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Behind the Black Box: Improving Stunting Determinants Analysis Through Explainable Artificial Intelligence

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ABSTRACT

Stunting is a public health problem that has a long-term impact on the quality of human resources. This study aims to analyze the performance of machine learning algorithms and identify the dominant factors of stunting using the Explainable Artificial Intelligence (XAI) approach. The dataset used was 120,999 toddlers with age, height, gender, and nutritional status attributes. The research stages include data pre-processing, normalization, separation of training and testing data (80:20), modeling using C4.5 algorithms, Support Vector Machine (SVM), and Random Forest, and evaluation using accuracy, precision, recall, and F1-score. The results showed that Random Forest and C4.5 achieved the best performance with an accuracy of 99.93%, while SVM achieved 98.37%. Interpretive analysis using SHAP revealed that height and age were the most dominant factors in the stunting classification with a contribution of 0.59 and 0.41, respectively, while gender contributed relatively small. These findings show that the integration of multi-algorithmic evaluation and XAI not only results in accurate prediction models, but also transparent and interpretive, thus supporting data-driven decision-making in efforts to accelerate stunting reduction in Indonesia.

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INTRODUCTION

Stunting, characterized by impaired growth in early childhood, is a pressing problem in Indonesia resulting from long-term nutritional inequalities (Masdalena, 2024) . Addressing this issue is crucial, given its role in shaping children's developmental trajectories and, consequently, the productivity of future generations. High rates of chronic malnutrition among children underscore the need for rapid and effective remedial action (Kurniawati et al., 2025) .

Statistical monitoring by the Ministry of Health through the Indonesian Nutritional Status Study (SSGI) shows a consistent decline in stunting prevalence, recorded at 27.7% in 2019, 24.4% in 2021, and 21.6% in 2022 (Arini & Peranto, 2023) . A specific demographic peak is seen in children aged 3–4 years, where prevalence reaches 6%. However, these figures still do not meet the WHO threshold of below 20%. In response, the government has set a strategic reduction target of 17% by 2023, with a further target of 14% by 2024 (Manalu et al., 2024) .

Under the framework of Presidential Regulation No. 72/2021, Indonesia has implemented a convergence-based strategy to reduce stunting, overseen by the National Population and Family Planning Agency (BKKBN) (Setiyawati et al., 2024) . This initiative aligns specific health interventions, such as micronutrient supplementation and standardized anthropometric monitoring, with nutrition-sensitive programs including WASH (Water, Sanitation, and Hygiene) and social safety nets (Agussalim et al., 2024). This integrated service delivery model focuses on the first 1,000 days of life, serving as a foundation

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for achieving the ambitious national prevalence target of 14% by 2024 (Putri et al., 2024) .

A study using data from the 2023 Indonesian Health Survey revealed that 19.69% of children under five in Indonesia experienced stunting, with the highest risk associated with incomplete immunization status, unsafe water consumption, and low household wealth. The analysis emphasized that geographic disparities in Eastern Indonesia, along with social and environmental factors, necessitate comprehensive, nutrition-sensitive interventions beyond immunization (Arief et al., 2025) . According to a 2023 study in Healthcare, the prevalence of stunting in priority villages in Indonesia reached 22.3%, with poor nutritional intake identified as a critical driver, increasing the risk of stunting by up to 14-fold. The study emphasized that inadequate maternal knowledge and suboptimal parenting practices were significant determinants. Consequently, the findings suggest that interventions should prioritize a holistic educational framework over traditional supplementary feeding alone (Atamou et al., 2023) . Data from both studies indicated a 14-fold increased risk due to malnutrition, exacerbated by inadequate immunization and environmental stressors such as unsafe water. Crucially, the persistence of stunting is closely linked to maternal knowledge gaps and socioeconomic inequalities. To achieve national targets, strategies must shift to a comprehensive model that combines clinical nutrition with intensive parental education and infrastructure development, particularly in high-prevalence areas. This holistic approach is crucial to address both the immediate symptoms and the underlying social determinants of stunting (Andriani et al., 2025) .

