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Optimized Ensemble Learning Using Boosting, Stacking, and Voting for Early Stunting Risk Prediction

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Abstract

Stunting remains a pressing health issue in Indonesia's coastal communities, where uneven access to nutrition services and maternal–child care can limit early prevention efforts. This study develops a machine learning framework to estimate stunting risk among children under five in the eastern coastal region of Aceh. The modeling process began with data cleaning and preparation, followed by class rebalancing with SMOTE and automated parameter tuning using Optuna. Four standalone classifiers were evaluated: Logistic Regression, Gaussian Naïve Bayes, Support Vector Machine, and Random Forest. Their outputs were then extended through three ensemble configurations, namely XGBoost-assisted boosting for each baseline model, a stacking scheme named Stackstun with Logistic Regression as the final learner, and an optimized weighted soft-voting model referred to as Votsstun. Performance was measured using accuracy, precision, recall, and F1-score. Among the single classifiers, Logistic Regression achieved the best result, with an accuracy of about 0.93. The strongest overall performance was obtained by the boosted Random Forest model, which reached an accuracy of 0.9952 and produced almost perfect class-level precision, recall, and F1-score. Votsstun also performed consistently, recording an accuracy of approximately 0.986, while its macro and weighted F1-scores approached 0.99. These results indicate that the combined use of class rebalancing, automated optimization, and ensemble learning can improve the robustness of stunting-risk classification. The proposed framework may assist local health agencies in identifying vulnerable children earlier, prioritizing limited intervention resources, and strengthening prevention programs in coastal communities.

Keywords: ensemble learning; Optuna; SMOTE; stunting prediction; XGBoost

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1. Introduction

Stunting continues to pose a substantial health concern in Indonesia, especially among coastal communities where access to adequate nutrition and maternal and child healthcare is often limited by local geographical and service-related conditions [1]. Coastal communities often have limited access to nutritious foods, inadequate sanitation, and constrained health services [2]. Socio-economic factors, such as poverty and income volatility from fisheries, can further worsen child nutritional status [3]. The East Coast of Aceh is one of the region's most vulnerable to stunting due to its geography and social conditions. A data-driven approach is therefore needed to identify the key drivers of stunting and to design more targeted, effective interventions.

Machine learning (ML) offers data-driven methods for uncovering complex relationships among factors associated with stunting [4]. Algorithms such as Random Forest, Support Vector Machine (SVM), and Neural Networks can estimate stunting risk by analyzing health, dietary, environmental, and socio-economic variables [5-7]. The resulting predictions can help health professionals identify children who require earlier attention and direct limited services toward those at greater risk. In addition, ML models can reveal which variables contribute most strongly to the prediction, thereby providing useful evidence for the development of more targeted public-health policies.

Prior work on stunting prediction has explored a variety of models. One study compared XGBoost, Random Forest, SVM, and k-NN on a Kaggle dataset, using SMOTE for imbalance and backward elimination for feature selection; XGBoost performed best with AUC = 0.9311, indicating strong early-detection capability [8]. Another study applied Support Vector Regression

(SVR) on big data from Stella Maris Hospital and combined models via a Voting Classifier, achieving 91.67% accuracy and demonstrating the value of big-data integration [9]. An ensemble approach using a voting classifier reached 97.43% accuracy for detecting stunting in Tasikmalaya, showing that model combinations can outperform single models [10]. Study [11] implemented LASSO-XGBoost in Papua New Guinea with AUC = 0.765, highlighting socio-economic variables as dominant predictors and using SHAP values to explain risks such as household economy and birth size. [12] compared Logistic Regression, Random Forest, and Naïve Bayes in Bojongsoang, reporting 99.25% accuracy for Random Forest, while noting challenges from class imbalance.

Current research predominantly applies established classifiers, including Random Forest, XGBoost, Support Vector Machine, Logistic Regression, and Naïve Bayes, either as standalone models or within relatively simple ensemble schemes such as bagging and voting. Although several studies report improved predictive performance through ensemble learning, the methods used are generally limited to standard combinations and rarely incorporate more sophisticated strategies, including stacking or boosting supported by structured hyperparameter optimization. Model configuration is also frequently determined through manual experimentation rather than automated tuning procedures. In addition, many previous studies rely on hospital records or secondary datasets, with limited attention to the specific conditions of coastal communities. Factors such as clean-water availability, dependence on marine-based food sources, and household capacity to withstand economic pressure may influence stunting risk, yet these variables remain insufficiently represented in existing prediction models.

