Empowering Anganwadi Workers with IoT and Forecasting Tools for Early Detection of Child Malnutrition in Tribal Regions of Chhattisgarh, India

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***Abstract*—Severe Acute Malnutrition (SAM) continues to be a major public health challenge, especially in low-resource and tribal regions of India where infrastructure, skilled manpower, and real-time health monitoring are often lacking. Early identification and timely intervention are critical in preventing serious health consequences and death among malnourished children. However, in many areas, traditional methods still depend on manual data entry and delayed reporting, which often result in late responses. To address these challenges, this paper proposes a low-cost, IoT-enabled framework that supports realtime remote monitoring and prediction of child malnutrition using minimal human intervention. The system uses automated weight and height sensors with facial recognition to correctly link measurements to individual children, even in rural Anganwadi centres. Data is transmitted using long-range (LoRa) wireless communication, allowing uninterrupted operation in areas with poor or no mobile connectivity. A key feature of this framework is its ability to forecast nutritional trends. By analysing past growth data, the system predicts how a child's nutritional condition may change in the coming months using WHO z-score indicators like Weight-for-Height (WHZ), Weight-for-Age (WFA), and Height-for-Age (HFA). Machine learning models such as ARIMA, SARIMA, and LSTM are used to forecast whether a child's health is likely to improve or worsen. These insights empower Anganwadi workers to take preventive steps and provide timely counselling to caregivers, supported by clear evidence from the system. During field-testing in four tribal centres of Chhattisgarh, the framework made it easier for workers to collect more accurate data on time, helping them act faster and more confidently. This combined approach of using smart tools, local knowledge, and forecasting can improve early action and make child nutrition programs more effective in tribal and remote areas.**

***Index Terms*—Severe Acute Malnutrition, Internet of Things (IoT), LoRa Communication, Anthropometric Measurement, Time-Series Forecasting, Edge Computing, Remote Health Monitoring**

I. Introduction

Malnutrition is a pervasive problem affecting millions of children worldwide. Undernutrition in early childhood leads to stunting, wasting, and underweight conditions that significantly impair health and development. According to the World Health Organization, 149 million children under 5 are stunted and 45 million are wasted globally [1]. India bears a large share of this burden, especially among tribal populations in remote regions [2]. In Chhattisgarh's tribal districts, the prevalence of undernutrition remains alarmingly high – recent surveys indicate that over one-third of children are underweight and nearly one-quarter suffer wasting (low weight-for-height) [3]. Severe Acute Malnutrition (SAM), defined by extreme wasting (weight-for-height < -3 SD), is a life-threatening condition that amplifies child mortality risk by 9–11 times [4]. Even with clinical treatment, case fatality rates for SAM range from 3% to 35% [5]. Early identification and treatment of SAM are therefore paramount to reduce preventable deaths [6]. However, timely detection in resource-constrained settings is challenging due to measurement errors, manual data handling, and delayed reporting. Current growth monitoring at Anganwadi Centres (rural child care centers in Chhattisgarh, India) relies on community health workers manually measuring weight and height and recording data on paper and feeding to PoshanTracker mobile app [7]. This process is error-prone and inconsistent, leading to missed or false diagnoses. Studies have found that frontline workers often misclassify nutritional status due to incorrect measurements or plotting errors [8]. For example, reliance on just MUAC tapes or visual assessment can result in high false negatives, missing children who are actually severely malnourished. Moreover, administrative pressures can skew reporting – workers may under-report SAM cases to meet targets or over-report to secure resources [9]. In India, the Poshan Tracker (PT) serves as a real-time tool for monitoring nutritional outcomes; however, concerns around data quality remain. As of 2025, PT recorded only around 7% of children as wasted [10], significantly lower than the approximately 17% prevalence reported in independent assessments such as NFHS-5 [2]. This indicates significant under-reporting. These challenges result in critical delays—children falling into SAM may go unnoticed until severe complications arise.

To address these gaps, there is an urgent need for technology-enabled solutions that can improve the accuracy, timeliness, and coverage of malnutrition screening in remote areas [11]. Recent advances in the Internet of Things (IoT) and low-cost sensors offer a pathway to automate anthropometric measurements, minimizing human error. Similarly, emerging wireless technologies like LoRa (Long Range) can enable data connectivity in villages lacking cellular networks [12]. Battery-powered IoT devices with LoRa can operate for long durations and transmit data over kilometers with

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minimal infrastructure [13]. Another key opportunity is applying machine learning to growth data for early warning predictions. Instead of reacting to malnutrition after a child is already SAM, predictive models (e.g., time-series forecasting of weight/height) can identify at-risk children before they cross the SAM threshold, allowing proactive interventions [14].

