ARTIFICIAL INTELLIGENCE-BASED MODEL FOR STUNTING RISK PREDICTION AND GROWTH MONITORING USING CHILD ANTHROPOMETRIC DATA

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ABSTRACT

Stunting remains a major public health problem that requires early identification and continuous growth monitoring. This study developed an artificial intelligence-based model for stunting risk prediction and child growth monitoring using anthropometric data. The proposed framework integrates stunting detection, growth monitoring, risk prediction, nutrition analysis, and health education through an AI Engine consisting of data input, data processing, feature extraction, AI modeling, and risk output. A total of 60 child records were evaluated using four anthropometric configurations: Weight-for-Age, Height-for-Age, Head Circumference-for-Age, and a combination of Weight, Height, and Head Circumference according to age. The results showed accuracies of 85.1%, 86.0%, 90.6%, and 82.3%, respectively. Head Circumference-for-Age achieved the highest accuracy of 90.6% in the evaluated dataset. These findings demonstrate the potential of anthropometric data and artificial intelligence for supporting stunting risk prediction and child growth monitoring. Further validation using larger and longitudinal datasets is required to establish model robustness and generalizability.

KEYWORDS

artificial intelligence; stunting; risk prediction; growth monitoring; anthropometric data.

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INTRODUCTION

Background

Stunting remains a public health issue of global concern, particularly in developing nations, including Indonesia. It is a condition characterized by impaired growth resulting from chronic malnutrition and various factors persisting over an extended period,

especially during early life. Data from the Indonesian Ministry of Health (2022) indicate that the prevalence of stunting among children under five in Indonesia stands at approximately 21.6%, within a population of roughly 30.73 million children in this age group [1],[2]. This situation highlights that stunting remains a serious challenge for human resource development. Stunting is associated with malnutrition during early life—specifically the 0–23 month age range—and is influenced by a variety of factors, such as maternal nutritional status, the child's nutritional intake, family socioeconomic conditions, parenting practices, sanitation, and environmental factors [3],[4]. The consequences of stunting extend beyond childhood into adulthood, manifesting as impaired cognitive development, reduced productivity, and an increased risk of chronic diseases [5].

Continuous monitoring of child growth is a crucial aspect of stunting prevention. Growth monitoring via anthropometric measurements—such as height or length, weight, and age-based growth indicators—enables the early identification of changes in a child's condition. A key indicator in growth assessment is the Height-for-Age Z-score (HAZ), which describes a child's height status relative to their age. However, in practice, growth measurement data are often used solely to determine nutritional status at a single point in time, meaning that information regarding growth trends and shifting risks over time is not optimally utilized. This situation can result in a failure to promptly detect changes in growth patterns that indicate an increased risk of stunting.

The next challenge lies in the early detection and risk prediction of stunting. Conventional approaches generally rely on measurements and interpretations made by healthcare professionals during periodic monitoring. While these approaches are important, they do not yet fully leverage computational capabilities to systematically analyze growth data patterns. Advances in Artificial Intelligence (AI)—specifically machine learning and deep learning—offer opportunities to develop models capable of learning patterns from anthropometric data and generating structured risk estimates. By utilizing data on height, weight, age, height-for-age Z-score (HAZ), and measurement history, AI can be employed not only to identify stunting but also to support risk-level prediction and continuous monitoring of child growth.

Another important consideration is that stunting prevention extends beyond mere anthropometric measurements. Dietary intake and nutritional quality are crucial for supporting child growth; therefore, information regarding food consumption provides valuable context for stunting prevention efforts. Advances in computer vision enable the automated analysis of food images to identify food types and subsequently link them to nutritional content data. In developing this system, food analysis is designed to complement child growth data, ensuring the system goes beyond simple risk identification to provide context regarding relevant nutritional aspects. Furthermore, an educational component is essential, as prediction results and nutritional analyses must be translated into information that is easily understood and actionable for both parents and healthcare professionals. Consequently, integrating AI-driven nutritional analysis and health education—including through chatbot mechanisms—can serve as a supporting component within the stunting prevention ecosystem.

