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IDENTIFICATION OF STUNTING CAUSES USING MACHINE LEARNING ON HEALTH AND SOCIO-ECONOMIC DATA IN INDONESIA

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Abstract

Stunting is a multifaceted nutritional issue that is impacted by the intricate interplay between family structural constraints and child health concerns. This study uses a machine learning approach to simulate the prevalence of stunting and determine the significant ranking of its major causes in Indonesia. Ten independent variables from the socioeconomic and health dimensions are integrated using the Random Forest Regressor technique. With an R-Squared value of 0.89, the model evaluation results demonstrated a very high level of performance, demonstrating the algorithm's dependability in mapping data variance. With a contribution of 36.36%, the Percentage of Poor Population was shown to be the most significant predictor based on the extraction of the Feature Importance measure, followed by Complementary Feeding (18.36%) and Per Capita Expenditure (12.75%). When taken as a whole, these results demonstrate that the incidence of stunting is significantly more influenced by economic welfare determinants than by clinical health interventions alone. According to the study's findings, stunting is mostly caused by poverty and low purchasing power, necessitating comprehensive policy approaches centered on reducing cross-sectoral structural poverty rather than merely focusing on particular medical treatments.

Keywords: Stunting, Socio-economic, Prediction, Machine Learning, Random Forest Regressor

INTRODUCTION

Stunting remains a critical global health issue, particularly in developing countries such as Indonesia (Andriani et al., 2025; Ayue et al., 2025). Beyond causing permanent impairments to a child's physical and cognitive development, stunting also serves as a primary catalyst for the decline of a nation's future economic productivity (Galasso & Wagstaff, 2019; Vaivada et al., 2020). In the long term, a high prevalence of stunting at the national level significantly impedes economic growth. Empirical studies indicate that the potential economic loss due to childhood stunting can lead to a decline in the Gross Domestic Product (GDP) by approximately 1% to 2% and potentially higher as it drastically diminishes the overall quality and productivity of the future workforce (Kustanto, 2021; Suryana, 2023). The underlying causes are not solely dictated by nutritional intake but are profoundly contingent upon complex socio-economic conditions, including structural poverty and limited access to proper sanitation (Arief et al., 2025; Hidayat, 2023; Beal et al., 2018).

Based on data from the 2024 Indonesian Nutritional Status Survey, the prevalence of stunting in Indonesia currently stands at 19.8%. While this percentage has successfully met the World Health Organization (WHO) standard of falling below the 20% threshold. At the national level, the Indonesian government has set an accelerated target to reduce stunting prevalence to 14% (Alfiyaty et al., 2026; Kurniawati et al., 2025). The formidable challenge of drastically reducing the prevalence

rate to achieve this 5% target necessitates the implementation of precise, evidence-based, and highly targeted intervention strategies.

Recent studies emphasize that the high prevalence of stunting is not solely attributed to nutritional deficiencies, but is rather a multidimensional issue driven by a complex interplay of broader socio-economic, environmental, and maternal factors. Given the multidimensional determinants of stunting, which involve intricate interactions between child health factors and socio-economic conditions, identifying the most dominant root causes presents a significant analytical challenge that often requires advanced computational approaches. Specifically, these socio-economic conditions encompass critical household indicators, including poverty rates, maternal education, and access to essential infrastructure such as clean water and proper sanitation (Beal et al., 2018; Sinharoy et al., 2026). Conventional statistical approaches in practice often exhibit limitations when applied to large-scale survey data characterized by complex and non-linear relationships. Consequently, the implementation of machine learning has emerged as a highly promising alternative. Compared to traditional linear modeling, machine learning algorithms have demonstrated superior capabilities in extracting valuable insights and accurately mapping hidden patterns within complex datasets (Shahid et al., 2026; Li et al., 2025; Bjerre et al., 2024; Shen et al., 2023)

