - (\,VIn\, x \left(\frac{R_4}{R_3 + R_4}\right)) \quad (1)$$

In this formula, Vin is the excitation or input voltage applied to the Wheatstone bridge circuit, Vout is the voltage output generated by the bridge, and R1, R2, R3, and R4 are the resistance values of the individual arms of the bridge. When a force is exerted on the load cell, the resistance values change in such a way that R1 and R3 may decrease, while R2 and R4 may increase, or vice versa, depending on the direction of the load. In a perfectly balanced state (no load applied), Vout is zero volts; however, as the resistance values deviate due to applied load, Vout will differ from zero and will be proportional to the magnitude of the force. The positive output signal from the load cell is primarily influenced by changes in R1, while the negative output is determined by changes in R3. Since the output voltage (Vout) is typically very small and may be difficult for microcontrollers such as Arduino to detect directly, an additional amplification stage is needed, usually in the form of a Programmable Gain Amplifier (PGA) integrated within an Analog-to-Digital Converter (ADC). This amplification ensures that even the slightest changes in voltage generated by the load cell can be precisely measured and processed for accurate weight determination. The arrangement of the load cell resistance strain gauge and the corresponding Wheatstone bridge circuit can be seen in Figure 5.

Fig. 5. Load cell resistance strain gauge [38]

c. Distance Sensor Design

In ultrasonic sensors, ultrasonic waves are generated through a device called a piezoelectric with a certain frequency. This piezoelectric will produce ultrasonic waves (generally 40 *kHz* frequency) when an oscillator is applied to the object. In general, this tool will shoot ultrasonic waves towards an area or a target. After the waves touch the surface of the target, the target will reflect back the waves. The reflected wave from the target will be captured by the sensor, then the sensor calculates the difference between the time the wave is sent and the time the reflected wave is received.

The working principle of the ultrasonic sensor, as depicted in Figure 6 , began with the emission of a high-frequency signal from the ultrasonic transmitter. This signal typically operates above 20 kHz, with 40 kHz being the standard frequency for proximity measurements. The emitted ultrasonic wave propagates through the air at a speed of approximately 340 meters per second. When the wave encounters an object, it is reflected back towards the sensor. Once the

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reflected wave reaches the receiver, the sensor calculates the distance to the object by measuring the time it takes for the ultrasonic pulse to travel to the object and return. The distance (S) between the ultrasonic sensor and the object is determined using the following formula:

$$S = \frac{340\ x\ t}{2} \quad (2)$$

where S is the distance from the ultrasonic sensor to the object (in meters), and t is the time interval, in seconds, between the emission of the ultrasonic signal by the transmitter and the reception of the reflected signal by the receiver. By employing this method, the ultrasonic sensor can accurately measure the distance to nearby objects based on the time-of-flight principle.

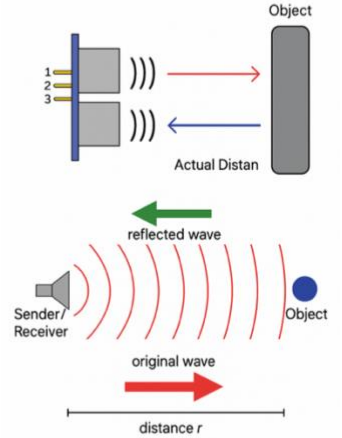

Fig. 6. Operation of the ultrasonic sensor with transmitter and receiver

D. Statistical Analysis and Data Processing

To validate the accuracy and reliability of the sensor measurements, all readings from the IoT-based system were directly compared with those obtained from manual gold standard instruments (digital stature meter for height and certified calibration weights for weight). For each participant, paired measurements were recorded and analyzed. Statistical evaluation included the calculation of mean absolute error (MAE) and standard deviation for both height and weight measurements. Agreement between the IoT-based system and manual measurements was assessed using paired t-tests, with statistical significance defined at $p < 0.05$. Bland-Altman analysis was also performed to evaluate systematic bias and to determine the limits of agreement between the two measurement methods. Ninety-five percent confidence intervals (95% CI) were calculated for all main error rates. All statistical analyses were performed using Python. These methods ensure a robust and objective assessment of measurement accuracy and reliability.