While research on AI applications for child health has advanced, a gap remains regarding the continuous integration of growth monitoring and stunting risk prediction based on anthropometric data. AI models developed in various studies often focus on specific tasks—such as classifying stunting status or making predictions based on anthropometric data at a single point in time. Such approaches do not yet fully accommodate the need for a system capable of managing child profiles, longitudinal measurement data, growth indicators, stunting status, and risk predictions within a unified, integrated workflow. Furthermore, prediction outputs must be translatable into actionable

information that supports decision-making and interventions, rather than merely providing raw predictive values from the model.

To address these issues, this study developed an Artificial Intelligence-based model for predicting stunting risk and monitoring child growth using anthropometric data. The model utilizes child measurement data and growth indicators to perform data processing, feature extraction, and AI modeling, ultimately generating a risk score and risk category. This model is integrated into a system that supports stunting detection, child growth monitoring, stunting risk prediction, nutritional analysis, and health education. The developed architecture enables the structured storage of child data and measurement history, allowing for the monitoring of growth progress over time. Image-based nutritional analysis and health education components serve as supporting modules, expanding the system's functionality from simple risk prediction to a comprehensive tool for stunting prevention. The developed system incorporates modules for child data management, measurements, HAZ-based screening, risk prediction, computer vision-based food analysis, and a nutrition education chatbot.

Thus, the novelty of this research lies not merely in the use of AI to detect stunting, but in the development of an approach that integrates anthropometric data, growth monitoring, and risk prediction into a single, sustainable AI framework. This integration is expected to provide more systematic information regarding a child's growth status and risk level, thereby supporting early detection and the prevention of stunting. Furthermore, the nutrition analysis and health education modules extend the utility of the analysis results, translating them into information and recommendations that are more accessible and practical for parents and healthcare professionals.

Based on the preceding description, the research problems are formulated as follows:

1. How can an Artificial Intelligence model be developed to predict stunting risk based on children's anthropometric data?
2. How can longitudinal measurement data be utilized to support child growth monitoring and the identification of changes in stunting risk?
3. How can the results of stunting detection, growth monitoring, and risk prediction be integrated into a system that provides easily interpretable information?
4. How can image-based nutritional analysis and AI-driven health education be integrated as supporting components within a stunting prevention system?
5. How well does the AI model perform in predicting stunting risk based on children's anthropometric data?

State of the Art and Novelty

Previous research relevant to the proposed topic is presented in Table 1.

Table 1. Relevant Previous Research

No	Author	Year	Method	Weakness
1	Hao Shen [6]	2023	least absolute shrinkage and selection operator (LASSO) and random-forest- recursive	*This method is an unstable model estimator, where small changes in the data can result in a different model (Agus M. Soleh, 2013).*
2	Misaal Khan [7]	2023	deep learning VGG	Another drawback of deep learning is the difficulty of interpreting the models, as deep learning is capable of learning highly complex patterns.
3	Nur Fitriyani Sahamony [8]	2024	*Random Forest, Logistic Regression, Naïve Bayes,* SVM dan *Neural Networks*	Learning can proceed slowly, depending on the parameters used, and the resulting model cannot be iteratively improved.

No	Author	Year	Method	Weakness
4	Obvious Nchimunya Chilyabanyama [9]	2022	Regresi logistik (LR), Random Forest (RF), klasifikasi SV (SVC), XG Boost (XgB), dan algoritma Naïve Bayes (NB)	prone to underfitting on imbalanced datasets, resulting in low accuracy.
5	Stefanus Pieter Manongga [10]	2023	k-Means clustering	If the randomly generated values for the centroids are poor, the resulting clustering will be suboptimal. It is quite difficult to use this approach for searching... distance from high-dimensional data
6	Sutarmi [11]	2023	Random Forest dengan Support Vector Machine	The SVM algorithm is not suitable for large datasets because it requires a long training time.
7	Syahrial [12]	2022	support vector machine - kernel rbf (SVM-RBF)	The SVM algorithm is not suitable for large datasets because it requires a long training time.
8	Muhammad Al-Husaini [13]	2023	*Random Forest dan* xGBoost	Determining the value of each parameter is difficult, thereby consuming a significant amount of time.

