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Explainable Artificial Intelligence Using SHAP and Multilayer Perceptron for Transparent Stunting Risk Prediction in Sukoharjo, Indonesia

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Abstract

Childhood stunting remains a critical public health challenge in Indonesia, with national prevalence at 19.8% in 2024 per SSGI data, hindering human capital development toward Indonesia Emas 2045. This study addresses the opacity of AI models in stunting prediction by integrating machine learning with Explainable AI (XAI) to enhance transparency for non-technical stakeholders. Using a survey dataset of 273 children from Sukoharjo Regency, risk factors encompassing key stunting determinants consist of maternal characteristics, household socioeconomic conditions, sanitation practices, and sociodemographic, were preprocessed via cleaning, label encoding, min-max scaling, and train-test split. Three classifiers; Logistic Regression (LR), Naïve Bayes (NB), and a Multilayer Perceptron (MLP) with ReLU/softmax were trained and evaluated on accuracy, precision, recall, and F1–score. MLP with 16 hidden nodes, achieved the highest performance: 82% accuracy, 87% precision, 82% recall, and 82% F1-score, outperforming baselines. Kernel SHAP was applied to decompose predictions, revealing mother's education, age, number of children, birth length, household size, and income as top influencers. This XAI enhanced framework promotes trust and actionability in public health interventions, advancing informatics by bridging high accuracy neural networks models with interpretable insights for targeted stunting reduction in resource–limited settings.

Keywords : *XAI, Stunting, MLP, Logistic Regression, Naïve Bayes.*

1. INTRODUCTION

Healthy child growth constitutes a fundamental prerequisite for establishing of a resilient society, which is Indonesia's strategic foundation for realizing the vision of Indonesia Emas 2045, a centennial milestone that aspires to position the nation among the world's leading economies and develop globally competitive human capital. This vision, however, is undermined by the number of stunting prevalence. Stunting refers to a condition of impaired growth resulting from prolonged malnutrition. According to the Indonesia Toddler Survey Status (known as SSGI), the national stunting prevalence in 2023 remain 21.5% and 19.8% in 2024, which is slightly higher than the government's target by 14% in 2024 [1]. At the regional level, the prevalence of stunting in Sukoharjo Regency was recorded at 24.3% in 2023 and 14.57% in 2024 [1]. These figures highlight that despite the significant policy efforts, stunting remains present as a critical barrier to achieving optimal human capital development. Therefore, this condition demands an innovative approach of early detection and targeted intervention.

The occurrence of stunting is not merely a health concern but a multidimensional factor ranging from biological, socioeconomic, and environmental determinants [2], [3], [4]. Biological risk factors are the physical conditions that might compromise children growth and health-related issues. These factors include inherent, prenatal, perinatal complications, and postnatal vulnerabilities. The genetic predisposition might contribute to the occurrence of stunting due to inherited genetic variation [2]. Prenatal and perinatal complications such as low birth weight, restricted fetal growth, and preterm

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delivery could establish an early disadvantage in children's growth [5]. While postnatal vulnerabilities such as diarrhea could disturb nutrient absorption, this could lead to nutrient deficiency.

In addition, socioeconomic and environmental factors could exert a profound influence on stunting prevalence [6]. Poverty, food security, access to clean water, and sanitation exacerbate nutritional deficiency and expose children to a higher risk of infectious diseases [4], [7]. Furthermore, disparities in access to education could also be linked to the persistence of stunting. Limited education opportunities might lead to a lack of knowledge and resources to make informed decision especially in terms of hygiene, nutrition, and child-rearing practices [8]. In addition, lower levels of parental education are strongly associated with reduced earning potential which subsequently limits household food security and access to essential services. These interconnected determinants underscore that stunting cannot be addressed through biomedical interventions alone but requires a comprehensive multisectoral strategies.