Previous studies have adopted machine learning algorithms, such as Random Forest and Extreme Gradient Boosting (XGBoost), to predict the risk of malnutrition in toddlers (Juwariyem et al., 2024; Rao et al., 2025). These studies consistently demonstrated that machine learning models significantly outperformed traditional statistical approaches, yielding higher predictive accuracy and demonstrating a superior capability to capture complex, non-linear relationships among various stunting determinants. The primary advantage of employing these ensemble methods lies not only in their high predictive accuracy but also in their capacity to conduct feature importance analysis. Through this technique, it is possible to quantitatively identify and rank the variables that contribute most significantly to stunting cases in a specific region, encompassing both health and household economic dimensions (Bagur & Pratama, 2026).

Although machine learning-based studies on stunting have begun to develop, the majority of these studies predominantly focus on analyzing clinical factors in isolation from economic factors. Comprehensive integrated analyses that simultaneously evaluate and compare toddler health data with socio-economic conditions remain highly limited (Firmansyah et al., 2025). To bridge this research gap, this study aims to identify the primary determinants of stunting in Indonesia by applying machine learning algorithms to integrated health and socio-economic datasets.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

Human Capital Theory

This study is grounded in the Human Capital Theory pioneered by Schultz (1961) and Becker (1964), which asserts that early childhood health and nutrition are fundamental investments in an individual's future productivity and cognitive capacity. Within an economic framework, stunting is not merely a medical condition but signifies a failure in human capital accumulation (Galasso & Wagstaff, 2019). The occurrence of stunting in toddlers is profoundly influenced by a complex interplay of health and socio-economic factors, where limitations in household economic capital such as income level, environmental sanitation, and parental education directly impede a family's ability to provide adequate nutritional intake and a healthy living environment (Headey & Alderman, 2020). Consequently, the health economics perspective posits that socio-economic factors serve as underlying causes that are as critical as the child's intrinsic health factors (Victora, 2022).

This first hypothesis examines the model's reliability in explaining the variance within stunting prevalence data. By employing an ensemble learning approach, the algorithm is expected to capture the complex relational patterns between health and socio-economic variables, thereby

yielding a strong coefficient of determination R-Squared. This robust metric indicates that the model is highly suitable for further analytical purposes (Schonlau & Zou, 2020; Shen et al., 2023).

H1: The Random Forest Regressor algorithm is capable of effectively modeling stunting prevalence with a high degree of accuracy using a combination of health and socio-economic variables.

This second hypothesis aims to address the core objective of the research, which is to identify the most influential factors. Through the extraction of the Feature Importance metric, the relative influence of the ten independent variables examined will be mapped and ranked. This hypothesis posits that dominant variables stemming from either health or socio-economic dimensions will emerge with the highest scores, thereby significantly dictating the fluctuations of stunting rates in Indonesia.

H2: There is a significance ranking among the independent variables, in which specific factors occupy the top positions as the primary determinants of stunting.

RESEARCH METHODS

This study employs a quantitative approach utilizing machine learning-based regression analysis. The primary focus of this research is to identify, quantify, and rank the significance of independent variables encompassing child health dimensions and household socio-economic conditions on the prevalence of stunting. The dataset utilized is sourced from the 2024 Indonesian Nutritional Status Survey (SSGI) and official publications from Statistics Indonesia (BPS).

