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IoT-Based Smart Detector with SVM and XGBoost for Real-Time Child Growth Monitoring and Stunting Risk Prediction

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Abstract

Stunting is a major public health issue, particularly in developing countries, causing long-term physical and cognitive impairments in children that reduce their quality of life and future productivity. To address this challenge, this study aims to develop an IoT-based smart detection system for child growth monitoring, enabling quicker and more accurate detection of stunting risks. The proposed system combines both hardware and intelligent software components to measure key growth indicators—height, weight, and BMI—using digital sensors and microcontrollers, transmitting the collected data to a cloud platform for real-time analysis. Machine learning algorithms, such as Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost), are employed to predict stunting risk. Experimental results show that the XGBoost model outperforms SVM, achieving an accuracy of 80%, precision of 82%, recall of 78%, and F1-score of 79.9%, compared to SVM's accuracy of 70%, precision of 68%, recall of 65%, and F1-score of 66.4%. This research provides a scalable technological framework for real-time stunting monitoring and early intervention, with the potential for implementation in resource-limited settings. By supporting national stunting reduction initiatives, the system enhances public health innovation and child welfare.

Keywords : *Early Detection, Health Technology, IoT, Machine Learning Algorithms, Prediction, Stunting.*

1. INTRODUCTION

Stunting is a critical public health issue in Indonesia and other developing countries, caused by chronic malnutrition, particularly during the first 1,000 days of life. According to the World Health Organization (WHO) [1][2], stunting is defined as impaired growth and development in children due to insufficient nutrition, affecting not only physical growth but also cognitive development, educational performance, and long-term productivity [3][4]. The consequences of stunting extend beyond childhood, increasing the risk of non-communicable diseases in adulthood. Therefore, early detection and continuous monitoring of children's growth are vital in preventing stunting and mitigating its negative impact on future generations [5][6].

In Indonesia, stunting remains a significant public health challenge, with recent data showing alarmingly high prevalence rates, making it a top priority for health interventions [7][8]. Delayed detection and intervention result in irreversible physical and cognitive impairments that are difficult to reverse later in life [9]. Despite ongoing national programs and interventions, child growth monitoring in Indonesia still heavily relies on manual methods, which are not only time-consuming but also prone to human error. Furthermore, existing systems often do not provide real-time data, making it difficult to respond quickly to emerging stunting risks [10][11]. These challenges highlight the urgent need for innovative, technology-based solutions that can provide accurate and timely monitoring for both healthcare workers and the community[12].

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Recent advancements in Internet of Things (IoT) technology [13][14] offer promising solutions for real-time child growth monitoring. IoT allows physical devices such as height and weight sensors to be connected to digital networks, enabling automatic and continuous data collection. By connecting these devices to a central platform, growth data can be accessed in real-time by healthcare providers and parents, eliminating[15][16] the delays inherent in manual systems. Moreover, the integration of machine learning (ML) algorithms with IoT technology can enhance the predictive capabilities of these systems. In this study, we propose combining IoT-based growth monitoring with two advanced ML algorithms: Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost). These algorithms are used to classify and predict the risk of stunting based on key anthropometric data such as height, weight, and body mass index (BMI).

The novelty of this research lies in the integration of IoT-based child growth monitoring with machine learning models to create a smart, mobile-accessible platform. Unlike traditional methods, this system not only measures growth indicators but also analyzes data and provides real-time alerts to parents and healthcare professionals when signs of stunting risk are detected. This integrated approach allows for early intervention, ensuring that children at risk of stunting can receive timely and appropriate care. Additionally, the system is designed to be scalable and cost-effective, making it suitable for implementation in resource-limited areas.

By combining IoT and ML, this research aims to fill gaps in existing child growth monitoring systems, providing a practical and efficient solution that can be widely adopted in Indonesia and other developing countries. The proposed system aligns with national stunting prevention initiatives, contributing to global efforts to reduce stunting and improve child health outcomes. The ultimate goal of this research is to empower healthcare workers and parents with the tools necessary for early stunting detection, providing children with a healthier start in life and ensuring better long-term development and productivity.