The table above indicates that existing research has been limited to developing AI-based models for the early detection of stunting. A fully integrative approach that combines various determinants of stunting into a single AI-based system remains rare. Methods employed by previous researchers suffer from several shortcomings, including model instability—where minor data changes can yield different models—difficulty in model interpretation, slow learning processes, susceptibility to underfitting on imbalanced datasets, suboptimal clustering results, long training times, and the difficulty of determining specific parameter values. Meanwhile, the proposing team aims to conduct research featuring the novelty of developing an integrative approach model for stunting prevention based on Artificial Intelligence (AI), which can be implemented within digital systems to facilitate early detection and more effective intervention.

RESEARCH METHOD

Developed Model

The model developed in this study is an integrated artificial intelligence model designed to support stunting detection, child growth monitoring, stunting risk prediction, nutritional analysis, and health education. The model operates by integrating data—such as child anthropometrics, growth history, food imagery, and user inquiries or educational needs—into an AI engine that generates information on stunting status, growth trends, risk levels, nutritional analysis, and health recommendations. Through this approach, the system functions not merely as a detection tool but also as a support system for continuous stunting monitoring and prevention. The developed model is illustrated in Figure 1.

Conceptually, the model consists of five main components: (1) Stunting Detection, (2) Child Growth Monitoring, (3) Stunting Risk Prediction, (4) Nutrition Analysis, and (5) Health Education. These five components are interconnected via an AI engine and a database, allowing information generated by one component to support the others.

1. Stunting Detection

The Stunting Detection component serves as the initial stage for identifying a child's growth status based on anthropometric data—specifically, height/length-for-age

(HAZ). Measurement data are compared against growth standards used by the system to classify the child's growth status (e.g., normal, moderate stunting, or severe stunting). The results of this detection process form the basis for subsequent growth monitoring and risk assessment.

2. *Child Growth Monitoring*

The Child Growth Monitoring component is used to track a child's growth progress periodically. Data on height, weight, BMI, HAZ, and other growth indicators are stored as a growth history, enabling the system to identify growth patterns and trends. This information is then visualized through growth charts, making it easier to monitor changes in the child's condition over time.

3. *Stunting Risk Prediction*

The Stunting Risk Prediction component serves as the model's artificial intelligence core. Processed anthropometric data and growth indicators serve as inputs for the AI/ML model. This stage encompasses data processing, feature extraction, AI modeling, and risk assessment. Features such as HAZ, WAZ, BMI-for-Age, and other growth indicators are used to generate a risk score and risk categories (e.g., Low, Medium, and High). The system is also designed to identify factors contributing to the risk level, thereby making the prediction results easier to interpret.

4. *Nutrition Analysis*

The Nutrition Analysis component expands the system from mere growth monitoring to an analysis of a child's nutritional needs. Food images serve as input for computer vision-based food recognition; the identified food items are then linked to nutritional data to estimate energy and nutrient content and assess dietary adequacy. Consequently, the analysis results can be used to provide dietary recommendations better suited to the child's growth status and risk profile.

5. *Health Education*

The Health Education component provides an AI-based education and communication mechanism via a chatbot. This module can be used to deliver information regarding child growth, stunting prevention, nutrition, dietary habits, and child health. User inquiries are processed using a health knowledge base, enabling the system to provide information and recommendations that are easily understood by both parents and healthcare professionals.

