

IoT-enabled smart nutrition scale using fuzzy logic for dietary assessment and recommendation

Wahyu Wijaya Widiyanto¹, Edy Susanto², Sri Suparti¹

¹Applied Health Information Management Study Program, Politeknik Indonusa Surakarta, Sukoharjo, Indonesia

²Applied Software Engineering Technology Study Program, Politeknik Indonusa Surakarta, Sukoharjo, Indonesia

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ABSTRACT

Childhood malnutrition, particularly stunting, remains a major public health challenge that requires preventive and technology-supported nutritional interventions. This study presents an IoT-enabled smart nutrition scale integrated with fuzzy logic to support real-time dietary assessment and personalized recommendation. The system combines IoT-based sensing, mobile and web applications, and a fuzzy inference engine that evaluates child profiles and food composition data to generate nutritional adequacy scores and tailored dietary guidance. Experimental validation demonstrates high measurement accuracy of the sensing system, achieving a strong linear correlation ($R^2 \approx 0.9995$). Comparison with expert nutritionist assessments shows strong agreement, supported by low error values (mean absolute error (MAE) = 2.96; root mean square error (RMSE) = 3.41), and Bland–Altman analysis. Usability evaluation involving community health workers and caregivers yields an excellent system usability scale (SUS) score, indicating strong acceptance for practical deployment. By integrating IoT sensing with fuzzy reasoning, the proposed system shifts nutritional monitoring from retrospective assessment toward proactive dietary intervention. This work highlights the potential of intelligent nutrition technologies to enhance decision-making in community-based stunting prevention programs and provides a scalable foundation for preventive digital health applications.

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Corresponding Author:

Wahyu Wijaya Widiyanto

Applied Health Information Management Study Program, Politeknik Indonusa Surakarta

St. Palem No. 8, Jati, Cemani, Grogol, Sukoharjo, Central Java-57552, Indonesia

Email: wahyuwijaya@poltekindonusa.ac.id

1. INTRODUCTION

Childhood malnutrition, particularly stunting, remains one of the most pressing global health challenges, with long-term implications for cognitive development, physical growth, and future productivity [1]. In Indonesia, the prevalence of stunting among children under five reached 21.5% in 2023, exceeding the national target of 14% and highlighting the urgent need for preventive and technology-assisted interventions [2]. Traditional monitoring approaches that rely on anthropometry or manual dietary records are often slow, error-prone, and reactive, failing to provide real-time nutritional guidance [3].

Artificial intelligence (AI) has emerged as a promising tool in health and nutrition applications. Expert systems and fuzzy logic models have been applied in dietary management and disease prediction, showing reliable performance in uncertain and imprecise conditions [4]. Clinical decision support systems based on fuzzy logic, for example, have achieved more than 97% accuracy in recommending dietary adjustments for patients with chronic conditions [5]. Similarly, IoT-fuzzy approaches have been implemented for remote patient

monitoring [6] and agricultural soil health optimization [7]. Despite these advances, most AI-based solutions focus on diagnostic or monitoring tasks rather than proactive, context-aware dietary recommendation.

Recent literature emphasizes the growing importance of AI-driven and IoT-enabled systems for personalized nutrition. Survey studies reveal the increasing integration of recommender systems, IoT devices, and machine learning for food intake analysis [8], [9]. Image-based methods have also shown promise, with deep learning models such as ResNet-50 achieving up to 98% accuracy in predicting malnutrition from facial images [10], and RGB-D vision systems reporting correlation coefficients above 0.91 for nutrient estimation [11]. Nevertheless, these systems predominantly address recognition and measurement, while the function of preventive dietary recommendation remains underdeveloped.

Several new frameworks underline the relevance of personalization in nutrition. For example, personalized meal planning systems have been validated for individuals with diet-related health conditions [12], and the personalized food score (PFS) introduces a flexible nutrient profiling model adaptable to national dietary guidelines [13]. In the Indonesian context, IoT-based nutritional assessment tools for toddlers [14] and multisensor anthropometric systems for early stunting detection [15] demonstrate the feasibility of technology integration into community health programs. However, these efforts remain fragmented and lack a unified architecture that combines sensing, intelligent reasoning, and real-time recommendation.