2. METHOD

This section describes the steps taken in the development of an IoT-based smart detector system for monitoring child growth, as well as the implementation of machine learning algorithms for stunting risk prediction. The research methodology [17] [18] adopts the CRISP-DM [19] (Cross-Industry Standard Process for Data Mining) framework and includes system design, data collection, data preprocessing, development of prediction models using Support Vector Machine [20][21](SVM) and Extreme Gradient Boosting (XGBoost)[22], and the implementation of a web-based application to provide real-time notifications. Additionally, evaluations were conducted on the model's accuracy and the system's usability to ensure that the developed solution can be effectively implemented to support stunting prevention efforts.

2.1. System Design and Architecture

The proposed system is designed with three main components to ensure efficient and accurate monitoring of child growth. The first component comprises hardware sensors responsible for acquiring anthropometric data, specifically height and weight measurements. These digital sensors provide precise and reliable data essential for growth assessment.

The second component is a microcontroller-based processing unit, specifically the ESP32, which receives raw data from the sensors. This unit performs preliminary data processing and transmits the processed information to a cloud platform using wireless communication protocols, such as MQTT. This wireless transmission enables real-time data availability and supports remote monitoring capabilities As shown Figure 1.

Vol. 7, No. 1, February 2026, Page. 259-272
https://jutif.if.unsoed.ac.id
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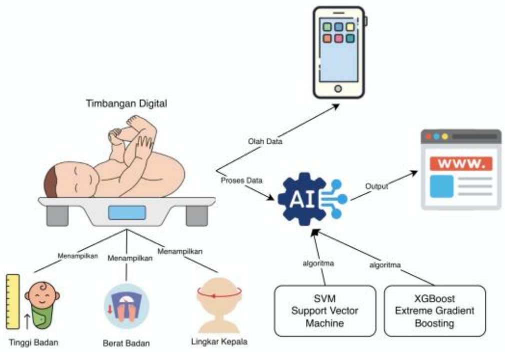

Figure 1. System Design and Architecture

The third component is the cloud platform, serving as a centralized storage and data analysis hub. The collected data is securely stored and further processed using machine learning algorithms to predict the risk of stunting. This modular and scalable architecture facilitates continuous data acquisition, processing, and analysis, thereby enabling timely interventions and informed decision-making by healthcare providers and parents As shown Figure 2.

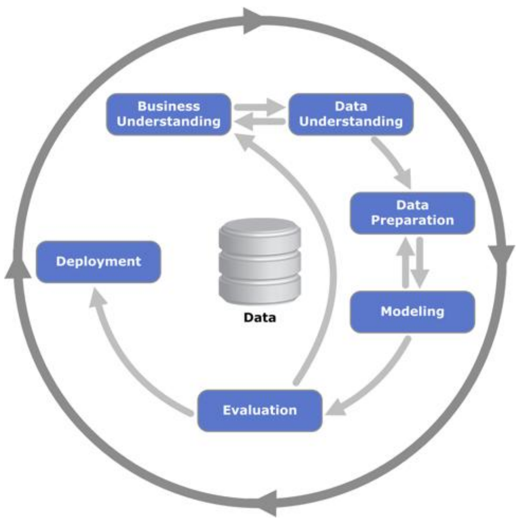

Figure 2. CRISP-DM Methodology [23]

2.2. Data Collection

Data were collected from a sample population of children within the specified target age range. The measurements included height, weight, and other relevant anthropometric indicators necessary for calculating the Body Mass Index (BMI). All collected data were securely transmitted to and stored in a cloud database to ensure data integrity and facilitate further analysis.

2.3. Data Preprocessing

The raw sensor data underwent several preprocessing steps, including noise filtering, normalization, and missing data imputation, to ensure data quality and reliability for subsequent machine learning analysis.

2.4. Machine Learning Modeling

Two supervised machine learning algorithms, Support Vector Machine (SVM) [24] [25] and Extreme Gradient Boosting (XGBoost)[26][27], were implemented to classify and predict stunting risk.