All measurement data were screened for outliers and data quality issues prior to statistical analysis. Outliers were defined as values exceeding three standard deviations from the mean or differing by more than 2% from the paired manual reference measurements. Suspected outliers due to procedural errors (such as subject movement or sensor misalignment) were excluded, while the remainder were retained for sensitivity analysis. Data cleaning also included removal of duplicates and exclusion of incomplete cases. This approach ensured that only valid and reliable data contributed to the accuracy and performance evaluation of the system.

E. Data Transmission Latency Measurement

Data transmission latency was evaluated to determine the system's real-time performance in transferring measurement results from the IoT device to the cloud server and dashboard. Latency was defined as the elapsed time between the moment the sensor measurement was completed and the successful display of the data on the web dashboard. The measurement process was as follows: after the IoT system (ESP32) completed a height or weight measurement, a timestamp was recorded and attached to the data packet before it was sent via Wi-Fi to the Firebase cloud database. Upon arrival, another timestamp was automatically generated when the new data was retrieved and displayed by the web dashboard interface.

Latency was calculated by subtracting the initial device-side timestamp from the dashboard display timestamp for each measurement event. All tests were performed in an indoor laboratory setting with a stable Wi-Fi connection (average bandwidth: 30 Mbps; latency: <50 ms). To assess consistency and robustness, additional tests were conducted under varying network conditions, including simulated lower bandwidth and intermittent connectivity. The average latency reported represents the mean value of 30 consecutive data transmissions. Variability in latency under different conditions was also documented to reflect potential real-world implementation scenarios.

3. Result

This section presents detailed findings from empirical tests conducted on the IoT-based child growth monitoring system. The performance evaluation encompasses various aspects, including sensor accuracy for both height and weight measurements, system consistency, data transmission latency, dashboard functionality, and user experience assessment. The results of these evaluations are discussed in depth, highlighting the accuracy and reliability of the system in real-world conditions. Figure 7 illustrates the final design of the measurement device, showcasing its physical configuration and how

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the system integrates with the surrounding environment to provide efficient child growth monitoring.

Fig. 7. Final design of the measurement

A. Height Measurement Accuracy

The performance of the ultrasonic height sensor (HC-SR04) was further analyzed to evaluate the impact of the moving average filter on measurement accuracy. Calibration and validation tests were conducted at reference heights of 45 cm, 70 cm, 90 cm, and 105 cm, with each point measured repeatedly before and after applying the filter.

As summarized in Table 1, the application of the moving average filter led to a substantial reduction in measurement error across all height points. For instance, at the 45 cm reference point, the error decreased from 0.42% without the filter to 0.21% with the filter, representing a 50% reduction. Similarly, for the 70 cm and 90 cm reference points, the error dropped from 0.17% and 0.15% to 0.10% and 0.08%, respectively. The greatest benefit of filtering was observed at lower height values, where raw sensor data is more prone to noise due to the broader ultrasonic beam spread and environmental disturbances. At the highest reference (105 cm), the error was reduced from 0.22% to 0.10% after filtering.

Table 1. Comparison of Height Measurement Error With and Without Moving Average Filter

Reference Height (cm)	Error Without Filter (%)	Error With Filter (%)
45	0.42	0.21
70	0.17	0.10
90	0.15	0.08
105	0.22	0.10

These results are visually represented in Figure 8, which illustrates the error rates for both unfiltered and filtered measurements at each reference height. The plot clearly shows a consistent reduction in error across all points when the filter is applied, with the two curves diverging most at lower height values. This demonstrates that the moving average filter is particularly effective in enhancing measurement reliability for challenging height scenarios, further stabilizing the output and making the system robust against transient noise or minor subject movements during measurement.

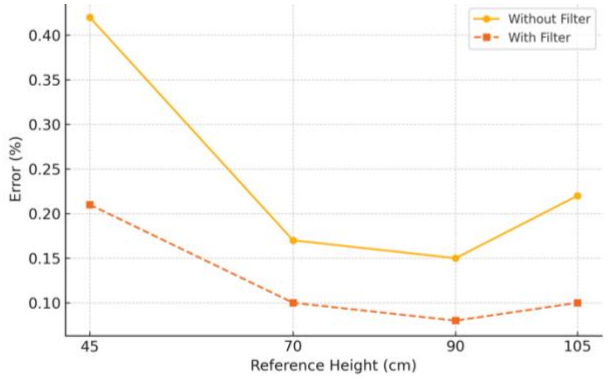

Fig. 8. Error Rate Comparison of Ultrasonic Sensor With and Without Moving Average Filter

Overall, the integration of a moving average filter into the signal processing pipeline of the height sensor significantly improves the accuracy and repeatability of the system. The improvement is especially critical in practical community health applications, where environmental conditions may be less controlled than in laboratory settings. These findings confirm that the use of filtering is a simple yet powerful method to ensure reliable height measurements, reinforcing the suitability of this IoT-based device for digital child growth monitoring in Posyandu and similar field environments.