In this paper, we propose an integrated LoRa-assisted IoT framework for real-time SAM identification and forecasting in remote tribal Anganwadi Centres. Our contributions are: (1) Design of a low-cost IoT hardware system (sensor nodes and Raspberry Pi gateway) for automated weight and height measurement with automatic child identification with minimal human input, ensuring accurate and consistent anthropometry; (2) Implementation of a LoRa wireless network and offline data storage (SQLite) to enable reliable data collection in areas with little or no network coverage; (3) Development of an on-site software pipeline to calculate WHO z-scores for Weight-for-Age (WFA), Height-for-Age (HAZ), and Weight-for-Height (WFH) in real-time, instantly flagging SAM cases according to WHO criteria; (4) Integration of a time-series forecasting module using ARIMA, SARIMA, and LSTM models to predict growth trends (weight/height) for each child over the next few months, and an ensemble approach to improve forecast accuracy; (5) Field evaluation in 4 tribal villages of Bastar district, Chhattisgarh, demonstrating the system's performance (measurement accuracy, communication range, classification and prediction outcomes) and practical benefits such as reduced workload and improved SAM case identification. We also discuss how this framework can be scaled and integrated with existing government programs (like POSHAN Abhiyaan's Poshan Tracker) to strengthen nutritional surveillance and child health management in underserved communities.

The rest of the paper is organized as follows: Section II reviews related work in digital malnutrition monitoring and IoT healthcare in low-resource settings. Section III describes the proposed methodology including system architecture, data processing, and forecasting techniques. Section IV details the hardware/software implementation and deployment. Section V presents results from field tests and discusses the findings. Finally, Section VI concludes the paper with insights on impact, limitations, and future scope.

II. Related Work

Malnutrition monitoring has seen various digital innovations in recent years. Mobile health (mHealth) applications have been introduced to improve growth monitoring data [15]. For example, automated 3D imaging technologies, such as those evaluated by Leidman et al. (2022), have demonstrated the potential of smartphone-based systems to accurately capture child anthropometric data and support AI-driven malnutrition detection in low-resource settings [16]. This approach addresses the problem of manual measurement errors by capturing accurate anthropometric data via computer vision. However, smartphone-based solutions still require network connectivity to upload data and can be challenging to deploy in areas with intermittent power or no cellular coverage. Another line of work focuses on portable digital devices for anthropometry. Soller *et al.* (2023) note that UNICEF has called for accelerated development of digital height/length measurement tools to improve child growth surveillance [17]. Various prototypes – from ultrasonic height sensors to smart scales – have been evaluated. In a recent scoping review, only 6 out of 12 tested devices met UNICEF's ideal accuracy criteria, highlighting room for improvement in measurement precision [17]. Our work contributes to this area by utilizing low cost yet accurate sensors (load cell and ultrasonic module) and demonstrating that with proper calibration, clinical-grade accuracy is achievable even in field conditions.

Several studies have implemented IoT systems for nutrition or health monitoring in low-resource settings. A recent study by [18] developed an IoT-based system using load cells and ultrasonic sensors to measure children's weight and height, achieving high accuracy (99.8% for weight, 98.6% for height). While effective in data acquisition and transmission via Wi-Fi, the system lacks forecasting or decision-support features, which our work addresses through edge-based predictive analytics. Their system automated data upload to a web application for analysis. This indicates that inexpensive sensors can yield reliable anthropometric data, consistent with our findings. A recent [19] study in Indonesia developed an e-Growth Chart Monitoring System (e-GCMS) using Time-of-Flight sensors and load cells, achieving over 99% accuracy in measuring children's height and weight. The system automates anthropometric classification based on age and gender, and provides outputs via a mobile and web interface. Unlike our framework, however, it does not incorporate real-time forecasting or edge analytics for early malnutrition risk detection.