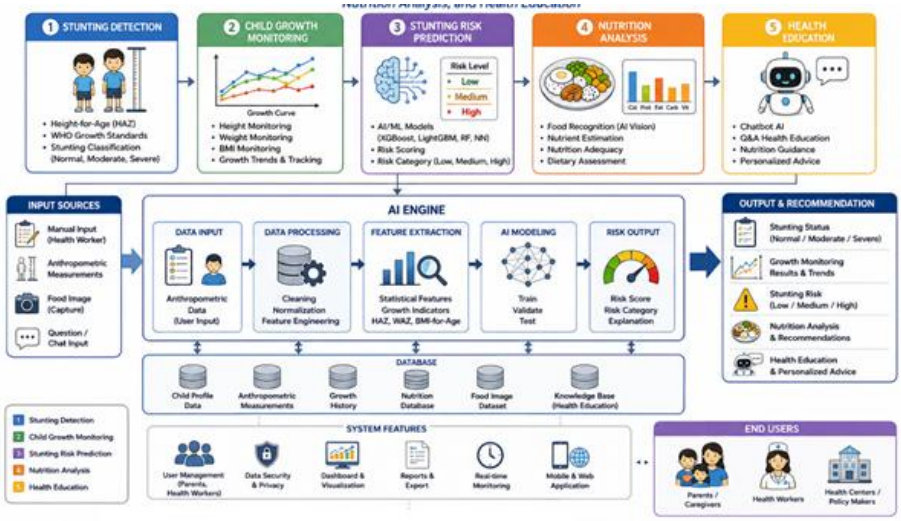


Figure 1. The Developed Model

AI Engine Architecture

The five components are integrated via the AI Engine, which consists of several key stages, as shown in Figure 2.

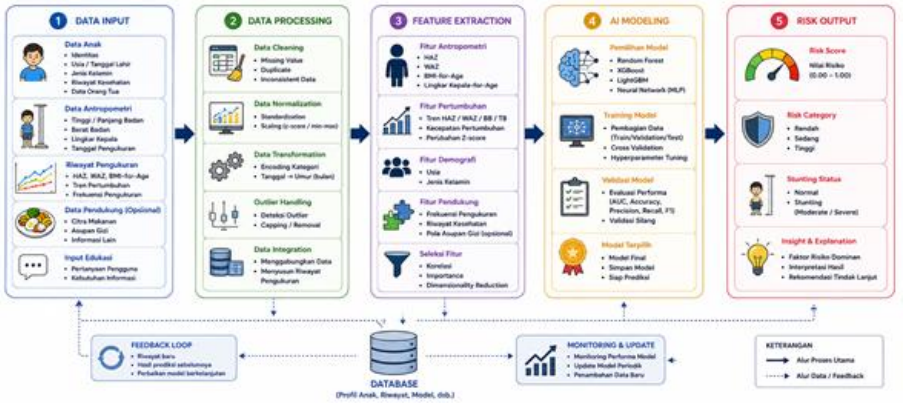


Figure 2. AI Engine Stages

In the Data Input stage, the system receives the child's anthropometric data, measurement results, food images, and user queries. Subsequently, Data Processing performs data cleaning, normalization, and feature engineering. In the Feature Extraction stage, the system derives growth indicators such as HAZ, WAZ, and BMI-for-Age. These features are then utilized in AI Modeling for training, validation, testing, and prediction processes. The final stage generates a Risk Output comprising a risk score, risk category, stunting status, and information supporting the interpretation of the results.

Database Integration

The entire process is supported by a database that stores various types of information: child profiles, anthropometric data, growth history, a nutrition database, food datasets/images, and a knowledge base for health education. Storing historical data enables the system to conduct longitudinal monitoring and compare changes in a child's condition over time. With this architecture, SMART-STUNTING establishes an integrated workflow, as illustrated in Figure 3.

The system's final output consists of stunting status, growth and development information, stunting risk levels, and nutritional analysis results, as well as health recommendations and educational materials that can be utilized by parents, healthcare professionals, and health program administrators.

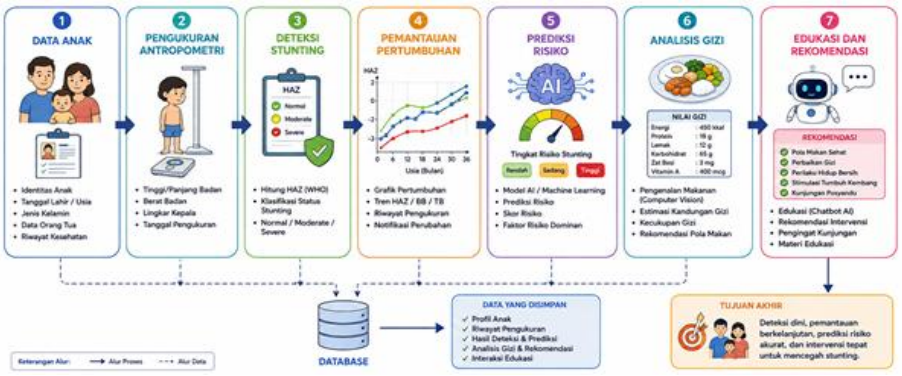


Figure 3. SMART-STUNTING Integrated Workflow

RESULT AND DISCUSSION

Results

The developed artificial intelligence-based model was evaluated using 60 child anthropometric data records. The evaluation was conducted to investigate the predictive performance of different anthropometric configurations for stunting risk prediction. Four testing scenarios were performed using Weight-for-Age, Height-for-Age, Head Circumference-for-Age, and a combination of Weight, Height, and Head Circumference according to age. The evaluation results are presented in Table 1.