Using a hybrid machine learning framework, previous research combined K-Means clustering and classification models to improve the accuracy of stunting prevalence prediction in Aceh. The analysis revealed that this approach not only isolates key determinants such as sanitation and maternal nutritional status but also segments geographic areas into distinct risk groups, enabling high-precision policy interventions (Hasdyna et al., 2024a) . Research conducted by (Pratama et al., 2024) showed that the Random Forest algorithm produced superior performance in predicting stunting prevalence in Indonesia with a 90.5% success rate, surpassing Decision Tree and Linear Regression. This underscores the need to utilize advanced machine learning methods to obtain high-precision data, ultimately supporting more effective government decision-making processes. In a related investigation comparing Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes, Random Forest demonstrated superior stability with an accuracy rate of [X]%. Unlike SVM, which exhibits sensitivity to data noise, RF proved more robust in processing complex categorical features inherent in child growth records. These findings suggest that ensemble-based architectures are optimal for developing automated stunting screening tools to support clinical decision-making (Sahamony et al., 2024) .

Stunting estimation models in previous studies prioritized performance over transparency, leaving gaps in local interpretation for clinical use. Previous studies focused on global metrics of interest, ignoring individual heterogeneity and non-linear feature interactions. To address this gap, this study uses SHAP (SHapley Additive exPlanations) within an Explainable AI (XAI) framework to provide transparent feature attribution for personalized risk assessment. This methodological novelty transforms opaque computational models into interpretable diagnostic tools, providing the accountability needed for precision-based nutrition interventions in Indonesia.

This study used three main machine learning algorithms that have been proven effective in stunting analysis. Decision Tree: A decision tree algorithm that builds a predictive model in the form of a tree structure with decision nodes and leaf nodes. The advantages of Decision Trees include the ability to handle categorical and numerical data, easy interpretation, and the ability to capture non-linear interactions between variables (Pasaribu et al., 2026) . Support Vector Machine (SVM): An algorithm that builds *an optimal hyperplane* to separate data classes. SVM excels in handling high-dimensional data and is able to solve non-linear classification problems through kernel functions (Hasdyna et al., 2024) . Random Forest: *Ensemble learning* that combines more than one decision tree to improve accuracy and reduce *overfitting* . Random Forest can handle large data, overcome overfitting, and provide feature importance estimates (Hendy et al., 2025). (Ayele et al., 2025) . SHAP (SHapley Additive exPlanations) is an XAI framework based on cooperative game theory, capable of individually contributing each feature to model predictions (Khosravi et al., 2022) , (Givisis et al., 2025) . SHAP provides local and global interpretations, enabling researchers to comprehensively understand the dominant factors influencing stunting. With the integration of SHAP, machine learning models are no longer considered "black boxes." SHAP enables accurate identification of dominant factors and provides insight into the contribution of each variable to stunting prediction (Pasaribu et al., 2026) . This approach aims to explain the processes underlying decision-making (Sopiandi et al., 2025) .

The scientific novelty of this study lies in addressing the limitations of model interpretation (*black-box*) through a comprehensive comparative integration of multi-algorithms (C4.5, SVM, and Random Forest) combined with an in-depth SHAP (*Shapley Additive exPlanations)-based Explainable Artificial Intelligence (XAI) approach*. As a comparison, recent research by (Elim & Utami, 2025) and a comparative study in (Widyawati et al., 2025) have explored the use of Random Forest and SVM algorithms to predict stunting risk in toddlers in

Indonesia using anthropometric data. However, both works still focus on optimizing and evaluating global performance metrics without thoroughly explaining the transparency of the decisions behind the models. This study fills this *research gap* by utilizing a large-scale dataset covering 120,999 toddler data records to produce a predictive model that not only excels in performance but also provides visualization of local and global feature contributions to identify the clinical significance of the interaction of age, height, and gender variables on stunting conditions in Indonesia.

