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Explainable Machine Learning Models SHAP-based for Feature Importance Affecting Stunting Prevalence

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Abstract **-** Stunting is a form of chronic nutritional deficiency in toddlers and remains a major public health concern due to its impact on child growth and development. Efforts to reduce its prevalence continue to be strengthened in Indonesia, particularly in Sumatra Province. This study aims to evaluate the accuracy of a logistic regression model and three machine learning models—decision tree, random forest, and support vector machine (SVM)—in classifying stunting prevalence. The response variable is defined as the prevalence of stunting among toddlers, categorized into two classes: exceeding the national target and not exceeding the national target, based on the 2024 national threshold. Although classification models can provide accurate predictions, they often lack interpretability. Therefore, this study applies the SHAP method to the best-performing machine learning model to identify the key factors influencing stunting. The use of Shapley values is justified through the uniqueness theorem, which establishes it as the only attribution method satisfying desirable fairness properties. SHAP values are employed to explain the model by referencing both the trained model and the underlying data. The results show that the random forest model achieves the highest accuracy (90.00%), outperforming the other models. SHAP analysis reveals that Underweight is the most influential predictor contributing to stunting prevalence in Sumatra Province. These findings highlight the relevance of machine learning interpretability in supporting policy decisions for stunting reduction.

Keywords: feature importance; logistic regression; explanaible machine learning; SHAPE value; stunting prevalence

I. INTRODUCTION

Stunting is a condition of growth failure in children caused by chronic malnutrition, resulting in a child's height being shorter than that of their peers. Stunting is a serious problem currently facing the world (Rifada et al., 2023). particularly in poor and developing countries such as Indonesia (Ashari et al., 2023). Stunting is one of the challenges facing the Indonesian government in developing a national strategy for stunting prevention. Stunting is a condition of reduced height in children caused by malnutrition and persisting over a long period. This results in a child's height being shorter than that expected for their age. Efforts to reduce prevalence in Indonesia are being made to align with global targets, namely the National target, namely efforts to accelerate the reduction of stunting from the current condition so that the prevalence of stunting in toddlers can decrease to 19.4% in 2024. According to (Purnamasari et al., 2022), the impact of stunting on children can have an impact in the near future and in the future. Short-term impacts include impaired or damaged brain development, decreased intelligence quotient (IQ), and a weakened immune system, making them more susceptible to infection and disease. Therefore, stunting management, particularly in Indonesia, requires an understanding of the factors that influence its prevalence.

Several studies on stunting have been conducted by other researchers previously using various statistical methods. Research on stunting using logistic regression models has been conducted by (Asmare et al., 2025; Fadmi et al., 2025; Juniarti et al., 2025; Kassie & Asgedom, 2025). Researchers have also used spatial regression models to determine the factors influencing stunting, as conducted by (Asgedom et al., 2024; Fahrani et al., 2025; Falah et al., 2025; Girma et al., 2025; Muhaimin et al., 2025).

Furthermore, because child stunting is influenced by complex interactions of various factors, traditional linear models such as logistic regression may not adequately capture the potential nonlinear relationship. In this case, the use of SHAP-based Explainable Machine Learning (EXAI) models can help us identify these complex relationships, which cannot be identified with conventional approaches. Methods for model interpretation such as global feature importance or partial dependence plots tend to provide only a conventional overview of the influence of features on the model, but do not consistently explain the contribution of features to the prediction of each object or the direction in positive or negative of the influence. Conventional methods such as global feature importance, PDP/ICE, and linear model coefficients are often inadequate when applied to complex ML models because only provides a global overview, not local (individual predictions), does not handle feature interactions or model non-linearity well, and it is sometimes difficult to interpret the direction and magnitude of a specific feature's contribution.

Therefore, the decision to use SHAP in this study arises from several methodological advantages that make it highly relevant for interpreting machine learning models in public health research. First, SHAP provides a quantitative and theoretically grounded method for attributing feature contributions to each individual prediction, drawing directly from Shapley value principles in cooperative game theory. This ensures that every feature's contribution is allocated fairly, consistently, and without bias, fulfilling key axioms such as efficiency, symmetry, and additivity. Second, SHAP not only offers precise local explanations at the individual level but also enables the aggregation of these explanations to obtain a coherent global understanding of model behavior. This dual capability ensures that insights derived at the micro level remain aligned with broader model patterns, enhancing interpretability across different analytical scales. Third, SHAP is inherently model-agnostic, meaning it can be applied across a wide range of algorithms—including decision trees, ensemble methods, and deep neural networks—without requiring modifications to model structure or training procedures. This flexibility makes SHAP particularly valuable in comparative studies such as this one, where multiple machine learning models are evaluated. Altogether, these strengths justify the use of SHAP as a robust and versatile interpretability tool capable of supporting transparent decision-making in stunting research and other complex health-related modeling tasks.

Explainable Machine Learning has become quite popular among researchers today. This method has been widely used in various fields. Explainable Machine Learning in the health sector has been conducted by (Houssein et al., 2025; Shifa et al., 2025; Sun et al., 2020; Ullah et al., 2025). In psychology, the use of Explainable Machine Learning has been used by (Fedyk & Ray, 2023; Henninger et al., 2023; Rehman et al., 2025; Uban et al., 2022). The use of Explainable Machine Learning in the financial sector has been carried out by (Arsenault et al., 2025; Mohsin & Nasim, 2025; Shah et al., 2024).