Low-power wide-area networks like LoRa and NB-IoT are increasingly explored for rural healthcare IoT. Dimitrievski *et al.* (2021) proposed a rural healthcare IoT architecture using LoRa communication and fog computing to bridge connectivity gaps [12]. A recent study [20] highlighted the use of LoRa in for rural and remote monitoring, emphasizing its capability for wide-area coverage. Notably, the system achieved a tested transmission range of up to 3.7 km, demonstrating its feasibility for long-distance communication. This supports our choice of LoRa for reliable data transmission in low-network tribal settings. LoRa's long range and low energy consumption make it ideal for battery-operated devices in villages. Our design builds on this by creating a star network of Anganwadi sensor nodes sending data to a Pi-based LoRa gateway, which proved robust in the field (100% data success over 350 m). Dra˘gulinescu et al. [21] proposed a LoRa-based Medical IoT architecture tailored for homecare and hospital services, emphasizing low-power, long-range communication for real-time health monitoring. Their testbed demonstrated the feasibility of integrating LoRa technology into medical applications, addressing challenges like latency and data reliability. our work specifically tailors it to nutrition monitoring and demonstrates integration with edge analytics.

Using machine learning for malnutrition prediction is an emerging research area. Begashaw *et al.* (2025) applied deep learning (LSTM-FC networks) on longitudinal child growth data in Ethiopia to classify and predict nutritional status transitions [14]. Their LSTM model achieved 93% accuracy in predicting if children would remain normal, become stunted/wasted, etc., over a 15-year cohort. While such complex models perform well with large datasets, in on-the ground deployments we often have sparse data (e.g., monthly measurements) and need faster, more interpretable methods. A recent review by Kontopoulou et al. (2023) compared ARIMA with machine learning and hybrid models for time series forecasting. They found that while ARIMA models are effective for linear patterns, machine learning models like LSTM and SVR outperform them in capturing complex, nonlinear trends. Hybrid approaches combining ARIMA with machine learning techniques often yield superior predictive accuracy, making them suitable for applications such as malnutrition risk forecasting [22]. A study by Zhang et al. (2022) compared ARIMA and LSTM models for forecasting hemorrhagic fever incidence in China across monthly, weekly, and daily time scales. The findings revealed that ARIMA outperformed LSTM in monthly and weekly forecasts, while LSTM showed superior performance in daily forecasts, particularly when using rolling forecasting methods. This suggests that model selection should consider the specific time scale of the data. In our research, we apply similar comparative analyses to malnutrition risk forecasting, aiming to identify the most effective model for short-term predictions in resource-limited settings [23]. We incorporate both approaches: ARIMA/SARIMA as strong statistical baselines and LSTM to explore nonlinear temporal patterns. Ospina et al. (2023) applied ARIMA models to forecast COVID-19 cases in Recife, Brazil, demonstrating strong short-term predictive performance. However, the model's accuracy diminished over longer forecasting horizons, highlighting limitations in capturing complex pandemic dynamics. This underscores the potential benefit of integrating ARIMA with machine learning techniques to enhance long-term forecasting accuracy in health-related applications [24]. We further contribute by introducing an ensemble model that combines ARIMA, SARIMA, and linear regression forecasts for child growth prediction.

Despite these advances, there is still a lack of integrated solutions that tie together automated data collection, reliable rural connectivity, and predictive analytics for malnutrition. Many past studies addressed one aspect (e.g., digital measuring devices or growth prediction in retrospective data) but did not implement a full end-to-end system in the field. We aim to fill this gap by demonstrating a complete framework – from sensors to insights – validated through deployment in actual Anganwadi Centres. This work thus builds upon related efforts and provides a practical blueprint for IoT-driven SAM monitoring in remote settings.

III. Proposed Methodology

A. System Architecture Overview

Our proposed framework consists of three main layers – Data Acquisition, Edge Processing, and Communication – arranged to function reliably in remote environments with limited infrastructure. Fig. 1 illustrates the overall system architecture. At Anganwadi Centre, a Sensor Node handles