Within the complex and multifactorial determinants, Artificial Intelligence (AI) technology are increasingly being explored as a potential tool to support decision making in complex problem. In recent years, healthcare sector has experienced rapid progress in AI with techniques like Deep Neural Networks (DNNs) providing highly successful in addressing demanding problems ranging from diagnostic imaging, anomaly detection, to cancer pre-diagnosis [4], [9], [10], [11]. Alongside these advanced neural based architecture, a wide range of machine learning techniques have also been widely employed in predictive medical challenges such as logistic regression, k-nearest neighbours (KNN), random forest, and support vector machine (SVM). These methods are valued for their robustness, adaptability, and its effectiveness to process large multidimensional data.

Nevertheless, the successful integration of these techniques into real world healthcare systems faces persistent challenges, most notably those concerning trust, interpretability, and practical applicability [9], [12], [13]. Much of the prevailing AI research has been narrowly focused on optimizing algorithmic accuracy, sensitivity, and specificity. However, users especially those who are responsible in making a decision, frequently overlooking the equally critical requirement of transparency. As a result, the knowledge conveyed to end users is often reduced to numerical outputs such as probability scores, classifications, or accuracy levels without adequate explanation of the reasoning process that produced them. For healthcare professionals, policymakers, and community stakeholders who may lack technical expertise, this opacity raises legitimate concerns, especially when algorithmic outputs are intended to inform life altering interventions or diagnostic decisions [13], [14]. In such contexts, the absence of interpretability risks undermining user confidence and may ultimately impede the adoption of AI driven solutions, regardless of their advancement of statistical performance.

The absence of interpretability risks undermining user confidence and may ultimately impede the adoption of AI driven solutions especially in public health where trust, clarity, and accountability are as essential as the advancement in accuracy performance [15], [16]. In contrast to earlier studies [17], [18], [19] that primarily focused on maximizing predictive accuracy, this paper addresses the critical transparency gap in stunting prediction by adopting the SHAP Explainable Artificial Intelligence (XAI) approach. SHAP is well suited for increasing transparency since it provides consistent, model agnostic feature attributions based on rigorous game theoretic foundations [20]. By quantifying the marginal contribution of each feature to individual predictions [21], [22], SHAP enables stakeholders to understand why the model arrives at a certain outcome instead of merely accepting the output as a black box. Moreover, SHAP's visual explanation tools could translate complex model behaviour into intuitive representations that can be understood by non-technical stakeholders. These explanations make the AI model's reasoning interpretable and actionable in revealing how risk factors shape the predicted risk of stunting. As a result, SHAP not only enhances transparency but also empowers non-technical users to justify AI results, communicate stunting risk effectively, and design targeted interventions. Thus, the

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integration of SHAP fulfils the novelty of this research by maintaining strong predictive performance while delivering interpretable and trustworthy AI explanations absent in accuracy centric prior models.

2. METHOD

This research adopted an integrated design combining machine learning, explainable artificial intelligence (XAI), and human-centered design principles which implemented in several steps shown in Figure 1: (1) Data Collection, (2) Data Preprocessing, (3) Classification Model Development, (4) Model Evaluation, (5) SHAP based Model Explanation