Operational Definition of Variables

Table 2. Operational Definition of Variables

Variable	Definition	Unit
Stunting (STUNT)	The percentage of toddlers experiencing stunting in the observation area.	%
Maternal Factor (MF)	The percentage of mothers receiving and consuming Iron-Folic Acid (IFA) supplements.	%
Household Factor (HF)	The percentage of social assistance received by the household.	%
Complementary Feeding (CFEED)	The percentage of children aged 6-23 months meeting the minimum dietary diversity requirement.	%
Breastfeeding (BF)	The percentage of infants aged 0-5 months receiving exclusive breastfeeding within a 24-hour period.	%
Access to Child Health Services (CHS)	The proportion of toddlers receiving standard and appropriate growth monitoring.	%
Infectious Diseases (INFEC)	The percentage of toddlers who experienced diarrhea in the past 1 month.	%
Percentage of Poor Population (POOR)	The poverty rate within the observed population.	%
Per Capita Expenditure (PCE)	The average monthly expenditure per capita of the population.	IDR
Mean Years of Schooling for Women (MYSW)	The average duration of formal education completed by women. Indicator of maternal education.	Years
Access to Proper Sanitation & Clean Water (WASH)	The percentage of the population with access to improved sanitation facilities and safe drinking water.	%

RESULTS AND DISCUSSION

RESULT

Model Evaluation

The initial testing phase was conducted to evaluate the performance of the Random Forest Regressor algorithm in modeling the prevalence of stunting. Based on the computational results, the model yielded a coefficient of determination R-Squared value of 0.89. This figure indicates that 89% of the variance in stunting prevalence can be simultaneously explained by the ten independent variables from the model, while the remaining 11% is attributed to other factors beyond the scope of this study. This high R-Squared value directly addresses and supports Hypothesis 1, proving that the Random Forest Regressor algorithm is capable of modeling stunting prevalence with a very high degree of accuracy and mapping the combination of health and socio-economic variables.

