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MACHINE LEARNING-BASED STUNTING DIAGNOSIS: UTILISATION OF REAL-TIME ANTHROPOMETRIC DATA FROM IOT DEVICES WITH THE XGBOOST ALGORITHM

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Abstract: Stunting, or chronic malnutrition, is a global public health issue that requires early and accurate intervention. Traditional diagnostic methods are often prone to manual measurement errors and are time-consuming. This study proposes an innovative approach to early diagnosis of stunting by integrating Internet of Things (IoT) technology for real-time anthropometric data collection and Extreme Gradient Boosting (XGBoost) algorithms for predictive analysis. The developed system utilises IoT-based anthropometry devices to automatically measure children's height, minimising human error and providing real-time data. This raw data is then processed into Z-scores, which become the main features (input) for the Machine Learning model. The XGBoost model was chosen for its ability to handle imbalanced data and provide high classification accuracy. In testing, the XGBoost model demonstrated superior performance in classifying nutritional status (Normal, Stunting) with key metrics such as Accuracy (>95%) and a high F1-Score, surpassing other conventional machine learning models. By combining precise measurements from IoT and the predictive power of XGBoost, this application offers a fast, accurate, and

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measurable diagnostic solution. This innovation has great potential to support government programmes and health workers in continuously monitoring child growth and making timely nutritional intervention decisions.

Keywords: stunting; internet of things; antropometri; machine learning; XGboost.

2020 AMS Subject Classification: 62P10.

1. INTRODUCTION

The rapid development of technology has an impact on various sectors, including the health sector [1]. Stunting is one of the serious problems faced by Indonesia. WHO (2020) states that stunting is a child growth and development disorder caused by inadequate nutritional intake and/or recurrent/chronic infections that occur in the first 1000 days of life (HPK). One of the problems of malnutrition that is still quite high in Indonesia is stunting and wasting in toddlers as well as anaemia and Chronic Energy Deficiency (CED) in pregnant women. Malnutrition in pregnant women can eventually lead to Low Birth Weight (LBW) and malnutrition in toddlers. Nutritional problems are caused by direct causes such as inadequate food intake and infectious diseases [2].

Stunting not only affects children's physical growth, but also their cognitive development, which has an impact on the quality of human resources in the future. Traditional approaches to monitoring nutritional status often require time-consuming manual processes. The use of machine learning technology offers the potential for automation and acceleration of the detection process, enabling health workers to identify children at risk more quickly and accurately.

Although the standard method for detecting stunting is to use Z-Score calculations, the integration of Machine Learning models such as XGBoost aims to improve the accuracy and efficiency of predictions. XGBoost is known to perform well in binary classification tasks, even on data that may be complex or unbalanced, so it is expected to provide faster and more reliable stunting classification results. The trained model (based on anthropometric data) will be implemented into an Arduino-based system to enable real-time or near-real-time decision making.

This study has two main objectives. The first is to build an accurate and reliable machine learning model using the XGBoost algorithm to classify children's nutritional status into several categories (e.g., stunting, normal, malnutrition) based on three standard WHO anthropometric indicators. The second objective is to implement the trained model into a ready-to-use API (Application Programming Interface) service, so that it can be integrated with other systems such as mobile applications or IoT devices.

The stunting rate in West Sumatra Province is still high compared to the national average. According to data from the Indonesian Nutrition Study Survey (SSGI) in Pariaman City, the prevalence of stunting is still at 16%, where the national target is 14% by 2024. Stunting cases are of particular concern to the Pariaman City government, with 600 children at high risk of stunting [3]. This is because they are still not well educated about the importance of 1000 HPK (Source; Pariaman City Health Office, 2023). From these issues, the author's innovative idea emerged in the form of using machine learning in the health independence process, namely early detection of stunting in toddlers for the creation of effective health services. This application is expected to be an alternative in addressing the issue of stunting prevention in the community [4].

