A Systematic Literature Review on the Application of Machine Learning for Predicting Stunting Prevalence in Indonesia (2020–2024)

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***Abstract*— Stunting remains a serious public health issue in Indonesia, with persistently high prevalence and long-term impacts on children's physical and cognitive development. The growing need for data-driven early detection systems has encouraged the adoption of technologies such as machine learning (ML) to more effectively predict stunting prevalence. This study employed a Systematic Literature Review (SLR) to examine 20 scientific articles published between 2020 and 2024, focusing on the application of ML algorithms in stunting research. Literature was sourced from Scopus and Google Scholar, with inclusion criteria covering studies relevant to the Indonesian context or comparable global settings. The analysis focused on the algorithms used, data types, model performance, and implementation challenges. The findings indicate that Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN) are the most frequently used algorithms, with prediction accuracy ranging from 72% to 99.92%. Dominant predictor variables include maternal education, economic status, sanitation, and spatial-temporal data. The main challenges include data imbalance, limited model interpretability, and a lack of external validation. In conclusion, machine learning holds strong potential to support predictive systems and data-driven policies for stunting prevention in Indonesia. This study recommends future research to focus on integrating spatial-temporal data, implementing Explainable AI (XAI), and conducting cross-regional validation to enhance model reliability and policy relevance.**

Keywords*— *Stunting, Machine Learning, Nutrition Prediction, Spatial Data, Health Classification

I. Introduction

Stunting remains one of the major public health challenges in Indonesia. This condition is characterized by a child’s height being shorter than the standard for their age, caused by chronic malnutrition occurring from pregnancy through the first two years of life. According to the Indonesian Nutrition Status Survey (SSGI), the prevalence of stunting in Indonesia remains above 20%, exceeding the threshold set by the World Health Organization (WHO). Stunting not only affects children’s physical growth but also has long-term consequences on cognitive development, future individual productivity, and increases the risk of intergenerational poverty.

The Indonesian government has launched various strategies and intervention programs to reduce stunting rates, including specific and sensitive nutritional interventions, strengthening maternal and child health services, and public behavior change campaigns. However, the effectiveness of these policies still faces challenges, one of which is the suboptimal early detection system for identifying children at risk of stunting.

In recent years, the advancement of artificial intelligence (AI) and machine learning (ML) technologies has brought new breakthroughs in public health data analysis. Machine learning enables efficient processing of large datasets to uncover hidden patterns and generate data-driven predictions. Various studies have demonstrated that ML algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) are capable of classifying children’s nutritional status with high accuracy—sometimes exceeding 90% [1], [2], [3].

Lestari et al. [1] compared the performance of Deep Neural Networks and Random Forest in multiclass classification of stunting among toddlers and found that Random Forest yielded very high accuracy with better interpretability. Meanwhile, a study by Islam et al. [2] used an explainable machine learning approach to identify key predictors of childhood stunting in Bangladesh, highlighting the importance of model transparency for non-technical users. Another study by Haque et al. [3] integrated predictive modeling with socioeconomic and demographic variables to assess stunting risk among children aged 12–23 months.

Nevertheless, to date, there is a lack of systematic studies that summarize and analyze the development and application of ML in the context of stunting, especially in Indonesia. Most existing research is fragmented and focuses on individual algorithms or specific regions. Therefore, a comprehensive review is needed to identify trends, methodologies, model effectiveness, and the challenges and opportunities arising from the use of ML in stunting studies.

This study aims to fill that gap through a Systematic Literature Review (SLR) of 20 recent academic journals. By synthesizing relevant studies, this research is expected to provide a comprehensive overview of the application of machine learning in analyzing stunting prevalence and offer

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strategic recommendations for future research and policy development.

II. METHOD

Systematic Literature Review (SLR) is a research approach used to systematically and structurally identify, evaluate, and interpret all relevant studies addressing a specific research question. In this study, SLR is employed to comprehensively review literature related to the use of predictive modeling techniques in Machine Learning to examine the prevalence of stunting in Indonesia.

Stunting refers to a condition of impaired growth in children under five due to chronic malnutrition, typically occurring during the first 1,000 days of life. This SLR aims to explore how Machine Learning algorithms are used to identify risk factors, predict stunting status, and support health policy decision-making processes.

The SLR process was carried out systematically to minimize bias and produce valid synthesis. The first stage involved formulating the Research Question, which guided literature selection and analysis direction. This was followed by research planning, including a search strategy using keywords such as "stunting Indonesia machine learning", and the establishment of inclusion and exclusion criteria.