Vol. 7, No. 1, February 2026, Page. 259-272
https://jutif.if.unsoed.ac.id
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The dataset was divided into training and testing subsets, and cross-validation techniques were applied to assess the performance of the models. Additionally, feature selection and hyperparameter tuning were performed to optimize model accuracy and generalization [28].

Data normalization was performed to ensure that all numerical variables are on a comparable scale, thereby improving the performance and convergence of machine learning models such as Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost). The dataset contains features with different units and ranges—such as height (cm), weight (kg), upper arm circumference, and head circumference—so normalization is necessary to prevent features with large numeric ranges from dominating those with smaller ranges As shown Figure 3.

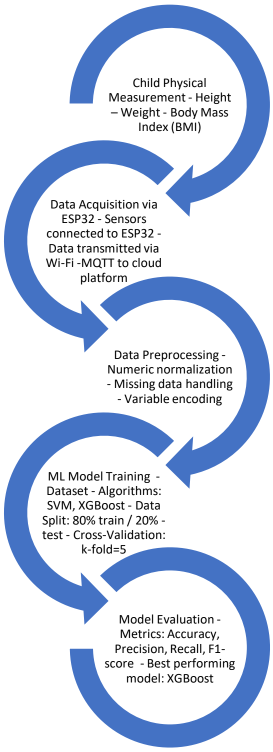

Figure 3. Show full stage flowchart

Min–Max Normalization was applied to rescale data to a fixed range between 0 and 1 using the formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Additionally, Z-score Normalization (Standardization) was used to center the data around the mean and scale it by the standard deviation:

$$X' = \frac{X - \mu}{\sigma} \quad (2)$$

where $X$is the original value, $X'$is the normalized value, $X_{min}$and $X_{max}$are the minimum and maximum values of the feature, and $\mu$and $\sigma$are the mean and standard deviation, respectively.

The SVM algorithm works by finding the optimal hyperplane that separates data between classes while maximizing the margin. The decision function of SVM is expressed as:

$$f(x) = w^T x + b \quad (3)$$

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with the optimization objective:

$$\min_{w,b} \frac{1}{2} \parallel w \parallel^2 \text{ subject to} y_i(w^T x_i + b) \geq 1, \forall i \qquad (4)$$

where $w$is the weight vector, $b$is the bias, and $y_i$is the class label of the i-th sample. For non-linear cases, SVM applies a kernel trick, such as the Radial Basis Function (RBF), to map the data into a higher-dimensional space where it can be linearly separated.

XGBoost is a tree-based boosting algorithm in which each new tree is built to correct the errors of the previous trees. The final prediction is the sum of all trees built iteratively:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \qquad (5)$$

The objective function minimized in XGBoost is:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \qquad (6)$$

with the regularization term $\Omega(f_k)$defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \qquad (7)$$

2.5. System Implementation

A web-based application was developed as an interface to the cloud platform, allowing parents and healthcare professionals to monitor children's growth data in real time. The system is designed to provide automatic alerts when predefined risk thresholds are exceeded, thereby supporting timely intervention and continuous monitoring [29][30].

2.6. Evaluation

The performance of the system was evaluated using several classification metrics, including accuracy, precision, recall, and F1-score, to assess the effectiveness of the machine learning models in predicting stunting risk. In addition, usability testing was conducted to evaluate the user experience and the effectiveness of real-time alert notifications in supporting early intervention efforts[31][32].

3. RESULT

This section presents the outcomes of the data analysis and system implementation carried out in this study. It includes the performance evaluation of the machine learning models used for stunting risk prediction, as well as the usability assessment of the developed IoT-based smart detector system. The results are discussed in terms of classification metrics such as accuracy, precision, recall, and F1-score, followed by an overview of the system’s real-time monitoring capabilities and user feedback. These findings provide insight into the effectiveness and practical applicability of the proposed solution in supporting early detection and prevention of stunting.