Table 1. Performance of AI Model Based on Anthropometric Configurations

Testing	Anthropometric Configuration	Accuracy
Testing 1	Weight-for-Age	85.1%
Testing 2	Height-for-Age	86.0%
Testing 3	Head Circumference-for-Age	**90.6%**
Testing 4	Weight + Height + Head Circumference/Age	82.3%

The results demonstrate that all four configurations produced classification accuracies above 80%. Testing 1 using Weight-for-Age achieved an accuracy of 85.1%, indicating that weight-related anthropometric information provided useful predictive information for the evaluated dataset. Testing 2 using Height-for-Age achieved a slightly higher accuracy of 86.0%, showing an improvement of 0.9 percentage points compared with the Weight-for-Age configuration. The highest performance was obtained in Testing 3 using Head Circumference-for-Age, with an accuracy of 90.6%. This result represents an improvement of 5.5 percentage points compared with Testing 1 and 4.6 percentage points compared with Testing 2. In contrast, Testing 4, which incorporated Weight, Height, and Head Circumference according to age, achieved an accuracy of 82.3%, which was the lowest performance among the four evaluated configurations. Overall, the experimental results indicate that the predictive performance of the model varied according to the anthropometric configuration used as input. In the evaluated dataset, Head Circumference-for-Age produced the highest classification accuracy, whereas the combination of the three anthropometric measurements did not result in improved predictive performance. The implementation of the developed model is shown in Figures 4 and 5.



Figure 4. Stunting Screening Results Display.

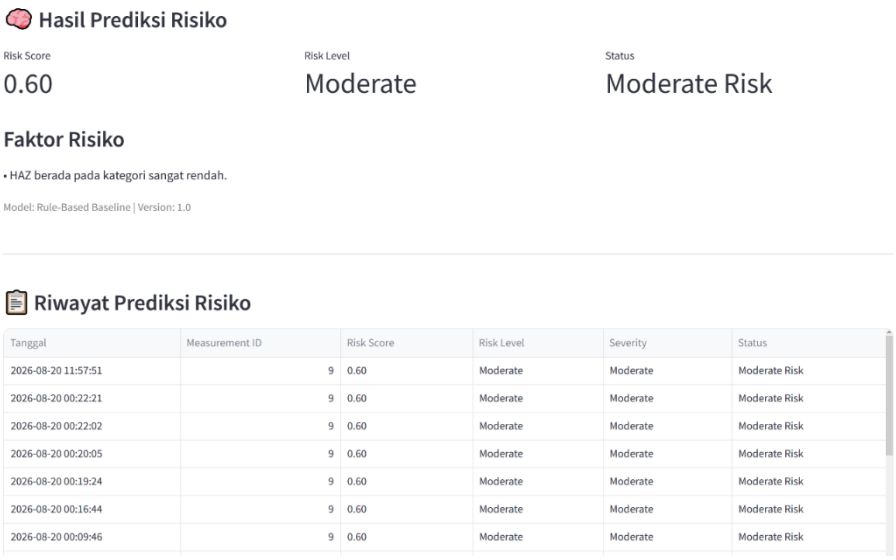


Figure 5. Risk Prediction Results

Discussion

The results demonstrate that anthropometric variables can provide useful information for artificial intelligence-based stunting risk prediction. However, the variation in accuracy across the four testing scenarios indicates that the contribution of each anthropometric indicator to the prediction is not necessarily equivalent. The difference in performance suggests that the selection and representation of anthropometric features may influence the ability of the AI model to distinguish between the evaluated classes. The Weight-for-Age configuration achieved an accuracy of 85.1%, indicating that body weight relative to age contains relevant information for the prediction task. Weight is an important indicator of a child's nutritional and growth condition; however, weight alone may not fully represent linear growth impairment. This may explain why the performance of the Weight-for-Age configuration was lower than that obtained using Height-for-Age and Head Circumference-for-Age in the present experiment.