Data collection was conducted through several academic databases, including Scopus and Google Scholar, covering publications from 2020 to 2024. A total of 20 journal articles meeting the criteria were analyzed. Subsequently, study quality was assessed based on research methodology, clarity of result reporting, and contributions to the issues of stunting and Machine Learning.

During the data analysis stage, it was found that the most commonly used algorithms include Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Naïve Bayes, XGBoost, and hybrid approaches. The analysis revealed model accuracy rates ranging from 72% to 99.92%, with Random Forest and KNN consistently demonstrating stable performance across various contexts.

The studies also identified key predictors of stunting, including maternal education and height, body mass index (BMI), economic status, access to clean water, sanitation, and breastfeeding initiation. Additionally, Machine Learning approaches were employed to map spatial factors using geographically weighted regression models, particularly in analyzing the regional distribution of stunting.

The final stage of the SLR was data synthesis, presented in both narrative form and comparative tables, to provide a comprehensive understanding of trends, effectiveness, and challenges in applying Machine Learning to stunting prevalence studies. Several studies emphasized the importance of explainable AI models and the integration of spatial and temporal data to enhance intervention precision.

TABLE I. RESEARCH QUESTION

No	Research Question (RQ)	Tujuan
RQ1	What machine learning methods are used in stunting research in Indonesia?	To identify ML techniques and algorithms commonly used in stunting-related studies.
RQ2	What types of data are used in the application of ML for stunting in Indonesia?	To identify the sources and types of data utilized in ML models related to stunting.
RQ3	How effective are ML models in predicting or classifying stunting?	To analyze model evaluation results based on metrics such as accuracy, precision, recall, etc.
RQ4	What are the challenges and limitations in applying ML to stunting cases in Indonesia?	To identify issues such as data imbalance, model interpretability, and other limitations.
RQ5	How do spatial and socioeconomic factors influence the predictive model outcomes?	To examine the integration of spatial data and the influence of social factors in stunting distribution.

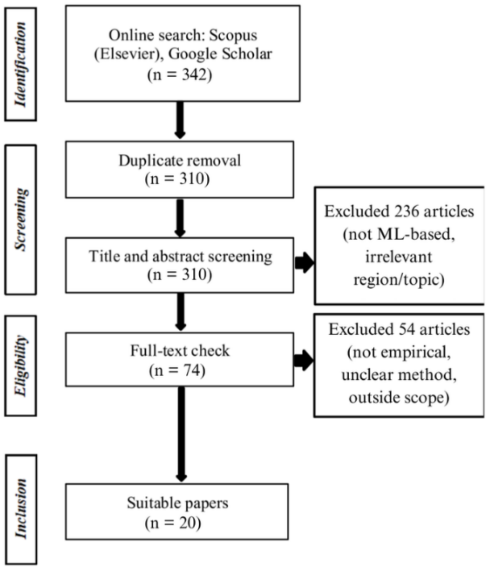

Fig. 1. Flow Diagram of Literature Review

The literature review process in this study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and systematicity in the selection of reference sources. At the identification stage, literature searches were conducted online through two main databases, namely Scopus (Elsevier) and Google Scholar, with a publication year range of 2020–2024. From the initial search results, 342 relevant articles were found based on the keywords "stunting", "Indonesia", and "machine learning". After removing duplications, 310 articles remained which were then filtered based on title and abstract. At this stage, 236 articles were eliminated because they did not meet the inclusion criteria, such as not using a machine learning approach or not being relevant to the context of the Indonesian region. A total of 74 articles then entered the full-text screening stage. At this stage, 54 articles were again eliminated because they were not empirical, had unclear methods, or were outside the scope of the study. Finally, 20 articles were obtained that met all eligibility criteria and were included in the qualitative synthesis as a basis for analysis of the use of machine learning

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in predicting the prevalence of stunting in Indonesia.

III. Results and Discussion

A total of 20 scientific journal articles were collected from the Scopus and Google Scholar databases, covering publications between 2020 and 2024. The selection of journals was based on their relevance to the topic of predictive modeling techniques in machine learning for studying the prevalence of stunting in children under five, both in the context of Indonesia and globally.

Table II presents the list of analyzed journals, including information such as title, author(s), year of publication, and source. All selected journals specifically address the application of machine learning algorithms in identifying, classifying, or predicting stunting status, as well as evaluating associated risk factors.

This literature analysis aims to address the five previously formulated research questions, namely regarding the methods used, types of data, model effectiveness, implementation challenges, and the influence of spatial and socio-economic factors.