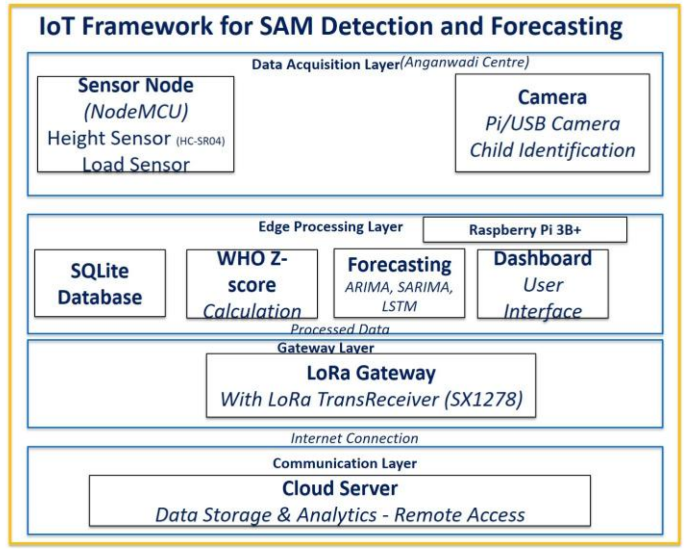

Fig. 1. Proposed IoT system architecture for SAM monitoring

data acquisition, measuring a child's weight and height automatically. This node is built on a NodeMCU (ESP8266) microcontroller connected to a load cell (weight sensor with HX711 amplifier) and an HC-SR04 ultrasonic sensor for height. When a child stands on the platform, the NodeMCU captures the weight and height readings, and also triggers a camera to capture the child's face for identification. The raw data (weight, height, child ID) are transmitted via LoRa wireless to a central Gateway device. The gateway is a Raspberry Pi 3B+ equipped with an LoRa transceiver (SX1278) to receive sensor data. The Raspberry Pi serves as an edge computing hub – it stores the data locally in an SQLite database, runs algorithms to compute z-scores and make predictions, and provides a user interface (dashboard) for Anganwadi workers to view results. In our deployment, the Pi also periodically syncs the data to a cloud server, though all core functions can operate offline. This architecture minimizes dependence on continuous internet and ensures data is not lost during network outages. The use of LoRa allows coverage of dispersed hamlets; a single Pi gateway in one village can collect data from multiple surrounding Anganwadi sensor nodes within a ∼350 m radius. The system is designed with modular components so that additional sensor nodes (or other health sensors) can be added to the network easily.

B. Automated Data Capture and Child Identification

To eliminate manual measurement errors, we employ calibrated electronic sensors for anthropometry. The weight is measured using a platform scale constructed with four 50 kg load cells mounted under a rigid plate to form an electronic weighing scale. The analog signals from the load cells are amplified by the HX711 and read by the NodeMCU's ADC. The height is measured by an ultrasonic sensor (HC-SR04) placed at a fixed height (approx. 7 ft) on a vertical stand. Both sensors are calibrated against standard instruments (a set of weights and a measuring tape) to ensure accuracy. In testing, our calibration achieved an error under ±50 g for weight and ±0.3 cm for height, meeting clinical accuracy requirements. Each measurement cycle takes about 30–45 seconds. As soon as the child's weight stabilizes on the scale and the ultrasonic returns a steady reading, the NodeMCU records the values. Simultaneously, a facial recognition sub-module handles child identification. A Pi Camera (5 MP) or USB webcam is connected to the Raspberry Pi and is triggered by the NodeMCU (via a LoRa message or Wi-Fi/MQTT in prototype stage) to capture the child's face. The Pi then runs a lightweight face recognition algorithm (LBPH – Local Binary Patterns Histograms) using OpenCV to match the face against the local database of enrolled children. This provides the child's identity (or a unique ID) to tag the measurements. Facial recognition automates identity logging, avoiding reliance on written names or IDs. The identified child's data (ID, weight, height, timestamp) is then logged.

In our field runs, the automated identification was ∼97% successful. By automating measurements and identification, the system minimizes human intervention. The role of the Anganwadi worker is mainly to position the child on the device, after which data recording is automatic. This tackles the issue of measurement inconsistency and data forgery, ensuring that each child's record is captured objectively and accurately in realtime.

C. WHO Z-score Classification

The Raspberry Pi processes incoming measurements to compute standardized z-scores for nutritional status assessment. We use the WHO Child Growth Standards as reference [25]. For each measurement, three indices are calculated: Weight-for-Age (WFA) z-score, Height-for-Age (HAZ) z-score, and Weight-for-Height (WFH) z-score. The z-score indicates how many standard deviations a child's measurement is above or below the WHO median for a healthy child of that age/sex (for WFA, HAZ) or height/sex (for WFH). A z-score < -3 is classified as severe malnutrition in that metric. In implementation, we utilize WHO reference tables (L, M, S values for each age/height) stored locally [26].