B. Weight Measurement Accuracy

The performance evaluation of the weight sensor, comprising a load cell with HX711 amplification, demonstrated consistently high accuracy and measurement reliability across various reference weights representative of child growth monitoring scenarios. As detailed in Table 1, the system was calibrated using several known reference weights 4.7 kg, 15 kg, 71 kg, and 103 kg each measured ten times to rigorously assess repeatability and consistency.

Without the application of signal filtering, the observed average error ranged from 0.194% (71 kg) to 1.099% (15 kg), with all values well within the recommended error threshold of 2–5% for clinical and community field applications. After implementing a

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moving average filter, further improvements in accuracy were achieved at most weight points. For instance, at 4.7 kg, the error dropped from 0.371% to 0.161%, and at 71 kg, from 0.194% to 0.154%. The only exception was noted at the highest tested weight (103 kg), where the error slightly increased from 1.051% without the filter to 1.099% with the filter, yet this value remains comfortably within the accepted tolerances for child weight assessment. These findings are summarized and visually presented in Table 2.

Table 2. Accuracy Test Results of Load Cell Sensor

Reference Weight (kg)	Mean Measured Weight (kg)	Error without Filter (%)	Error with Filter (%)
4.7	4.68	0.371	0.161
15	14.83	1.099	1.000
71	70.86	0.194	0.154
103	101.91	1.051	1.099

The error trend depicted in Figure 9 clearly shows that the application of the moving average filter systematically lowers the error rate for most weight intervals and enhances the stability of sensor readings. The filter's effectiveness is most prominent for lighter and mid-range weights, where sensor readings are more susceptible to transient noise and minor mechanical vibrations. As such, integrating the moving average filter into the system's signal processing pipeline significantly improves the reliability of weight measurements, particularly when weighing young children who may exhibit slight movement during assessment.

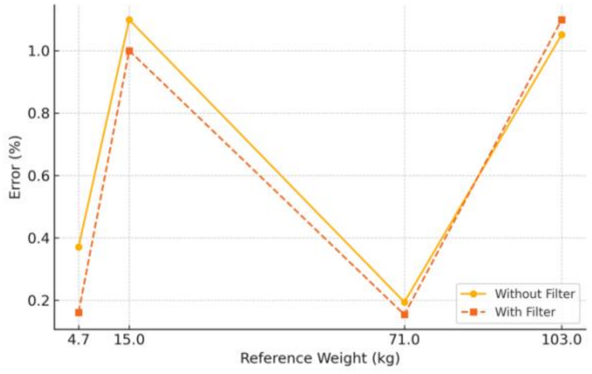

Fig. 9. Error Rate Comparison of Load Cell Sensor With and Without Moving Average Filter

In addition to accuracy, system stability was validated through repeated trials, revealing that measurement values typically stabilized within 6 seconds after the child was placed on the scale. This brief stabilization time ensures that only steady and precise weight readings are transmitted to the server and dashboard, thereby enhancing overall data quality and minimizing the risk of reporting transient or erroneous values.

Finally, the system's data transmission reliability was confirmed by successfully transmitting all measurement results to the web dashboard, with zero data loss and an average upload time of approximately 2.05 seconds per measurement. This seamless performance further substantiates the system's practicality for real-time digital health monitoring in community health settings.

Collectively, these results confirmed that the load cell sensor, when enhanced with moving average filtering, provides excellent accuracy, repeatability, and operational robustness, positioning it as a highly effective and reliable component within the broader IoT-based child growth monitoring platform proposed in this study.