This research addresses these gaps by proposing an IoT-enabled smart nutrition scale integrated with fuzzy logic to support real-time dietary evaluation and personalized recommendation for children at risk of stunting. The system integrates load cell sensors, a microcontroller, a smartphone interface, a camera, a radio frequency identification (RFID) reader, and a thermal printer, combined with an android application and a web-based platform. A fuzzy inference engine processes child profiles and food composition data to assess adequacy and generate tailored menu suggestions. The novelty of this work lies in its preventive focus, merging IoT hardware and fuzzy reasoning to bridge the gap between raw dietary data and actionable recommendations. This contribution differentiates it from prior works that are diagnostic in nature, offering instead a proactive and adaptive tool to empower parents, caregivers, and community health workers. Accordingly, this study aims to design, implement, and evaluate an IoT-enabled fuzzy logic nutrition scale that supports preventive dietary assessment and real-time recommendation in community health settings.

2. METHOD

This study was conducted through a structured development and evaluation process encompassing system design, hardware–software integration, fuzzy logic formulation, and validation procedures. An overview of the research workflow is presented in Figure 1. System validation focused on two core aspects: verification of sensor performance and functional evaluation of the fuzzy logic–based dietary assessment against expert nutritionist judgments.

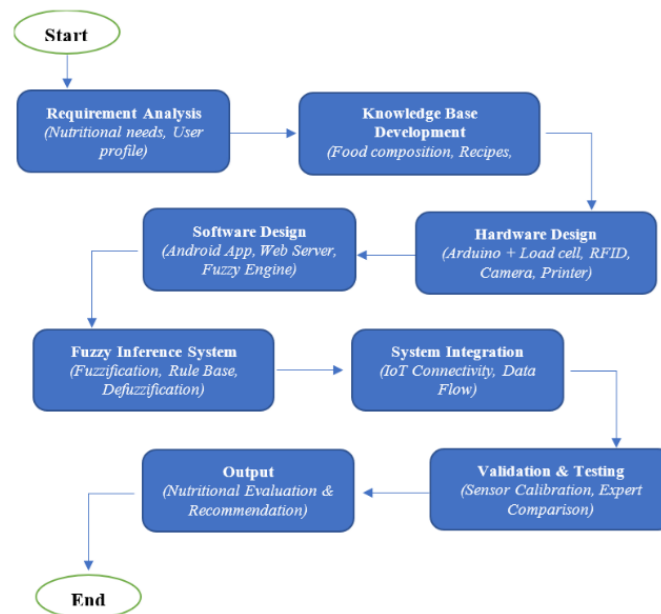


Figure 1. Flowchart of the IoT-enabled fuzzy logic nutrition scale research method

2.1. Research design

The study followed an engineering research and development framework, beginning with requirement analysis and system modeling, followed by prototype implementation and iterative testing [16]. The system architecture integrates IoT-based hardware components—including a load cell sensor, Arduino microcontroller, camera, RFID reader, and thermal printer—with software modules comprising an Android application, a web-based management platform, and a fuzzy inference engine. This integrated design enables real-time data acquisition, processing, and feedback within community health settings.

2.2. Research procedures

The research procedures were organized into four main phases. First, a knowledge base was constructed using national food composition databases, relevant literature, and consultations with nutrition experts [17]. Second, the fuzzy inference algorithm was designed by defining input variables related to child characteristics and food nutrient composition, along with output variables representing nutritional adequacy scores and dietary recommendations [18]. Third, system implementation involved integrating the hardware components with the android application via Bluetooth and Wi-Fi, enabling automated food weighing, nutrient calculation, and inference execution [19]. Finally, testing and validation were conducted to verify sensor accuracy and to evaluate system outputs against expert nutritionist assessments.

2.3. Fuzzy logic inference system

Dietary adequacy assessment was implemented using a Mamdani-type fuzzy inference system, selected for its interpretability and effectiveness in handling uncertainty in nutritional decision-making [20], [21]. The model evaluates dietary intake by considering key macro- and micronutrients relevant to early childhood growth and stunting prevention. Input variables include energy, protein, fat, fiber, iron, calcium, and vitamin adequacy, defined in accordance with guidelines from the World Health Organization (WHO) and the Indonesian Ministry of Health.