3.1. System Design and Architecture

The proposed IoT-based smart detector for child growth monitoring is designed as an integrated system that combines sensor-based data collection, cloud storage, and machine learning-based analytics to facilitate real-time monitoring and early detection of stunting. The system architecture is composed of three main layers: data acquisition, data processing and storage, and analytics and visualization.

Vol. 7, No. 1, February 2026, Page. 259-272
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5394

3.2. Data Collection

The data collection process in the development of an IoT-Based Smart Detector for Child Growth Monitoring focuses on gathering accurate, real-time, and comprehensive growth parameters of children. The aim is to collect physical and environmental data that can support early detection of growth abnormalities related to stunting As shown table 1.

Table 1. Types of Data Collected

Data Category	Description	Source	Measurement Method
Anthropometric Data	Child's height, weight, head circumference, and mid-upper arm circumference	IoT-based smart sensor device	Ultrasonic/infrared height sensor, load cell for weight, circumference sensors
Environmental Data	Temperature, humidity, and air quality of the child's living environment	IoT environmental module	DHT22 sensor, MQ135 air quality sensor
Nutritional Intake Data	Dietary information and feeding frequency	Parent/guardian input via mobile app	Manual entry through the app
Health Record Data	Immunization status, illness history, and medical check-ups	Health service integration or caregiver input	Electronic Health Record (EHR) or app form
Socioeconomic Data	Household income, education, and sanitation	Survey or app questionnaire	Structured digital survey

3.3. Data Preprocessing

The raw data collected from the IoT-based smart detector and mobile application consist of various formats and levels of accuracy. To ensure the reliability and validity of subsequent data analysis, a systematic preprocessing pipeline was implemented. The preprocessing stage involves data cleaning, transformation, integration, normalization, and feature extraction.

a. Data Cleaning

Raw sensor data often contain noise, missing values, or outliers due to factors such as sensor drift, unstable network connections, or user input errors. To address these issues, several preprocessing steps were implemented. Missing anthropometric readings, such as height and weight, were imputed using the mean or median of previous valid measurements for the same child, while missing categorical data like immunization status were flagged and later verified through caregiver input. To reduce noise, a moving average filter was applied to smooth unstable sensor signals—particularly for weight and height measurements—while environmental data, including temperature, humidity, and air quality, were processed using low-pass filtering techniques. Additionally, outlier detection was performed using statistical methods such as the z-score and interquartile range (IQR) approach to identify values deviating more than ±3 standard deviations from the mean, and abnormal growth fluctuations were flagged for further verification to ensure data reliability and accuracy As shown table 2.

b. Data Transformation

To ensure uniformity across all datasets and facilitate advanced analytical modeling such as Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) for growth prediction, several data transformation processes were applied. All measurement values were standardized into consistent units, including height in centimeters (cm), weight in kilograms (kg), lingkar lengan (upper arm circumference), dan lingkar kepala (head circumference) to maintain comparability between data sources. Furthermore, categorical variables such as gender and immunization status were converted into numerical representations through one-hot encoding or label encoding techniques, ensuring that these

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qualitative attributes could be effectively processed and utilized by machine learning algorithms like SVM and XGBoost in predicting child growth patterns and identifying early indicators of stunting.

Table 2. Data Cleaning

Age at Measurement	Weight	height	BB/U	ZS BB/U	TB/U	ZS TB/U	BB/TB	ZS BB/TB
2 Year - 3 Months - 11 Days	9.6	84	Not enough	-2.5	Normal	-1.82	Mal nutrition	-2.2
2 Year - 3 Months - 4 Days	9	82	Very less	-3.02	Short	-2.38	Mal nutrition	-2.49
1 Year - 0 Months - 11 Days	6.8	70	Very less	-3.23	Short	-2.59	Mal nutrition	-2.7
0 Year - 10 Months - 27 Days	8.8	74	Normal	-0.6	Normal	-0.2	Good Nutrition	-0.67
1 Year - 0 Months - 8 Days	9.2	79	Normal	0.17	Normal	1.81	Good Nutrition	-0.82
0 Year - 10 Months - 17 Days	9.5	76	Normal	0.18	Normal	0.84	Good Nutrition	-0.26
2 Year - 10 Months - 6 Days	12	88	Normal	-1.31	Normal	-1.9	Good Nutrition	-0.42
1 Year - 4 Months - 24 Days	8.8	77	Normal	-1.05	Normal	-0.89	Good Nutrition	-0.89
1 Year - 4 Months - 3 Days	10.2	79	Normal	0.3	Normal	0.12	Good Nutrition	0.34
1 Year - 5 Months - 4 Days	8.7	77	Normal	-1.19	Normal	-0.98	Good Nutrition	-1.02