TABLE II. List of Reference Journals

No	Reference	No	Reference
[1]	Lestari, W. S., et al. (2024)	[11]	Lonang, S., et al. (2023)
[2]	Islam, M. M., et al. (2024)	[12]	Saragih, V. R., et al. (2024)
[3]	Haque, M. A., et al. (2023)	[13]	Satria, B., et al. (2024)
[4]	Prabiantissa, C. N., et al. (2024)	[14]	Juwariyem, et al. (2024)
[5]	Ndagijimana, S., et al. (2024)	[15]	Daffa, M., & Gunawan, P. H. (2024)
[6]	Bitew, F., et al. (2021)	[16]	Hidayat, F. M., et al. (2024)
[7]	Abid, D. M. H., et al. (2020)	[17]	Chen, K., et al. (2024)
[8]	Shahriar, M., et al. (2019)	[18]	Nduwayezu, G., et al. (2024)
[9]	Novichasari, S. I., et al. (2024)	[19]	Dewi, Y. S., et al. (2024)
[10]	Saragih, N. H., et al. (2024)	[20]	Hasdyna, N., et al. (2024)

A. Machine Learning Methods Used

Berbagai Various machine learning methods have been applied in research to predict and classify the prevalence of stunting in children under five. Based on the review of 20 analyzed journal articles, the most commonly used method is Random Forest, which was applied in more than 50% of the studies. Random Forest demonstrated excellent performance in multiclass classification and feature importance detection, with model accuracy reaching up to 99%.

Another frequently used method is Support Vector Machine (SVM), which achieved a maximum accuracy of 97.56%, particularly in studies focusing on early childhood education-level stunting prediction. Artificial Neural Networks (ANN) were also widely utilized for handling nonlinear data, with accuracy levels ranging from 72% to 93%.

Additionally, some studies employed algorithms such as XGBoost, K-Nearest Neighbors (KNN), Naïve Bayes, and ensemble models like Voting Classifier and Bagging to enhance model stability and accuracy. The results of these studies indicate that the applied algorithms successfully identified patterns within the data and made significant contributions to decision-making in the context of stunting prevention.

Overall, the variation in algorithm usage highlights that no single model is universally superior. The selection of a method depends on data structure, sample size, and the predictive features used.

TABLE III. Machine Learning Methods Used In Stunting Studies

Method	Main Functions	Reference	Acc	Additional Information
Random Forest (RF)	Stunting status classification, feature selection	Lestari et al., Lonang et al., Saragih et al., Hasdyna et al.	85–99.92%	Stable, interpretable
Support Vector Machine	Binary and multiclass classification	Novichasari et al., Chen et al.	97.56%	Effective for imbalanced data
Artificial Neural Network	Nutritional status prediction, risk factor classification	Haque et al., Prabiantissa et al., Ndagijimana et al., Shahriar et al.	72–93%	Suitable for complex, nonlinear data
XGBoost	Boosting-based stunting prediction	Islam et al., Zhang et al.	~90%	High accuracy, requires tuning
K-Nearest Neighbors	Stunting classification in toddlers	Juwariyem et al.	94.85%	Requires oversampling for balance
Naïve Bayes	Simple probabilistic classification	Hidayat et al.	~94.65 %	Fast but less accurate for large data
Decision Tree	Interpretable model for classification	Lonang et al.	~85%	Easy to interpret
Bagging/Voting	Model ensemble for improved accuracy	Daffa & Gunawan, Chen et al.	>90%	Suitable for large datasets

Comparative analysis shows that Random Forest consistently outperforms simpler classifiers such as Naïve Bayes, particularly in datasets incorporating spatial attributes. In studies by Lestari et al. and Saragih et al., Random Forest achieved accuracy rates above 95% when applied to geospatial and household-level data. In contrast, Naïve Bayes showed lower performance, likely due to its assumption of feature independence and limited capacity to model complex interactions. This finding highlights the advantage of ensemble models in capturing multifactorial determinants of stunting.

