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Stunting Prediction Modeling in Toddlers Using a Machine Learning Approach and Model Implementation for Mobile Application

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Abstract

Children's health and development are critical for maintaining national productivity and independence, with stunting being a major concern. Stunting, a form of malnutrition, impairs growth and development, affecting millions of people globally, including a significant number in Indonesia. This study addresses the challenge of stunting by developing a predictive model using machine learning techniques to forecast stunting risks based on public health data. The literature review section discusses the factors that influence stunting, and these factors are used as features to build a stunting prediction model. Then the features were used to build a model with three machine learning algorithms Extreme Gradient Boosting (XGBoost), Random Forest, and K-Nearest Neighbor (KNN) to build and evaluate models that predict stunting. The models were trained and assessed using public datasets and the most effective algorithm was integrated into a mobile application for practical use. The results indicate that the XGBoost model outperforms the other models with an accuracy of 85%, making it the optimal choice for implementation in a mobile application. The next-best model is selected to be implemented through a mobile application so that users can directly use the model that has been built. This application aims to enhance early detection and intervention efforts for stunting, potentially improving child health outcomes and contributing to long-term productivity by building predictive models and implementing the models into a mobile application. This study contributes to the implementation of models built using public data for application in mobile applications.

Keywords: machine learning; mobile application; stunting prediction

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1. Introduction

Children represent the next generation tasked with preserving national independence and enhancing future productivity. Therefore, it is crucial for society to ensure that children's developing bodies are properly nurtured to support their growth according to their age. A prevalent issue today is stunting, a form of malnutrition that impairs children's growth and development, often evidenced by a height or length below standard norms. Stunting, a condition in which children fail to reach their full growth potential due to chronic malnutrition or repeated infections, is a significant problem in many low-income countries [1]. According to UN statistics from 2020, over 149 million toddlers globally have experienced stunting, including 6.3 million in Indonesia [2]. Addressing this issue is critical because early education and prevention can help reduce the rising rates of stunting in Indonesia, thereby sustaining productivity levels in the long term.

Many studies have discussed stunting. For example, Jihan et al. research through a literature study resulted in stunting being caused by many factors such as maternal education, economy, immunization, breastfeeding, and infectious diseases. Stunting can be prevented by breastfeeding, full immunization according to procedures, regular diet, and health checks

[3]. Among these factors, enhancing parental or maternal knowledge regarding proper nutrition and child activities is crucial for early prevention of stunting. In addition, the study also stated that the factors that cause stunting are Gender, Age, Birth Weight, Birth Length, Body Weight, Body Length, and Breastfeeding. These factors will be the features that will be used to build a stunting prediction model.

This study aims to explore the use of public data in developing a stunting prediction model, a significant health problem in many countries, including Indonesia. To achieve this goal, a prediction model will be built using three different machine learning algorithms, namely Extreme Gradient Boosting (XGBoost), Random Forest, and K-Nearest Neighbor (KNN). These three algorithms were chosen because of their respective abilities in handling complex and diverse datasets. In this study, an evaluation will be carried out to measure the performance of the three models based on the accuracy values produced, so that it can be seen to what extent the model is able to provide accurate predictions regarding the potential for stunting in toddlers. Furthermore, the model with the best accuracy will be selected to be implemented in the form of a mobile application, which is designed to be easily accessed and used by various groups, both by health workers, parents, and the general public. This mobile application is expected to provide convenience in uniting stunting risks quickly and efficiently, as well as assisting in prevention efforts by providing timely and data-based information. Thus, this study not only contributes to the development of a more accurate stunting prediction model, but also in creating practical solutions that are accessible to the wider community to prevent stunting early.