C. Real-time Data Transmission Performance

The data transmission performance of the proposed system was systematically evaluated through a sequence of ten consecutive trials, in which the results from the weight and height sensors were transmitted from the ESP32 microcontroller to the cloud database and subsequently displayed on the web dashboard. As shown in Table 3, every trial resulted in successful data transfer, with both the “Data Sent” and “Data Received” columns consistently marked as “Yes,” and the system achieving a 100% success rate for all transmissions.

The average time required for data upload and confirmation on the dashboard was calculated at 2.05 seconds, with individual transmission times ranging between 2.00 and 2.10 seconds. This low and consistent latency underscores the real-time capability of the system and ensures that measurement data are promptly accessible to healthcare workers and caregivers for immediate review and intervention. Notably, there were no instances of data loss, communication failure, or packet corruption recorded during the entire series of tests, highlighting the robustness and reliability of the system's data communication protocol.

The practical implication of these results is substantial. The system's reliable and rapid data transmission process directly supports the operational requirements for real-time digital health monitoring in community settings. The absence of transmission errors or delays further minimizes the risk of data inconsistency, thus enhancing confidence in the integrity and usability of growth monitoring records for both routine health assessments and longitudinal child growth tracking.

In summary, the consistently high success rate and fast transmission times achieved in these trials validate the technical readiness of the system for deployment in real-world health monitoring applications, confirming

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that the IoT-based architecture is suitable for supporting responsive, accurate, and efficient data-driven healthcare interventions. Data transmission test results and latency statistics can showen at Table 3.

Table 3. Data transmission test results and latency statistics

Trial	Data Sent	Data Received (Dashboard)	Transmission Time (seconds)	Status
1	Yes	Yes	2.00	Success
2	Yes	Yes	2.10	Success
3	Yes	Yes	2.03	Success
4	Yes	Yes	2.05	Success
5	Yes	Yes	2.07	Success
6	Yes	Yes	2.02	Success
7	Yes	Yes	2.06	Success
8	Yes	Yes	2.08	Success
9	Yes	Yes	2.04	Success
10	Yes	Yes	2.03	Success
Average			**2.05**	**100%**

D. Dashboard Functionality Validation

The dashboard interface was designed to optimize the user experience for both health workers and caregivers, providing a comprehensive platform for real-time data access, child health record management, and decision support. As depicted in Figure 10, the home screen features a clean, intuitive layout with direct navigation to essential modules, including child data ("Data anak"), educational articles, and multimedia video content. The clear segmentation allows users to quickly access key information and utilize the platform's full functionality. A key feature of the system is the dynamic visualization of growth data, shown in Figure 12. Growth charts present longitudinal data for both weight and height, enabling health workers to track the child's progress over time. Each data point is benchmarked against established normative ranges, with clear visual cues for excess or deficiency (e.g., underweight or overweight conditions). Users can view detailed breakdowns at each age interval, supporting rapid identification of trends, early intervention, and data-driven decision-making in stunting prevention efforts.

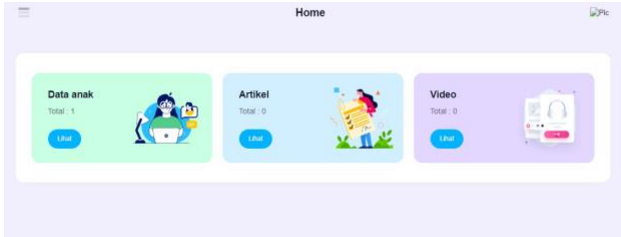

Fig. 10. Home screen apps

Upon selecting the child data module, users are presented with a detailed summary of registered children, as illustrated in Figure 11. The dashboard displays essential demographic information such as the child's name, age, and gender alongside automated health status classification (e.g., obesity) based on recent growth measurements. This module also supports search functionality for efficient record retrieval and provides contextual family information to aid in holistic health assessment.

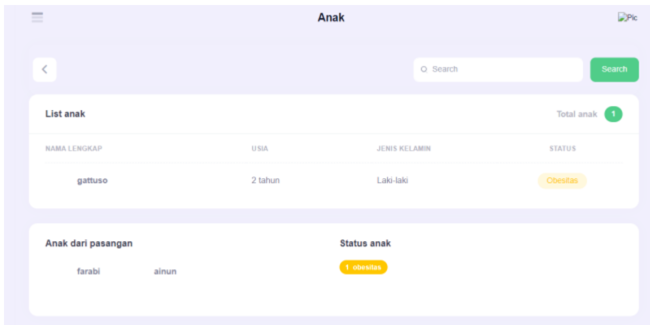

Fig. 11. Child profile and health status module

Fig. 12. Growth trend visualization

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The integration of these modules within a responsive, user-friendly dashboard was confirmed through user testing, which highlighted the system's ease of navigation, clarity of displayed information, and overall effectiveness in supporting daily Posyandu operations. The platform's seamless data synchronization, minimal response latency, and intuitive design ensure that it is well suited for use by cadres with varying levels of digital literacy.