One technique in Explainable Machine Learning to identify influential factors is using SHAP. The Shapley value offers a fair method to distribute a collective gain among a group of collaborating players. Just as the Shapley value is used in SHAP to interpret machine learning models, they are often regarded as black boxes. Based on the explanation above, the purpose of this study is to determine the accuracy of the logistic regression model and the machine learning approaches of decision trees, random forests, and support vector machines (SVM). Furthermore, the SHAP method is applied to the best machine learning model to identify the main risk factors for stunting cases in Sumatra.

II. METHODS

The most prevalent kind of malnutrition is stunting (PE/micronutrients), which affects toddlers pertaining to fetal growth, pregnancy nutrition, and maternal size, both before and shortly after birth. Sudiman said that stunting in toddlers is one indicator of long-term nutritional state that can give insight into general socioeconomic disorders previously and in the first 2 years of a child's life. This study uses secondary data, specifically raw data from the 2023 Indonesian Health Survey (SKI) report on the prevalence of stunting in the Sumatra Province. Additionally, data on influencing variables were acquired from the Central Bureau of Statistics (BPS). The Indonesian Health Survey (SKI) 2023 integrates the Basic Health Research (Riskesdas) and the Indonesian Toddler Nutrition Status Survey (SSGI). Dataset of SKI 2023 was conducted to assess the achievements of health development over the past five years in Indonesia and to measure trends in toddler nutritional status annually from 2019 to 2024. The data generated can provide an overview of health status at the national level down to the district/city level.

The unit of analysis in this study is toddlers suffering from stunting in the Sumatra Province. The acceleration of stunting reduction among toddlers is a government priority program, as According to the RPJMN, the National Medium-Term Development Plan in 2020-2024. The national target for 2024 is to reduce stunting prevalence to 14%. Therefore, this study uses the national stunting target threshold of 14% for 2024.

The dependent variable is the prevalence of stunting at the district/city level in the Sumatra Province. Stunting diagnosis status is categorized into two groups: stunting cases that do not meet the national target and those that meet the national target. Individuals diagnosed with stunting are identified based physical examinations and supporting tests conducted by healthcare professionals. The independent variables used in this study were acquired from the Central Bureau of Statistics (BPS) and are presented in Table 1. All of the districts and cities in the Nanggroe Aceh Darussalam, North Sumatra, Riau, South Sumatra, Bangka Belitung Islands, Bengkulu, Jambi, and Lampung provinces are included in this study.

The analysis methods used in this study include descriptive analysis, inferential analysis, and machine learning techniques like Support Vector Machine, Random Forest, and Decision Tree, along with an explainable model using SHAP (Shapley Additive Explanations). Descriptive analysis is used to provide a general overview of the prevalence of stunting in Sumatra Province, Indonesia. Inferential analysis is conducted using a binary logistic regression model to examine the independent variables that influence the prevalence of stunting in 2023, with reference to the national target in Sumatra Province, Indonesia. The national stunting reduction target for 2024 is set at 14%.

In this study, the machine learning method is part of the method without using SHAP. The method without SHAP is a method that only focuses on evaluating model performance, without explaining the reasons behind the model's predictions. So, these method compare the results without SHAP and with SHAP. The binary logistic regression model is a data analysis model used to determine the connection between a response variable that is binary (y) and predictor variables (x), as described by the logistic regression model for stunting prevalence in 2023 in Sumatra Province, using eight predictor variables from Table 1, can be expressed as follows in Equation (1).

$$\frac{P(Y=1)}{1-P(Y=1)} = \beta_0 + \sum_{i=1}^{7} \beta_i X_i \qquad (1)$$

β_0 : Intercept

$\beta_1, \beta_2, \ldots, \beta_7$: Regression coefficients for independent variables

$x_1, x_2, \ldots, {}_x\beta_7$: Independent Variable

Next, when using machine learning techniques when making decisions, model interpretation is crucial. The machine learning models used in this study include Random Forest, Decision Tree, and Support Vector Machine. Exploring with three classification algorithms described. Decision trees are made using rules. Decision trees are structuring algorithms that describe features in a tree-like manner and are based on rules and trees. Each node stands for a feature, each node-to-node connection for a decision rule, and the leaf nodes for the output. DTs are sometimes viewed as a flow chart, with the predictions made on the leaves marking the end of the flow, which begins at the root node. It is a tool for decision assistance that may also be viewed as a plot that resembles a tree that shows the predictions made by a series of feature-based divisions.

Furthermore, One classification method is the random forest model, sometimes referred to as a forest of decision trees that incorporates randomness to reduce the danger of overfitting. Several decision trees are combined, samples with replacements are created, and nodes are divided based on the optimal split using a random subset of features to do this kind of trimming. One of the most effective methods with minimal data preprocessing is the RF classifier. A learning algorithm is used to train the Support Vector Machine (SVM), a learning system that employs a hypothesis space made up of linear functions in a high-dimensional feature space and applies a learning bias derived from statistical learning theory (Shah et al, 2024).

Table 1 Variables of Dependent and Independent

Variables	Category/Unit
Dependent Variable	
Stunting Prevalence in accordance with National Target of 14% (Y)	1 = Not yet reached target 0 = Achieve the target
Independent Variable	
Wasting (X1)	Percentage (%)
Underweight (X2)	Percentage (%)
Poor people (X3)	Percentage (%)
Gross Regional Domestic Product per Capita (X4)	Trillion Rupiah Indonesia
Households that have adequate sanitation (X5)	Percentage (%)
Number of health workers (X6)	Person
Proportion of Ever-Married Women Aged 15-49 Who Gave Birth to a First Live Child Under 20 Years of Age by District/City (X7)	Percentage (%)

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

The selection of metrics is very important to use in a model to be evaluated. This paper uses a problem about classification. The metric that is often used is accuracy, precision, and recall which is defined in the following Equation (2), Equation (3), and Equation (4), respectively. This formula is defined based on the confusion matrix. Defined *TP* states True Positive, which states the number of correct predictions when the model predicts that an example is included in the positive class, and it turns out to be true in the positive class, while *TN* is true negative, which states a correct negative prediction. *FP* is false positive which states a false positive prediction, and *FN* is false negative, which states a false negative prediction.