The use of machine learning in this study enabled the detection of complex patterns in stunting data that elude conventional linear analysis, thus improving the accuracy of risk assessment. To mitigate the interpretation challenges associated with sophisticated algorithms, the study employed SHAP as an Explainable AI framework. SHAP deciphers the model's decision-making process, providing in-depth insights into how individual determinants, from environmental factors to maternal health, influence growth outcomes. By providing localized interpretation, this framework bridges the gap between computational complexity and clinical practice, offering an evidence-based foundation for personalized stunting mitigation strategies and transparent public health governance.

RESEARCH METHODS

At this research stage, a systematic explanation of the processes carried out in this study is provided. The processes carried out in this study are shown in Figure 1. The process begins with the collection of *the Stunting dataset*, followed by data pre-processing to clean, convert data to numeric, and normalize the data. Next, the dataset is divided for model training and testing. The selection of algorithms for modeling is done with Python programming on *the Google Colab Platform*. Finally, a model evaluation is carried out to assess the performance and effectiveness of the algorithm used. Then, the results of the model evaluation are retested to determine the most influential features so that conclusions and recommendations can be drawn for this study.

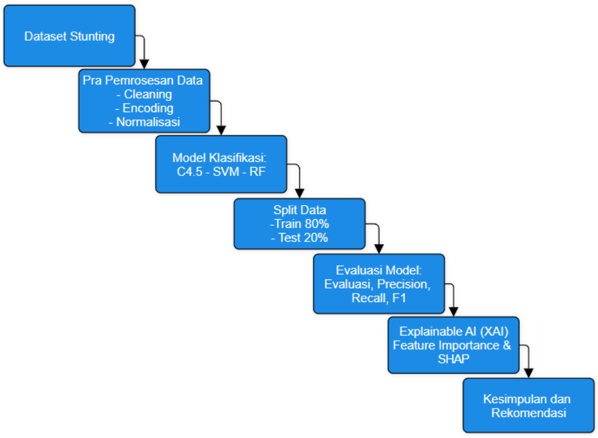


Figure 1. Research Flow

1. Data collection

The dataset used in this study was obtained from Kaggle with the title "Toddler Stunting Detection – 121K Rows" and includes 120,999 toddler records that have four main attributes, which are summarized in Table 1.

Table 1. *Description of Data Set*

Attribute	Type	Information	*Missing Values*
Age	Numeric	Age in months	There isn't any
Tall	Numeric	Height in cm	There isn't any
Gender	Categorical	Male or female	There isn't any
Nutritional status	Categorical (Label)	Normal, stunted growth, severely stunted growth, tall	There isn't any

2. Pre-processing

Data preprocessing aims to improve data quality before it is used in modeling (Khodijah & Rizki, 2025) . This stage includes *data cleaning* to address missing data and inconsistencies, *encoding* to convert categorical data to numeric data, and normalization to equalize feature scales, which is crucial for algorithms like SVM. Without proper preprocessing, machine learning models are at risk of bias or instability.

3. Separate Data

At this stage, the data is then divided into two parts: 80% training data and 20% testing data. *Data separation* is a crucial process in machine learning to ensure that the model can be trained on some data and tested on previously unseen data, thus providing a more objective and accurate performance evaluation (Arman et al., 2025) .

4. Classification Model

Modeling is the process of representing or simplifying data into a model that is easier to understand, analyze, or manipulate.

a. C4.5 Algorithm (Decision Tree)

The C4.5 algorithm is a decision tree method used for data classification. This algorithm selects the best attributes based on *the gain ratio* to divide the nodes in the decision tree. C4.5 can handle both numeric and categorical data and performs *pruning* to reduce overfitting (Rahmaddeni et al., 2024) .

b. SVM Algorithm

SVM is a supervised learning algorithm that works by finding the optimal hyperplane that separates data classes with the maximum margin. By using kernel functions such as RBF or polynomials, SVM is able to handle nonlinear data (Bilqisth & Ikhsanuddin, 2025) .

c. Random Forest Algorithm

Random Forest is an ensemble learning method that builds multiple decision trees from random subsets of data and attributes, then votes to produce a final prediction. Its main advantages are high accuracy, resistance to overfitting, and good noise handling (Fadillah et al., 2024) .