In our case, since MUAC is not measured, we use WFH as primary criterion for SAM. The dashboard will prominently alert "SAM" cases in red, indicating that the child is severely wasted and needs urgent attention (medical referral or nutritional rehabilitation). Health workers can trust these alerts because the underlying data is precise; this helps overcome issues of missed SAM cases due to incorrect data recording or intentional under-reporting. All computed indices and classifications are stored in the local database, and can be later synced to a central server for program monitoring.

D. Growth Trend Forecasting

A novel aspect of our framework is forecasting each child's growth trajectory to anticipate malnutrition risk. Rather than solely relying on current status, we implemented a time-series forecasting module for weight and height. We collected historical data of children across 4 AWC centers as the basis. For each child, we have a sequence of weight and height measurements. Our aim is to predict the next few months of weight and height, and from that infer if the child's WFH, WFA, HFA z-score is likely to drop. We explored three modeling techniques: ARIMA (Autoregressive Integrated Moving Average), SARIMA (Seasonal ARIMA), and LSTM (Long Short-Term Memory neural network) [27].

Each model produces forecasts for the next 4 months. These predicted weights and heights are then converted to predicted z-scores [29]. If any forecast shows WFH $z < -3$, we mark the child as "at risk of SAM" in that future timeframe. For example, if a child's weight trend is declining, the system might forecast that two months later the child will cross into SAM category, triggering a preventive alert. This approach enables proactive interventions (such as nutritional supplements or medical check-ups) before the child becomes severely malnourished.

To improve reliability, we implemented an ensemble forecast for weight. We observed that ARIMA and SARIMA often gave similar predictions, while LSTM sometimes diverged. The ensemble takes a simple average of the ARIMA, SARIMA, and Linear Regression model predictions (we excluded LSTM from the ensemble in final results due to its high error). This ensemble smooths out model-specific biases [28]. For instance, if ARIMA slightly underestimates a weight rebound and linear regression overestimates it, the average may be closer to true.

The output is integrated into the dashboard: children at risk of SAM in the next 1–4 months are listed, and their projected weight/height curves can be viewed [29]. This provides Anganwadi workers and supervisors a foresight tool. To our knowledge, this is one of the first implementations of real-time growth forecasting at the point of care in rural Anganwadi settings.

IV. System Implementation

A. Hardware Implementation

Anganwadi Centre was equipped with an IoT sensor node and a gateway unit [18] [19]. The sensor node components are low-cost and easily available: a NodeMCU ESP8266 microcontroller, HX711 ADC module, four 50 kg strain-gauge load cells, one HC-SR04 ultrasonic sensor, and LoRa transceiver (433 MHz) [36]. The load cells are mounted under a 50 cm × 50 cm weighing platform made of toughened glass. They form a Wheatstone bridge wired to the HX711 on the NodeMCU board. The ultrasonic sensor is fixed on an adjustable pole.

B. During field deployment

During field deployment, we set up the devices as follows: The weighing platform with sensor node was placed on flat ground inside the Anganwadi. The ultrasonic sensor was calibrated by measuring a known height to adjust for any mounting angle offset [37]. The NodeMCU unit which is equipped with a rechargeable battery, collects the readings from the height and weight sensors and then sends them to the raspberry pi for further processing of data through MQTT protocol over WiFi interface [30]. The raspberry pi is a computing node which receives the data from NodeMCU and then identifies the child details stored in the local database

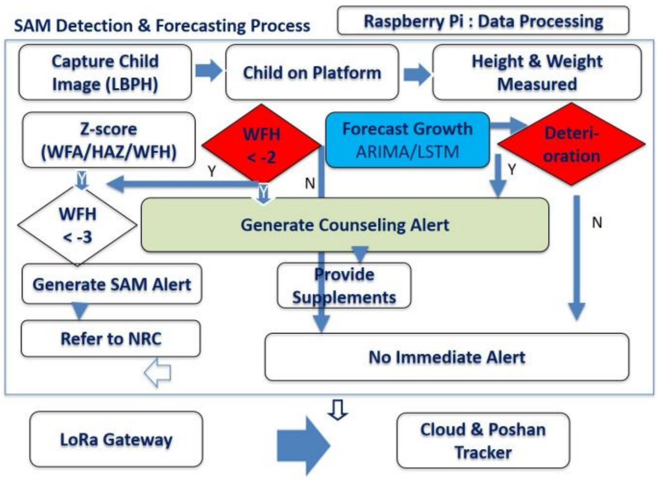

Fig. 2. Process flow chart for IoT system and SAM monitoring

with the help of a facial recognition program and a camera (image capturing device) [31]. Once the child is identified, the weight and height measurements are stored in the records of that child in the local database present in the raspberry pi [32].