The system produces a nutritional adequacy score ranging from 0 to 100, linguistically classified into four categories: deficient, moderate, sufficient, and excessive. A total of 42 fuzzy rules were formulated to represent different nutrient adequacy conditions. The rule base was developed through expert consultation involving licensed nutritionists and a public health specialist, and was subsequently aligned with national dietary standards and scientific literature to ensure clinical relevance.

An illustrative example of a fuzzy rule is: IF energy intake is Low AND protein intake is Low AND iron intake is Low, THEN nutritional adequacy is Deficient. For clarity, Table 1 presents a simplified representation of adequacy categories using only energy and protein inputs, while the full system incorporates additional macro- and micronutrients. Defuzzification was performed using the centroid method to generate a crisp nutritional adequacy score, which serves as the basis for dietary evaluation and personalized recommendation generation.

2.4. Dataset characteristics and limitations

The dataset comprised nutritional composition data derived from Indonesian food composition tables and approximately 200 validated toddler meal recipes commonly used in community health programs. Child profile data—including age, body weight, and daily dietary intake—were collected in collaboration with partner posyandu and puskesmas. While the dataset reflects typical dietary patterns within the study area, its geographic scope and size remain limited. Consequently, dietary diversity across different regions and socioeconomic groups may not be fully represented. This limitation is addressed in planned future work through multi-site and longitudinal data collection.

2.5. Data privacy, security, and ethical considerations

Given the sensitive nature of pediatric health data, privacy and security were integral to the system design. Personal identifiers were anonymized prior to storage, and system access was controlled through user authentication and role-based authorization. Data transmission between IoT devices, mobile applications, and the web server employed encrypted communication protocols. Ethical approval was obtained prior to data collection, and informed consent was secured from all participating parents or caregivers in accordance with established ethical standards for pediatric research.

Table 1. Illustrative adequacy categories based on energy and protein inputs

Input (energy/protein)	Output (adequacy score)
Low/Low	Deficient (0–40)
Adequate/Low	Moderate (41–60)
Adequate/Adequate	Sufficient (61–80)
High/Adequate	Excessive (81–100)

2.6. System scalability and deployment considerations

The system architecture was designed to support scalable deployment across multiple community health centers. Modular IoT hardware enables additional units to be installed without substantial system modification, while the web-based platform facilitates centralized data management and monitoring across sites. This design supports potential expansion from single-posyandu deployment to district- or provincial-level implementation, aligning with broader public health nutrition initiatives. Future integration with cloud-based health information systems is anticipated to further enhance interoperability and scalability.

2.7. Data acquisition

Data acquisition encompassed three categories. First, nutritional data sourced from Indonesian food standards and validated toddler recipes. Second, user data derived from child profiles collected at partner posyandu and puskesmas. Third, testing data, including calibration weights and controlled meal plans used for system evaluation.

2.8. Validation and testing

System validation was conducted in two stages as shown in Figure 2. First, sensor calibration was performed by comparing load cell measurements with standard calibration weights using the experimental setup shown in Figure 2(a). Second, functional validation involved comparing nutritional adequacy scores generated by the fuzzy inference system with expert nutritionist assessments, as illustrated in Figure 2(b). The quantitative results of these validation procedures are presented and discussed in the results section. The overall evaluation produced dietary adequacy scores and corresponding recipe recommendations, with the complete research workflow illustrated in Figure 1.