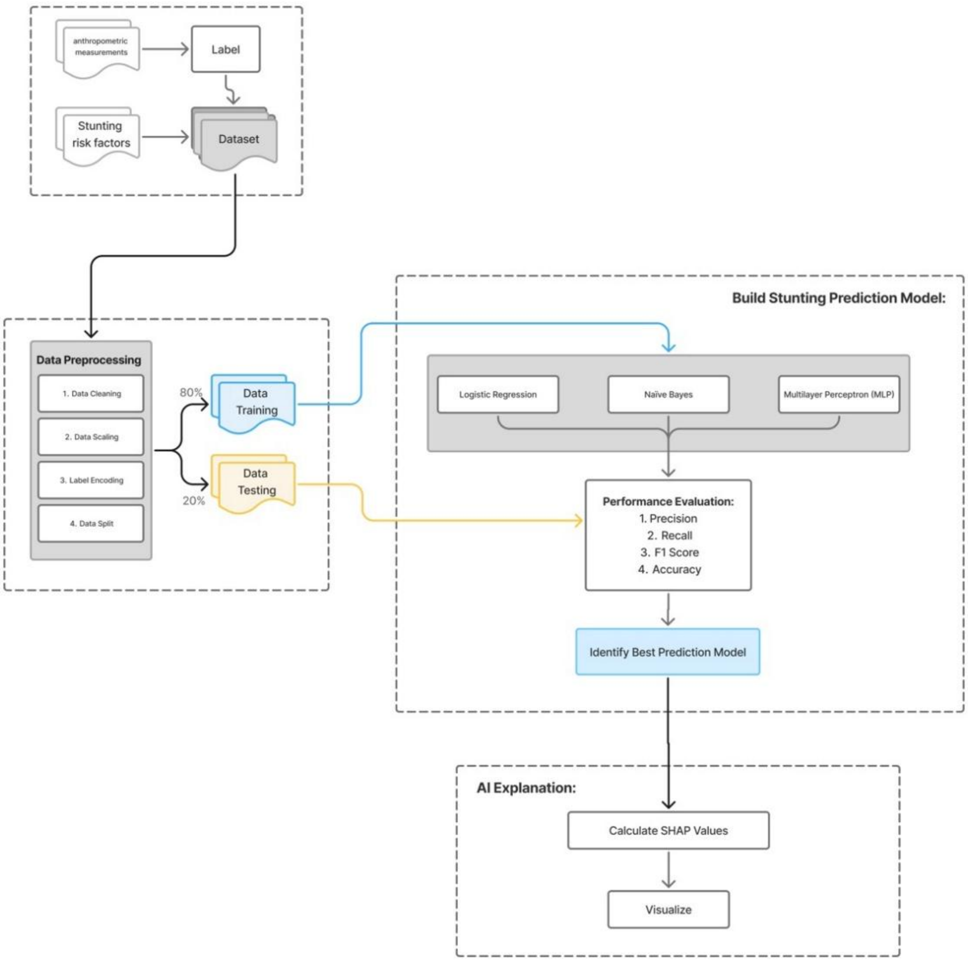

Figure 1 End-to-end methodological workflow inspired by CRISP-DM, comprising data acquisition, preprocessing, model development (LR, NB, MLP), and SHAP explainability.

2.1. Stunting Risk Factors

The dataset used in this paper was obtained by the survey in Sukoharjo regency, Central Java. The data collection process adhered to national and institutional ethical guidelines for research involving human participants. All respondents were informed about the study objectives, data confidentiality, voluntary participation, and the right to withdraw at any time. Personally identifiable information was removed prior to analysis, and all records were anonymized following data-minimization principles. This survey collected two categories of variables: dependent and independent variables. The dependent

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variable in this study comprises anthropometric measurements, including height or body length, gender, and age, which serve as the basis for determining the label. The independent variables employed in this research represent various stunting risk factors, encompassing biological, socioeconomics, and environmental determinants [2], [4]. These risk factors defined as conditions or circumstances that may influence the likelihood of stunting among children which are shown in Table 1. The final dataset consisted of 273 child records and 21 features, including maternal height, maternal education, birth weight, sanitation conditions, household income category, and waste management.

Table 1 Description of Independent Variables Used in the Study

Variable	Description
Birth Weight	The child's weight at birth (kg).
Birth Length	The child's length at birth (cm).
Gender	Biological sex of the child (male/female).
Child's Illness	Presence of any congenital or chronic illness.
Diarrhea History	Whether the child experienced diarrhea within the past three months.
Mother's Age	Age of the mother (years).
Mother's Height	Mother's height (cm).
Mother's Pre-Pregnancy Weight	Weight of the mother before pregnancy (kg).
Mother's Illness	Presence of any chronic or hereditary illness in the mother.
Number of Children	Total number of children born to the mother.
Antenatal Check-ups	Whether the mother regularly attended antenatal examinations during pregnancy.
Household Size	Total number of family members living in the same household.
Father's Occupation	Main occupation of the household head.
Household Income	Monthly family income.
Father's Education	Education level of the father (Primary/Junior Highschool /Senior Highschool /University).
Mother's Education	Education level of the mother (Primary/Junior Highschool /Senior Highschool /University).
Water Source	Type of water source used for daily cooking (well, tap water, bottled).
Private Latrine	Whether the family owns a private toilet facility.
Flood Exposure	Whether the house has ever been affected by flooding.
Waste Management	Household method of waste disposal or environmental sanitation.
Social Assistance	Whether the household receives any government social assistance.