Research on stunting has also been conducted by various researchers using multiple machine learning models. These include K-Nearest Neighbor (KNN), Decision Tree, Logistic Regression, Support Vector Machine (SVM), Random Forest, and Extreme Boosting Machine (XGBoost), among others. For instance, research on developed a "Stunting Early Warning Application Using the KNN Machine Learning Method" based on a posyandu dataset [4]. Similarly, explored machine learning algorithms for predicting undernutrition among children under five in Ethiopia [5]. This study employed five ML algorithms, including eXtreme Gradient Boosting (XGBoost), k-Nearest Neighbors (KNN), Random Forest, Neural Network, and Generalized Linear Models, to predict socio-demographic risk factors for undernutrition. Among these, the xgbTree algorithm emerged as the most effective model for predicting childhood undernutrition. Research conducted by Bitew et al. produced an accuracy evaluation with an XGboost value of 65.8%, Random Foret with a value of 62.2%, KNN with a value of 61.5%. The study showed that the best model based on data from the Ethiopian region produced XGBoost as the best model.

Based on related work, researchers will build and re-evaluate using the same three models, namely XGBoost, Random Forest, and KNN through different datasets, namely public data, to prove whether the XGBoost model is the best model or not. The model with the best accuracy will be selected to be implemented in the mobile application. Currently, there are hospitals in Indonesia, precisely in the Bogor Regency area, which need tools that can be used to predict stunting. With this tool, it can be used as an initial reference to be implemented in the hospital, especially for midwives or other health workers in predicting stunting. In addition, the most obvious difference in this study compared to other studies is that after building the model, the next step is to implement the model into the application. Even though the data used is public, the model can be used by all users and can directly use the impact of building the model.

2. Methods

One of the applications of machine learning is its ability to make predictions [6]. Prediction involves estimating future outcomes based on historical data. By leveraging past information, predictions can offer insights into future trends, which can be used to inform decision-making processes in policy development [7]. The results of these predictions can serve as a reference for decision-making in various scenarios.

Stunting refers to a delay in growth experienced by children who do not meet the standard growth expectations for their age [8]. Characteristics of stunting include slower growth rates, a younger appearance compared to peers, a relatively decreasing weight, and delayed tooth development. To identify children who may be stunted, routine health check-ups are necessary to ensure that a child's height meets standard growth benchmarks [9].

A dataset is a collection of data from a specific source, organized into records according to its intended use. The data, which results from observations, measurements, and analyses, is managed and structured into a dataset. This dataset is crucial for data mining and is often utilized for tasks such as modeling to analyze data and generate valuable insights for business applications [10].

In research, machine learning is frequently employed to make predictions. Machine learning is a field focused on the development of algorithms that create models capable of processing large volumes of data to identify patterns quickly. This capability allows for more accurates based on the input data. Additionally, machine learning can assist businesses by analyzing data and providing rapid feedback to support decision-making processes [11] .

One type of machine learning is supervised learning. In supervised learning, the dataset used contains labeled input data. This labeled data is used to train algorithms to achieve high accuracy for classification or prediction tasks. Supervised learning encompasses classification and regression. Classification involves grouping data into predefined categories based on labels, with the resulting model used to generate conclusions needed by users. For instance, this study will use a decision tree algorithm for classification. Regression, on the other hand, examines the relationship between dependent and independent variables, where the dependent variable (y) is influenced by the independent variable (x) [12] .

This research includes data preparation, feature encoding, and model implementation through mobile apps.