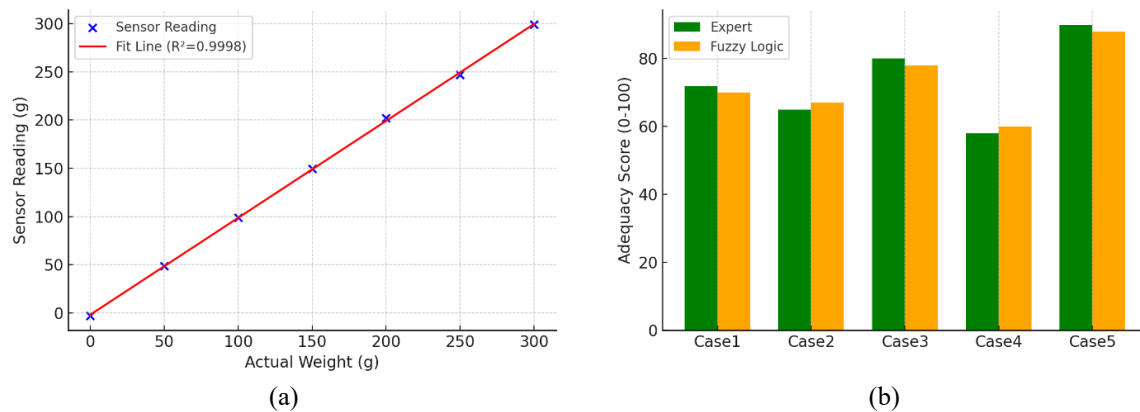


Figure 2. Validation results showing (a) sensor accuracy calibration curve and (b) system adequacy evaluation compared to expert nutritionist

3. RESULTS AND DISCUSSION

This section reports the experimental evaluation of the proposed IoT-enabled fuzzy logic nutrition scale. Covering sensor calibration, dietary adequacy assessment, prototype implementation, and usability analysis. Quantitative results are complemented by qualitative observations and contextualized through comparison with related studies [20]–[22].

3.1. Sensor calibration and accuracy validation

Load cell performance was evaluated using calibration weights ranging from 0 g to 300 g. As illustrated in Figure 2(a), the measured weights exhibit a strong linear relationship with reference values. Regression analysis yields a coefficient of determination of $R^2 \approx 0.9995$, indicating high measurement fidelity across the tested range.

The calibration relationship is expressed as:

$$E_w = \alpha W_a + \varepsilon \quad (1)$$

Where E_w is estimated weight, W_a is actual weight, α is calibration coefficient, and ε denotes measurement error. The small value of ε across repeated trials confirms system stability. These findings are consistent with other IoT-based sensing systems reporting R^2 values above 0.99 for healthcare applications [23]–[25].

3.2. Fuzzy logic adequacy evaluation

Dietary adequacy assessment was performed using a Mamdani-based fuzzy inference mechanism with max–min composition. The firing strength of each rule was computed using the minimum operator across the relevant nutrient membership functions, followed by aggregation using the maximum operator:

$$\mu_{Adequacy}(x) = \max_i \{ \min (\mu_{Energy,i}(x), \mu_{Protein,i}(x), \mu_{Fat,i}(x), \mu_{Fiber,i}(x), \mu_{Iron,i}(x), \mu_{Calcium,i}(x), \mu_{Vitamin,i}(x)) \} \quad (2)$$

Where $\mu_{Adequacy}(x)$ represents the aggregated membership degree of nutritional adequacy, and $\mu_{Energy,i}(x)$, $\mu_{Protein,i}(x)$, $\mu_{Fat,i}(x)$, $\mu_{Fiber,i}(x)$, $\mu_{Iron,i}(x)$, $\mu_{Calcium,i}(x)$, and $\mu_{Vitamin,i}(x)$ denote the membership values of each nutrient under the i -th fuzzy rule.

Representative results comparing expert nutritionist assessments and fuzzy inference outputs are summarized in Table 2. Across the evaluated cases, deviations between expert scores and system-generated scores remain within a narrow range, indicating close agreement. To quantify agreement more systematically, the mean absolute error (MAE) and root mean square error (RMSE) were computed using paired expert–system scores. The resulting MAE of 2.96 and RMSE of 3.41 indicate low prediction error. Agreement was further examined using Bland–Altman analysis, which shows that most differences fall within the ± 1.96 standard deviation limits, with no evident systematic bias across adequacy levels. Together, these findings suggest that the fuzzy inference system produces dietary adequacy assessments closely aligned with expert judgment, consistent with prior fuzzy-based clinical decision support studies [26], [27].

Table 2. Comparison of expert and fuzzy adequacy scores

Case	Expert score	Fuzzy score	Deviation (%)
1	72	70	-2.7
2	65	67	+3.1
3	80	78	-2.5
4	58	60	+3.4
5	90	88	-2.2

3.3. Prototype implementation

Figure 3 illustrates the realized system prototype and its mobile application interface. The hardware unit as shown in Figure 3(a) integrates a load cell sensor, Arduino microcontroller, RFID reader, camera, and thermal printer, enabling real-time food measurement, identification, and reporting. The Android application interface as shown in Figure 3(b) supports child profile management, dietary intake evaluation, visualization of adequacy scores, and generation of personalized dietary recommendations. This integration facilitates seamless interaction between users and the underlying sensing and inference components.