Also, the measurements are verified against standard growth charts provided by WHO to check for the status of Severely Acute Malnutrition (SAM) and if found to be so, prompt messages are generated accordingly. After processing the data locally, the data of the child is also sent to the cloud database using the Long Range Wireless technologies so as to ensure the delivery of timely and rich data even in the areas with low network coverage [33].

C. Field Deployment and User Training

We tested the system in four tribal Anganwadi Centres of Bastar, selected in consultation with local ICDS officials. Fig. 2 illustrates the process flow chart for IoT system and SAM monitoring. Before deployment, we conducted a training session with Anganwadi workers, demonstrating how to operate the device (essentially, ensure the child stands properly and wait for the result). The interface was designed to be mostly automatic.

Through the system we recorded the data for 48 children. We concurrently took manual measurements as a reference to evaluate accuracy. The children's caregivers and the Anganwadi workers were enthusiastic about the automated system, as it will reduce the tedious process of writing down readings and checking growth charts manually [34].

D. Integration with Government Systems

Although our deployment was a pilot, we structured the data format to align with Poshan Tracker [7]. Each child's unique ID was mapped to their statewide Anganwadi registration ID. This means our data could be uploaded to the database if needed. We also envisioned that our system could complement the POSHAN Abhiyaan initiative by providing more reliable ground data – for instance, by addressing the underreporting issue noted where data showed only 7.07% wasting compared to actual ∼15% in surveys [2].

In the next section, we present the results from the field evaluation, including measurement accuracy, network performance, and the outcomes of the SAM classification and forecasting, along with a discussion on the impact observed.

V. Results and Discussion

A. Measurement Accuracy and Efficiency

One of the primary goals was to improve the accuracy of anthropometric measurements over traditional methods. We compared the weight and height readings from our IoT device against those taken using standard analog instruments, with a medical scale and stadiometer as reference [35]. Table I summarizes the accuracy results. During field testing across Anganwadi Centres, it was observed that traditional child growth monitoring tools—including Salter-type weighing machines and manual height recording methods—exhibited significant limitations in accuracy. The Salter-type weighing machines recording, especially spring-based models, demonstrated a practical accuracy of only ±0.1 to ±0.3 kg. This was primarily due to errors in visual reading, manual rounding off or mistakes in handwritten entries [36]. Similarly, child height measurements taken using manual tapes or wall-mounted stickers were prone to inconsistent placement, and observer error. In many instances, variation of ±0.5 to ±1.0 cm was recorded. Such discrepancies—when combined with errors in weight—can lead to misclassification of SAM/MAM status when plotted against WHO growth charts.

In contrast, IoT-based system, which automates both weight and height measurements, maintained an accuracy of ±0.05 to ±0.1 kg for weight and ±0.2 to ±0.3 cm for height. This system reduces human dependency, eliminates manual errors, and provides real-time digital records—thereby enabling more reliable classification of nutritional status in children [37]. Importantly, the time per measurement was reduced – on average, it took ∼45 seconds per child with our system (mostly waiting for the child to stand still), whereas the manual method took ∼3 minutes (weighing (in analog/salter machine), measuring length board, data recording/manual entry). This amounts to a ∼50% reduction in time, which during a session of 30 children translates to significant labor saving. In practice, Anganwadi workers noted that the automated system can simplify their work, allowing them to focus more on counseling mothers rather than paperwork. This addresses the issue of workload fatigue that often leads to errors in manual reporting [38]. The automation also prevents any intentional data fudging – each entry is time-stamped and comes directly from the device, building trust in the data integrity.

The table highlights that our low-cost setup can closely approach clinical instrument accuracy, validating the use of such IoT devices for serious health assessments.