Visualization of Model Logic Structure

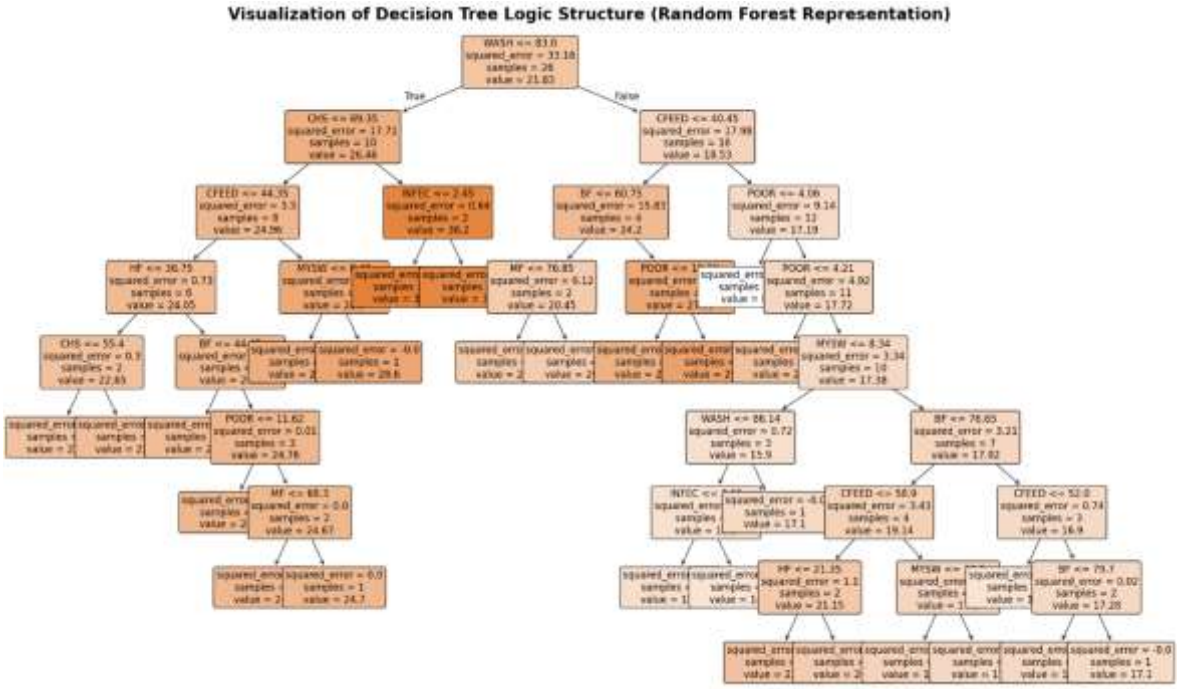


Figure 1. Visualization of Model Logic Structure

To elucidate the internal decision making process of the algorithm, this figure 1 illustrates a single decision tree extracted from the Random Forest Regressor ensemble. The mechanism works by recursively partitioning the data based on specific variable thresholds, starting with the root node splitting at WASH 83.0 that are mathematically computed to optimally minimize the Mean Squared Error (MSE). As the data flows down through the branches based on these sequential True/False conditions, it eventually reaches the terminal nodes (leaves) at the bottom of the tree. The word value displayed in these final leaf nodes represents the ultimate predicted outcome specifically, it indicates the estimated stunting prevalence for a sample (province) that satisfies the specific sequence of socio-economic and health conditions leading to that exact node.

Practically, this indicates that the algorithm divides the dataset based on whether a region's sanitation access is less than or equal to 83%, effectively distinguishing the severity levels of stunting prevalence at that node. This decision path subsequently branches into further stratifications involving other variables such as CHS, CFEED, and POOR. Each node encapsulates crucial metrics, indicating the prediction error variance, representing the number of data observations within that branch and value, denoting the estimated stunting prevalence for that

specific node. Although the Random Forest algorithm ultimately aggregates the average prediction values from hundreds of distinct trees to prevent overfitting, this visualization provides highly valuable interpretability, showcasing the complex hierarchical interactions between health and socio-economic variables in predicting stunting rates.

From a macroeconomic and household economics perspective, these algorithmic splits logically reflect the realities of budget constraints and resource allocation. When a region suffers from inadequate sanitation, children are highly susceptible to infectious diseases. This not only biologically hinders nutrient absorption but also economically forces low income households to divert their severely limited financial resources toward out of-pocket healthcare expenditures rather than investing in highquality protein rich foods (CFEED). This financial strain is exponentially compounded when interacting with high poverty rates (POOR) and lower maternal education (MYSW), which restrict purchasing power and limit the mother's capability to make optimal economic decisions regarding family nutrition. Consequently, the tree's hierarchical structure perfectly captures the vicious economic cycle where poor infrastructure and poverty synergistically drive up the stunting prevalence.

Significance Ranking and Feature Importance Analysis

To identify the variables that provide the greatest contribution to the model, Feature Importance values were extracted utilizing the Mean Decrease Gini Metric (Breiman, 2001; Doğruel, 2026; Setiawan et al., 2025). In the context of machine learning, this metric calculates the average reduction in node impurity specifically the reduction in prediction error or Mean Squared Error (MSE) every time a particular variable is used to partition the data. Essentially, it measures how effectively a variable improves the accuracy of the model's decision making process.

The extraction results reveal a highly varied range of scores across the variables, from the lowest at 0.0195 to the highest at 0.3636. The highest value designates the most dominant predictor, meaning this variable provides the most substantial contribution to minimizing prediction errors and strongly dictates the overall stunting prevalence. Conversely, the lowest value signifies a variable with a marginal impact, indicating that its role in splitting the data and influencing the final prediction is relatively weak compared to the others (Adebayo et al., 2026; Cappelli et al., 2024)(Cappelli et al., 2024). These findings empirically validate and support Hypothesis 2, demonstrating a distinct significance ranking among the independent variables, wherein secure the top positions as the primary determinants of stunting.