Figure 3. System prototype: (a) hardware unit and (b) Android application interface

3.4. Performance and usability testing

System performance was evaluated by measuring response time from food placement to adequacy score generation. Across 50 trials, the average response time was 1.85 seconds, satisfying real-time operational requirements for community health settings. Usability evaluation was conducted in collaboration with a partner posyandu, involving 15 community health cadres and 25 caregivers. The system achieved a

system usability scale (SUS) score of 82.5, classified as “excellent”. Participants reported that the system was intuitive to use, with clear recommendations and practical value, particularly appreciating the automatically generated printed reports.

Qualitative feedback gathered during pilot deployment further highlighted ease of operation with minimal training. Reported challenges included reliance on stable internet connectivity for data synchronization and limited coverage of certain local food items in the database. These observations inform ongoing development efforts, including dataset expansion and support for offline operation.

3.5. Discussion of findings

The experimental results indicate that the proposed IoT-enabled fuzzy logic nutrition scale is accurate, reliable, and well-suited for preventive nutritional monitoring in community health contexts. In contrast to conventional anthropometric approaches, which typically detect nutritional problems after they manifest, the proposed system supports proactive intervention. It assesses daily dietary intake and delivers actionable recommendations in near real time.

Within the Indonesian context, this work represents an early implementation of an IoT–fuzzy framework designed specifically for stunting prevention. Compared with existing AI-based nutrition systems that focus primarily on food recognition or intake estimation [28], the key contribution of this study lies in the integration of IoT-based sensing, interpretable fuzzy reasoning, and personalized dietary recommendation within a unified platform. The consistently low deviation between system outputs and expert assessments, together with high usability scores, suggests strong potential for adoption by community health workers and caregivers. These results support the feasibility of deploying intelligent nutrition technologies in resource-constrained settings.

3.6. Subgroup performance analysis

To assess robustness, system performance was examined across selected subgroups. When stratified by child age (12–24 months and 25–59 months), adequacy score deviations relative to expert evaluations remained below 5%. Stable agreement was also observed across different food categories, including staple foods, animal protein sources, and complementary foods. Although subgroup analyses by gender and geographic region were exploratory due to sample size limitations, no notable performance disparities were observed. Overall, these findings suggest that the proposed system maintains consistent performance across diverse usage scenarios.

4. CONCLUSION

This study presented an IoT-enabled smart nutrition scale integrated with fuzzy logic for preventive dietary assessment and personalized recommendation in early childhood nutrition. The proposed system demonstrated high measurement accuracy, with a calibration coefficient of determination of $R^2 \approx 0.9995$, and strong agreement with expert nutritionist evaluations, supported by low error metrics (MAE =2.96; RMSE =3.41) and Bland–Altman agreement analysis. Usability evaluation further confirmed excellent acceptance among community health workers and caregivers (SUS score: 82.5), indicating that the system is suitable for real-time deployment in posyandu and puskesmas settings. By integrating IoT-based sensing and fuzzy logic reasoning into a unified framework, the proposed solution shifts nutritional monitoring from retrospective assessment toward proactive dietary intervention for stunting prevention. Future work will focus on the development of hybrid fuzzy–machine learning models for adaptive recommendation, larger longitudinal evaluations across multiple provinces, cloud-based interoperability with public health information systems, and cost-effectiveness analysis to support large-scale government adoption.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Wahyu Wijaya Widiyanto	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓
Edy Susanto		✓			✓	✓		✓	✓	✓	✓		✓	
Sri Suparti	✓		✓	✓			✓			✓	✓		✓	✓

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

We have obtained informed consent from all individuals involved in this study. All participants, including posyandu cadres and parents who contributed to usability testing, provided consent for their participation and for the use of anonymized data in this research.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. Due to privacy considerations and the inclusion of sensitive participant information, the data are not publicly available. Aggregated and anonymized datasets used for sensor calibration, fuzzy logic evaluation, and usability testing have been included within the article and its supplementary materials.