These shortcomings reveal several important research gaps. One major issue is the uneven distribution of classes commonly found in health datasets. Such imbalance can lead predictive models to become biased toward the dominant class, thereby weakening their ability to accurately detect children who are genuinely at high risk of stunting. Second, manual or trial-and-error parameter tuning may lead to suboptimal and less reproducible model performance. Third, limited studies have compared and integrated multiple ensemble strategies, such as boosting, stacking, and soft voting, under the same stunting dataset. Fourth, coastal-specific characteristics remain underrepresented in ML-based stunting prediction studies. Therefore, a more robust and context-aware framework is needed to improve predictive performance and support region-specific public-health decision-making.

To respond to these limitations, this study proposes a broader and context-sensitive framework for predicting stunting risk in communities along the East Coast of Aceh. The framework combines several ensemble learning strategies with automated hyperparameter optimization through Optuna. In the boosting stage, XGBoost is integrated with each individual classifier to improve the model's ability to recognize complex and nonlinear relationships among the predictor variables [13]. The stacking model, referred to as Stackstun, uses Logistic Regression as the meta-classifier to combine the outputs of multiple base learners into a final prediction [14]. In addition, an optimized soft-voting model, termed Votstun, integrates SVM, Random Forest, Naïve Bayes, Logistic Regression, and XGBoost. The voting weights are determined automatically using Optuna so that models with stronger validation performance make a greater contribution to the final classification.

The principal contribution of this research lies in the design and assessment of an integrated machine learning framework that brings together SMOTE-based class balancing, Optuna-driven hyperparameter tuning, and multiple ensemble strategies for early stunting-risk detection. In contrast to earlier studies that generally evaluate individual algorithms or relatively basic ensemble methods, this work conducts a consistent comparison of single classifiers, boosting, stacking, and optimized soft voting using the same coastal stunting dataset.

2. Methods

Figure 1 presents the overall workflow used to build and assess the stunting prediction system. The diagram covers the sequence from dataset preparation and class rebalancing to model training, parameter optimization, ensemble construction, and final performance evaluation.

The data were provided by the Langsa City Health Office in the eastern coastal region of Aceh and covered the period from January to December 2023. The original dataset contained 620 records of children under five. Before analysis, duplicate entries and records with incomplete values were excluded. The remaining variables were prepared for modeling by converting categorical attributes into numerical form and scaling the numerical features [15], [16]. The dataset was then separated into training and testing subsets. To reduce bias caused by the unequal number of stunted and non-stunted cases, SMOTE was applied only to the training subset. This technique enlarges the minority class by creating new synthetic samples from the characteristics of existing minority observations [17-19].

The experiments were carried out through several modeling stages. Support Vector Machine, Random Forest, Naïve Bayes, Logistic Regression, and XGBoost were first evaluated independently to establish reference results [20-24]. The next stage examined boosting configurations in which XGBoost was combined with the individual classifiers to improve learning from difficult or previously misclassified observations and to capture nonlinear relationships within the data [25], [26]. A stacking model was also developed by using SVM, Random Forest, Naïve Bayes, and XGBoost as first-level learners, while

Logistic Regression served as the second-level classifier. In this arrangement, the predictions generated by the base models became the input for the final classifier, allowing the model to exploit their complementary strengths [27]. In addition, a voting ensemble was formed from SVM, Random Forest, Naïve Bayes, Logistic Regression, and XGBoost, with the final class determined from the combined predictions of all participating models [28].

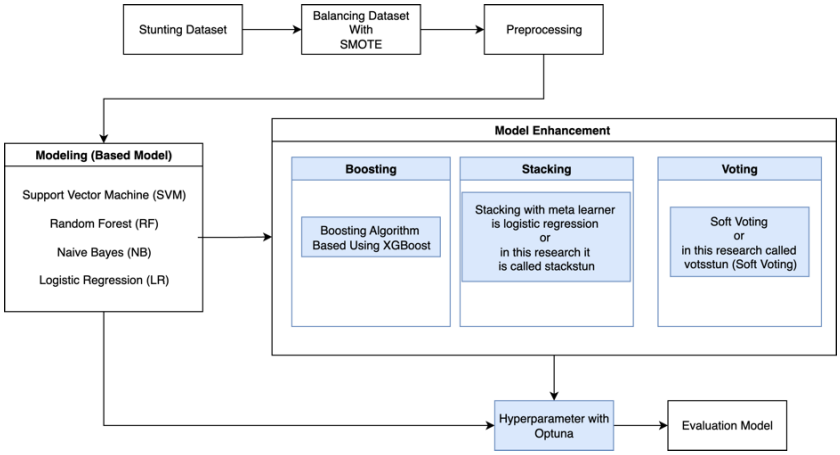


Figure 1. Methodology Flow

Hyperparameter selection for the models was performed automatically using Optuna. Through its optimization procedure, Optuna explored alternative parameter configurations and identified combinations that produced the strongest validation performance, thereby reducing dependence on manual trial-and-error experimentation [29], [30].