B. Types and Sources of Data

The studies analyzed in this Systematic Literature Review (SLR) utilized a variety of data sources, reflecting the diversity of approaches in gathering information related to stunting prevalence. The chart above illustrates the distribution of

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dataset types used across the 20 reviewed studies. Several commonly used data sources include:

1) *Demographic and Health Survey (DHS)*
This is the most frequently used data source (6 studies). DHS provides nationally representative data with comprehensive variables related to individual and household characteristics, making it highly suitable for machine learning studies that require diverse features.
2) *Riskesdas / Primary Health Centers (Puskesmas) / Hospitals*
Used in 5 studies. These are administrative health datasets integrated into Indonesia's health service systems. They are typically more up-to-date and localized in nature.
3) *Local Datasets (District/City Level)*
Utilized in 4 studies. These datasets are usually obtained from local health departments or regional surveys, and are suitable for spatial analysis or small-area intervention models.
4) *International Datasets*
Used in 5 studies focusing on stunting in countries such as Bangladesh, Ethiopia, Rwanda, and Pakistan. These datasets are often used for cross-country comparison or to strengthen model generalization across different populations.

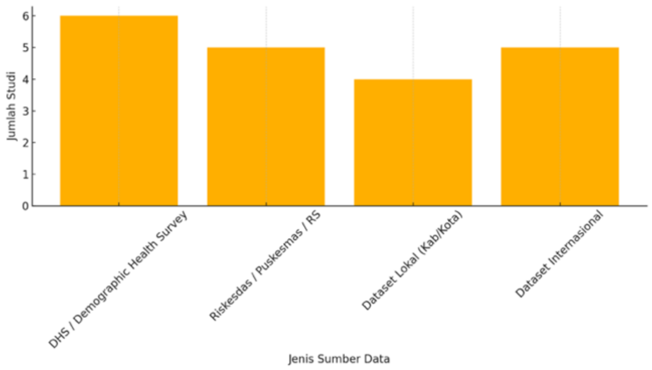

Fig. 2. Number of Studies By Type Of Data Source

C. Model Effectiveness

The effectiveness of machine learning models in predicting stunting was evaluated using several performance metrics, such as accuracy, precision, recall, F1-score, and AUC-ROC. These metrics are critical in ensuring that a model is not only accurate overall but also capable of handling imbalanced data and is sensitive to classification errors.

1) *Accuracy*
Accuracy is a basic metric that indicates the proportion of correct predictions over the total dataset. Based on the review, model accuracy ranged from 72% to 99.92%, depending on the algorithm used and the preprocessing applied. Random Forest recorded the highest accuracy, followed by SVM and ANN.

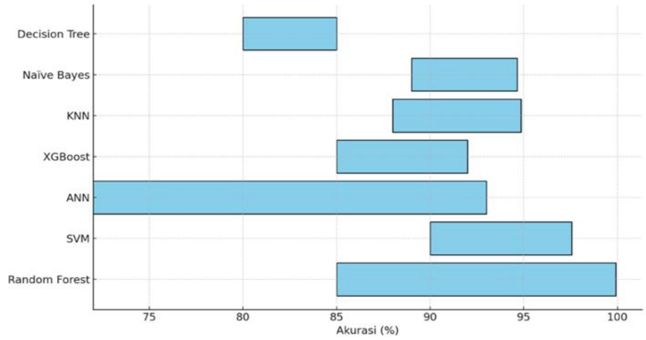

Fig. 3. Machine Learning Model Effectiveness

2) Precision, Recall, dan F1-Score
In the context of stunting prediction, recall is a critical metric as it reflects the model's ability to detect actual stunting cases. A high recall reduces the likelihood of missing children who are at risk of stunting. The F1-score, which balances precision and recall, is used particularly for imbalanced datasets, which are common in stunting-related data. Most studies reported F1-scores above 0.80, especially for models based on Random Forest, XGBoost, and ANN.
3) AUC-ROC
The Area Under the Curve – Receiver Operating Characteristic (AUC-ROC) is used to measure a model's ability to distinguish between stunting and non-stunting classes. Several studies reported AUC values ranging from 0.84 to 0.92, particularly for ANN and Random Forest models, indicating strong predictive performance.
4) Feature Selection and Optimization
Top-performing studies combined algorithms with feature selection techniques to enhance model performance, such as:
   a) Recursive Feature Elimination (RFE)
   b) Genetic Algorithm (GA)
   c) Principal Component Analysis (PCA)

These techniques help improve accuracy while simplifying the models, making them more efficient and interpretable.

D. Challenges and Limitations

Implementasi The implementation of machine learning (ML) in stunting prediction research still faces various challenges that can affect the accuracy, reliability, and practical usability of the models. The most frequently observed challenge in the analyzed studies is data imbalance. This occurs when the number of stunted children in the dataset is significantly smaller than that of non-stunted children. As a result, models tend to be biased toward the majority class, leading to low recall rates—particularly in identifying actual stunting cases. Several approaches were employed to address this issue, including oversampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique), cost-sensitive learning, and the use of ensemble algorithms like Bagging and Boosting.

