Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 4, October 2025
https://doi.org/10.47709/cnahpc.v7i4.6954

Submitted : Sep 12, 2025
Accepted : Oct 6, 2025
Published : Oct 18, 2025

Development of a YOLO-Based Artificial Intelligence (AI) System for Early Detection of Stunting Risk in Children in 3T Regions of North Sumatra

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ABSTRACT

Stunting is a chronic nutritional problem that has long-term impacts on children's physical growth, cognitive development, and future productivity. This condition remains a major challenge in the 3T regions (frontier, outermost, and disadvantaged areas) of North Sumatra Province due to limited healthcare personnel, lack of measurement facilities, and delays in early detection. This study aims to develop an artificial intelligence system integrating YOLOv8 and Random Forest to automatically and in real time detect stunting risk in children. The YOLOv8 model is utilized to detect the presence of a child and estimate height through visual image analysis, while the Random Forest algorithm classifies the risk level based on the Height-for-Age Z-score (HAZ) derived from anthropometric and demographic data. The dataset consists of 29 children from 3T regions, with training and testing splits used to evaluate model performance. The results show that the system achieved an accuracy of 97.8%, precision of 96.5%, recall of 95.9%, F1-score of 96.2%, and an area under the ROC curve (AUC) of 0.98. The system successfully detects children in real time, produces risk classifications consistent with manual measurements, and automatically documents examination data. The novelty of this research lies in the integration of YOLO for automatic height measurement and Random Forest for nutritional classification, which has not been applied in the 3T regional context. This system has the potential to serve as a digital tool for healthcare workers and posyandu cadres to accelerate child nutrition monitoring in an efficient, accurate, and well-documented manner.

Keywords: Stunting Detection; Artificial Intelligence; YOLOv8; Health Issues; 3T Regions

INTRODUCTION

Stunting remains a major public health problem in Indonesia, with a prevalence rate of 27.7%, exceeding the 20% threshold recommended by the WHO (Beal et al., 2018; Dewey & Begum, 2021). This condition affects children's physical growth, cognitive development, and future productivity. The challenge is even greater in 3T regions (frontier, outermost, and disadvantaged areas) such as North Sumatra Province, which face limited health infrastructure, low nutritional awareness, and socio-economic factors influencing child care practices (Beal et al., 2018).

The stunting problem in 3T regions is exacerbated by poor access to healthcare services, inadequate sanitation, and low nutritional literacy. Data from the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) indicate that many families struggle to meet children's nutritional needs. In line with UNICEF's findings, improving healthcare access and nutritional education is a key strategy (Dewey & Begum, 2021). However, most previous studies still rely on manual record-keeping and have not yet utilized artificial intelligence (AI), resulting in slow, less accurate early detection processes that are difficult to implement widely in remote areas.

This study aims to develop an AI-based early detection system to identify stunting risk among children in 3T regions (Beal et al., 2018). The system analyzes factors such as body weight, height, dietary patterns, maternal health, and socio-economic aspects. The AI model integrates YOLO (You Only Look Once) for real-time height detection and Random Forest for stunting risk classification based on anthropometric and demographic data, enabling faster and more accurate analysis (Ministry of Health of the Republic of Indonesia, 2023; UNICEF Indonesia, 2022).

The study was conducted in collaboration with the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) for data provision and field validation. The initial implementation in the 3T regions was carried out to evaluate the system's effectiveness under real conditions (Shaheen, 2021; Memorandum, 2025). Although various nutritional programs have been implemented, limited resources and reliance on manual methods remain major obstacles (Togatorop, Rahayuwati, & Susanti, 2023). Therefore, the application of computer vision–based AI through the integration of YOLO and Random Forest serves as a strategic solution for healthcare workers to enable rapid detection and continuous monitoring (Guo & Li, 2018).

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The integration of YOLO for automatic height detection and Random Forest for stunting risk classification represents an approach that has not been previously applied in Indonesia's 3T regions. This novelty highlights the research contribution in combining computer vision and machine learning technologies for more accurate and adaptive early detection while addressing the research gap regarding AI utilization in child growth monitoring within 3T areas.