Model performance was evaluated through accuracy, precision, recall, and F1-score. Since the original dataset contained an uneven class distribution, the analysis also reported class-specific scores together with macro-averaged and weighted-averaged F1 values. Confusion matrices were further reviewed to examine the distribution of false-positive and false-negative errors and to assess whether each model maintained balanced predictive behavior for both the stunting and non-stunting classes.

3. Results and Discussions

This section reports the experimental findings obtained from the stunting-risk classification process using individual machine learning algorithms and several ensemble configurations. The evaluation was conducted according to the proposed analytical pipeline, starting with data preparation and class balancing through SMOTE. The processed dataset was then used to evaluate the baseline classifiers, followed by boosting, stacking, and optimized soft-voting approaches. The baseline stage involved Support Vector Machine, Random Forest, Gaussian Naïve Bayes, and Logistic Regression. The subsequent experiments examined XGBoost-based boosting, the Stackstun model, and the Votstun model to assess whether ensemble integration and automated parameter optimization could provide better predictive performance than the standalone classifiers. Model performance was examined using accuracy, precision, recall, F1-score, and confusion matrices to provide both an overall assessment and a detailed analysis of classification errors.

3.1 Baseline Model Performance

The baseline testing was conducted to determine the initial performance of individual machine learning models before ensemble learning methods were applied. The models were trained using preprocessed and SMOTE-balanced data to reduce the influence of class imbalance. This stage provides an important reference for evaluating whether boosting, stacking, and soft voting methods can improve classification performance compared with the individual baseline models. The classification results of the Logistic Regression model are illustrated through the confusion matrix presented in Figure 2.

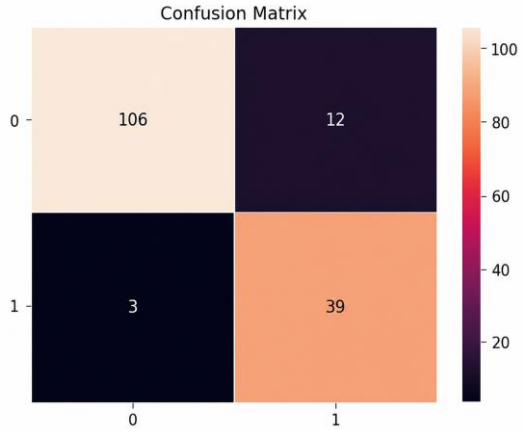


Figure 2. Confusion Matrix with Logistic Regression

Figure 2 shows that Logistic Regression correctly identified 106 children in the non-stunting group and 89 children in the stunting group. Misclassification occurred in 15 cases, consisting of 12 non-stunting children predicted as stunting and three stunting

children predicted as non-stunting. The very low number of missed stunting cases suggests that the model is highly sensitive to children who may require further attention. This characteristic is particularly valuable in public-health screening because an undetected stunting case may delay nutritional evaluation and appropriate intervention. Additional performance details, including precision, recall, and F1-score, are provided in Figure 3.

	precision	recall	f1-score	support
0	0.97	0.90	0.93	118
1	0.88	0.97	0.92	92
accuracy			0.93	210
macro avg	0.93	0.93	0.93	210
weighted avg	0.93	0.93	0.93	210

Accuracy : 0.9285714285714286

Figure 3. Classification Report for Logistic Regression

Figure 3 provides a more detailed view of the Logistic Regression results. The model reached an overall accuracy of approximately 92.86%, while both the macro-averaged and weighted-averaged F1-scores were 0.93. For non-stunting cases, the precision, recall, and F1-score were 0.97, 0.90, and 0.93, respectively. For stunting cases, the corresponding values were 0.88, 0.97, and 0.92. The high recall for the stunting class indicates that the model successfully detected most children who were actually affected. Therefore, Logistic Regression can be considered a reliable baseline, particularly for screening applications where reducing missed stunting cases is an important priority.