5. Model Evaluation

The model was evaluated using evaluation metrics such as accuracy, *precision*, *recall*, and f1-score. However, these results were still analyzed critically, considering the potential for overfitting and data imbalance. The use of more than one metric is necessary to ensure that the evaluation is not biased solely by accuracy (Helmiyah & Pramestiawan, 2025) , as seen in equations (1), (2), (3), and (4).

Table 2. Model Evaluation Formula

Symbol	Information
TP (True Positive)	Stunting data that predicts stunting
TN (True Negative)	Data on non-stunting is predicted as non-stunting
FP (False Positive)	The data does not indicate stunting, but rather a prediction of stunting.
FN (False Negative)	Stunting data but predicted not to experience stunting

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{TP + TN + FP + FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

$$Precision = \frac{TP}{\mathrm{TP} + \mathrm{FP}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

$$F1 - Score = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

6. Explainable Artificial Intelligence (XAI)

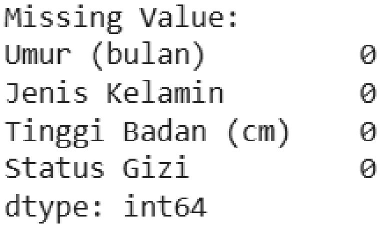
Explainable Artificial Intelligence (AI) is used to explain how a model makes decisions. It describes the important features that contribute to classification (Ramadhan & Zeniarja, 2025) . The methods used are: *Feature Importance* to see the influence of features globally, SHAP (SHapley Additive explanations) to explain the contribution of each feature both globally and to specific data (Nourani et al., 2025) . This approach is very important in the health sector so that model results can be understood and trusted.

7. Conclusion and Recommendations

The final stage involves determining the best algorithm, identifying the dominant factors causing stunting, and recommending further policies. These results are expected to support data-driven decision-making.

RESULTS AND DISCUSSION

In this study, testing was performed by normalizing *the dataset* to determine whether there were any missing values in the entire data set. After processing all the complete features, there were no missing data points, with the results shown in Figure 2.



```
Missing Value:
Umur (bulan)         0
Jenis Kelamin        0
Tinggi Badan (cm)    0
Status Gizi          0
dtype: int64
```

Figure 2: *Stunting Missing Values Data Set*

Figure 3 shows *the normalization of the dataset* using the StandardScaler method to equalize the feature scale with a mean of zero and a standard deviation of one. Visualizations before and after normalization show that the feature distribution becomes more uniform, thus improving the performance of the Support Vector Machine algorithm, which is sensitive to differences in data scale. Because SVM is based on distance and margin calculations, differences in feature scale can cause bias in *the resulting hyperplane.*

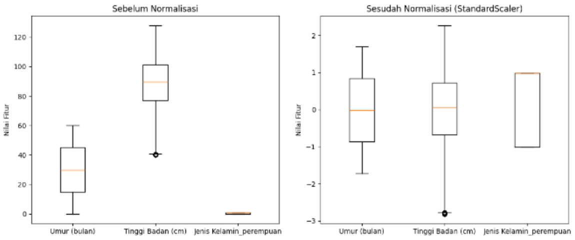
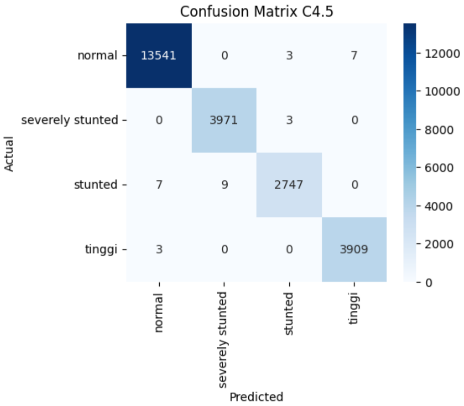