REFERENCES

- [1] A. Deshpande and R. Ramachandran, "Early childhood stunting and later life outcomes: A longitudinal analysis," *Economics and Human Biology*, vol. 44, Jan. 2022, doi: 10.1016/j.ehb.2021.101099.
- [2] Kemenkes, "Stunting in Indonesia and its determinants," *Ministry of Health: Health Development Policy Agency of Indonesia*, 2024.
- [3] D. Tsolakidis, L. P. Gymnopoulos, and K. Dimitropoulos, "Artificial intelligence and machine learning technologies for personalized nutrition: a review," *Informatics*, vol. 11, no. 3, 2024, doi: 10.3390/informatics11030062.
- [4] L. P. Wanti, O. Somantri, N. W. A. Prasetya, and L. Puspitasari, "Fuzzy expert system design for detecting stunting," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 1, pp. 556–564, 2024, doi: 10.11591/ijeecs.v34.i1.pp556-564.
- [5] L. M. -Hosseini, S. Jafarirad, and A. M. Hadianfard, "A fuzzy based dietary clinical decision support system for patients with multiple chronic conditions (MCCs)," *Scientific Reports*, vol. 13, no. 1, pp. 1–8, 2023, doi: 10.1038/s41598-023-39371-4.
- [6] M. Z. U. Rahman *et al.*, "An IoT-fuzzy intelligent approach for holistic management of COVID-19 patients," *Heliyon*, vol. 10, no. 1, Jan. 2024, doi: 10.1016/j.heliyon.2023.e22454.
- [7] R. Prasad, R. Tiwari, and A. K. Srivastava, "Internet of things-based fuzzy logic controller for smart soil health monitoring: a case study of semi-arid regions of India†," *Engineering Proceedings*, vol. 58, no. 1, 2023, doi: 10.3390/ecsa-10-16208.
- [8] F. Yousefi *et al.*, "Artificial intelligence in health promotion and disease reduction: rapid review," *Journal of Medical Internet Research*, vol. 27, 2025, doi: 10.2196/70381.
- [9] J. N. Bondevik, K. E. Bennin, Ö. Babur, and C. Ersch, "A systematic review on food recommender systems," *Expert Systems with Applications*, vol. 238, 2024, doi: 10.1016/j.eswa.2023.122166.
- [10] S. Aanjangkumar *et al.*, "Prediction of malnutrition in kids by integrating ResNet-50-based deep learning technique using facial images," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, doi: 10.1038/s41598-025-91825-z.
- [11] W. Shao *et al.*, "Vision-based food nutrition estimation via RGB-D fusion network," *Food Chemistry*, vol. 424, Oct. 2023, doi: 10.1016/j.foodchem.2023.136309.
- [12] X. Wu *et al.*, "A scoping review of artificial intelligence for precision nutrition," *Advances in Nutrition*, vol. 16, no. 4, 2025, doi: 10.1016/j.advnut.2025.100398.
- [13] H. J. Hwang *et al.*, "Personalized food score (PFS): a flexible nutrient profiling framework based on national nutrient guidelines and estimated energy requirements," *Journal of Food Composition and Analysis*, vol. 137, 2025, doi: 10.1016/j.jfca.2024.106907.
- [14] A. Rosari *et al.*, "Developing a nutritional assessment tool for toddlers using anthropometry and IoT technology," *International Journal of Advanced Health Science and Technology*, vol. 4, no. 2, pp. 67–71, 2024, doi: 10.35882/ijahst.v4i2.319.
- [15] A. Yaseen, M. T. Rasheed, K. Abbas, and D. Zhaira, "Artificial intelligence in smart healthcare applications: benefits, challenges, and ethical considerations," *Journal of Neonatal Surgery*, vol. 14, no. 32S, pp. 7530–7536, Aug. 2025, doi: 10.63682/jns.v14i32s.8889.
- [16] X. Gao, P. He, Y. Zhou, and X. Qin, "Artificial intelligence applications in smart healthcare: a survey," *Future Internet*, vol. 16, no. 9, pp. 1–32, 2024, doi: 10.3390/fi16090308.