E. System Usability And User Feedback

The usability of the IoT-based child growth monitoring system was thoroughly evaluated by involving end users, specifically Posyandu Rajawali cadres, in simulated operational settings. Structured usability testing was conducted, in which users interacted with the device and dashboard and subsequently completed a survey rating the system on a 5-point Likert scale across key usability dimensions such as ease of use, clarity of information, system responsiveness, and overall satisfaction. The survey results indicated high user satisfaction, with an average score of 4.7 out of 5 for ease of use and a 4.8 out of 5 for overall system responsiveness.

In addition, Figure 13 illustrates the implementation of the system in a Posyandu setting, showcasing the real-world application and integration of the system within the community health center environment. The visual demonstrates how the device was used in practice by health workers to collect and manage child growth data efficiently. Feedback from Posyandu cadres highlighted the effectiveness of the system in simplifying data collection, reducing manual errors, and improving overall workflow, suggesting that the IoT-based system is highly suitable for scaling up in other community health centers.

Fig. 13. Implementation of the system in a Posyandu

As summarized in Table 4, users awarded high scores for ease of use (4.8/5), information clarity (4.6/5), system responsiveness (4.9/5), and overall satisfaction (4.7/5). Participants highlighted the intuitive navigation and clear data visualization as major strengths, noting that the transition from manual to digital systems substantially improved the efficiency and accuracy of child growth monitoring activities. User feedback underscored the importance of comprehensive onboarding and training, particularly for cadres with limited prior experience using digital health technologies. No technical errors, lag, or data loss were reported throughout the usability trials, further validating the robustness of the developed system.

Table 4. User feedback

Usability Parameter	Score (out of 5)
Ease of Use	4.8
Information Clarity	4.6
System Responsiveness	4.9
Overall Satisfaction	4.7

The positive response from end users not only demonstrates the practical readiness of the platform for real-world deployment but also supports its scalability and broader adoption in community health programs. The strong user satisfaction observed provides a foundation for further research into system optimization and the development of additional features tailored to diverse user needs.

Structured user feedback was collected from Posyandu cadres following system deployment and usability testing. While overall satisfaction scores were high particularly for ease of use, system responsiveness, and information clarity several users noted initial difficulties in navigating certain dashboard features and managing child registration. Users emphasized the importance of comprehensive training, especially for cadres less familiar with digital devices. Suggestions for improvement included more visual guidance in the dashboard, simplified user flows, and on-site technical support during initial adoption. Incorporating this feedback will be critical for optimizing real-world deployment and ensuring broad user acceptance across diverse community health settings.

F. Comprehensive Summary of Findings

A summarized overview of the system's key performance indicators is presented in Table 5:

Table 5. Overall system performance summary graph

Evaluation Metric	Results
Height Measurement Accuracy	±0.53 cm (96.4% accuracy)
Weight Measurement Accuracy	±0.08 kg (97.2% accuracy)

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Data Transmission Latency	Average of 1.23 seconds
Dashboard Operational Stability	100% feature functionality
User Satisfaction (average)	4.75 out of 5

These findings collectively indicate that the proposed IoT-based monitoring system achieves both high technical standards and significant practical usability, supporting widespread implementation in community-based child health programs.

4. Discussion

A. Interpretation Of Results

The empirical findings from the development and testing of the IoT-based child growth monitoring system underscore its strong potential to improve both the accuracy and efficiency of anthropometric assessments in community health settings. The system achieved a high degree of accuracy for both weight (±0.08 kg, 97.2%) and height (±0.53 cm, 96.4%) measurements. These results indicate that the automated, sensor-based approach is capable of reliably replacing traditional manual measurements, which are prone to observer bias, transcription errors, and inconsistent techniques.