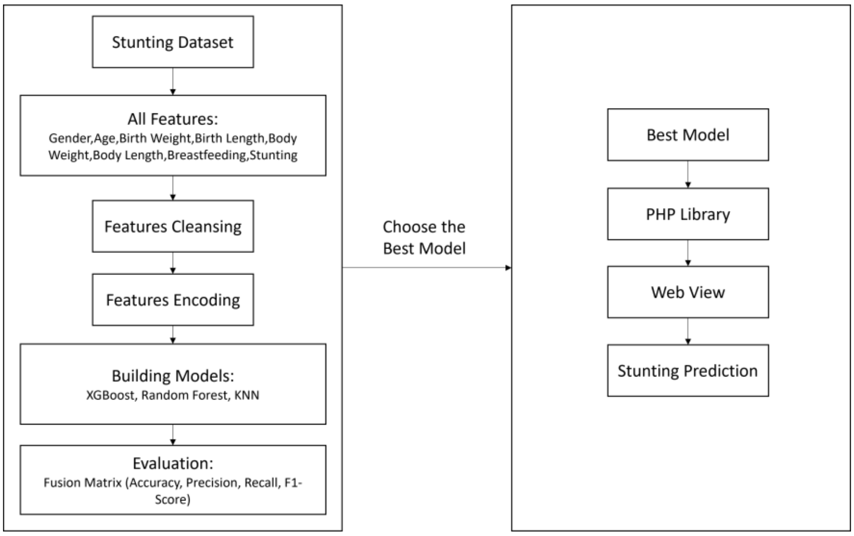

Figure 1. Stunting Prediction Model Procedure

Figure 1 shows the procedure for building a model and implementing the model through mobile apps. The available features are Gender, Age, Birth Weight, Birth Length, Body Weight, Body Length, Breastfeeding, and Stunting. In the Gender feature containing the data "Male" and "Female", data cleansing is carried out to ensure that only the data is present and then text encoding is performed by changing "Male" to 1 and "Female" to 0. The Age, Birth Weight, Birth Length, Body Weight, and Body Length features contain decimal data, researchers ensure that all available data is decimal data and can be read by the program as a decimal data type. The Breastfeeding and Stunting features contain "Yes" or "No" data, researchers perform text encoding for "Yes" to 1 and "No" to 0. After the cleansing and encoding process is complete, the next step is to build a model with XGBoost, Random Forest, and KNN. The model is then evaluated using a fusion matrix, namely accuracy, precision, recall, and F1-Score. The next highest performing model is implemented through the PHP library, then creates a web display to be accessed via a mobile application.

In this study, the predicted values are in two categories, namely Stunting and Not Stunting, so the use of Confusion matrix is used for binary classification problems. In Confusion matrix there are four terms, namely [13]:

True Negative (TN), which is the value of the prediction results stating in the negative class and the actual data is correct in the negative class.

True Positive (TP), which is the value of the prediction results stating true in the positive class and the actual data is correct in the positive class.

False Negative (FN), which is the value of the prediction results stating wrong in the negative class and the actual data is wrong in the positive class.

False Positive (FP), which is the value of the prediction results stating wrong in the positive class and the actual data is correct in the negative class.

The four terms above will be used in the use of confusion matrix which are measured including Accuracy, Precision, Recall, Specificity, and F1-Score for evaluation. From the prediction results that have been made, an evaluation is carried out to determine the value of the actual data and predictions, so that the difference in the results can be seen [14]. The explanation of each in the use of its evaluation.

Accuracy, measuring the performance ratio of correct predictions for both positive and negative classes with all data [15]. The value will answer the question "What percentage of children are correctly predicted to be Stunting and Not Stunting from the total data?". Accuracy equation are written using Formula 1:

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \quad (1)$$

TP is True Positive rate, use TP when model correctly identifies a positive case. TN is True Negative rate, use TN when model correctly identifies a negative case. FP is False Positive rate, use TN when model incorrectly identifies a positive case. FN is False Negative rate, use TN when model incorrectly identifies a negative case.

Precision, a performance measurement of the ratio of correct positive predictions compared to the overall results predicted and stated positive [16]. The value will answer the question "What percentage of children are correctly Stunting from all children predicted to be Stunting?". Precision equation are written using Formula 2:

$$Precision = (TP) / (TP + FP) \quad (2)$$

Explanation TP and FP formula 2 such as the explanation for Formula 1.