3.4. Machine Learning Modeling

Data normalization was performed to ensure that all numerical variables are on a comparable scale, thereby improving the performance and convergence of machine learning models such as Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost). The dataset contains features with different units and ranges—such as height (cm), weight (kg), upper arm circumference, and head circumference—so normalization is necessary to prevent features with large numeric ranges from dominating those with smaller ranges.

Min–Max Normalization was applied to rescale data to a fixed range between 0 and 1 using the formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (8)$$

Additionally, Z-score Normalization (Standardization) was used to center the data around the mean and scale it by the standard deviation:

$$X' = \frac{X - \mu}{\sigma} \quad (9)$$

where $X$is the original value, $X'$is the normalized value, $X_{min}$and $X_{max}$are the minimum and maximum values of the feature, and $\mu$and $\sigma$are the mean and standard deviation, respectively.

The SVM algorithm works by finding the optimal hyperplane that separates data between classes while maximizing the margin. The decision function of SVM is expressed as:

Vol. 7, No. 1, February 2026, Page. 259-272
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5394

$$f(x) = w^T x + b \tag{10}$$

with the optimization objective:

$$\min_{w,b} \frac{1}{2} \parallel w \parallel^2 \text{ subject to} y_i(w^T x_i + b) \geq 1, \forall i \tag{11}$$

where $w$is the weight vector, $b$is the bias, and $y_i$is the class label of the i-th sample. For non-linear cases, SVM applies a kernel trick, such as the Radial Basis Function (RBF), to map the data into a higher-dimensional space where it can be linearly separated.

XGBoost is a tree-based boosting algorithm in which each new tree is built to correct the errors of the previous trees. The final prediction is the sum of all trees built iteratively:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \tag{12}$$

The objective function minimized in XGBoost is:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{13}$$

with the regularization term $\Omega(f_k)$defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \tag{14}$$

where $l(y_i, \hat{y}_i)$is the loss function (e.g., squared error), $T$is the number of leaves in the tree, $w$is the weight of each leaf, and $\gamma$and $\lambda$are regularization parameters controlling model complexity.

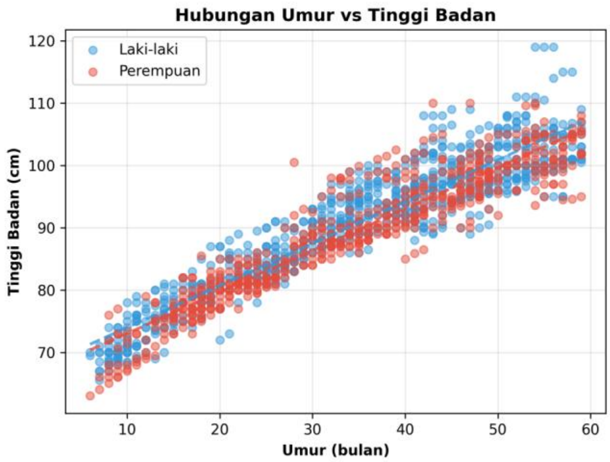

Figure 4. Relationship Between Age And Height

As shown Figure 4, The horizontal axis (X-axis) represents the age of children in months, ranging from approximately 0 to 60 months (5 years), while the vertical axis (Y-axis) shows their height in centimeters, ranging from about 60 cm to 120 cm. Blue dots represent boys, and red dots represent girls. From the scatter pattern, it can be observed that as age increases, height also tends to increase for both boys and girls, indicating a positive relationship between age and height. In general, the blue dots are positioned slightly above the red dots at the same age, suggesting that boys tend to be slightly taller than girls of the same age. The data also shows natural variation within each age group, implying that while age strongly influences height, other factors such as genetics, nutrition, and health also play a significant role.