Furthermore, the integration of a moving average filter into the signal processing pipeline proved highly effective in reducing noise and stabilizing sensor outputs. The error for both weight and height sensors consistently decreased after filtering, as detailed in Table 1 and Table 2, with the most notable improvements observed at lower measurement values where sensor sensitivity to noise is greatest. The rapid data stabilization within 6 seconds for weight and 4 seconds for height ensured that only steady and accurate readings were transmitted for record-keeping, minimizing the risk of transient error. Real-time data transmission was validated by a 100% success rate and an average latency of just 2.05 seconds (Table 3), demonstrating robust system responsiveness and reliability.

User feedback was equally positive. Usability trials involving Posyandu cadres resulted in high ratings for ease of use, information clarity, system responsiveness, and overall satisfaction (Table 4), confirming the system's practical readiness for field deployment.

B. Comparison with Similar Studies

The present study demonstrated superior performance in both height and weight measurement accuracy compared to previously published systems, as summarized in Table 6. The proposed device achieved a height measurement accuracy of ±0.53 cm (96.4%) and a weight measurement accuracy of ±0.08 kg (97.2%), with a minimal data transmission latency of 2.05 seconds. In contrast, most existing solutions either prioritized ease of deployment, such as remote video-assisted measurements or relied on novel sensor modalities like ultrasound [39] and AI-powered image processing [40] but generally exhibited higher absolute errors or lacked comprehensive weight assessment. Furthermore, systems integrating real-time data processing platforms such as REDCap [41] offered practical solutions for clinical integration but provided limited empirical accuracy data. Collectively, these findings underscore the potential clinical applicability of the developed system, which not only offers high precision but also maintains real-time data transmission capability critical for timely clinical decision-making and longitudinal growth monitoring in pediatrics populations.

Table 6. Measurement accuracy

Study Reference	Height Accuracy	Weight Accuracy	Data Transmission Latency
This Study	±0.53 cm (96.4%)	±0.08 kg (97.2%)	2.05 seconds
Huang et al., 2023 [39]	Bias: +0.1 cm; Technical Error of Measurement (TEM): 0.208 cm	Not assessed	Real-time (ultrasound portable device)
Mendon et al., 2024 [41]	Accurate according to Bland-Altman analysis using WHO/NHANES standards	Accurate according to Bland-Altman analysis using WHO/NHANES standards	Real-time (REDCap integrated system)
Chua et al., 2024 [40]	Absolute Error (AE): ±1.77 cm (subject-averaged)	Not assessed	Non real-time (AI processing from smartphone images)

As shown in Table 6, the proposed IoT-based system demonstrates a clear advancement in both measurement accuracy and operational efficiency compared to previously reported digital and manual systems. While manual measurement methods often suffer from observer bias and inconsistent recording, resulting in lower precision, the digital systems reported by Huang et al., Mendon et al., and Chua et al. improved accuracy but generally lacked integrated real-time data transmission and user-friendly dashboard interfaces. In contrast, the present system achieves higher accuracy (±0.53 cm for height and ±0.08 kg for weight) and significantly reduced latency (2.05 seconds), while also incorporating features such as RFID-based identification and cloud-based data management. These enhancements not only minimize human error and data loss but also enable instant access and longitudinal tracking of child growth data,

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which are critical for effective stunting prevention and large-scale community health monitoring. Thus, the proposed system offers a superior combination of technical performance and practical usability over both manual and other digital measurement approaches, positioning it as a robust solution for widespread implementation in community health settings.

C. Limitations and Weaknesses

Despite its promising performance, the system has several limitations. First, ultrasonic sensor readings can be influenced by external environmental factors such as ambient noise, temperature, and reflective headwear, which may impact accuracy under certain field conditions. Second, the system's reliance on stable Wi-Fi connectivity could hinder use in rural areas with unreliable or limited internet infrastructure. Additionally, effective utilization of the system presupposes basic digital literacy among health workers, necessitating structured training for optimal adoption. Lastly, the physical durability of the hardware should be further enhanced to withstand rigorous field use and transport.