Based on Table 1, Logistic Regression provides the strongest baseline performance compared with GNB, SVM, and RF.

Table 1. Performance Metrics of Baseline Algorithms

Algorithm	Metric	Class 0	Class 1	Weighted Average
GNB	Precision	0.92	0.86	0.89
	Recall	0.89	0.90	0.90
	F1-score	0.91	0.88	0.89
	Accuracy			0.90
	Support	118	92	210
RF	Precision	0.73	0.60	0.66
	Recall	0.63	0.71	0.67
	F1-score	0.68	0.65	0.66
	Accuracy			0.66
	Support	118	92	210
SVM	Precision	0.98	0.80	0.89
	Recall	0.81	0.98	0.90
	F1-score	0.89	0.88	0.89
	Accuracy			0.89
	Support	118	92	210

GNB delivers fairly consistent results, recording an accuracy of 0.90 and a weighted F1-score of 0.89. SVM is effective in identifying stunting cases, as indicated by its high recall, although its lower precision suggests that more non-stunting children may be incorrectly flagged as at risk. In contrast, RF yields the lowest baseline performance, with both accuracy and weighted F1-score at 0.66. Overall, the results suggest that linear and probabilistic classifiers are better suited to the current dataset, whereas RF needs additional tuning or feature refinement before it can achieve comparable predictive performance.

3.2 Boosting Model Performance

Boosting was applied to improve the predictive capability of the baseline models. In this study, XGBoost was used as the boosting approach because it can learn complex nonlinear relationships and reduce prediction errors through sequential learning. The boosting models were also optimized using Optuna to obtain better hyperparameter configurations.

Table 2 shows that Boosted-RF achieved the best performance among all boosting models, with accuracy of 99.52% and near-perfect precision, recall, and F1-score for both classes. This result indicates that the combination of Random Forest and XGBoost is highly effective in capturing complex patterns related to stunting risk. Random Forest contributes by modeling feature interactions and reducing variance, while XGBoost improves prediction by correcting residual errors from previous learning stages. The use of Optuna further improves the model by selecting optimal hyperparameter values automatically.

Table 2. Performance Metrics of Ensemble Boosting

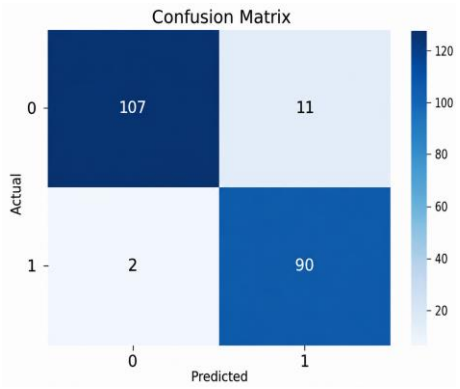
Algorithm	Metric	Class 0	Class 1	Weighted Average
Boosted-LR	Precision	0.90	0.72	0.81
	Recall	0.73	0.89	0.81
	F1-score	0.80	0.80	0.80
	Accuracy			0.80
	Support	118	92	210
Boosted-GNB	Precision	0.60	0.57	0.58
	Recall	0.83	0.28	0.56
	F1-score	0.70	0.38	0.54
	Accuracy			0.59
	Support	118	92	210
Boosted-RF	Precision	0.99	1.00	1.00
	Recall	1.00	0.99	0.99
	F1-score	1.00	0.99	1.00
	Accuracy			0.9952
	Support	118	92	210
Boosted-SVM	Precision	0.76	0.65	0.70
	Recall	0.69	0.72	0.71
	F1-score	0.73	0.68	0.70
	Accuracy			0.70
	Support	118	92	210

In contrast, Boosted-LR, Boosted-GNB, and Boosted-SVM did not outperform the best baseline model. Boosted-LR achieved accuracy of 0.80, Boosted-SVM achieved accuracy of 0.70, and Boosted-GNB produced the lowest performance with accuracy of 0.59. These results show that boosting does not always improve all models equally. The effectiveness of boosting depends on the suitability of the base learner and the structure of the dataset. Therefore, Boosted-RF can be considered the strongest boosting-based model in this study.