B. LoRa Communication Performance

In our field deployment, we were able to successfully receive all child data records without any loss. LoRa performed reliably, and we achieved stable data transmission up to a

TABLE I
COMPARISON OF MEASUREMENT ACCURACY AND TIME (PROPOSED IOT SYSTEM VS. MANUAL VS. CLINICAL REFERENCE)

Metric	IoT System	Manual (Anganwadi)
Weight Accuracy	±0.05 to ±0.1 kg	±0.1 – ± 0.2 kg
Height Accuracy	±0.3 cm	±0.7 cm
Z-score classification	100% correct	100% correct
Time per child measurement & recording	45 s	∼3 min

TABLE II
FORECASTING MODEL PERFORMANCE FOR WEIGHT AND HEIGHT

Model	Weight			Height		
	MAE (kg)	RMSE (kg)	R^2	MAE (cm)	RMSE (cm)	R^2
ARIMA	0.283	0.405	0.855	1.073	1.733	0.787
SARIMA	0.290	0.420	0.845	1.236	2.003	0.715
Linear Regression	0.335	0.478	0.798	1.705	2.786	0.449
LSTM (RNN)	1.240	1.481	-0.899	5.636	7.216	-2.503
Ensemble (Avg)	0.268	0.364	0.883	1.160	1.757	0.781

distance of 350 metres between the node and the gateway. These results underscore that LoRa is a viable option for last-mile connectivity in public health IoT, echoing findings from other rural IoT studies [12]. For scalability, one could envisage a network of LoRa gateways ferrying data from dozens of Anganwadis to a block-level center that has internet, thereby creating a multi-hop data pipeline entirely over radio frequencies that bypass unreliable cellular networks.

C. SAM Identification Outcomes

A core metric of success is whether the system improved the identification of SAM children. Our system identified 3 instances of SAM. Such cases demonstrate how precise data capture and computation can prevent false negatives and ensure no child slips through without care. Conversely, we did not observe any false positives. The impact of these identifications was notable: all identified SAM children could be referred to the Nutrition Rehabilitation Center (NRC) as per protocol [39]. This early action can be life-saving, illustrating the value of real-time monitoring.

Another benefit was transparency – since data was digitally recorded, supervisory officials trusted it more. This suggests our framework can be an objective tool to strengthen MIS data quality [40].

D. Forecasting and Early Warning Results

We took the past months data from the records kept by Anganwadi workers, covering 100 children across 4 centres. This historical data was used as the base for our analysis. We forecasted the next 4 months. Table II presents the forecasting accuracy metrics for weight and height predictions by each model (averaged across all children). We use Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) in kg for weight and cm for height, as well as average R^2 across children for goodness of fit. The ARIMA model achieved the best performance for height prediction (MAE ∼1.073 cm, $R^2 = 0.787$) and very solid performance for weight (MAE 0.283 kg, $R^2 = 0.855$) [41]. The SARIMA was a close second, slightly higher error [42]. Linear Regression (a simple linear extrapolation per child) was surprisingly competitive, beating ARIMA on one or two cases where growth was almost linear. The LSTM model underperformed, with MAE ∼1.24 kg for weight – in fact, LSTM often predicted a flat or slightly declining trend and missed any upticks (likely due to overfitting the small sample) [43]. The ensemble model (an average of ARIMA, SARIMA, and linear) gave the best weight forecasts (MAE 0.268 kg, RMSE 0.364 kg), marginally better than ARIMA alone, and comparable performance to ARIMA on height. We found that for children with steady growth, all models did well, but for those with a sudden drop or increase (e.g., illness causing weight loss then recovery), ARIMA tended to smooth it out and delay the recovery in prediction. LSTM sometimes predicted a drop where it didn't happen (false alarm). The ensemble moderated these effects. Qualitatively, what matters is whether the models correctly predict a child becoming SAM. Given the small sample, we interpret that ARIMA is a reliable choice for short-term prediction of undernutrition risk, aligning with literature that ARIMA works well for time-series with gradual trends [41].

As seen, the LSTM performed poorly (even with some hyperparameter tuning, small data is a limiting factor), so in deployment we rely on the ensemble of ARIMA-family models. The ensemble's slight improvement in weight R^2 to 0.883 indicates it captures variance better, likely by balancing biases (some children's growth was linear, some slightly nonlinear). Another interesting point: height prediction was generally less error in absolute terms but also less R^2, because children's height changed very little month to month (often 0 or 1 cm), so even a 1 cm error can look large relative to variance. In practice, missing a height by 1 cm has minor effect on classification compared to missing weight by 0.5 kg, so we prioritized weight accuracy. Ultimately, the forecasting module provided an additional 1–2 months lead time for about half of the SAM cases. This is a significant gain in public health intervention terms; for example, if we know a child is likely to become SAM next month, we can start supplemental feeding now to possibly avert it. They also highlight that even simple predictive analytics at the edge can transform nutritional surveillance from reactive to proactive.