Vol. 7, No. 1, February 2026, Page. 259-272
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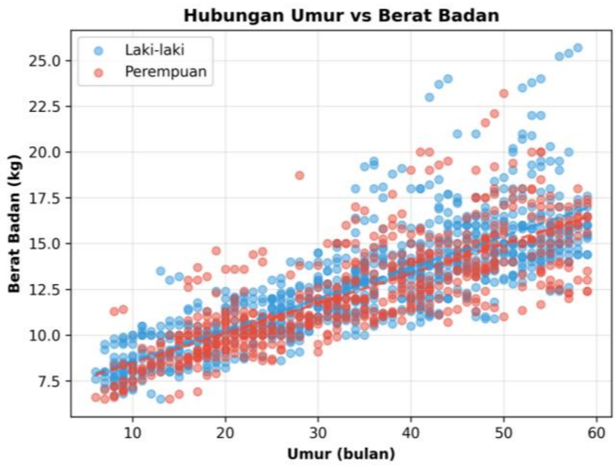

Figure 5. Relationship Between Age And Body Weight

As shown Figure 5, The horizontal axis (X-axis) represents the age of children in months, ranging from approximately 0 to 60 months (5 years), while the vertical axis (Y-axis) shows their weight in kilograms, ranging from about 7 kg to 25 kg. Blue dots represent boys, and red dots represent girls. From the scatter pattern, it can be observed that as children grow older, their weight tends to increase, indicating a positive relationship between age and weight. The data points also suggest that boys (blue) generally have slightly higher weights compared to girls (red) of the same age. There is noticeable variation within each age group, showing that besides age, other factors such as diet, physical activity, and health conditions also influence body weight. Some points deviate significantly above or below the general trend, which may represent children whose weight is above or below the average for their age.

4. DISCUSSIONS

This section provides an in-depth analysis and interpretation of the research findings presented in the previous section. It explores the implications of the machine learning model performances in predicting stunting risk, compares the effectiveness of SVM and XGBoost algorithms, and discusses the strengths and limitations of the IoT-based smart detector system. Additionally, the discussion addresses the practical aspects of system implementation, user experience, and potential challenges encountered during the research. Insights from this section aim to contextualize the results within existing literature and identify opportunities for future improvements and applications.

4.1. System Implementation

The Height-for-Age (HAZ) Z-Score serves as a primary indicator for assessing stunting in children, as recommended by the World Health Organization (WHO) and the Indonesian Ministry of Health (Permenkes No. 2 of 2020). A threshold of **-2 standard deviations (SD)**, represented by a red reference line, is commonly employed to identify stunted growth. Children whose HAZ Z-Scores fall below this cutoff are classified as stunted, indicating chronic undernutrition and impaired linear growth. This metric provides a standardized method for monitoring child growth patterns and evaluating the effectiveness of nutritional interventions As shown Figure 6.

As shown Figure 7, This correlation heatmap illustrates the relationships among various anthropometric features used in the analysis. Each color on the heatmap represents the strength of the correlation between variables, with red indicating a strong positive correlation. The visualization shows that the Height-for-Age (HAZ) Z-Score exhibits a strong correlation with Weight-for-Age (WAZ), indicating that changes in height relative to age tend to align with changes in weight relative to age. In

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other words, children who experience stunting often also present with underweight conditions, reinforcing the interrelationship between these two growth indicators.