Figure 3. SVM normalization

To deepen the analysis of the algorithm, *the Confusion Matrix is displayed* on the best performing algorithm, so that the distribution of correct and incorrect predictions between classes as well as the pattern of misclassification errors can be seen.



	normal	severely stunted	stunted	tinggi
normal	13541	0	3	7
severely stunted	0	3971	3	0
stunted	7	9	2747	0
tinggi	3	0	0	3909

Figure 4. C4.5 *Confusion Matrix*

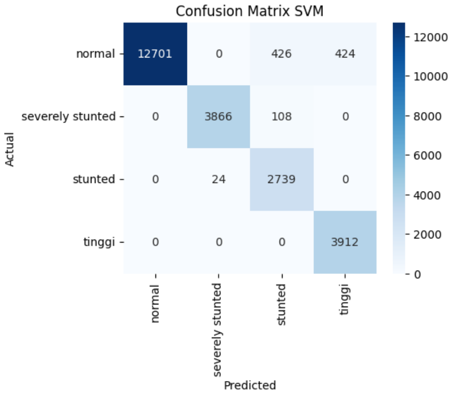


Figure 5. SVM *Confusion Matrix*

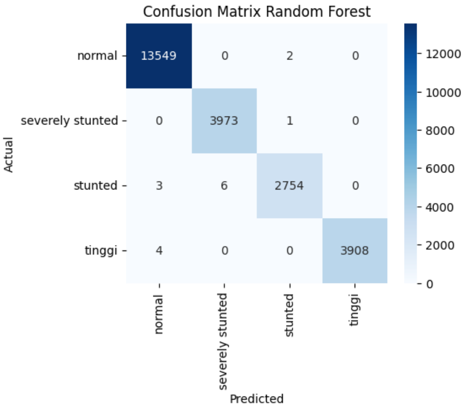


Figure 6. Random Forest *Confusion Matrix*

Confusion Matrix visualizations in Figures 4, 5, and 6, an in-depth analysis was conducted to evaluate the distribution of correct predictions and the patterns of misclassification (*False Positives* and *False Negatives*) of the three algorithms. The Random Forest Confusion Matrix model demonstrated a very high classification performance in predicting the nutritional status of toddlers. Most of the data were correctly classified, as evidenced by the dominant values on the diagonal of the matrix, with 13,549 normal data, 3,973 severely stunted data, 2,754 stunted data, and 3,908 tall data correctly predicted. The number of misclassifications (False Positives and False Negatives) was very small, with only a few stunted data incorrectly predicted as normal or severely stunted. These results demonstrate that the Random Forest algorithm is very good at recognizing patterns of relationships between features and has a high level of stability in the classification process.

After initial exploration, the data was cleaned and normalized using the StandardScaler method. Then, the data was randomly divided into 80% training data and 20% testing data. Three supervised learning algorithms were selected: C4.5 Decision Tree (for simplicity), Support Vector Machine (SVM), and Random Forest (RF). The RF model is expected to handle data complexity well. Evaluation metrics include accuracy, precision, recall, and F1 score (as shown in Table 3).