2.2. Data Preprocessing

Raw data collected from the survey are not ready for immediate data analysis. Therefore, to ensure the readiness for analysis, the raw needed to be preprocess through several stages. The first stage of preprocessing was data cleaning in which the missing, incomplete, or inconsistent entries were identified and addressed. These irregularities were corrected to ensure that all variables have a uniform data structure [23], [24]. The second stage is data encoding. This process was essential to convert categorical data into a numerical format interpretable by machine learning algorithms. Several features such as gender, type of water source, and sanitation access were categorical and thus required transformation into numerical format using label encoding. This approach allowed algorithms to recognize and process non-numerical variables while preserving categorical distinctions.

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The next stage is data scaling which focused on normalization to eliminate disparities in numerical magnitude across features [24]. In this research, variables such as maternal height (measured in centimeters) and variable number of children (a small integer count) differ substantially in scale. Variables with larger numerical ranges could dominate the optimization process during model training which potentially leading to biased weight assignments. To prevent this imbalance, min–max scaling was applied to all numerical variables, linearly transforming its values into a uniform range between −1 and +1. This normalization technique not only improved algorithmic stability but also enhanced comparability between features, ensuring that all input variables contributed proportionately to model learning.

The final stage of the preprocessing pipeline was data splitting, which aimed to evaluate the model's generalization ability. To achieve a balanced and statistically valid assessment, the dataset was divided into 80% for data training and 20% for data testing. The training data was used to train the models, while the testing data was used to evaluate the trained model performance. This approach ensured that performance metrics could reflected the model's predictive ability while applied to unseen, real-world data.

2.3. Classification

There are three algorithms were compared in this research to identify the most accurate and robust AI model for stunting prediction. The models under comparison were Logistic Regression, Gaussian Naïve Bayes, and Multilayer Perceptron each representing a distinct family of predictive approaches of linear, probabilistic, and neural-network-based methods, respectively. These algorithms were selected not only for their methodological diversity but also due to evidence from prior research [17], which highlights Neural Networks, Logistic Regression, and Naïve Bayes as consistently strong performers in nutritional risk and health-related classification tasks. In line with these findings, all three models demonstrated solid predictive capabilities in the present study, thereby providing a robust basis for determining the most suitable model for stunting prediction.

Logistic Regression (LR) is one of the most popular algorithms served as a baseline model, providing interpretable probabilistic predictions through the sigmoid function [18], [25]. LR models are well-suited for binary and categorical outcomes, mapping a linear combination of input features to a probability value between 0 and 1. The sigmoid function is defined in the following equation (1).

$$f(x) = \frac{1}{1+ e^{-ax}} \qquad (1)$$

Where a represents the slope parameter controlling the steepness of the curve. The sigmoid function produces an S-shaped curve that maps any real-valued input into a probability within the [0, 1] range. Around the central region near $x = 0$, the function exhibits its steepest gradient, making it highly sensitive to small variations in input values. LR could also be used for multi-class classification by extending the binary logistic framework to handle multiple categorical labels. In this setting, the model simultaneously estimates the probability of each category using a softmax activation function. The softmax activation function ensures that the sum of predicted probabilities across all classes equals one, thereby maintaining a valid probabilistic interpretation.

The Naïve Bayes (NB) classifier is a probabilistic algorithm which expresses the posterior probability of a class given a set of features as the product of the class prior and the likelihood of the observed features under that class shown in equation (2) [26], [27]. This algorithm grounded by Bayes Theorem, assuming conditional independence among predictors given the class label, meaning that the contribution of each feature to the posterior probability can be treated as statistically independent [27].

$$P(class|features) = \frac{P(class)*P(features|class)}{P(features)} \qquad (2)$$

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This algorithm determines the likelihood of a data point belonging to a certain class depends on two key elements; how common that class is in general (prior probability) and how likely the observed features are if the data point belongs to that class (likelihood). Naïve Bayes classifier is commonly used in classification task both binary and multiclass classification which has been widely applied to the numerous cases. This algorithm is particularly effective and efficient computational process and require a relatively small amount of training data.