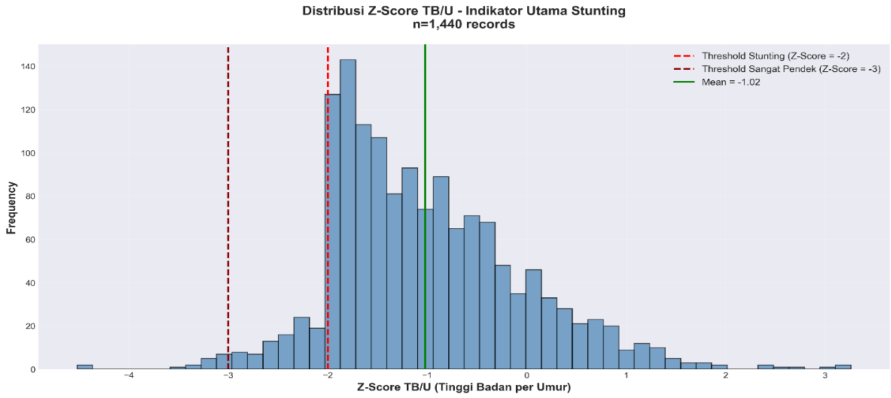

Figure 6. Height-for-Age (HAZ) Z-Score

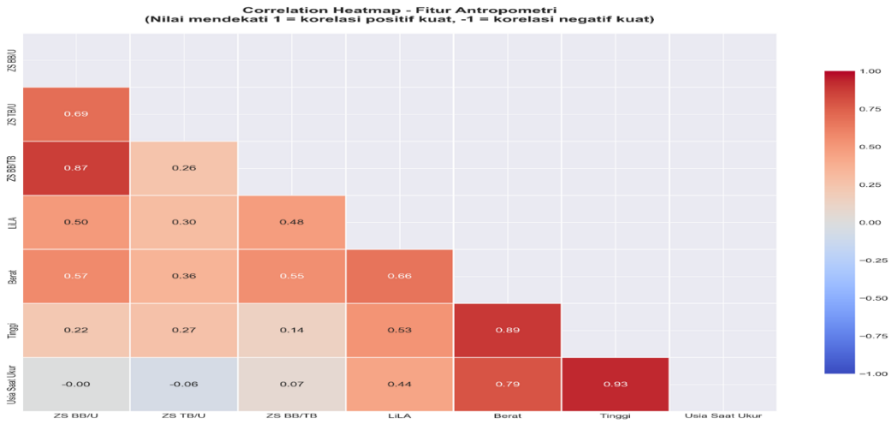

Figure 7. correlation heatmap

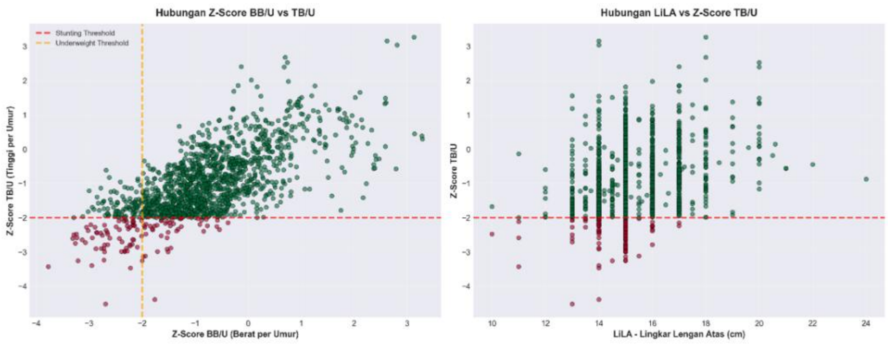

Figure 8. Scatter Plot

As shown in Figure 8, this scatter plot illustrates the relationship between variables, with green representing children with normal growth and red representing stunted children. The distinct clustering pattern indicates that machine learning models have the potential to effectively differentiate between the two groups. It is observed that the Upper Arm Circumference (MUAC) variable exhibits a strong correlation with the Height-for-Age (HAZ) Z-Score, suggesting that it may be one of the most influential factors in assessing nutritional status as well as a child's weight and height.