Table 2 Performance Metrics

	Predictive Positive	**Predicted Negative**
Actual Positive	TP	FN
Actual Negative	FP	TN

However, because it typically favors the dominant class, this statistic is constrained and does not necessarily reflect reality when the data is unbalanced. The explanation of this metric that the values from the confusion matrix stated in Table 2 below. The results of each machine learning algorithm before using SHAP is conducted by performance metrics in confusion matrix.

This section looks at one way to evaluate the collective techniques employed, specifically game theory in Stunting case in Sumatera Province. In this section, we present the rationale and salient features for utilizing game theory to explain student prediction models. This results display Shapley values and their role in enhancing model transparency and prediction accuracy. Shapley values, a term used in game theory, are referred to as SHAP values. The two main components of these numbers are players and game, where "players" stand for the model's qualities and "game" indicates the outcome of the prediction model. Shapley determines the amount that each participant contributes to the game. The SHAP value determines the feature's contribution to the model's output by applying these factors to our case.

Each player's contribution is calculated by taking into account every conceivable coalition of players, or every possible combination of i features (where i is between 0 and n, which is the total number of features accessible). The forecast is influenced by the sequence in which the features are added to the model. This strategy was put forth by Lloyd Shaply in 1953. "Shapley Values" for phi values measured in this manner. Let p p be prediction (this is the prediction by the complex model), the Shapley value in Equation (5) for a specific function i (out of n total features, and S is a subset of n) is

$$\emptyset_i(p) = \sum_{S \subseteq \setminus\{i\}} \frac{|S|!(n - |S| - 1)!}{n!}[p(S \cup \{i\}) - p(S)] \quad (5)$$

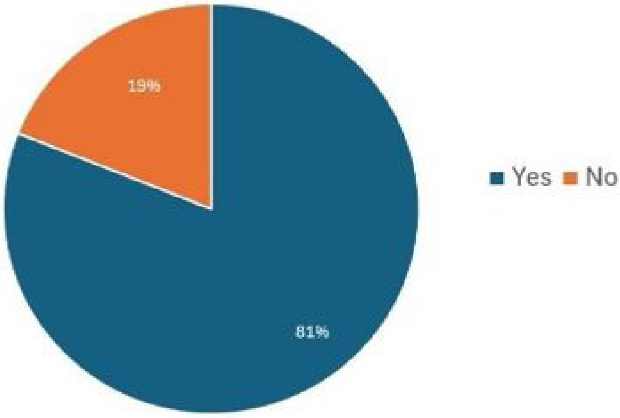
Calculating the difference between the model forecast and the actual value, this formula assists in determining the significance or impact of a characteristic. without feature *i*. Equation (5) is calculated using the data will be difficult to do, Equation (5) will be done in the shapley value plot. The feature's effect is basically the change in model estimation. Furthermore, SHAP values are employed whenever that deal with an input-output model and wish to comprehend the choice made by this model; for example, the model recommended a Stunting excess National objective for the year 2024 in Sumatera Province, Indonesia.

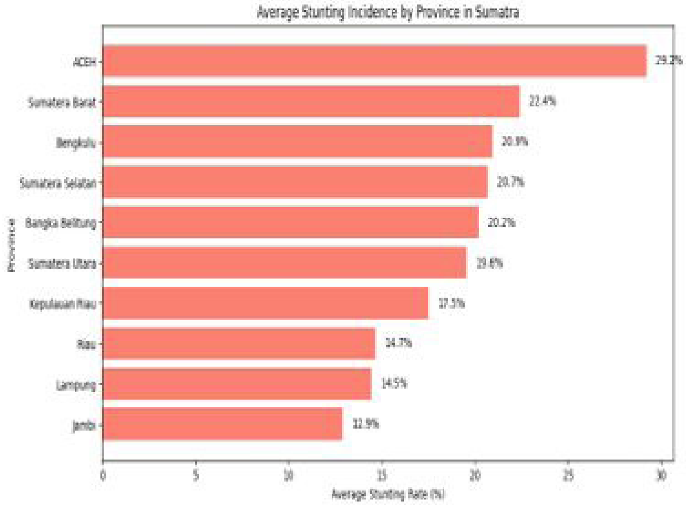
III. RESULTS AND DISCUSSIONS

Based on SKI 2023 dataset of Stunting cases in Sumatra Province in Figure 1, it can be seen that as many as 81% of provinces in Sumatra have a stunting prevalence above 14%. It means not reaching the National target and 19% of provinces in Sumatra that have reached the National target. Based on information from the Coordinating Ministry for Human Development and Culture which states that the prevalence of Stunting in 2023 is 21.5%. Therefore, Indonesia is targeted to achieve a Stunting case of 14% in 2024. Sumatra is one of the islands in Indonesia that is included in the stunting case with a high prevalence, especially in the Province of Nanggroe Aceh Darussalam (NAD).

Descriptive statistics of Stunting cases in Sumatra Province can be seen in Table 3 below. The descriptive statistics calculated include the Minimum value, Maximum value, Mean value, and Standard deviation value. Based on Figure 1, it represents the overall sequence of prevalence of Stunting cases in Sumatra in 2023 from the highest to the lowest, namely Nanggroe Aceh Darussalam (NAD) Province, West Sumatra Province, Bengkulu Province, South Sumatra Province, Bangka Belitung Islands Province, North Sumatra Province, Riau Islands Province, Riau Province, Lampung Province, and Jambi Province.