- [17] K. Agrawal, P. Goktas, N. Kumar, and M. F. Leung, "Artificial intelligence in personalized nutrition and food manufacturing: a comprehensive review of methods, applications, and future directions," *Frontiers in Nutrition*, vol. 12, 2025, doi: 10.3389/fnut.2025.1636980.
- [18] A. Phalle and D. Gokhale, "Navigating next-gen nutrition care using artificial intelligence-assisted dietary assessment tools—a scoping review of potential applications," *Frontiers in Nutrition*, vol. 12, 2025, doi: 10.3389/fnut.2025.1518466.
- [19] N. Purwati, R. R. Isnanto, and M. I. Kartasurya, "Computer vision for food nutrition assessment: a bibliometric analysis and technical review," *Journal of Robotics and Control*, vol. 6, no. 5, pp. 2141–2151, 2025, doi: 10.18196/jrc.v6i5.27525.
- [20] A. Ikram, H. Mehmood, M. T. Arshad, A. Rasheed, S. Noreen, and K. T. Gnedeka, "Applications of artificial intelligence (AI) in managing food quality and ensuring global food security," *CYTA-Journal of Food*, vol. 22, no. 1, Dec. 2024, doi: 10.1080/19476337.2024.2393287.
- [21] A. S. Kishore, G. R. Chinni, G. Jayalakshmi, and K. S. K. Reddy, "Smart healthcare monitoring system using IoT technology," in *11th International Conference on Internet of Everything, Microwave Engineering, Communication and Networks, IEMECON 2023*, 2023, pp. 141–152, doi: 10.1109/IEMECON56962.2023.10092300.
- [22] S. L. Rosa, M. F. Evizal, and F. Assidiqi, "Patient monitoring system used smart sensor technology internet of things and AI," *International Journal of Scientific Research*, vol. 4, no. 2, pp. 43–48, 2025, doi: 10.25299/ijsr.2024.21941.
- [23] T. Tahtouh *et al.*, "Technological enhancements in personalized dietary management for chronic conditions," *Biomedical Engineering Advances*, vol. 10, 2025, doi: 10.1016/j.bea.2025.100181.
- [24] T. Hulsen and M. Scheper, "AI in healthcare: do not forget about allied healthcare," *AI*, vol. 6, no. 6, pp. 1–10, 2025, doi: 10.3390/ai6060114.
- [25] A. Mishra, Y. I. Alzoubi, and N. Gavrilovic, "Quality attributes of software architecture in IoT-based agricultural systems," *Smart Agricultural Technology*, vol. 8, 2024, doi: 10.1016/j.atech.2024.100523.
- [26] R. Sharma, S. S. Gaur, A. Ajay, R. Shams, and K. K. Dash, "Artificial intelligence and precision nutrition: tailoring diets with data-driven insights," *Nutrire*, vol. 50, no. 2, 2025, doi: 10.1186/s41110-025-00360-4.
- [27] N. K. P. Pushparaj, L. Mohan, A. K. Ambikalekshmi, E. Cherian, R. Rajan, "AI and IoT in nutritional science: transforming digestion research and precision nutrition," *Current Research in Nutrition and Food Science*, vol. 14, no. 1, 2025.
- [28] A. Arefeen, S. Fessler, S. M. Mostafavi, C. S. Johnston, and H. Ghasemzadeh, "MealMeter: using multimodal sensing and machine learning for automatically estimating nutrition intake," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, pp. 1–6, 2025, doi: 10.1109/EMBC58623.2025.11254728.

BIOGRAPHIES OF AUTHORS







Wahyu Wijaya Widiyanto     is a lecturer in the Applied Health Information Management Study Program at Politeknik Indonusa Surakarta, Indonesia. He holds a master's degree in Informatics Engineering from Universitas AMIKOM Yogyakarta and has published research in areas including computer vision, healthcare information security, and IoT system development. His expertise lies in information systems, data security, and applied AI in health informatics. He can be contacted at email: wahyuwijaya@poltekindonusa.ac.id.



Edy Susanto     is a faculty member at Politeknik Indonusa Surakarta in the Applied Software Engineering Technology Study Program. He co-authors works on digital health services and academic enterprise systems targeting enhancements in health institution operations. His interests include software architecture and integration of ICT in health service delivery. He can be contacted at email: edysusanto@poltekindonusa.ac.id.



Sri Suparti     is a public health professional and lecturer at Politeknik Indonusa Surakarta with specialization in Epidemiology. She holds an M.Kes. with a specialization in Epidemiology and is actively involved in health promotion, public health interventions, and education, contributing to community-based health programs and research projects. She can be contacted at email: srisuparti@poltekindonusa.ac.id.