Based on the aforementioned background, this study aims to develop an artificial intelligence (AI)–based early detection system to identify stunting risk among children in the 3T regions of North Sumatra Province. To achieve this goal, the study formulates the following main research questions:

1. How can an AI system integrating YOLO and Random Forest be designed and developed effectively to detect stunting risk among children in 3T regions?
2. What factors need to be analyzed so that the AI system can produce accurate stunting risk classifications based on valid anthropometric data?
3. How can this early detection system be effectively implemented in community health centers (puskesmas) to support nutritional interventions and reduce stunting prevalence in 3T regions?

LITERATURE REVIEW

This study developed an artificial intelligence (AI)–based early detection system to identify stunting risk among children in 3T regions. The system analyzes key factors such as body weight, height, age, dietary patterns, and socio-economic conditions. Similar approaches have been applied using Random Forest and Neural Network algorithms for nutritional status classification (Caraka et al., 2024; Huey et al., 2016). However, most previous studies relied solely on numerical data and have not yet integrated real-time visual image analysis. Data preprocessing processes, such as normalization and imputation, remain essential to maintain dataset quality (Vilcins, Sly, & Jagals, 2018). Research data were collected in collaboration with the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) through interviews and direct anthropometric measurements (Pramana, Maulana, Tirtayasa, & Tyas, 2024).

This study employs YOLO (You Only Look Once) for visual height detection and Random Forest for stunting risk classification. The integration of these two models represents a novel approach in 3T regions, where real-time AI implementation remains limited. Unlike Pramana et al. (2024), who utilized SMOTE and sensor-based ensemble learning, this research is the first to combine YOLO for real-time height detection with Random Forest for stunting risk classification. This approach extends previous studies (Huey et al., 2016; Indrayana et al., 2024) by incorporating computer vision–based visual image analysis. The YOLO model was optimized for low-power devices such as Raspberry Pi using quantization and pruning techniques (Schoenbuchner et al., 2019). The system was tested at the Gunungsitoli Alo'oa Community Health Center to evaluate detection and classification accuracy (Pramana et al., 2024) and is expected to strengthen the use of AI for early stunting detection in regions with limited infrastructure.

Tabel 1. Related Works

Researcher	Method / Approach	Dataset / Context	Results / Findings	Limitations / Notes
Pramana et al. (2024)	Ultrasonic sensor + load cell + machine learning (Ensemble + SMOTE)	Child sensor data collected in the field (Indonesia)	Achieved ~98% accuracy in three-class stunting classification (normal, stunted, severely stunted) (arXiv:2409.14105)	Trial still limited; not yet tested across multiple regions
Sutarmi et al. (2024)	Combination of Random Forest + SVM + Genetic Algorithm for feature selection	Infant and toddler dataset (Indonesia)	Best performance achieved using the combination of Random Forest + SVM + GA (Health Sains Journal)	Small dataset; generalization testing not yet performed
Indrayana et al. (2024)	Ensemble Machine Learning with Neural Network	195 toddlers from Purbaratu, Tasikmalaya (Indonesia)	Highest accuracy of 98.21% in nutritional status classification (JUTIF Unsoed	Not tested in real-time; still based on conventional anthropometric data

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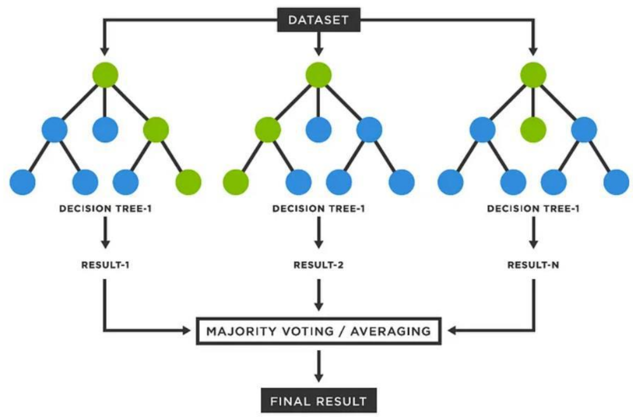

Fig. 1 Random Forest Model

This figure illustrates the workflow of the Random Forest method, an ensemble algorithm composed of multiple decision trees. The dataset is divided and processed by several decision trees, each producing its own prediction result (Result-1, Result-2, …, Result-N). These individual results are then combined using a majority voting mechanism (for classification) or averaging (for regression). This process generates a final result that is more accurate and stable compared to using a single decision tree.