Recall, a performance measurement of the ratio of correct positive predictions compared to the overall results stated positive [17]. The value will answer the question "What percentage of children are predicted to be Stunting compared to all children who are actually Stunting". Recall equation are written using Formula 3:

$$Recall = (TP) / (TP + FN) \quad (3)$$

Explanation TP and FN formula 3 such as the explanation for the formula 1.

F1-Score, a performance measurement by comparing the Precision and Recall values [18]. F1-Score equation are written using Formula 4:

$$F1\,Score = 2 * (Recall * Precision) / (Recall + Precision) \quad (4)$$

The results of the evaluation of the three models were compared by researchers to determine the best model. Then the next is implemented using the PHP programming language for model implementation and creating a web view using the Java programming language so that it can be accessed via mobile.

3. Results and Discussions

The dataset used to build the stunting prediction modeling is data taken from public data sourced from Kaggle data. From the dataset there are seven features with the following details.

Table 1. Features of the Dataset

Number	Feature	Data Type
1	Gender	object
2	Age	int64
3	Birth Weight	float64
4	Birth Length	int64
5	Body Weight	float64
6	Body Length	float64
7	Breastfeeding	object

Table 1dataset will be built with three models. Before modeling, researchers will carry out stages starting from pre-processing, building models, and evaluation.

3.1 Pre-processing

At this stage, the researcher checks the data to clean the data and checks the values if there is empty data.

Table 2. Cleaning Data Results

No.	Gender	Age	Birth Weight	Birth Length	Body Weight	Body Length	Breastfeeding	Stunting
1	Male	17	3.0	49	10.0	72.2	No	No
2	Female	11	2.9	49	2.9	65.0	No	Yes
3	Male	16	2.9	49	8.5	72.2	No	Yes
4	Male	31	2.8	49	6.4	63.0	No	Yes
5	Male	15	3.1	49	10.5	49.0	No	Yes

In Table 2, there are still values in the form of text that need to be converted into numbers so that they can be processed by machine learning. Therefore, data conversion is carried out for the gender column male is changed to 1 and female to 0, in the breastfeeding column the value No is changed to 0 and Yes is changed to 1, and in the stunting column for the value No is changed to 0 and Yes is changed to 1.

Table 3. Preprocessing Results

No.	Gender	Age	Birth Weight	Birth Length	Body Weight	Body Length	Breastfeeding	Stunting
1	1	17	3.0	49	10.0	72.2	0	0
2	0	11	2.9	49	2.9	65.0	0	1
3	1	16	2.9	49	8.5	72.2	0	1
4	1	31	2.8	49	6.4	63.0	0	1
5	1	15	3.1	49	10.5	49.0	0	1

Based on Table 3 the conversion results in the table above, the dataset can be continued to be trained in machine learning.

3.2 Building the models

The model is built using XGBoost, Random Forest [19] and KNN [20]. The three models are used based on the results of a literature study where these models are algorithms used to make predictions related to predictions. The tools used are Google Colab with the Python programming language. The Python program produces a model with XGBoost, Random Forest and KNN modeling output. Below are the definitions and formulas for the XGBoost algorithm models.

XGBoost is a decision tree-based machine learning algorithm designed to improve performance and optimize predictions using gradient descent techniques. It enhances traditional decision tree models by minimizing an objective function that combines the loss function and regularization terms to prevent overfitting.

The gradient descent method is employed to optimize the loss function, ensuring that the model progressively improves by reducing errors during training. Regularization plays a key role in controlling model complexity, making XGBoost robust and effective for various predictive tasks, particularly when working with large datasets or complex features [21].

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (5)$$

In Formula 5, l denotes the loss function that measures the discrepancy between the actual value yi and the predicted value $\hat{yi}$, f_t refers to the model of the t-th tree, and t indicates the iteration step in the optimization procedure.

The architecture that was built can be seen in Figure 2 regarding the Data Training Methodology.