Another major challenge is the quality and availability of data. Many studies relied on secondary data, which are not

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always designed for predictive modeling purposes. Consequently, issues such as missing values, unstandardized variables, and limited longitudinal or real-time information are common. These conditions can degrade model input quality and lead to less accurate predictions. Solutions implemented to mitigate this challenge include data imputation techniques, feature engineering, and the integration of multiple data sources to enrich the predictive context.

The next challenge involves the low interpretability of models, especially in complex algorithms such as Artificial Neural Networks (ANN) and XGBoost. Although these models achieve high accuracy, they are often difficult to explain to non-technical stakeholders such as nutrition officers or local policymakers. To address this, several studies have applied Explainable AI (XAI) approaches—such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations)—which allow researchers to transparently explain the contribution of each variable in the prediction process.

Another limitation of concern is the lack of external validation of developed models. Many studies only perform internal validation using cross-validation on the same dataset. This increases the risk of overfitting and limits the model's generalizability to other regions or datasets. Therefore, external validation based on geographic or temporal variations is essential to ensure that the model remains accurate and reliable when applied beyond the original training context.

The use of static and cross-sectional data without accounting for time and environmental dynamics also presents a unique challenge. Models built under these conditions only represent the circumstances at the time the data was collected, making them less adaptive to social, economic, or environmental changes that may affect stunting prevalence. To overcome this, some recent studies have begun to integrate spatial and temporal data, aiming to enhance the model’s long-term accuracy and relevance.

Overall, these challenges highlight the importance of not only building accurate models but also ensuring data quality, model transparency, and sustained real-world applicability.

E. Spatial and Socioeconomic Factors

Spatial and socioeconomic factors are increasingly recognized as critical dimensions in the development of machine learning-based stunting prediction models. Based on the literature reviewed, these factors are not only significant input variables for prediction but also contribute to a more contextualized understanding of the distribution of stunting across different regions.

From a spatial perspective, several studies have integrated Geographically Weighted Regression (GWR) and Geographically Weighted Random Forest (GWRF) into modeling systems. These models go beyond general predictor values by incorporating local geographic influences, allowing for the measurement of regional effect variation. For instance, in areas with high stunting prevalence, variables such as access to sanitation and clean water were found to have a greater impact than in urban areas with more developed infrastructure. A study by Dewi et al. (2024) used a multiscale spatial approach to reveal stunting clusters in rural areas of East Java that were not evident using conventional statistical methods.

From a socioeconomic perspective, variables such as parental education level, household income, asset ownership, and access to healthcare facilities were the most frequently used features and showed strong correlations with child nutritional status. Maternal education, in particular, emerged consistently as a key predictor across nearly all models due to its strong association with nutritional knowledge, health behavior, and caregiving decisions. Meanwhile, economic status is often estimated through proxies like asset ownership (e.g., vehicles, permanent housing) and access to electricity and clean water, reflecting a family’s capacity to meet a child's basic needs.

Some studies have also begun to explore the importance of combining spatial and temporal dimensions in predictive models. Although not yet widely adopted, spatial-temporal modeling is considered promising as it captures the dynamics of stunting prevalence over time and across regions. Such models are not static but adaptive, accounting for evolving factors like infrastructure development, demographic shifts, and government intervention programs. A study by Hasdyna et al. (2024) demonstrated that a hybrid model integrating location and time data can improve prediction accuracy and reliability in prioritizing intervention areas.

Overall, the integration of spatial and socioeconomic factors into machine learning models adds significant value—not only in terms of accuracy but also in enhancing the model’s utility for policy planning. With geographic and social risk mapping, intervention programs such as nutritional aid, maternal education, and healthcare facility development can be more targeted and evidence-based. Future research is encouraged to further strengthen this spatial-temporal approach and expand the use of geolocation and longitudinal data to build adaptive and sustainable prediction models.

F. Implications and Future Research Directions

Hasil The results of this Systematic Literature Review (SLR) indicate that the use of machine learning (ML) in studies on stunting prevalence is not only theoretically relevant but also holds great potential as a practical approach to support stunting reduction programs, particularly in Indonesia. Data-driven predictive models present opportunities to accelerate the identification of stunting risks, accurately classify vulnerable groups, and design more targeted interventions based on regional and population-specific characteristics.