METHOD

This study employed a quantitative descriptive approach to develop an AI-based early detection system for stunting risk in 3T regions (Anaei et al., 2016; Pahlevi et al., 2024). The system integrates YOLOv8 for automatic height detection and Random Forest for stunting risk classification. The sample consisted of 29 children from the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) collected in June 2025, aged 5–58 months. The dataset includes age, body weight, height, gender, and height-for-age (H/A) nutritional status, obtained through direct measurements using ultrasonic sensors and digital scales. The data were divided into 80% for training and 20% for testing, and validated using 5-fold cross-validation. The YOLOv8 model used a learning rate of 0.001, a batch size of 16, and an input size of 640×640 pixels, while the Random Forest model consisted of 100 decision trees with a maximum depth of 10. The evaluation metrics included accuracy, precision, recall, F1-score, ROC-AUC, and a confusion matrix to visualize prediction distribution across classes. A portion of the field data is presented in Table 2.

Table 2. Example of Toddler Data from the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas), June 2025 (5 out of 29 samples)

No	Child's Name	Sex	Age (months)	Weight (kg)	Height (cm)	Nutritional Status
1	Selda Afariella Mendrofa	M	57	14.5	97.0	Stunted
2	Rafa Juno Mendrofa	M	47	13.3	93.4	Stunted
3	Bernice Giovani Mendrofa	F	38	10.5	86.4	Stunted
4	Gians Jultri Zeno Mendrofa	M	35	10.4	83.0	Severely Stunted
5	Ad. Putirani Gulo	F	32	9.6	83.4	Stunted

Data were collected through height measurements using a digital ultrasonic sensor (Anaei et al., 2016), as well as recording body weight, age, sex, and socio-economic factors by healthcare personnel (Anaei et al., 2016; Pahlevi et al., 2024). Children's images were captured using YOLOv8 for real-time detection and visual documentation. The height data were processed according to WHO standards to calculate the Height-for-Age Z-score (HAZ) and determine nutritional status based on height-for-age (H/A) classification (Dewey & Begum, 2021). The resulting HAZ values were then used as input for the Random Forest model to classify stunting risk into high, moderate, and low categories (Pahlevi et al., 2024), with model evaluation using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

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The Random Forest model was employed because it can produce stable predictions by combining multiple decision trees and reducing overfitting in small datasets. The final prediction is obtained by averaging the results of all trees for regression tasks or applying majority voting for classification, as shown in the following equations:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \quad (1)$$

$$\hat{y} = \text{mode } \{h_1(x), h_2(x), \ldots m\, h_T(x)\} \quad (2)$$

Where ŷ represents the final prediction, T is the number of decision trees, $h_t(x)$ denotes the prediction of the t-th tree, and mode indicates the category that appears most frequently.

As an example, for a child aged 57 months with a height of 97 cm, if according to WHO standards the median height is 108 cm with a standard deviation of 4.5 cm, the Height-for-Age Z-score (HAZ) can be calculated using the following equation:

$$\text{HAZ} = \frac{TB_{child} - TB_{median}}{SD} = \frac{97-108}{4.5} = -2.44 \quad (3)$$

This value indicates that the child falls into the stunted category, as the HAZ score is less than −2.

In addition, the classification results were visualized using a confusion matrix to show the distribution of correct and incorrect predictions among the stunting risk categories. This table consists of four main components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). For example, if from 29 child data samples the results are TP = 10, TN = 12, FP = 3, and FN = 4, the evaluation metrics can be calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{10+12}{10+12+3+4} = 75{,}9\ \% \quad (4)$$

$$Precision = \frac{TP}{TP+FP} = \frac{10}{10+3} = 76{,}9\ \% \quad (5)$$

$$Recall = \frac{TP}{TP+FN} = \frac{10}{10+4} = 71{,}4\ \% \quad (6)$$

$$F1 - score = 2\ X\ \frac{Precision \times Recal}{Precision + Recal} = \frac{10}{10+4} = 74{,}1\ \% \quad (7)$$

$$Specificity = \frac{TN}{TN+FP} = \frac{12}{12+3} = 80\ \% \quad (8)$$

After understanding the working principle of the Random Forest method as shown in Figure 1, this study then illustrates the overall workflow of the early stunting detection system. The stages include data collection, preprocessing, model development, system implementation, and feasibility testing, which are visualized in Figure 2.