Lastly, the Multilayer Preceptron (MLP) model was constructed to capture the nonlinear and hierarchical interactions among predictors [28]. The architecture consisted of one input layer, one hidden layer, and one output layer. The number of nodes in input layer matching the number of stunting risk factor used in this paper while the number of nodes in one output layer corresponding to the stunting categories. The Rectified Linear Unit (ReLU) activation function was applied to introduce nonlinearity, while the output layer employed the softmax activation to generate normalized probability distributions. Model optimization was conducted using the Adam optimizer, which adaptively adjusts learning rates based on first and second order moments of the gradient, providing faster and more stable convergence. The categorical cross-entropy loss function was used to minimize the difference between predicted and true class probabilities.

2.4. SHAP Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) encompasses a set of techniques designed to articulate the reasoning behind the AI model's outputs [29]. This concept enabling users to understand the factors driving its decisions, its inherent strengths and limitations, and analysed its likely behaviour in future scenarios. The objective of XAI is to advance a diverse portfolio of methodological approaches that collectively offer developers flexible design choices. These options allow for a deliberate balancing of predictive performance and interpretability therefore ensuring that AI systems can achieve high levels of accuracy while remaining transparent, trustworthy, and comprehensible to non-technical stakeholders.

This paper employed SHapley Additive exPlanations (SHAP) framework to address the interpretability and transparency challenges commonly associated with complex machine learning models. SHAP framework is a game-theoretic approach derived from Shapley value originally developed to quantify the fair contribution of individual players within cooperative game settings [30]. Proposed by Lunberg and Lee in 2017 [31] SHAP offers a unified and theoretically grounded approach to assess feature importance across diverse architectures. In this study, SHAP values were computed using the classical Shapley formulation, which defines each feature's contribution as the average marginal impact it has across all possible subsets of features as defined in equation (3) [32].

$$\phi_v(i) = \sum_{S \subseteq n\{i\}} \frac{|S|!(n-|S|-1)!}{n!} \left(v\left(S \cup \{i\}\right) - v(S)\right) \quad (3)$$

The equation (3) denotes the attribution assign to feature i as ϕ_v. Where n represents the full set of features and S refers to any subset of features excluding i. The term $v\ (S\ \cup \{i\}) - v(S)$ captures the incremental change in the model's output attributable to feature i, while factorial weighting ensures fair and mathematically consistent distribution of contributions across all feature coalitions. Through this mechanism, SHAP decomposing a model's prediction into additive components, assigning to each input feature a portion of the output that reflects its marginal contribution to the outcome. The resulting SHAP values then can be visualized in order to provide a transparent summary of the model's reasoning process [22]. This level of interpretability bridges the gap between algorithmic decision-making and human reasoning, allowing wider range of stakeholders to understand why the model produced a specific outcome rather than merely what it predicted.

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3. RESULT

3.1. Dataset

The dataset employed in this paper comprises of 273 records through sampling-based survey conducted in Sukoharjo, Central Java, Indonesia. After collection, the data were organized into dependent and independent variables. The dependent variables: Gender, Children's height or length, and Age, serve as the basis for determining each children nutritional status using height-for-age indicator which was subsequently used as the classification label in the dataset. This classification adhered to the standards set forth in the Indonesian Ministry of Health Regulation (PMK) No. 2 of 2020 on Child Anthropometry [33]. The distribution and characteristics of the sample data used for this classification are presented in Table 2.