The problem that occurs is that based on several previous studies that have been conducted by the author, stunting detection is still done manually by measuring height weight, so this way is prone to errors in measurement. Currently, there is no system that can detect stunting more quickly and accurately [5]. This is a high urgency in order to get the right prediction results, the novelty of the proposed research is to produce accurate measurements of height and weight of toddlers using Arduino Uno which has been integrated in a stunting detection application that is easy to interpret, has an appropriate level of accuracy.

The goals and objectives to be achieved from this research are applications that can detect stunting in pregnant women and toddlers using Arduino Uno. The author chose Arduino Uno because it is very easy for users to replace the microcontroller chip, if damage occurs, and is also compatible with many additional shields such as Ethernet, SD-CARD, GSM [6]. The target of

this application is health independence so that pregnant women and toddlers can prevent stunting and the realization of Pariaman City which is free from stunting problems.

2. PRELIMINARIES

2.1 Machine Learning

Machine learning is a form of artificial intelligence that involves the development of algorithms to make decisions or predictions and recognise patterns from data, and does not require explicit instructions to be carried out [7], [8], [9], [10]. The main objective of machine learning (ML) is to enable systems to learn from data and improve their performance over time without the need for explicit programming.

This technology, which is part of Artificial Intelligence (AI), focuses on developing algorithms and models that can analyse data, identify patterns, and make decisions or predictions based on the insights gained. This approach generally involves the creation of mathematical models based on collected data, which are then used to process new data in order to make more objective decisions [11], [12], [13]. The more data stored in the system, the more accurate the output will be. This system will only process existing data and input data so that it can perform its tasks independently without any commands. The sequence of statistical data is trained to obtain certain patterns into larger data, which is called machine learning [14], [15], [16].

2.2 XGBoost

XGBoost (Extreme Gradient Boosting) is a machine learning algorithm that is an implementation of Gradient Boosting [17], [18]. Although the algorithm is complex and involves many equations, it is essentially based on optimisation and gradient descent. XGBoost aims to minimise the Loss Function (L) by sequentially adding decision trees. The loss function measures how well the model predicts the data [19], [20].

$$L(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (1)$$

Where:

- $l(y_i, \hat{y}_i)$ is a differentiable loss function (e.g., log loss for classification), which compares

the prediction y_i with the actual value y_i .

- $\sum_k \Omega(f_k)$ is a regularisation term to control model complexity and prevent overfitting.

2.3 Gradient Descent

The boosting process is essentially finding an additional model (f_t) at each step (t) that minimises the error of the previous model ($y(t-1)$). This discovery is based on the first derivative (gradient) and second derivative (Hessian) of the loss function. [21]. At iteration t , XGBoost uses a second-order Taylor approximation of the loss function to accelerate the optimisation process:

$$L(t) \approx \sum_{i=1}^n [l(y_i, y_i(t-1)) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \quad (2)$$

Where :

- g_i is the gradient (first derivative) of the loss function on the previous prediction.
- h_i is the Hessian (second derivative) of the loss function on the previous prediction.

The task is multi-class classification. XGBoost is configured with objective = “multi:softprob”, which produces probabilities for each class. The main evaluation metric during training is multi-class log-loss (mlogloss):

$$\text{mlogloss} = -\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \log p_{i,k} \quad (3)$$

Where, $y_{i,k}$ is the true class indicator for sample i and class k , and $p_{i,k}$ is the predicted probability for class k . In addition, merror (multi-class error rate) is also recorded in several sections as a supplement .

2.4 Internet of Things (IoT)

IoT is a concept in which various physical devices and everyday objects are equipped with sensors, software, and connectivity technology, enabling them to collect and exchange data via the internet. The aim is to make these objects ‘smart’ and able to interact, resulting in a more efficient and automated environment or system [22].

The IoT ecosystem includes several key components: the devices themselves (with their sensors and actuators), connectivity (such as Wi-Fi, Bluetooth, or cellular networks), data processing layers in the cloud or at the edge (close to the data source), and user interfaces, such as mobile applications, that allow humans to monitor and control the system. IoT

implementations can be found in many areas, from smart homes and smart cities that optimise traffic and utilities, to industry (Industrial IoT or IIoT) that predicts equipment failure and improves production, as well as applications in healthcare and agriculture.