The lowest and highest prevalence of districts/ cities in Nanggroe Aceh Darussalam Province were 15.40% and 40.20% respectively. This indicates that Nanggroe Aceh Darussalam Province did not achieve the National target for Stunting cases. Aceh has 23





(a) (b)

Figure 1 (a) Pie Chart and (b) Bar Chart of Stunting Prevalence in Sumatera Province

Table 3 Statistic Descriptive of Stunting Prevalence in Sumatera Province

Province	**Min**	**Max**	**Mean**	**Standard deviation**
Naggroe Aceh Darussalam (NAD)	15.40	40.20	29.21	5.52
North Sumatera	5.70	33.80	19.55	7.64
West Sumatera	14.70	33.70	22.43	5.64
Riau	7.60	23.00	14.68	4.82
Riau Island	15.20	21.60	17.51	2.60
South Sumatera	7.80	33.10	20.71	7.89
Kepulauan Bangka Belitung	17.30	23.20	20.21	1.93
Bengkulu	6.70	28.60	20.93	6.77
Jambi	4.10	23.70	12.94	6.23
Lampung	5.00	24.60	14.45	5.91

districts/cities with Stunting prevalence that does not reach the national target. South Aceh Regency is the area with the highest prevalence in Aceh. Aceh Tamiang Regency is ranked second in Aceh with a Stunting prevalence of 35.9%. Aceh Singkil Regency is ranked third in Aceh with a Stunting prevalence of 34.1%. The lowest prevalence of Stunting in toddlers is in Gayo Lues Regency. Banda Aceh City is ranked 21st for Stunting cases in Aceh.

The lowest and highest prevalence of regencies/ cities in North Sumatra Province are 5.70% and 33.80% respectively. This indicates that there are regencies in North Sumatra that have met the National target. According to Table 4 that it can be seen that there are 7 regencies/cities that have achieved the National target. Deli Serdang City is the area with the highest prevalence in North Sumatra.

The lowest prevalence of stunting intoddlers is in Tanjungbalai Regency. Medan City is ranked 8th for stunting cases in North Sumatra. The lowest and highest prevalence of regencies/cities in West Sumatra Province are 14.70% and 33.70% respectively. This indicates that West Sumatra Province has not achieved the national target for stunting cases. Mentawai Islands Regency is the area with the highest prevalence in West Sumatra. West Pasaman Regency is ranked second in West Sumatra with a stunting prevalence of 29.7%. South Solok Regency is the lowest prevalence regency in West Sumatra. Padang City is ranked 8th for stunting prevalence in West Sumatra.

The lowest and highest prevalence of Regency/ City in Riau Province are 7.60% and 23.00% respectively. Kuantan Singingi Regency is the area with the highest prevalence in Riau Province. Kepulauan Meranti Regency is ranked second in Riau Province with a prevalence of 19.6%. The lowest prevalence of Stunting in toddlers is in Kampar Regency. Pekanbaru City is ranked 11th in Stunting prevalence in Riau Province.

The lowest and highest prevalence of districts/ cities in the Riau Islands Province are 17.30% and 23.20% respectively. Based on Table 4, it can be seen that the Riau Islands Province does not have a district/ city that has achieved the National target. Bintan

Table 4 List of Names of Districts/Cities that Achieved Targets

Province	**Number of Districts/ Cities**	**Number of districts/ cities that achieved the target**	**List of names of districts/cities that achieved the target**
Naggroe Aceh Darussalam	23	0	Not available
Sumatera Utara	33	7	Asahan, Sibolga, Tebing Tinggi, Labuanbatu Utara, Pematang Siantar, Medan, Tanjung Balai
Sumatera Barat	19	0	Not available
Riau	12	5	Indragiri Hulu, Siak, Pelalawan, Pekanbaru, Kampar
Kepulauan Riau	7	0	Not available
Sumatera Selatan	17	2	Ogan Komering Ulu Timur, Lahat
Kepulauan Bangka Belitung	7	0	Not available
Bengkulu	10	1	Kota Bengkulu
Jambi	11	6	Bungo, Kota Jambi, Muaro Jambi, Batang Hari, Kerinci, Sarolangun, Kota Sungai Penuh
Lampung	15	7	Bandar Lampung, Tulang Bawang Barat, Lampung Selatan, Pesawaran, Tulang Bawang, Metro, Mesuji

Regency is the area with the highest prevalence in the Riau Islands Province. Lingga Regency is ranked second in the Riau Islands Province with a prevalence of Stunting of 20.5%. The lowest prevalence of toddler Stunting is in the Anambas Islands Regency. Tanjungpinang City is the 6th prevalence of Stunting in the Riau Islands Province.

The lowest and highest prevalence of districts/ cities in South Sumatra Province are 7.80% and 33.10% respectively. North Musi Rawas Regency is the area with the highest prevalence in South Sumatra Province. Empat Lawang Regency is ranked 2nd in Stunting prevalence in South Sumatra with 32.6%. Ogan Komering Ilir Regency is ranked 3rd in Stunting prevalence in South Sumatra with 32.5%. The lowest prevalence of toddler Stunting is in Lahat Regency.

The lowest and highest prevalence of Regency/ City in Bangka Belitung Islands Province are 17.30% and 23.20% respectively. Bangka Regency is the area with the highest prevalence in Bangka Belitung Islands Province. Belitung Regency is ranked second in Bangka Belitung Islands Province at 20.80%. Pangkalpinang City is ranked third in Bangka Belitung Islands Province.