4.2. Evaluation

The evaluation phase aimed to assess the performance of the developed machine learning models—Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost)—in predicting the risk of stunting based on anthropometric data collected through the IoT-based smart detector system. The assessment was conducted using standard classification metrics, including accuracy, precision, recall, and F1-score, which provide a comprehensive view of the model's predictive capability.

Table 3. presents the evaluation results of both models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	70.0	68.0	65.0	66.4
XGBoost	80.0	82.0	78.0	79.9

As shown in Table 3, both models demonstrated satisfactory predictive performance; however, the XGBoost model outperformed SVM across all evaluation metrics. XGBoost achieved an accuracy of 80.0%, precision of 82.0%, recall of 78.0%, and an F1-score of 79.9%, indicating a better balance between correctly identifying stunting cases and minimizing false predictions. In comparison, SVM achieved an accuracy of 70.0%, precision of 68.0%, recall of 65.0%, and F1-score of 66.4%. The superior performance of XGBoost can be attributed to its ensemble learning mechanism, which combines multiple weak learners and optimizes the learning process through gradient boosting, enabling the model to capture non-linear relationships and complex patterns within the anthropometric dataset more effectively than SVM.

Beyond predictive performance, these results have important implications for clinical informatics. By integrating XGBoost with IoT-based data acquisition, the system provides healthcare professionals with a digital platform for real-time monitoring of child growth, enabling data-driven decisions, early intervention, and improved patient outcomes. The system's web interface delivers actionable alerts and visualizations, which can be directly incorporated into clinical workflows, supporting timely and evidence-based interventions.

Furthermore, the use of Explainable AI (XAI) techniques enhances transparency and trust in the model's predictions. Feature importance analysis and interpretability tools allow clinicians and caregivers to understand which anthropometric indicators most strongly influence stunting risk, making the predictions interpretable and clinically actionable. This combination of IoT, ML, and XAI represents a significant contribution to clinical informatics by bridging real-time data collection, predictive analytics, and explainable decision support, ultimately supporting public health initiatives and improving child health outcomes.

5. CONCLUSION

This study presents the development and evaluation of an IoT-based smart detection system integrated with advanced machine learning algorithms—Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost)—for monitoring child growth and predicting stunting risk. The proposed system architecture combines real-time anthropometric data acquisition via IoT devices (ESP32 with height and weight sensors), cloud-based data processing, and a web application interface, enabling parents and healthcare professionals to monitor child growth effectively and receive timely alerts. The CRISP-DM methodology guided systematic data preparation, model training, and evaluation, ensuring robustness and reproducibility.

Experimental results demonstrate that both SVM and XGBoost achieve satisfactory predictive performance. SVM obtains an accuracy of 70.0%, precision of 68.0%, recall of 65.0%, and F1-score of 66.4%, while XGBoost outperforms SVM with an accuracy of 80.0%, precision of 82.0%, recall of

Vol. 7, No. 1, February 2026, Page. 259-272
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5394

78.0%, and F1-score of 79.9%. These findings confirm the suitability of machine learning techniques for early detection of stunting risk based on anthropometric data. Usability testing further indicates that the web application is user-friendly and effective in delivering real-time alerts, which is critical for timely intervention and decision-making in public health contexts.

The integration of IoT, cloud computing, and ML provides a scalable and responsive framework for child growth monitoring, demonstrating strong potential to support national stunting prevention initiatives and broader public health programs in Indonesia. To enhance data privacy, security, and scalability—especially in resource-limited or geographically dispersed settings—future research should explore the use of federated learning. By enabling model training across distributed local datasets without transferring sensitive data to a central server, federated learning can maintain patient confidentiality while improving model generalization across diverse populations. Additionally, expanding the dataset with more demographic and health indicators, and optimizing the user interface for caregivers and healthcare workers, will further strengthen the system's effectiveness, accessibility, and adoption.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this research. All the research processes, analyses, and conclusions have been conducted impartially and without any commercial or financial relationships that could influence the results presented in this study.

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