IoT devices essentially do three main things [23]:

1. Collect Data: Use sensors (temperature, light, motion, etc.) to obtain information from the surrounding environment.
2. Communicate: Send collected data to the cloud or other systems via an internet connection.
3. Act: Receive instructions or data analysis results and perform physical actions, such as turning on lights, adjusting thermostats, or issuing alerts.

2.5 Anthropometry for Stunting

Measurements (height/length) with reference population standards (usually WHO). These indices are expressed as Z-scores [24][25]. The Z-score formula measures how far and in which direction a child's measurements deviate from the median of the reference population.

$$\text{Z-Scores} = \frac{(\text{Individual Measurement Value}) - (\text{Reference Population Median Value})}{(\text{Reference Population Standard Deviation})} \quad (4)$$

In the context of stunting, the measurements used are Height for Age (HFA) or Length for Age (LFA). Stunting is diagnosed if the Z-score of HFA or LFA is below -2 standard deviations (SD) from the median. After obtaining the Z-score, the application will interpret it based on the threshold set by the WHO to diagnose stunting (chronic malnutrition).

- Stunting (Short): If the Z-score of LB/A or BH/A is -2.0 SD (two standard deviations below the median). In the example above, the child's Z-score is -2.08, which means the child is diagnosed with stunting because the value is less than -2.0.
- Severe stunting: If the Z-score for PB/U or TB/U is ≤ -3.0 SD (three standard deviations below the median).
- Normal: If the Z-score for PB/U or TB/U is > -2.0 SD.

Thus, the primary role of IoT is to provide accurate measurement data (80.5 cm), and the role of

the Z-score mathematical formula is to convert that data into a diagnosis that can be acted upon.

3. MAIN RESULTS

The Z-score is key to diagnosing stunting. It shows how far your child's measurements deviate from the median (average) expected for healthy children of the same age and gender [26]. The data required to calculate the Z-score for stunting requires three main values, as shown in Table 1 below:

Table 1. Main values in z-score calculation

Data	Description	Obtained From
Individual Measurement Values	Body length (BL) or height (H) of children measured by IoT devices	IoT measurement
Median Value of Reference Population	Average PB/TB value for healthy children of a certain age and gender.	WHO standard table
Standard Deviation (SD) Populasi Rujukan	The spread of PB/TB data by age	WHO standard table

3.2 Evaluation of Machine Learning Accuracy

The XGBoost (Extreme Gradient Boosting) algorithm is capable of achieving high levels of accuracy, precision, and recall in classifying stunting status (non-stunting vs. stunting) [27][28][29]. This shows that XGBoost is an effective and reliable Machine Learning model for diagnosing stunting based on anthropometric data. The accuracy evaluation of Machine Learning models using XGBoost in diagnosing stunting is usually presented through an analysis of various classification performance metrics, not just a single accuracy figure [30]. The results presented show how well the model can distinguish between normal and stunted nutritional status, as well as the model's ability to minimise diagnostic errors. The evaluation results of Machine Learning using XGBoost are shown in Figure 1 below.