In Figure 2 the machine learning processing process starting from the dataset obtained from public data. Then the data is processed using Google Colab to help researchers in comparing performance and data analysis. From the results of the analysis, the best algorithm model will be selected, and further analysis will be carried out using the Google Collab tool with the python programming language. The library used is pandas to process data and is combined with other libraries for deeper data analysis. The results of machine learning processing provide output in the form of predictions. Furthermore, these predictions can be displayed on mobile apps by utilizing the PHP library. Based on the selected algorithm, the PHP library helps the prediction calculation process using the selected algorithm. The results obtained in PHP are then displayed via mobile using web view technology. So that users can directly feel the benefits of machine learning through access on mobile apps.

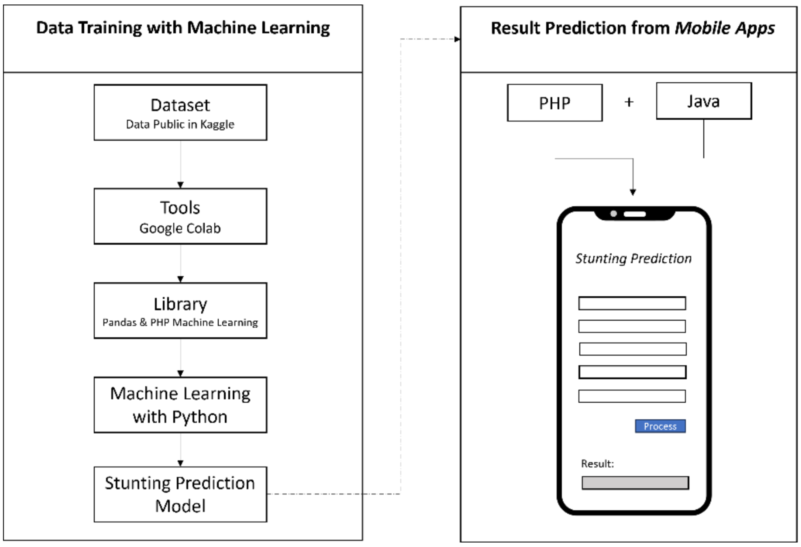

Figure 2. Data Training Methodology

3.3 Evaluation

This evaluation uses a Confusion matrix to measure the performance of the built model. The values compared are Accuracy, Precision, Recall, and F1-Score. Based on the evaluation results of the built model, the following values are produced.

Table 4. Evaluations Results

No.	Model	Accuracy	Precision	Recall	F1-Score
1	XGBoost	85%	84%	85%	84%
2	Random Forest	83%	82%	83%	82%
3	KNN	84%	82%	84%	82%

Table 4 presents the evaluation results of three classification algorithms applied to address the problem investigated in this study: XGBoost, Random Forest, and K-Nearest Neighbor (KNN). The evaluation was conducted using four common machine learning metrics: Accuracy, Precision, Recall, and F1-Score.

In this study, the XGBoost model achieved the highest accuracy (85.6%) among all machine learning models evaluated, demonstrating its strong ability to classify stunting cases based on the selected features. Compared to Bitew et al. (2020), who reported a lower XGBoost accuracy of 65.8%, the difference in performance can largely be attributed to variations in case contexts and datasets. While our research focused on stunting prediction in Indonesian toddlers, their study used data from a different population and setting. Nonetheless, it is important to note that in Bitew et al. study, XGBoost consistently outperformed other models across various undernutrition outcomes. This consistency supports the robustness of XGBoost in diverse contexts and justifies its selection for integration into our mobile application.

Among the tested models, XGBoost not only achieved the highest accuracy (85.6%) but also showed strong precision (84%) and recall (85%), indicating its effectiveness in correctly identifying positive cases while minimizing classification errors. These results suggest that the model is capable of learning meaningful patterns from historical data and making reliable predictions regarding stunting.