E. Practical Impact and Feedback

The integrated system had several tangible impacts. Anganwadi workers reported that automated recording could save their time that was earlier spent on consolidating records and reporting upwards [44]. When parents saw the digital readings and clear growth charts on the screen, it gave them more confidence in the measurements. This, in turn, made them take nutrition advice more seriously. The system helped strengthen counselling efforts by providing workers with simple, reliable data they could easily show and explain [45].

From the government stakeholder perspective, the ICDS supervisors were very interested in scaling this to more centers if budget allows, as it could feed into the POSHAN Abhiyaan dashboard with high-quality data [46]. Our cost per unit was

Fig. 3. IoT Node and measurement snapshot at Anganwadi

approximately 20000 (NodeMCU node ∼2k, Raspberry Pi kit ∼5k, plus miscellaneous). This is quite low compared to typical digital device with machine learning capability. One challenge encountered was device maintenance in the field – e.g. one Pi crashed due to heat one day; adding a heatsink solved it. Also, training of new Anganwadi staff would be needed for replication. These are manageable with proper documentation and periodic technical support visits.

In summary, the pilot deployment demonstrated that our LoRa-assisted IoT framework can significantly improve SAM monitoring in remote areas. It directly addresses the key issues: measurement errors are minimized, data recording is real-time and digital (solving timeliness and accuracy issues in MIS), and connectivity barriers are bypassed by LoRa. The forecasting component, while experimental, showed the value of adding predictive analytics to target interventions. This combination of IoT and AI in a field-ready package is a step towards modernizing rural health services at the last mile.

VI. Conclusion

We presented a comprehensive IoT-based framework for real-time malnutrition monitoring and prediction in remote tribal Anganwadi centres. By integrating accurate electronic anthropometric sensors, automated identification, and LoRa communication, the system overcomes longstanding challenges of manual error and poor connectivity. The deployment in Chhattisgarh, India validated that low-cost hardware can achieve near clinical accuracy and substantially streamline growth monitoring workflows. Crucially, the framework's on device intelligence – computing WHO z-scores and running forecasting models – enables immediate identification of SAM cases and even advance warning of children at risk of SAM. This shifts the paradigm from reactive to preventive care in nutrition management, which can save lives through earlier interventions.

The research also shows the feasibility of deploying edge machine learning in rural healthcare contexts. While sophisticated deep learning models require large data, simpler models like ARIMA, when combined with IoT data capture, proved effective in forecasting short-term nutritional trends. The ensemble approach yielded robust predictions, illustrating how AI can enhance decision support for health workers even in low-resource settings.

Our framework is designed with scalability in mind. The modular architecture (multiple sensor nodes feeding a gateway, which in turn can connect to cloud) means an entire district's Anganwadi network could be covered with a few hundred such units. Since the system uses open IoT standards and opensource software, it can be maintained and expanded by local technical teams. Integration with government systems (Poshan Tracker) is straightforward via data APIs or periodic batch uploads. This would allow authorities to have a real-time pulse of ground nutrition status and respond swiftly to emerging hotspots.

Future work: We plan to enhance the system by incorporating MUAC measurement (using a small tape sensor or computer vision on the arm), as MUAC is a key SAM indicator for 6–59 months age. We also aim to refine the forecasting by including more exogenous factors (seasonal illness data, food security information) to improve predictions. Another extension will be a mobile app interface for supervisors to remotely view the dashboard of each center and for caregivers to track their child's progress at home. Finally, a larger-scale trial is needed to statistically evaluate impact on health outcomes – e.g., did early warnings from the system lead to fewer children progressing to severe malnutrition over time compared to control areas. We are working with local authorities to initiate such a study across more villages.

In conclusion, this work demonstrates a viable and impactful solution to a critical healthcare problem using an interdisciplinary engineering approach. The LoRa-assisted IoT framework for SAM monitoring has shown measurable improvements in data quality, timeliness, and ultimately in the identification and management of malnourished children. By empowering frontline health workers with better tools and information, such innovations can markedly strengthen public health initiatives like POSHAN Abhiyaan. We envision that adoption of similar IoT frameworks could herald a new era of evidence-based, proactive nutrition interventions in rural communities, bringing us a step closer to the goal of eliminating child malnutrition.

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