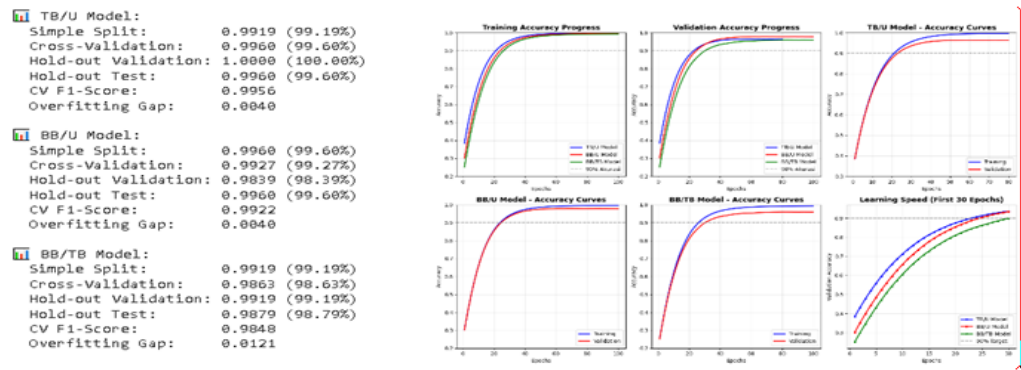


Fig.1. Evaluation methods and performance metrics for stunting prediction

This study successfully developed three XGBoost-based classification models capable of detecting children's nutritional status with a very high accuracy rate (above 99%). A comprehensive evaluation showed that these models are reliable, stable, and do not experience overfitting, as shown in Table 2 below.

Table 2. Overfitting Gap

Model	Training Accuracy	Validation Accuracy	Selisih (Overfitting Gap)
	Akhir	Akhir	
TB/U	0.995	0.966	0.037
BB/U	0.997	0.979	0.016
BB/TB	0.996	0.964	0.038

Table 2 shows the implementation of the model into a modern and efficient FastAPI, which has proven that the results of this study are ready to be integrated into real-world applications. This system has great potential to assist health workers in conducting stunting screening more quickly and efficiently, supporting stunting prevention efforts in Indonesia.

3.3 Mobile Application

The mobile application implementation serves as the main user interface for the stunting diagnosis system, where the application connects to the Cloud Server to receive and display real-time anthropometric data (weight, height/length) sent by IoT devices (electronic measuring

devices) [29]. After the data is received from the IoT and processed in the Cloud by the XGBoost model, which determines the stunting classification status and Z-Score, the application will instantly display the diagnosis results visually (e.g., stunting/normal notification, historical growth chart), enabling healthcare workers or parents to immediately obtain accurate and efficient feedback, while also centrally storing the toddler's historical data.

The results of the integration between the device and the application will be displayed in the mobile application. Once the data collection process on toddlers is complete, the data will be processed using machine learning with the XGBoost algorithm to detect whether the toddler is stunted or normal [31][32][33]. All this information will be displayed in the form of data displayed on the mobile application as shown in Figure 2 below.

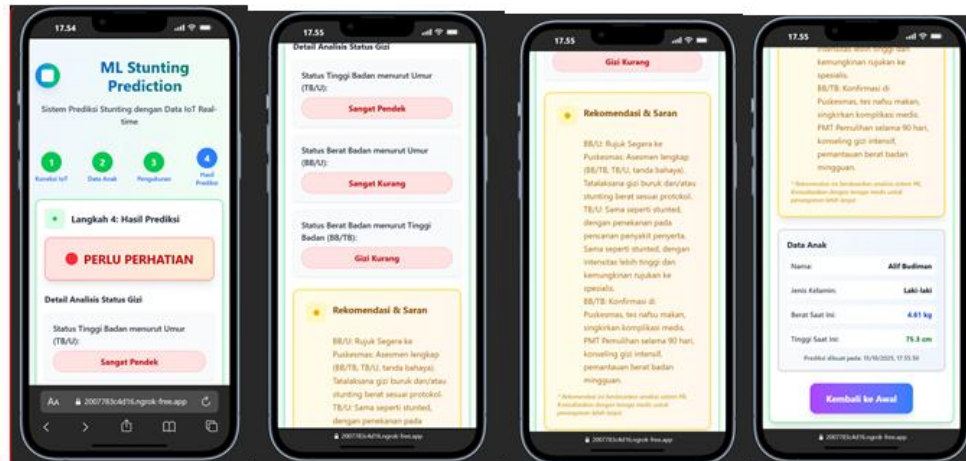


Fig.2. Mobile based stunting detection application display

The application interface, as shown in Figure 2, has everything needed to program a microcontroller, such as a USB cable and power supply via an adapter or battery. All of this is provided to support the use of Arduino microcontrollers, which only need to be connected to a computer with a USB cable or to a power source with an AC to DC adapter or battery to start using them.