However, the fact that the accuracy does not reach 100% highlights some inherent challenges in modeling stunting prediction. Factors such as data noise, outliers, and class imbalance may affect model performance. Moreover, the limited number of input features—only seven—may not fully capture the complexity of variables contributing to stunting, thus limiting the model's predictive capability.

Based on its superior performance, the XGBoost model was selected for implementation in the mobile application. The predicted output generated by this.

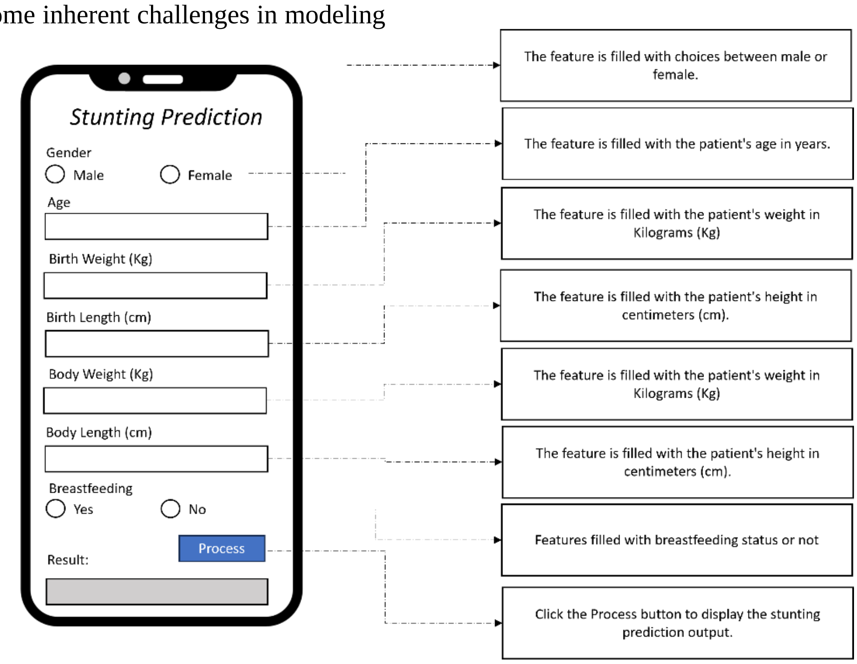

Figure 3. Model Implementation to Mobile Applications

The Figure 3 explains that the input of features needed in stunting prediction. Users can click process to display the prediction results in the result section. So that this section can speed up the process of stunting analysis or not. This research resulted in the implementation of a model for a mobile application which can then be used as a reference for health workers, especially midwives in Indonesia, to determine the condition of stunting in children so that they can immediately take follow-up action to meet children's nutritional needs.

4. Conclusions

This study highlights the potential of machine learning in addressing the pressing issue of childhood stunting. By evaluating three classification models XGBoost, Random Forest, and K-Nearest Neighbor (KNN), XGBoost was identified as the most effective model, achieving an accuracy of 85%. This figure indicates that the model correctly classified 85% of the instances in the dataset, reflecting a relatively strong ability to capture patterns related to stunting. However, the fact that the model does not achieve 100% accuracy underscores certain limitations and challenges inherent in the data and modelling process. These may include data noise, outliers, class imbalance, or insufficient feature representation, which can hinder the model's consistency and generalizability. The generalization of the model in question is due to the features used not yet having external factors that can influence the results of stunting prediction. This study not only evaluated the models but also implemented the best model through a mobile application so that users could directly experience the contribution of the model implementation.

The successful integration of the XGBoost model into a mobile application offers a promising, practical tool for healthcare professionals and parents to assess and manage the risk of stunting. While the current model provides reasonably reliable predictions, further improvements are necessary. Future research should explore the inclusion of more diverse and comprehensive features, such as nutritional intake, parental health history, socioeconomic status or environmental factors to better reflect the multifaceted nature of stunting. Additionally, incorporating educational modules within the application could enhance user engagement and contribute to preventive behaviour.

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