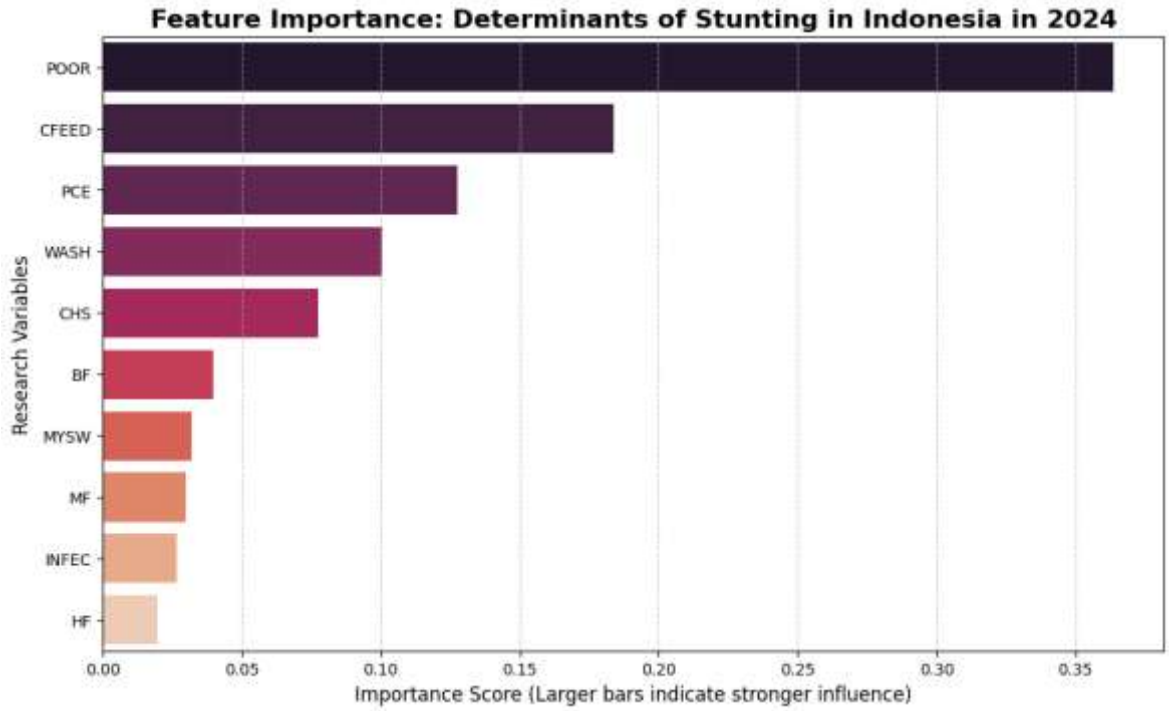


Figure 2. Feature Importance

Table 2. Feature Importance Score

Variable	Importance Score
POOR	0.3636
CFEED	0.1836
PCE	0.1274
WASH	0.1003
CHS	0.0777
BF	0.0395
MYSW	0.0320
MF	0.0298
INFEC	0.0265
HF	0.0195

DISCUSSION

Based on the ranking Table 2, variable POOR (Percentage of Poor Population) emerges as the most influential variable, contributing significantly at 36.36%. The absolute dominance of this poverty indicator is highly relevant to the health economics perspective and strongly corroborates the Human Capital Theory. This finding confirms that economic constraints serve as the primary root cause undermining the foundation of toddler nutrition. Poverty severely restricts household purchasing power, thereby limiting the ability to provide adequate nutritional intake (Headey & Alderman, 2020). This empirical finding is clearly reflected in the regional data patterns across Indonesia provinces with persistently high poverty rates and limited infrastructure, such as East Nusa Tenggara (NTT) and Papua, consistently record the highest prevalence of stunting, contrasting sharply with economically developed regions like DKI Jakarta (Tahir et al., 2025). Furthermore, the phenomenon of regions successfully achieving significant stunting reduction is heavily associated with the integration of poverty alleviation programs and conditional cash transfers, which directly elevate household purchasing power (Mirzal et al., 2025). The crucial implication of this finding is

that stunting cannot be eradicated solely through health-centric interventions, such as supplementary feeding. Sustainable stunting mitigation demands a structural policy shift where economic empowerment and poverty eradication become the fundamental prerequisites for improving national child health (Wanti, 2026).