Table 2 Sample of Stunting Risk Factor Dataset

Mother's Age	Gender	Birth Weight	Diarrhea History	Mother's Pre-Pregnancy Weight	…	Waste Management	Social Assistance	Category
24	Male	2.5	No	50	…	Yes	No	Normal height
38	Male	3.7	No	74	…	Yes	No	Normal height
31	Male	3.7	No	94	…	Yes	No	Stunted
34	Female	3.6	No	60	…	Yes	No	Normal height
24	Male	3.5	Yes	45	…	Yes	No	Normal height
34	Female	2.8	No	37	…	No	No	Stunted
37	Female	3.3	No	60	…	Yes	No	Normal height
29	Female	2.8	No	55	…	Yes	Yes	Stunted
31	Female	3.6	No	53	…	Yes	No	Normal height

The raw dataset could not be directly processed by machine learning algorithms; therefore, a series of preprocessing steps was required. These steps included data cleaning to address missing or inconsistent entries, data scaling to normalize feature values, label encoding to convert categorical variables into numerical representations, and data splitting (80:20) to separate the dataset into 80% for data training and 20% for data testing.

3.2. Stunting Prediction Model

The predictive modelling stage employed three machine learning algorithms; Logistic Regression, Naïve Bayes, and Multilayer Perceptron. Although multiple algorithms were initially explored, only one model would ultimately be selected for subsequent analytical stages and integration with XAI techniques. In this process, the training subset of the dataset was used to fit and optimize each

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model, while the testing subset served as an independent benchmark for evaluating their predictive performance. A rigorous comparative assessment was then conducted using key evaluation metrics such as accuracy, precision, recall, and F1-score.

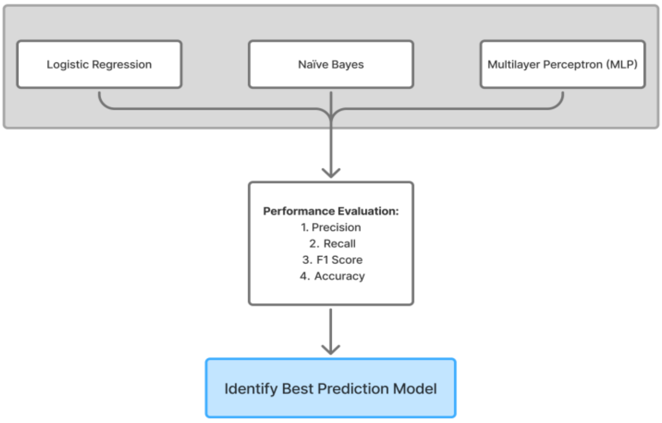

Figure 2 Predictive modelling workflow

This systematic workflow described in Figure 2 was crucial for identifying the algorithm that demonstrated the highest predictive accuracy and the most reliable performance when detecting stunting risk based on the underlying risk factors.

Table 3 Performance Evaluation of AI Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	48%	59%	48%	53%
Naïve Bayes	60%	92%	60%	72%
MLP (15 hidden node)	80%	84%	80%	80%
MLP (16 hidden node)	**82%**	**87%**	**82%**	**82%**
MLP (17 hidden node)	82%	86%	82%	82%
MLP (18 hidden node)	82%	85%	82%	82%
MLP (19 hidden node)	82%	85%	82%	83%

As shown in Table 3, the MLP model with 16 hidden nodes achieved the highest overall performance in terms of accuracy (82%), precision (87%), and recall (82%), while maintaining a balanced F1-score (82%). Although the MLP with 19 hidden nodes achieved a marginally higher F1-score (83%), the difference was statistically insignificant, and the 16-node model demonstrated better convergence stability and computational efficiency. In comparison, both Logistic Regression and Naïve Bayes models underperformed in this prediction task. Logistic Regression yielded the lowest accuracy (48%), indicating limitations in capturing the complex, nonlinear relationships between stunting determinants. Naïve Bayes, despite its simplicity, achieved higher precision (92%) but at the cost of lower recall (60%), suggesting that it tended to predict fewer false positives but missed a considerable proportion of true stunting cases. These results collectively demonstrate that deep neural architecture using MLP with 16 hidden nodes is more effective for modelling the multi-dimensional and nonlinear patterns present in stunting risk data. The model's strong recall indicates a high sensitivity in detecting children at risk of stunting an essential requirement for public health applications where false negatives could lead to missed interventions.