3.3 Stackstun Model Performance

Stackstun was developed by combining SVM, RF, GNB, LR, and XGBoost as base learners, while Logistic Regression was used as the meta-learner. The purpose of stacking is to combine the strengths of

several models so that the final prediction becomes more stable and accurate.



	precision	recall	f1-score	support
0	0.98	0.91	0.94	118
1	0.89	0.98	0.93	92
accuracy			0.94	210
macro avg	0.94	0.94	0.94	210
weighted avg	0.94	0.94	0.94	210

Accuracy : 0.9380952380952381

Figure 4. Testing with Stackstun

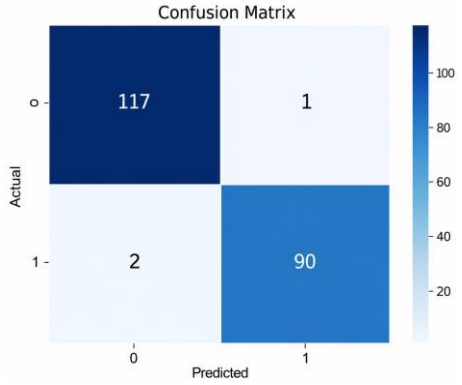
Stackstun correctly identified 107 non-stunting children and 90 stunting children. Only 11 non-stunting cases were incorrectly labeled as stunting, while two stunting cases were missed. This low false-negative count indicates that the model is highly effective in detecting children who may require further nutritional attention, while still preserving good recognition of the non-stunting group. Its classification report supports this result, with an overall accuracy of approximately 93.81% and macro- and weighted-average F1-scores of 0.94, indicating strong and well-balanced performance across both classes.

The improvement achieved by Stackstun indicates that combining several classifiers can reduce the weaknesses of individual models. SVM contributes strong decision boundaries, RF captures nonlinear feature interactions, GNB provides simple probabilistic learning, LR contributes stable linear classification, and XGBoost strengthens nonlinear pattern recognition. By using Logistic Regression as the meta-learner, Stackstun can learn from the outputs of the base models and produce a more reliable final prediction.

3.4 Votstun Model Performance

Votstun was developed using a weighted soft voting mechanism that combines SVM, RF, GNB, LR, and XGBoost. Unlike ordinary voting approaches, the voting weights in Votstun were optimized using Optuna so that each model contributes according to its predictive strength.

Votstun produced highly competitive results, making only three incorrect predictions. It correctly recognized 117 non-stunting cases and 90 stunting cases, while generating one false-positive and two false-negative outcomes. The classification report further shows an overall accuracy of approximately 98.57%, with both macro- and weighted-average F1-scores approaching 0.99. These findings indicate that Votstun maintains an excellent balance between precision and recall and performs consistently across both classes.



	precision	recall	f1-score	support
0	0.98	0.99	0.99	118
1	0.99	0.98	0.98	92
accuracy			0.99	210
macro avg	0.99	0.98	0.99	210
weighted avg	0.99	0.99	0.99	210

Accuracy : 0.9857142857142858

Figure 5. Testing with Votsstun

The strong performance of Votstun can be explained by its optimized soft voting mechanism. Since the model uses probability outputs from multiple classifiers, it can combine different learning perspectives and reduce the risk of relying on a single model. Optuna-based weight optimization further improves the voting process by giving greater influence to stronger classifiers while still preserving model diversity. This makes Votstun effective for stunting prediction, especially when the dataset contains complex and imbalanced patterns.

3.5 Overall Model Comparison

To provide a clearer overview of the experimental findings, all baseline and ensemble models are compared in a single summary table. This comparison is important to identify which model produces the most stable and accurate performance after applying SMOTE, Optuna optimization, and ensemble learning strategies. The overall comparison of model performance is presented in Table 3.

Table 3. Overall Performance Comparison of Baseline and Ensemble Models

Algorithm	Accuracy	Precision	Recall	F1-Score
LR	92.85%	93%	93%	93%
Boosted-RF	99.52%	100%	99%	100%
Stuckstun	93.80%	94%	94%	94%
Votstun	98.57%	99%	98%	99%

Overall, the experimental results show that ensemble learning improves prediction performance compared with single baseline models. Logistic Regression is the best baseline model, with accuracy of 92.86%. Stackstun improves the performance to approximately

93.81%, while Votstun achieves 98.57%. The highest performance is obtained by Boosted-RF, with accuracy of 99.52%. These results indicate that the integration of SMOTE, Optuna, and ensemble learning contributes significantly to improving stunting-risk prediction.