The lowest prevalence of toddler Stunting is in East Belitung Regency. The lowest and highest prevalence of Regency/City in Bengkulu Province are 6.70% and 28.60% respectively. Rejang Lebong Regency is the area with the highest prevalence of Stunting in Bengkulu Province. Mukomuko Regency is ranked 2nd highest prevalence in Bengkulu Province at 27.10%. The lowest prevalence of toddler Stunting in Bengkulu Province is Bengkulu City.

The lowest and highest prevalence of districts/ cities in Jambi Province are 4.10% and 23.70% respectively. Tanjung Jabung Timur Regency is the area with the highest prevalence in Jambi Province. Tebo Regency is ranked 2nd with the highest prevalence in Jambi Province at 22.70%. Jambi City is ranked 6th in Jambi Province. The lowest prevalence of stunting in toddlers is in Sungai Penuh City. The lowest and highest prevalence of districts/cities in Jambi Province. Tebo Regency is ranked 2nd with the highest prevalence in Jambi Province at 22.70%. Jambi City is ranked 6th in Jambi Province. The lowest prevalence of stunting in toddlers is in Sungai Penuh City. The lowest and highest prevalence of districts/ cities.

Lampung Province are 5.00% and 24.60% respectively. West Lampung Regency is the area with the highest prevalence of stunting in Lampung Province. The results of the logistic regression model using Stunting prevalence data in the province of Sumatra in 2023. Table 5 represents the results of the parameter estimation of the binary logistic regression model for Stunting cases in the province of Sumatra. As shown in Table 5, the estimation equation in Equation (6) can be determined as follows.

Based Based on Table 5, it can be seen that the independent variables that significantly influence the prevalence of Stunting in the province of Sumatra in 2023 are the variables Wasting, Underweight, Poor Population, and GRDP. These results indicate that the Wasting and GRDP values decrease, the prevalence of Stunting will increase. Conversely, if the Underweight and Poor population variables increase, the prevalence of Stunting will also increase. Table 6 shows the evaluation metric values based on the confusion matrix.

$$Logit(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = -8.0480 - 0.6278X_1 + 1.0798X_2 + 0.2816X_3 - 0.0551X_4 - 0.0199X_5 + 0.0004X_6 + 1.1748X_7 \quad (6)$$

Table 5 Parameter Estimation Results of the Binary Logistic Regression Model

Variable	Coefficient	Standard Error	z-value	p-value
Constant	-8.0480	2.726	-2.952	0.003
Wasting	-0.6278	0.163	-3.841	0.000
Underweight	1.0798	0.178	6.062	0.000
Poor People	0.2816	0.109	2.582	0.010
Gross Regional Domestic Product per Capita	-0.0551	0.026	-2.117	0.034
Households that have adequate sanitation	-0.0199	0.023	-0.853	0.393
Number of health workers	0.0004	0.000	0.929	0.353
Proportion of Ever-Married Women aged 15-49 who gave birth to a first	1.1748	2.610	0.450	0.653

Table 6 Evaluation Metric Values Based on Confusion Matrix

Model	Accuracy	Sensitivity	Specificity	Precision
Logistic Regression	0.8400	0.7600	0.9200	0.9050
Decision Tree (DT)	0.8800	0.8333	0.9231	0.9090
Random Forest (RF)	0.9000	0.8400	0.9600	0.8940
Support Vector Machine (SVM)	0.8800	0.8333	0.9231	0.9091

Table 7 SHAP Values and Features Importance Per Province

No.	Province	Feature Importance	SHAP Value
1	Aceh	X_4	0.050457
2	Bangka Belitung	X_2	0.065067
3	Bengkulu	X_2	0.053173
4	Jambi	X_2	0.022113
5	Kepulauan Riau	X_2	0.050257
6	Lampung	X_1	0.017603
7	Riau	X_4	0.041926
8	Sumatera Barat	X_2	0.090757
9	Sumatera Selatan	X_4	0.046935
10	Sumatera Utara	X_2	0.018422

The list result calculation of shapley value is then scan be seen in Table 7. Nanggroe Aceh Darussalam has the highest Shapley value.

Meanwhile, dependent variables such as the percentage of households with proper sanitation, the number of health workers, and the proportion of Ever-Married Women Aged 15-49 years who birth to their first live child. By examining Random Forest model as the finest model of the four models, Furthermore calculating the SHAP value. The construct of SHAP feature importance is simple. The average of each feature's SHAP values is used to calculate feature significance values. The most significant features are arranged in descending order in a feature significance plot. The feature importance of random forest model for Stunting prevalence in Sumatera Province is plotted in a traditional bar chart as ilustrated in Figure 2.

Based on Figure 2, Underweight (X_2) possess a greater impact than others, suggesting that altering this property may have a more obvious impact than others. If Underweight (X_2) are greater, then Stunting prevalence in Sumatera Province would be advancely. As described in Figure 2 at Gross Regional Domestic Product Per Capita (X_4), the result that Gross Regional Domestic Product Per Capitais higher then Stunting Prevalence would be reduced accordingly. By contrast, for features, such as Proportion of Ever-Married Women Aged 15-49 Who gave birth to a First, Number of health workers , and Poor people do not have a huge effect on Stunting Prevalence in Sumatera Province. This indicates that the change of these features does not have a noticeable influence on model prediction.

As shown in Figure 2, When it comes to summary plots, the y-axis depicts the feature values, the x-axis depicts the Shapley values. This color represents the degree of the effect (red means high, whereas blue means low). The higher the SHAP value, the larger the effect.