One key implication of this study is that machine learning can serve as an early detection tool for identifying children at risk of stunting. This is highly relevant in the context of primary healthcare services and government intervention programs such as Posyandu, Puskesmas, and the "First 1,000 Days of Life" initiative (1000 HPK). By utilizing existing data—whether from national surveys like Riskesdas and DHS or from local administrative records—predictive models can be developed and integrated into health information systems to facilitate real-time decision-making.

In addition, ML can identify key risk factors with greater

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specificity and localization, including those that may be overlooked by conventional statistical approaches. For example, algorithms such as Random Forest or XGBoost can automatically evaluate feature importance, thereby enabling more accurate risk mapping based on factors like maternal education, household economic status, access to clean water, or geographic location. These insights are highly valuable for helping governments set priorities for intervention in regions most in need of timely and targeted support.

Another significant implication is that ML supports the advancement of data-driven policy systems. Both central and local governments can use predictive models to simulate the potential impacts of specific policy measures—such as nutritional aid or sanitation infrastructure—on stunting reduction over time. This allows for more efficient and well-targeted policymaking in terms of budget allocation and program implementation.

To fully realize this potential, future research directions should focus on several key areas. First, the integration of spatial and temporal data is highly recommended. Most existing studies remain cross-sectional in nature and are unable to capture the dynamics of stunting over time or across regions. By incorporating both time and location dimensions, researchers can build predictive systems that are more adaptive to changes in social conditions, environmental factors, and policy implementation.

Second, future studies should adopt and refine Explainable AI (XAI) approaches. One of the main barriers to ML adoption in the public sector is the lack of interpretability for decision-makers. By applying techniques such as SHAP and LIME, model outputs can be explained more intuitively, thus increasing stakeholder trust and understanding of predictive results.

Third, future studies are encouraged to involve larger and more diverse populations, including variations in demographics, geographic regions, and socioeconomic backgrounds. This will enhance model generalizability for national-level application. For example, validating models using datasets from various provinces or islands in Indonesia can provide insights into the extent to which developed models are reliable across different regions.

Fourth, researchers should aim to utilize longitudinal datasets to predict long-term stunting trends. These datasets allow for monitoring child development over time and identifying critical points that may contribute to chronic stunting. This is essential for supporting long-term, sustainable preventive interventions.

By addressing these areas, machine learning-based prediction systems are expected to evolve into strategic tools for reducing stunting rates in Indonesia. The integration of advanced technology, rich data, and evidence-based policymaking will be a critical foundation in supporting Indonesia's efforts to achieve both national and global child nutrition targets, particularly within the framework of the Sustainable Development Goals (SDGs).

IV. Conclusion

This study concludes that machine learning (ML) algorithms hold strategic potential in supporting early detection systems and data-driven policymaking for addressing stunting in Indonesia. A systematic review of 20 peer-reviewed journal articles published between 2020 and 2024 revealed that Random Forest is the most frequently utilized algorithm and exhibits the highest predictive performance, with reported accuracy reaching up to 99.92%. Other prominent algorithms such as Support Vector Machine (SVM) and Artificial Neural Network (ANN) also demonstrated competitive results, with accuracies ranging from 72% to 97.56%. These findings suggest that ML models are capable of effectively classifying stunting status, although challenges related to data imbalance and model complexity persist.

Further analysis of Table III indicates that algorithm selection is influenced not only by accuracy but also by data structure, sample size, and model interpretability. Algorithms such as XGBoost and K-Nearest Neighbor (KNN) showed promising performance, particularly when enhanced through oversampling and feature selection techniques. Despite these advances, most studies relied solely on internal cross-validation, with limited efforts to perform external validation across different regions or populations. This restricts the generalizability of the models and underscores the need for future research to expand validation frameworks to improve robustness and applicability.

The review also highlights consistent use of key predictor variables such as maternal education, household economic status, sanitation access, and spatial information. Studies integrating spatial and temporal dimensions reported improved prediction accuracy and contextual relevance, supporting the design of geographically targeted intervention programs. However, Explainable AI (XAI) techniques—such as SHAP and LIME—remain underutilized, despite their critical role in enhancing model transparency and facilitating adoption by non-technical stakeholders.

From a policy perspective, these findings offer several actionable insights. ML-based predictive systems can be implemented by public health authorities to identify high-risk groups, optimize resource allocation, and support precision-targeted stunting interventions. To achieve sustained impact, future models must incorporate spatial-temporal data, adopt interpretable AI approaches, and ensure external validation. The strategic integration of ML into health policy frameworks represents a significant step toward realizing national and global goals for stunting reduction and child development.

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