From a practical perspective, high recall for the stunting class is particularly important because it reduces the possibility of missing children who are actually at risk. False negatives are more critical than false positives in stunting screening because missed cases may delay nutritional intervention. The proposed ensemble models, particularly Boosted-RF and Votstun, show strong potential for early detection because they maintain high accuracy, precision, recall, and F1-score simultaneously.

3.6 Comparison with Previous Studies

To assess the contribution of the proposed approach more clearly, its best-performing configurations were compared with findings reported in earlier stunting-prediction studies. This comparison places the proposed framework within the broader landscape of existing machine learning and ensemble methods. The resulting accuracy values are summarized in Table 4.

Earlier studies reported accuracies between 77% and 98% using methods such as SVM, Voting Classifier, Deep Neural Network, and Random Forest. In the present study, Boosted-RF produced the strongest result, reaching an accuracy of 99.52% and surpassing the highest value reported in the selected previous works. Votstun also achieved a high accuracy of 98.57%, indicating that an optimized soft-voting strategy can provide reliable and well-balanced predictive performance. Overall, these results show that the proposed ensemble configurations are highly competitive for stunting-risk classification.

Table 4. Accuracy Comparison Between the Proposed Model and Previous Studies

No	Researcher	Algorithm	Accuracy
1	[31]	SVM	98%
2	[9]	Voting Classifier	91.67%
3	[32]	Deep Neural network	93.83%
4	[33]	Random Forest	77%
5	[34]	SVM	91.3%
6	This Research	Boosted-RF	99.52%

However, cross-study comparison should be interpreted carefully because each study may use different datasets, sample sizes, preprocessing techniques, feature sets, and validation strategies. Nevertheless, the superior performance obtained in this study suggests that combining SMOTE for class balancing, Optuna for hyperparameter optimization, and ensemble learning for model integration can improve prediction robustness. This finding supports the use of optimized ensemble learning as a promising approach for stunting prediction, particularly in coastal public-health contexts.

3.7 Discussion

The results confirm that the proposed ensemble framework can improve stunting prediction performance. The main factors contributing to this improvement are class balancing using SMOTE, automatic hyperparameter optimization using Optuna, and the integration of several learning algorithms through ensemble learning. SMOTE helps reduce bias toward the majority class, Optuna improves model configuration, and ensemble learning combines different model strengths to produce more stable predictions.

Among all models, Boosted-RF achieved the highest accuracy. This suggests that the combination of RF and XGBoost is highly suitable for capturing nonlinear and complex relationships in the stunting dataset. Votstun also showed excellent performance because the weighted soft voting mechanism allows the model to combine probabilistic predictions from multiple classifiers. Stackstun improved the baseline performance, although its accuracy was lower than Boosted-RF and Votstun.

These findings have important implications for early stunting screening. A model with high recall can help health workers identify more children who are at risk, while high precision can reduce unnecessary follow-up for children who are not at risk. Therefore, the proposed framework can support more targeted and efficient public-health interventions. In coastal areas such as the East Coast of Aceh, where access to health services and nutritional resources may be limited, accurate prediction models can help prioritize children who require immediate attention.

In conclusion, the results demonstrate that optimized ensemble learning is effective for stunting-risk prediction. Boosted-RF provides the best overall performance, while Votstun offers a strong and balanced alternative through optimized soft voting. The proposed framework can be used as a foundation for developing an early-warning system to support stunting prevention and intervention programs.

4. Conclusions

This study demonstrates that an end-to-end machine learning pipeline integrating preprocessing, SMOTE-based class balancing, ensemble learning, and Optuna-guided hyperparameter optimization can produce highly reliable stunting-risk prediction in a coastal context. Logistic Regression achieved the strongest baseline performance, showing balanced precision and recall across both classes. However, ensemble learning provided substantial performance improvement. Boosted-RF achieved the best overall result with an accuracy of 99.52% and near-perfect classwise performance, while Votstun also produced highly competitive results with an accuracy of approximately 98.6% and macro/weighted F1-scores close to 0.99. Stackstun further improved baseline performance with

approximately 94% accuracy and F1-score.

These findings indicate that combining SMOTE, Optuna, and ensemble learning can improve model robustness, reduce classification bias, and support more accurate early detection of children at risk of stunting. Practically, the proposed models can assist health workers in prioritizing growth monitoring, nutritional intervention, sanitation improvement, and family counseling. Future studies should conduct external validation across different districts, incorporate longitudinal and environmental variables, and evaluate cost-sensitive thresholds that align with local public-health program capacity.

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