The Height-for-Age configuration produced an accuracy of 86.0%. The slightly higher performance compared with Weight-for-Age indicates that information related to linear growth was useful for the evaluated prediction task. Height-for-Age is particularly relevant in the context of stunting because stunting is fundamentally associated with impaired linear growth relative to age. Nevertheless, in the present dataset, Height-for-Age did not produce the highest accuracy. An important finding was obtained from Testing 3, where Head Circumference-for-Age achieved the highest accuracy of 90.6%. The result indicates that, within the evaluated dataset, this anthropometric configuration provided the strongest predictive performance among the four tested configurations. The finding is noteworthy because it demonstrates that the highest-performing feature configuration is not necessarily the variable that would be expected solely from the clinical definition of stunting. The AI model may capture patterns in the available dataset that are not apparent when considering individual anthropometric indicators independently.

However, the result should be interpreted cautiously. The dataset consisted of 60 records, and therefore the observed 90.6% accuracy should be interpreted as a result specific to the evaluated dataset rather than evidence that Head Circumference-for-Age is universally superior to other anthropometric indicators for stunting prediction. Further validation using a larger and more diverse dataset is necessary to determine whether this

performance is reproducible across different populations and age groups. Another important finding was obtained from Testing 4, where the combination of Weight, Height, and Head Circumference according to age achieved an accuracy of 82.3%. Interestingly, combining multiple anthropometric variables did not improve the predictive performance. Instead, the accuracy was 8.3 percentage points lower than the best-performing Head Circumference-for-Age configuration. This finding demonstrates that increasing the number of input variables does not necessarily result in better model performance.

One possible interpretation is that the combined configuration may contain redundant or less informative information for the evaluated dataset. The addition of multiple features can also introduce variability that makes the classification problem more difficult, particularly when the available dataset is relatively small. Nevertheless, this interpretation remains a hypothesis because the current results do not include feature importance, correlation analysis, or ablation analysis. Therefore, further experiments are required before concluding why the combined configuration produced lower accuracy. From the perspective of the proposed system, the findings support the importance of growth monitoring as a component of AI-based stunting risk assessment. Rather than relying on a single measurement at a particular time, the developed framework is designed to maintain child anthropometric records and use them to support continuous growth monitoring. This allows the system to associate anthropometric measurements with the child's growth history and subsequently provide risk-related information.

The proposed framework also extends beyond prediction by integrating stunting detection, growth monitoring, nutrition analysis, and health education. The prediction component provides information regarding the child's estimated risk, while the nutrition analysis component can provide additional information related to food intake. Meanwhile, the health education component is intended to translate the analytical results into information and recommendations that can be more easily understood by parents and health workers. Thus, the proposed framework is designed not merely as a classification model but as an integrated decision-support environment for stunting prevention.

Overall, the experimental results indicate that the proposed AI-based approach has promising potential for supporting stunting risk prediction and child growth monitoring. The 90.6% accuracy obtained using Head Circumference-for-Age represents the best result among the evaluated configurations. Nevertheless, the lower performance of the combined anthropometric configuration demonstrates the need for further investigation into feature selection, model optimization, dataset expansion, and validation using independent datasets.

CONCLUSION

This study developed an artificial intelligence-based model for stunting risk prediction and child growth monitoring using anthropometric data. Evaluation using 60 child records demonstrated accuracies of 85.1% for Weight-for-Age, 86.0% for Height-for-Age, 90.6% for Head Circumference-for-Age, and 82.3% for the combined anthropometric configuration. Head Circumference-for-Age achieved the highest predictive accuracy in the evaluated dataset, indicating the potential contribution of anthropometric feature selection to AI-based stunting risk prediction. The proposed framework integrates stunting detection, growth monitoring, risk assessment, nutrition analysis, and health education to support early identification and prevention of stunting. Further validation using larger, longitudinal, and independent datasets is required to assess the robustness and generalizability of the model.

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