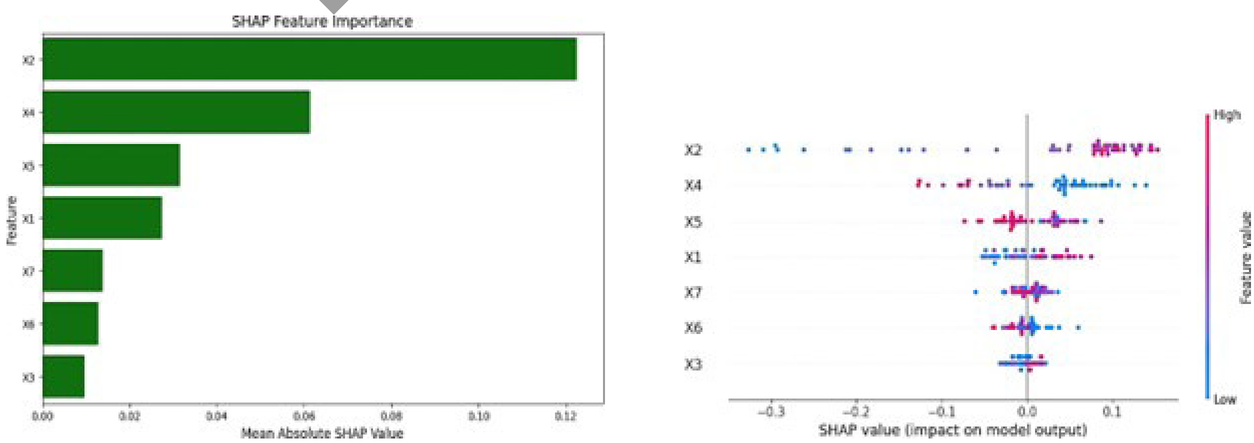
The features are ranked in accordance with their predictive power, and the graphs below show the features that affected the model's predicition. Each feature contributes either positively or negatively to the model output. In addition, which variables strongly correlate with the target variable, making SHAP is good tools with great benefit in variable selection. The plot in Figure 2 shows that the Underweight (X_2), Gross Regional (X_4), Household that adequate the Sanitation (X_5) features are the most important model features because the values of these features (high and low) are highly connected with both low and high SHAP scores. However, other aspects of the paradigm, including Proportion of Ever-Married Women Aged 15-49 Who gave birth to a First, Number of health workers, and Poor people are less important as their corresponding SHAP values are closer to zero and thus have less effect on the model. Table 5 below represent the parameter results logistic.

As described in the first rows of the summary plot, that a high level of attributes, such as Underweight, Gross Regional Domestic Product per Capita, and Households that have adequate sanitation have a high and positive effect on Stunting prevalence. The high comes from the color, and positive is shown on the x-axis. By taking a look at the first rows of the summary plot, the results that a high level of attributes, such as Underweight, Gross Regional Domestic Product per Capita, and Households that have adequate sanitation have a strong and favorable impact on Stunting prevalence. The color provides the high, and the x-axis displays a positive value.

Based on the SHAP values in Figure 3 and Table 7, it can be seen that the three most important features for per Capita (X_4), Underweight (X_2), and Households that have adequate sanitation (X_5). For Bangka Belitung Province, it can be seen in Figure 4 that the three most important features influencing stunting cases are Underweight (X_2), Number of health workers (X_6), and Poor people (X_3). For Bengkulu Province, the three key features are Underweight (X_2), Gross Regional Domestic Product per Capita (X_4), and Households that have adequate sanitation (X_5). For Jambi Province, the SHAP plot, which can be seen in Figure 5, shows that the three most important features are Underweight (X_2), Gross Regional Domestic Product per Capita (X_4), and Wasting (X_1).

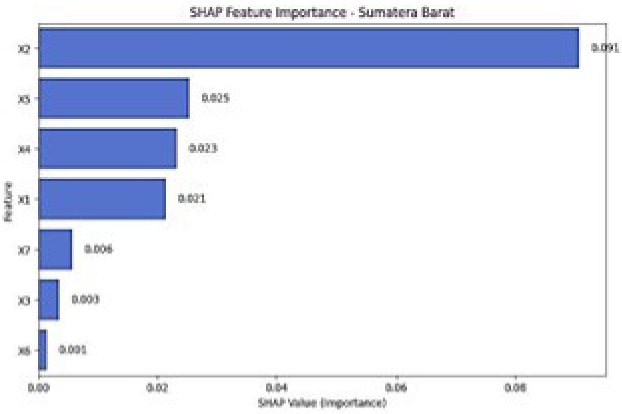
For Kepulauan Riau province, the three most important features are Underweight (X_2), Gross Regional Domestic Product per Capita (X_4), and Households that have adequate sanitation (X_5). For Lampung Province, it can be seen in Figure 5 that the three most important features are Wasting (X_1), Gross Regional Domestic Product per Capita (X_4), and Households that have adequate sanitation (X_5). For Riau Province, the three most important features are Gross Regional Domestic Product per Capita (X_4), Underweight (X_2), dan Proportion of Ever-Married womenaged 15-49 who gave birth to a first (X_7). three most important features are Gross Regional Domestic. Product per Capita (X_4), Underweight (X_2), and Households that have adequate sanitation (X_5).