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3.3. SHAP based Explainable AI

After the most accurate predictive model had been identified, the research advanced to the explainability phase by applying the SHapley Additive exPlanations (SHAP) framework. This stage aimed to generate transparent, human understandable explanations of how the stunting prediction model derived its classification outcomes. Such explainability is especially critical in this context, as the primary users are non-technical stakeholders who play pivotal roles in designing, implementing, and evaluating stunting mitigation dan intervention strategies. By providing clear insights into the internal reasoning of the model, SHAP enhances user trust, supports evidence-based decision-making, and ensures that the AI system aligns with the principles of accountability and transparency required in public health interventions.

The model evaluation process identified the Multilayer Perceptron (MLP) with 16 hidden nodes as the best-performing algorithm for stunting prediction. Given its superior accuracy and robustness, this model was selected for the subsequent explainability analysis. To interpret the model's internal logic, Kernel SHAP was applied to compute SHAP values, which quantify the contribution of each input feature to the model's predictions. Kernel SHAP is particularly suited for explaining complex architecture such as MLPs. Kernel SHAP approximates local model behaviour using weighted linear regressions around each prediction instances. The resulting SHAP values reveal not only the magnitude of each feature's influence but also the direction. This result enabling a clear explanation whether a feature increases or decreases the likelihood of a child being classified into a specific stunting category. This detailed attribution process provides deep insights into the model's decision pathways, ultimately enabling stakeholders to understand which risk factors most strongly drive stunting classifications and how these insights can inform targeted interventions.

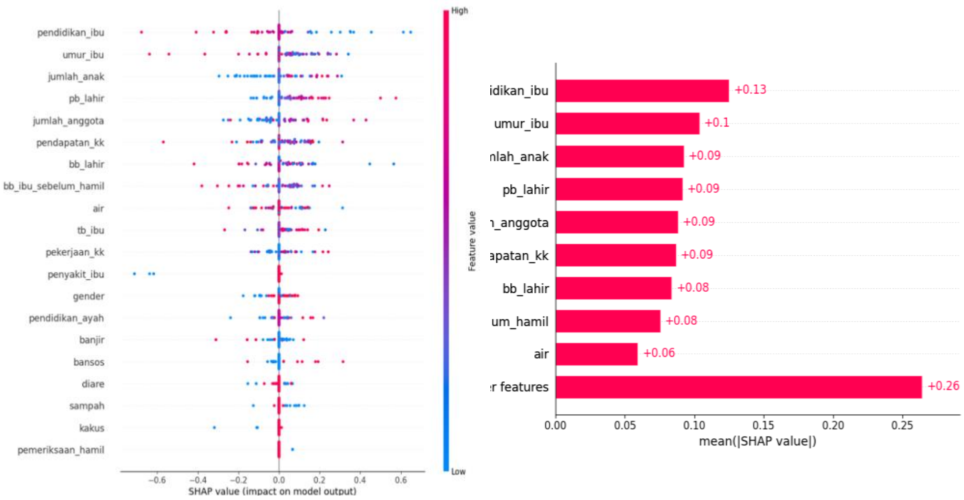

Figure 3 SHAP values illustrating the overall contribution of each feature to stunting prediction across the dataset. Higher absolute SHAP values indicate stronger influence.

SHAP values were computed for each feature to quantify its relative contribution to the model's predictions. The visualization of SHAP plots shown in Figure 3 revealed that the most influential determinants of stunting included:

- Mother's education, which showed an inverse relationship, suggesting that mothers with higher education levels were more likely to have children with normal growth status
- Mother's Age,
- The Number of Children in the family,
- Birth length,

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- Total number of family members living in the same household.
- and Household monthly income.

These findings are consistent with previous public health studies, confirming that biological, socioeconomic, and environmental factors operate jointly in determining child growth outcomes. The SHAP analysis thus not only provided interpretive depth but also validated the empirical plausibility of the AI model.

From a methodological perspective, the SHAP framework implemented in this paper could transform the MLP model from a traditional "black box" into an interpretable system capable of providing transparent, feature-level explanations. For each individual prediction, the system could display which variables increased or decreased the stunting probability, making the AI's decision process both traceable and defensible. This level of transparency is fundamental for integrating AI into real-world health decision-making environments, where accountability and clarity are as crucial as its accuracy.