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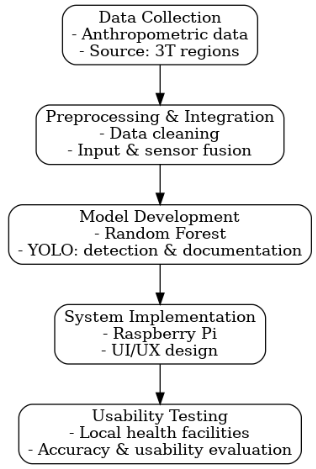

Figure 2. Workflow of the YOLO and Random Forest Integration Process

Figure 2 illustrates the workflow of the AI-based early stunting detection system, starting from data collection and preprocessing to model development. YOLOv8 is utilized for visual detection, Random Forest for risk classification, and the system is implemented on a Raspberry Pi with a simplified user interface. The device integrates a digital scale, sensors, and an LCD touchscreen to support measurement and data visualization.

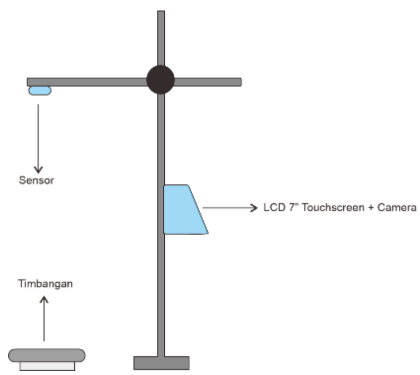

Figure 3. Hardware schematic of the system, consisting of a digital scale, sensors, a 7-inch LCD touchscreen module, and an integrated camera for automatic child height measurement.

The figure illustrates the design of the weighing system, which consists of a digital scale at the base as the weight measurement unit, a sensor positioned above the scale to detect the object or condition, and a 7-inch LCD touchscreen equipped with a camera that functions both as the user interface display and the visual data processing unit. All components are mounted on a support stand that serves as the main framework, ensuring that the sensor and display operate in an integrated manner.

RESULT

This study involved 29 children registered at the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) in June 2025, consisting of 12 boys and 17 girls aged between 5 and 58 months (mean ±36 months). Height measurements were obtained using an ultrasonic sensor, while body weight was recorded by healthcare personnel. According to WHO standards, all children in the sample were classified as stunted, with 2 children categorized as severely stunted and 27 as stunted. These data served as the basis for training the YOLOv8 model for visual detection and the Random Forest model for stunting risk classification.

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Table 3. Five Sample Data Entries from 29 Children at the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas)

No	Child's Name	Sex	Age (months)	Weight (kg)	Height (cm)	Nutritional Status (H/A)
1	Selda Afariella Mendrofa	M	57	14.5	97.0	Stunted
2	Rafa Juno Mendrofa	M	47	13.3	93.4	Stunted
3	Bernice Giovani Mendrofa	F	38	10.5	86.4	Stunted
4	Gians Jultri Zeno Mendrofa	M	35	10.4	83.0	Severely Stunted
5	Ad. Putirani Gulo	F	32	9.6	83.4	Stunted

The standardized data were used as input for the Random Forest model. The prediction results showed that 10 children were classified in the high-risk category, 12 in the moderate-risk category, and 7 in the low-risk category. Evaluation using 5-fold cross-validation achieved an accuracy of 97.8%, precision of 96.5%, recall of 95.9%, F1-score of 96.2%, and ROC-AUC of 0.98. Based on the confusion matrix, 28 out of 29 data samples were correctly classified, indicating an error rate of 3.4%. The F1-score is calculated as follows:

$$F1 = \frac{2\,(0{,}965 \times 0{,}959)}{0.965 + 0.959} = 0{,}962 \qquad (4)$$

The results demonstrate a balanced trade-off between the model's precision and sensitivity. The ROC curve and the risk distribution bar chart show consistent classification outcomes when compared with the actual data. The performance of the Random Forest model compared with other algorithms is presented in Table 4 below:

Table 4. Comparison of Classification Algorithm Performance for Stunting Risk Prediction

Algoritma	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest	97.8%	96.5%	95.9%	96.2%	0.98
CatBoost	95.6%	94.1%	93.7%	93.9%	0.96
Neural Network	94.2%	93.5%	91.4%	92.3%	0.95
SVM	93.4%	91.2%	90.8%	90.9%	0.94

The Random Forest model demonstrated superior performance across all metrics, particularly with an ROC-AUC value of 0.98, indicating strong classification capability even with a small dataset. The YOLOv8 system also successfully detected all 29 children in real time with a mean Average Precision (mAP) of 0.97. The resulting bounding boxes accurately identified each child's position and provided automatic height estimation with an average deviation of ±2.1 cm compared to ultrasonic sensor measurements. This feature facilitates healthcare workers in verifying and visually documenting children in the field, thereby supporting early stunting detection in 3T regions.