For West Sumatra Province, the three key features are Underweight (X_2), Households that have adequate sanitation (X_5), and Gross Regional Domestic Product per Capita (X_4), For South Sumatra Province, the North Sumatra Province, the three most important features are Underweight (X_2), Number of health worker (X_6), and poor people (X_3). Therefore, The success of this research is benchmarked by Model Performance Benchmark. Firstly, the Random Forest model demonstrates the highest predictive accuracy among all models tested (Decision Tree and Support Vector Machine), indicating superior performance in predicting stunting prevalence in Sumatra Province. Quantitatively, this is reflected in higher accuracy and lower prediction error compared

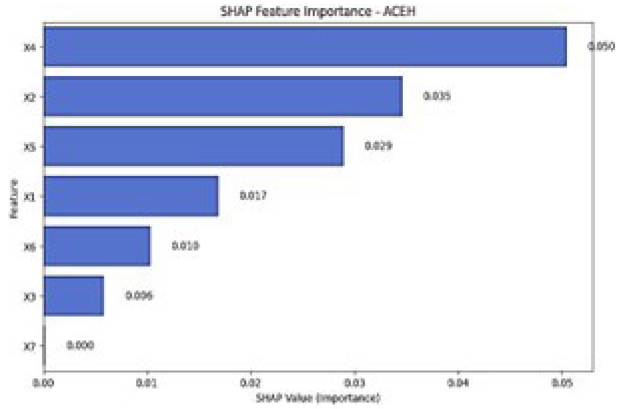


(a) (b)

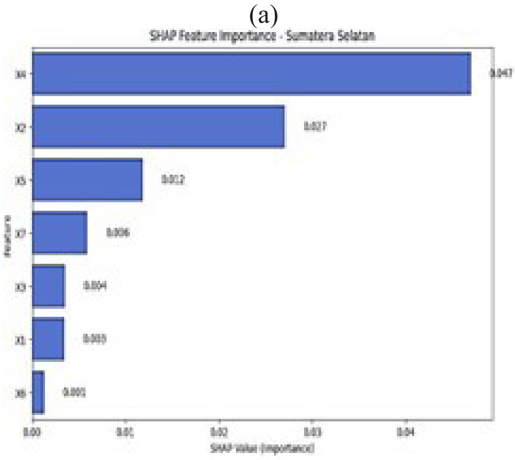
Figure 2 (a) Traditional Feature Importance SHAP Plots and (b) Shapley Value Plot



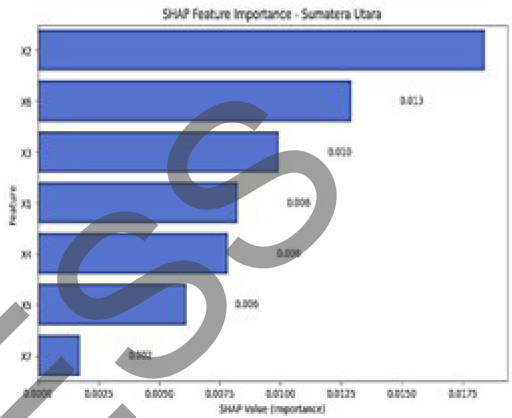
(a)



(b)

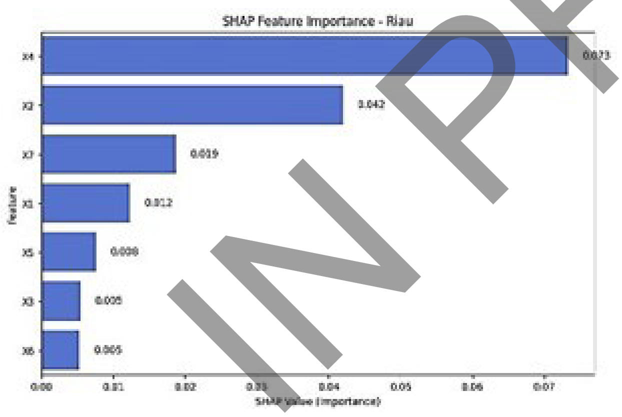


(c)

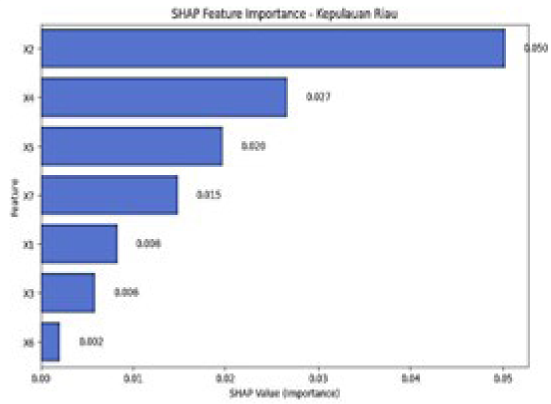


(d)

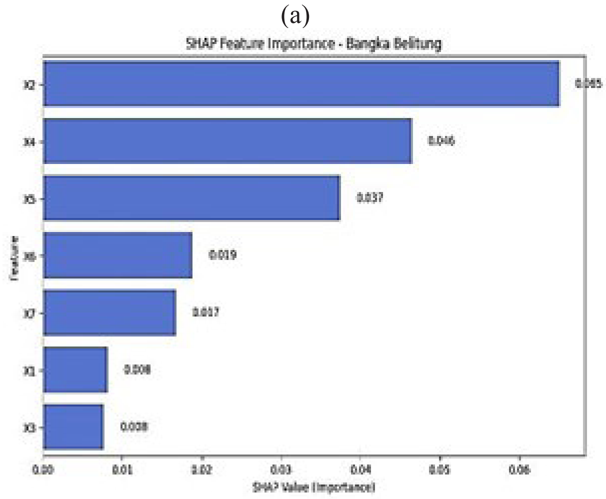
Figure 3 Traditional SHAP Plot by Province: (a) Aceh (b) West Sumatera
(c) North Sumatera (d) South Sumatera