This condition is directly linked to the variable in the second rank, namely CFEED (Complementary Feeding) with an influence of 18.36%, as well as the third rank, PCE (Per Capita Expenditure) at 12.75%. This pattern illustrates a robust causal chain: high poverty rates and low per capita expenditure directly constrain a family's capacity to fulfill the dietary diversity required for optimal child growth (Beal et al., 2018).

Furthermore, variable WASH (Access to Proper Sanitation & Clean Water) also demonstrates a significant contribution, ranking fourth at 10.03%. Cumulatively, determinants rooted in socio-economic welfare and basic environmental infrastructure (POOR, PCE, and WASH) account for a dominant influence of nearly 60%. These results confirm that stunting is fundamentally driven by socio-economic conditions rather than merely nutritional deficits. This aligns with regional disparities across Indonesia economically developed provinces with adequate infrastructure, such as DKI Jakarta and Bali, consistently report significantly lower stunting rates. Conversely, regions burdened by structural poverty and poor sanitation, such as Papua and East Nusa Tenggara, experience the highest stunting prevalence (Ashar et al., 2024; Kustanto et al., 2025). Consequently, poverty alleviation and infrastructure equity are absolute prerequisites for mitigating this crisis (Al Maraghi et al., 2025).

This yields a crucial policy implication to alleviating stunting in Indonesia cannot be adequately resolved solely through specific medical interventions at primary healthcare center. Rather, it necessitates structural resolutions focusing on poverty alleviation, the enhancement of household purchasing power, and the provision of adequate sanitation infrastructure (Cumming et al., 2019).

Therefore, this study firmly underscores that socio-economic determinants must be recognized as the primary frontline in combating stunting. Specifically, targeted cross sectoral interventions addressing POOR, PCE, and WASH are absolutely indispensable. These variables empirically demonstrate that a household's financial capacity, educational background, and environmental hygiene fundamentally dictate their resilience against chronic malnutrition. Treating stunting merely as a clinical issue while ignoring these structural socio-economic root causes will only result in temporary fixes rather than sustainable eradication (Gusliana et al., 2025).

CONCLUSION

This study successfully modeled the determinants of stunting in Indonesia utilizing a machine learning approach through the Random Forest Regressor algorithm. Based on the analysis and discussion, the following primary conclusions can be drawn

First, the Random Forest Regressor algorithm has proven to be highly effective in mapping the complex relationships between health and socio-economic variables regarding stunting prevalence. This is evidenced by the attainment of an R-Squared value of 0.89, signifying that the model is capable of explaining 89% of the data variance. This finding provides empirical validation to accept Hypothesis 1 (H1), indicating that the model possesses a high degree of accuracy to be utilized as a policy analysis instrument.

Second, the extraction results of the feature importance metric fail to reject Hypothesis 2 (H2) by demonstrating a distinct significance ranking among the variables. The Percentage of Poor Population (POOR) was identified as the most dominant determinant with an influence score of 36.36%, followed by Complementary Feeding (CFEED) at 18.36%, and Per Capita Expenditure (PCE) at 12.75%. Cumulatively, factors associated with economic welfare and environmental infrastructure, such as access to proper sanitation and clean water, exert a substantially greater contribution compared to pure health intervention variables.

Theoretically, this study confirms that stunting is not merely a clinical toddler health issue, but rather a structural problem deeply rooted in poverty and limited household purchasing power. Therefore, the recommended policy implication is the strengthening of sensitive interventions that are cross-sectoral in nature. The government must not focus solely on specific nutritional interventions; rather, it must be more aggressive in implementing poverty alleviation programs, enhancing family purchasing power for access to nutritious food, and accelerating the development of adequate sanitation and clean water infrastructure as the primary foundation for reducing stunting rates in Indonesia.

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