4. DISCUSSIONS

The findings of this study demonstrate that the integration of Explainable Artificial Intelligence (XAI) principles into predictive modelling for childhood stunting can produce a system that is both technically robust and humanly interpretable. The Multilayer Perceptron (MLP) model with 16 hidden nodes achieved the highest predictive performance among the tested algorithms, outperforming both Logistic Regression and Gaussian Naïve Bayes. This result underscores the capacity of deep learning architectures to capture the nonlinear and multifactorial nature of stunting determinants, which involve intricate interactions between biological, socioeconomic, and environmental variables especially in a small dataset. In contrast to previous studies [17], the present results reveal a notable deviation: the Multilayer Perceptron demonstrated considerably superior performance compared with Logistic Regression and Naïve Bayes. This result indicates the limitations of linear and conditional independence assumptions when modelling complex health outcomes used in this dataset. As a multidimensional public health phenomenon, stunting cannot be adequately represented through simple additive effects. The high recall of the MLP model (82%) suggests that it effectively identified most children at risk, an essential attribute in preventive health systems where false negatives carry substantial human and policy costs.

Beyond the predictive model accuracy, the use of SHapley Additive exPlanations (SHAP) significantly enhanced the model's interpretability [20], [30]. By decomposing model outputs into additive feature contributions, SHAP enabled transparent insights into how each determinant influenced stunting predictions. Importantly, the explainability analysis also facilitated contextual learning for non-technical stakeholders. Health workers and policymakers could interpret model outputs in familiar conceptual terms, understanding not only which children were at risk but also why they were identified as such. This aligns with the goals of transparency in AI model's decision, which emphasize cognitive alignment between AI systems and their human users. Trust in AI systems is often fragile, particularly when users lack technical literacy. However, this study demonstrates that trust can be cultivated through transparency and user-oriented design. Participants reported that being able to see why the system produced a specific prediction increased their confidence and willingness to rely on AI insights. This is consistent with research findings [14] who argue that explainability must be presented not as abstract algorithmic information but as contextualized reasoning framed in users cognitive.

4.1. Limitation and Future Direction

Despite its promising results, this study faced several limitations. The dataset, while diverse, was limited to 273 observations from one regency, constraining the generalizability of the model across broader geographic and demographic contexts. Future research should incorporate larger, multi-regional datasets and explore federated learning approaches to integrate data across health centres while preserving privacy. Future research may also integrate the current dataset with relevant external data sources. For example, instead of relying solely on monthly household income, the model could be enriched with additional socioeconomic indicators such as household expenditure patterns, prices of staple foods, access to protein sources, and overall consumption profiles. Incorporating these complementary datasets would provide a more holistic representation of the community's socioeconomic conditions. Such an expanded data ecosystem has the potential to enhance the predictive sensitivity of the model, offer deeper insights into structural determinants of stunting, and support more targeted and context specific intervention strategies.

5. CONCLUSION

This paper developed and evaluated a predictive model for assessing childhood stunting using machine learning techniques enhanced with Explainable Artificial Intelligence (XAI). This paper employed three classification algorithms, there are Logistic Regression (LR), Naïve Bayes (NB), and Multilayer Perceptron (MLP). The evaluation demonstrated that the MLP achieved the strongest performance, demonstrating its ability to capture the nonlinear and multidimensional patterns inherent in stunting determinants. Beyond predictive accuracy, the incorporation of Kernel SHAP provided transparent, fine-grained explanations of feature contributions, enabling stakeholders to interpret model outputs with clarity. Importantly, this research contributes in demonstrating how explainable artificial intelligence can be deployed in high stakes public health classification problems. The proposed MLP–SHAP pipeline advances current XAI practice by balancing performance with interpretability, addressing the broader disciplinary need for trustworthy, socially responsible AI systems. Given the national urgency of reducing stunting prevalence which underscores the role of AI driven decision support in strengthening early detection and informing targeted interventions.

CONFLICT OF INTEREST

There is no conflict of interest between the authors or with research object in this paper.

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