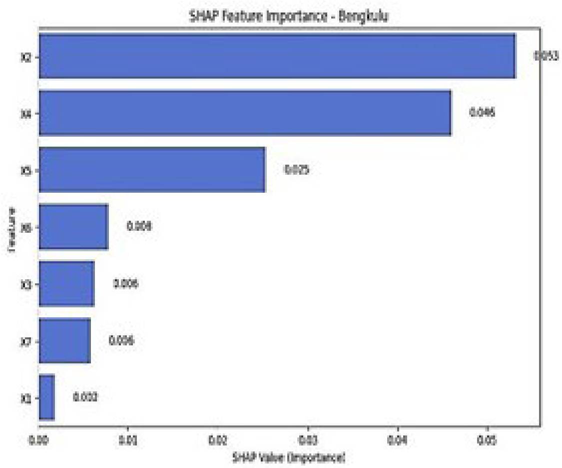
(a)



(b)

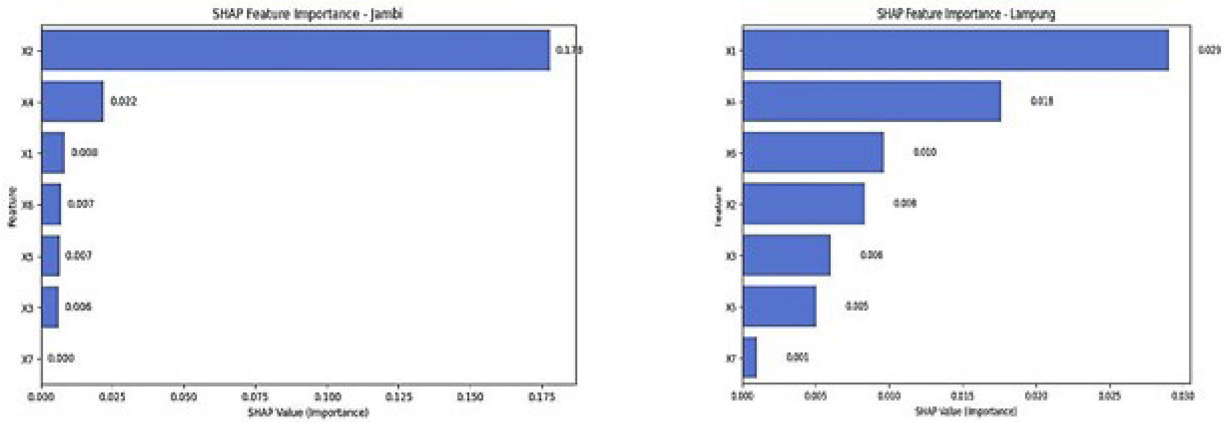


(c)



(d)

Figure 4 Traditional SHAP Plot by Province: (a) Riau (b) Kepulauan Riau (c) Bangka Belitung (d) Bengkulu



(a) (b)

Figure 5 Traditional SHAP plot by Province: (a) Jambi (b) Lampung

to the other models. The second reason is model explainability benchmark.

The application of SHAP values successfully identifies and explains the most influential features affecting stunting prevalence. The clear identification of key determinants—Underweight (X_2), Gross Regional Domestic Product per Capita (X_4), and Households with adequate sanitation (X_5)—shows that the model is both interpretable and aligned with domain knowledge and policy relevance. So, The benchmark for the success of this research is the ability of the Random Forest model to achieve the highest predictive accuracy and, through SHAP analysis, to provide interpretable and policy-relevant explanations of the factors influencing stunting prevalence in Sumatra Province.

IV. CONCLUSIONS

Random Forest model has the greatest accuracy compared to the Decision Tree and Support Vector Machine models. Random Forest model is used to stunting prevalence data in Sumatra Province. This results utilize SHAP values on Stunting prevalence data in Sumatera Province to explain feature importance affecting the Stunting.

The results show that Underweight (X_2) is the most influential feature as a strategy for the Indonesian government to minimize prevalence of Stunting in Sumatra Province. In addition, the Gross Regional Domestic Product per Capita (X_4) and Households that have adequate sanitation (X_5) features also need to be considered by the Indonesian government to address the reduction in the prevalence of Stunting in Sumatra Province.

A limitation of this study is the use of only seven independent variables and four model types. This study is limited by the use of only seven independent variables and four machine learning model types, which may constrain the predictive performance and reduce the opportunity to explore more advanced modeling approaches.

Future research is recommended to incorporate a broader set of predictor variables and to evaluate additional machine learning algorithms to further enhance model performance and generalizability. Moreover, deeper exploration of the SHAP framework is encouraged, particularly in its application across diverse and more complex machine learning models. Future studies could compare different SHAP variants—such as Kernel SHAP, Tree SHAP, and Deep SHAP—to determine their relative strengths, computational efficiency, and suitability for public health datasets.

Establishing clear benchmarks for SHAP visualization would also be valuable, as this could help users better interpret feature contributions, reduce ambiguity, and improve the practical utility of model explanations for policymakers and health practitioners. Additionally, investigating advanced visualization techniques or integrating SHAP with complementary interpretability tools may offer richer insights into model behavior. Such developments would not only broaden the methodological contribution of SHAP in classification problems but also create opportunities for identifying novel patterns and actionable factors related to stunting and other health outcomes.

AUTHOR CONTRIBUTIONS

Conceived and designed the analysis; Collected the data; Contributed data or analysis tools; Performed the analysis; Wrote the paper, A. A. P., N. F. S., K. A. N. and B. S.

DATA AVAILABILITY

The data that support the findings of this study are available in [Survei Kesehatan Indonesia Tahun 2023] at [https://www.badankebijakan.kemkes.go.id/hasil-ski-2023/]. These data were derived from the following resources available in the public domain: [https://www.badankebijakan.kemkes.go.id/hasil-ski-2023/].

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