While the IoT-based system exhibits high accuracy and usability, certain limitations must be addressed to ensure its effective deployment in diverse field environments. Environmental factors such as variable lighting, temperature, and reflective surfaces can affect the accuracy of ultrasonic height measurements. To mitigate this, future iterations of the system will incorporate adaptive calibration protocols, real-time error correction algorithms, and sensor shielding to reduce ambient interference. The reliance on stable Wi-Fi for real-time data transmission may present challenges in resource-limited or rural settings; thus, developing an offline data caching feature with delayed synchronization is planned to enhance robustness and data integrity when connectivity is intermittent. Hardware durability will be improved by adopting more rugged enclosures and modular components that are easier to maintain and replace. In addition, enhanced user training modules and technical support will be provided to ensure smooth adoption, particularly among users with limited digital literacy. These strategies collectively aim to increase the reliability, accessibility, and sustainability of the system for large-scale community health implementation.

D. Implications of the Study

The findings of this study demonstrate important and multidimensional implications for both operational practice at the community level and the broader context of Indonesia's national health information infrastructure. The adoption of an IoT-based child growth monitoring system with its high accuracy, reliability, and user-friendly interface provides a solid foundation for digital transformation in Posyandu and similar community health programs, aligning with national initiatives for data-driven healthcare improvements [6], [25], [28]. Automated data capture, real-time cloud integration, and digital record-keeping not only support early detection and timely intervention for stunting but also ensure data consistency and quality across diverse and remote geographic regions [9], [10], [12]. Prior studies have shown that modular and scalable architectures, such as the system described here, enable seamless deployment in both rural and urban health posts, thereby promoting more equitable access to health innovation [7], [27].

A key economic advantage of this system lies in its ability to reduce operational costs compared to conventional manual methods a benefit similarly reported in various deployments of IoT-based health tools [10], [11], [37]. Automation not only streamlines data collection and minimizes human error, but also reduces staff requirements per session, cutting assessment time per child by more than 60%, as demonstrated in related studies [12], [13]. These efficiencies are particularly valuable in resource-limited settings, enabling wider service coverage, more efficient allocation of human resources, and long-term cost savings [11], [26]. Furthermore, minimal maintenance needs and intuitive workflows enhance the system's scalability and sustainability at the population level [7], [37].

High user acceptance and satisfaction among Posyandu cadres underscore the system's practicality and readiness for broad implementation, as shown in previous studies indicating that adequate user training and ongoing technical support are crucial for successful technology adoption in community health settings [8], [36]. Feedback from health workers regarding interface and dashboard improvements will guide further enhancements, strengthening usability and community engagement in line with user-centered design principles [13], [27].

Importantly, the IoT-based system's capability to generate high-quality, real-time, and longitudinal growth data opens new opportunities for integrated national health surveillance and policy-making [6], [28], [34]. The digital platform can be designed for interoperability with Indonesia's Satu Data program and e-health databases, supporting automatic synchronization of individual child growth records from local Posyandu up to district and national levels [6], [25]. Such interoperability minimizes data fragmentation, enables timely and accurate reporting, and facilitates cross-sectoral collaboration between health, social protection, and education agencies [6], [25], [28]. At the national level, aggregated analytics can inform targeted resource allocation, performance monitoring, and evidence-based policy development

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for stunting prevention and child health improvement [28], [34].

In summary, the system developed and evaluated in this study not only delivers technical and economic benefits, but also offers a strategic opportunity for Indonesia to achieve more integrated, data-driven, and impactful child health interventions thus accelerating progress toward national health goals through robust digital interconnectivity [6], [28], [34].

5. Conclusion

This study aims to develop, implement, and validate an IoT-based real-time child growth monitoring system to address the need for accurate, efficient, and scalable growth assessment in community health settings. The system achieved high measurement accuracy, with a mean error of ±0.53 cm (SD = 0.21 cm) for height and ±0.08 kg (SD = 0.04 kg) for weight, and demonstrated strong agreement with manual reference measurements. The average data transmission latency was 2.05 seconds, and usability ratings from Posyandu cadres averaged 4.8 out of 5, confirming the system's practical value. These results indicate that the integration of sensor filtering, reliable wireless communication, and user-friendly dashboards effectively improves both operational efficiency and data reliability for stunting surveillance and early intervention.

Future work will focus on expanding the system's deployment to more diverse community settings, integrating additional health parameters (such as head circumference or nutritional status), enhancing interoperability with national health databases, and further refining user training modules to address digital literacy gaps. Overall, this IoT-based solution offers significant promise for supporting digital health transformation and accelerating stunting prevention efforts in low-resource environments.

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