Table 3. Evaluation of 3 Models

Model	*Accuracy*	*Accuracy*	*Recall*	*F1 Score*
C4.5	0.9986	1.00	1.00	1.00
SVM	0.9594	0.96	0.98	0.95
Random Forest	0.9993	1.00	1.00	1.00

Visualization of the comparison of the accuracy of 3 models with a bar trolley:

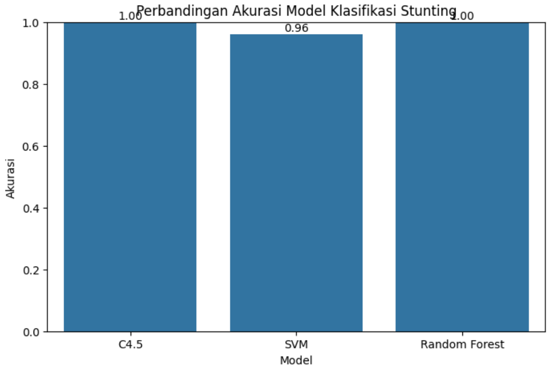


Figure 7. Comparison of 3 Models

visualization of the importance of generating *features*

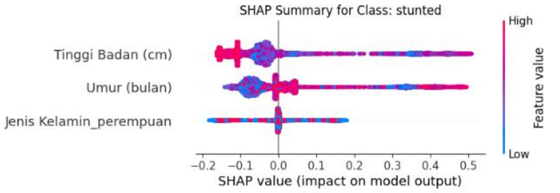


Figure 8. *SHAP Summary Plot*

Based on Explainable AI's analysis using the SHAP summary plot in Figure 8, child height and age were the most dominant factors influencing global stunting classification results. Meanwhile, gender had a relatively small impact on the model's decisions.

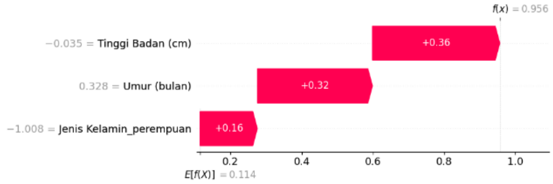


Figure 9. SHAP Waterfall Plot

In addition to analyzing global feature contributions, this study also implemented local interpretation using *SHAP Waterfall Plots* to dissect how *the machine learning model* makes decisions at the individual patient level. Figure 9 presents a visualization of feature contributions in a sample of toddlers that the model accurately predicted to be in the stunting class (*class:stunted*).

The calculation starts from a *base* value of 0.114 or E[f(x)] at the bottom of the graph, which represents the average of the model's log-odds predictions across the training dataset. From that starting point, each feature contributes either a positive (represented by the red/right-pointing bars) or a negative (represented by the blue/left-pointing bars) contribution until it reaches the final predicted value of

0.956 f(x) at the top of the graph. In this individual case, the Height feature is the primary dominant factor with the largest positive SHAP value, significantly driving the model's decision towards the 'stunting' classification. This clinically demonstrates that the negative deviation in the toddler's height from the standard growth chart is the most critical trigger for the model in detecting stunting.

CONCLUSION

Based on the analysis and testing of 120,999 toddler datasets, this study concluded that the Random Forest algorithm demonstrated the best classification performance with an accuracy value of 99.93%, followed closely by the C4.5 algorithm with an accuracy of 99.86%, while the Support Vector Machine (SVM) algorithm achieved a lower accuracy of 95.94%. The confusion matrix analysis also showed that Random Forest produced the fewest misclassifications, indicating a high level of stability and effectiveness in recognizing nutritional status patterns. These findings indicate that multi-algorithm approaches are effective in producing highly accurate stunting prediction models, with ensemble-based methods such as Random Forest showing superior robustness in handling complex anthropometric data.

Furthermore, the implementation of Explainable Artificial Intelligence (XAI) using the SHAP method revealed that height and age were the most dominant factors influencing stunting classification, while gender had a relatively small contribution. These results confirm that anthropometric indicators remain the primary determinants in stunting identification. Furthermore, the SHAP integration enhances model transparency by providing clear insights into feature contributions, thus supporting more interpretable and data-driven decision-making in stunting prevention efforts.

This study still relies on a single public dataset obtained from Kaggle and uses a simple train-test split approach. Future studies should incorporate external healthcare datasets and cross-validation techniques to improve model robustness and generalizability.

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