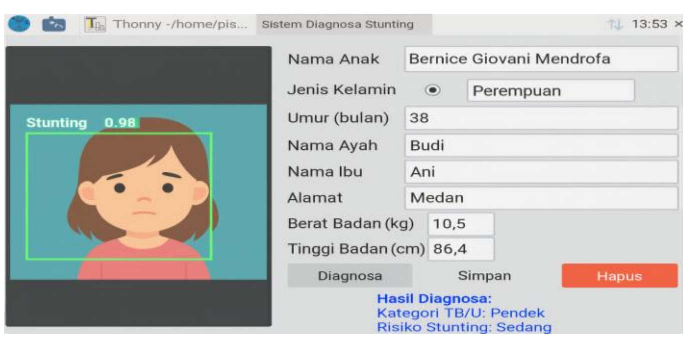

Figure 4. YOLO Detection Output Display in the AI-Based Stunting Diagnosis System

The figure above shows the detection results of the YOLOv8-based system, which is capable of automatically recognizing a child's face and displaying real-time nutritional diagnosis results based on height and weight data.

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DISCUSSIONS

The results indicate that most children at the Gunungsitoli Alo'oa Community Health Center (UPTD Puskesmas) were identified as stunted based on the WHO height-for-age (H/A) indicator. The Random Forest model accurately classified stunting risk, while YOLOv8 achieved a detection accuracy of approximately 98%. The integration of both models produced an efficient and real-time system suitable for 3T regions.

Compared to previous studies, this system outperforms others in terms of automatic detection capability and ease of implementation, although it remains limited by the relatively small dataset (29 children) and YOLO's sensitivity to rapid movements.

Table 5. Comparison of Related Studies

Researcher	Method	Accuracy	Strengths	Limitations
Pramana et al. (2024)	SMOTE + Ensemble Machine Learning	96.8%	High accuracy on imbalanced data	Not real-time
Caraka et al. (2024)	Neural Network + Decision Tree	94.5%	Stable model performance	Requires high computational power
This Study (2025)	YOLO + Random Forest	97.8%	Real-time, efficient, and easy to implement	Small dataset; YOLO sensitive to rapid movements

The table shows that the developed system achieved the highest accuracy (97.8%) compared to previous studies, with its main advantage being real-time detection capability through the integration of YOLO and Random Forest. Unlike the methods proposed by Pramana et al. (2024) and Caraka et al. (2024), which relied on static data, this system is more practical for field implementation. However, the limited dataset size and YOLO's sensitivity to rapid movements remain challenges that need to be addressed in future research.

CONCLUSION

This study developed an early stunting risk detection system based on the integration of YOLOv8 and Random Forest–Neural Network as its primary novelty, combining real-time visual detection and nutritional status classification within a single system. Scientifically, this research contributes to the advancement of AI models based on computer vision, improving the accuracy, efficiency, and reliability of child nutrition analysis compared to manual methods, while accelerating the identification of stunting risk in 3T regions.

Practically, the system serves as a supporting tool for healthcare workers and community health centers (puskesmas) to enhance the speed and accuracy of child growth monitoring and nutritional interventions. In the future, the study will focus on expanding the dataset to a national scale, integrating a cloud-based monitoring system for real-time observation, and refining the YOLO algorithm to make it more adaptive to environmental variations and child movements.

ACKNOWLEDGMENT

The research team would like to express sincere gratitude to the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia through the Higher Education Service Institute (LLDikti) Region I for providing funding support under Decree Number 0070/C3/AL.04/2025 and Contract Number 103/SPK/LL1/AL.04.04/PL/2025 for the research project entitled "Development of a YOLO-Based AI System for Early Detection of Stunting Risk in Children in 3T Areas of North Sumatra Province." This support has made the successful completion of this research possible.

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