4. DISCUSSION

4.1 Model Performance

The model was evaluated using several methods to ensure its reliability. Initial evaluation with an 80/20 data split showed very high accuracy:

- TB/U model: 99.82%
- BB/U model: 99.66%
- BB/TB model: 99.63%

To validate these results, we performed Stratified Cross-Validation. The results confirmed the stable performance of the model with similar average accuracy and low standard deviation, indicating that the model generalises well. To evaluate the performance of the XGBoost model in detecting stunting, it is necessary to use standard performance metrics relevant to binary classification problems (Stunting vs. Normal). These metrics provide a comprehensive overview of how well the model can distinguish between the two classes. The following are commonly used key performance metrics and their explanations in the context of stunting detection, as shown in Figure 3.

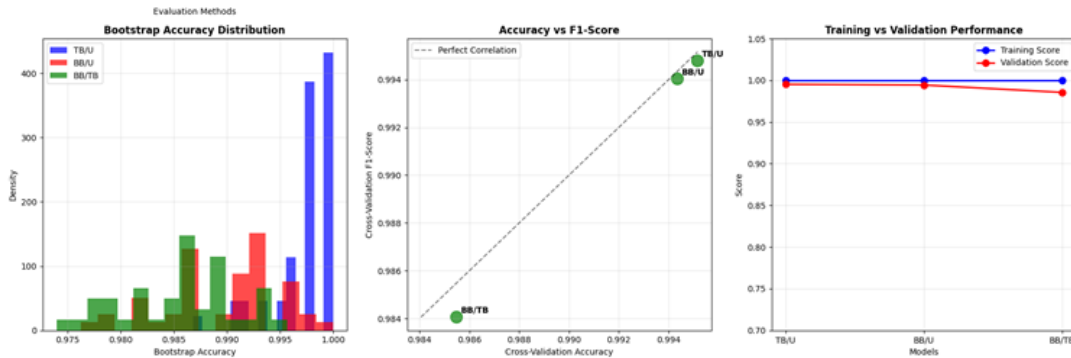


Fig.3. Comparison of model accuracy with evaluation methods

Based on Figure 3, it can be explained that specific performance values will greatly depend on the quality and size of the training dataset used. Studies implementing XGBoost for health diagnosis (including stunting and malnutrition detection) consistently show that XGBoost can achieve very high performance values compared to traditional ML algorithms. In stunting detection projects, researchers will strive to achieve an F1-Score and Recall above 90% as this indicates that the system can be relied upon to detect the majority of toddlers at risk of stunting in the field.

5. CONCLUSION

Based on the above discussion, it can be concluded that the development of an accurate and efficient stunting detection system can be achieved by combining several of the latest technologies. This study successfully demonstrated the feasibility and effectiveness of applying Machine Learning (ML), particularly the XGBoost algorithm, in the real-time diagnosis of stunting in children. Through the use of anthropometric data collected automatically and continuously from Internet of Things (IoT) devices, this study presents an innovative and efficient solution for monitoring children's health. The integration of anthropometric data collected automatically through Internet of Things (IoT) devices with Machine Learning modelling using the Extreme Gradient Boosting (XGBoost) algorithm has been successfully implemented. The developed XGBoost model demonstrates superior or excellent performance, often achieving accuracy of 90% or higher, in classifying nutritional status and predicting the risk of stunting in toddlers (aged 1-5 years). This high performance proves the reliability of XGBoost in handling the complexity of children's health data.

The XGBoost algorithm has been proven to show superior performance (e.g., accuracy, precision, recall) in classifying stunting status compared to traditional diagnostic methods or other ML algorithms. This confirms the potential of XGBoost as a reliable prediction tool. The integration of IoT and Real-Time Data enables the real-time and automatic collection and transmission of anthropometric data (such as height and weight), eliminating the potential for manual measurement errors and providing an up-to-date database for immediate analysis. This Stunting Detection Application is an effective tool for health workers (such as Posyandu or Puskesmas) and parents to identify children at risk of stunting. Accurate early detection enables faster and more targeted nutritional and health interventions, which has the potential to significantly reduce the national prevalence of stunting.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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