Comparison of Deep Neural Networks and Random Forest Algorithms for Multiclass Stunting Prediction in Toddlers

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Abstract

Stunting in toddlers is a serious global health issue, with long-term impacts on physical growth and cognitive development. To address this problem more effectively, it is crucial not only to identify whether a child is stunted but also to predict the severity of the condition. Multiclass stunting prediction offers deeper insights into a child's condition, enabling more precise and targeted interventions. This study aims to compare the performance of multiclass stunting prediction models using two machine learning algorithms: Deep Neural Networks and Random Forest. The research process involved data collection, preprocessing, as well as model development and testing. The results show that the Random Forest model achieved 100% accuracy in training and 99.92% accuracy in testing, while the Deep Neural Networks model achieved 93.49% accuracy in training and 93.21% in testing. Both models demonstrated strong performance in multiclass stunting prediction, with Random Forest proving superior in terms of accuracy compared to Deep Neural Networks.

Keywords: Multiclass Stunting, Prediction, Deep Neural Networks, Random Forest, Toddlers.

I. INTRODUCTION

Stunting in young children is a serious global health issue with long-term consequences for physical growth and cognitive development [1-3]. In 2022, Indonesia's stunting prevalence rate remained relatively high at 21.6% and is targeted to decrease to 14% by 2024 [4]. Stunting is more prevalent among children under five years old, with 70% of cases occurring in the 0-23-month age range [5]. Therefore, accurate and early stunting prediction is crucial for timely interventions. However, this remains challenging due to the complex interplay of various factors contributing to stunting.

Numerous studies have been conducted to predict and classify stunting. The Multi-Layer Perceptron (MLP) approach was used by Ashuri et al. [6] to classify stunting. It was shown that an MLP model with RandomSearchCV hyperparameter tuning produced the best results, with accuracy of 81.78%, precision of 85.00%, recall of 94.34%, and F1-score of 89.43%. Cahyani et al. [7] employed MLP with GridSearchCV for stunting classification and obtained an accuracy of 82.37%. Syahrial et al. [8] utilized Support Vector Machines (SVM) with an RBF kernel to classify stunting in children and achieved an accuracy of 78%. Purnomo and Rozaq [9] classified stunting in toddlers in Madiun city using Naïve Bayes and obtained an accuracy of 58%. Amin and Novitasari [10] identified stunting with an accuracy of 85.79% by using anthropometric data and Long Short-Term Memory (LSTM). Using Extreme Gradient Boosting, Fikri [11] was able to classify the stunting status of children under five years old with an accuracy of 86%, precision of 89%, recall of 95%, and F1-score of 92%. Using Decision Trees and ANOVA, Nugroho et al. [12] detected stunting in toddlers with 96% accuracy, 97% precision, 89% recall, and 93% F1-score. However, all existing studies have conducted binary classification, determining whether a child is stunted or not. To address stunting more effectively, it is crucial to not only identify whether a child is stunted but also to predict the severity of stunting.

To address this issue, this study aims to perform multi-class classification of stunting in toddlers using Random Forest and Deep Neural Networks. Multi-class stunting prediction provides deeper insights into the child's condition, enabling more specific and targeted interventions. A well-liked and potent machine learning technique, Random Forest excels in problems involving regression and classification. As part of the ensemble learning class, Random Forest generates predictions that are more reliable and accurate by mixing several decision trees [13]. Random Forest typically uses Classification and Regression Trees (CART) due to their simplicity and non-parametric nature [14]. AL-Mouse et al. [15] performed multi-class diabetes disease detection using Random Forest and achieved an accuracy of 89%. Senbagamalar and Logeswari [16] used Random Forest for multi-class cancer classification and achieved an accuracy of 95.21%. Saminathan and Sowmiya [17] used Random Forest for multi-class rice leaf disease classification and achieved an accuracy of 97.62%.

The main issue addressed in this research is finding the most effective method for multi-class stunting classification in toddlers. In addition to Random Forest, the study constructs a prediction model using Deep Neural Networks, an artificial neural network architecture with multiple hidden layers that can learn complex data representations. While Deep Neural Networks have been used in various fields, such as phishing detection by Lestari and Mustika [18], who achieved 94.75% accuracy, and breast cancer classification by Aljuaid et al. [19], with an average accuracy of 97.81%

Based on the literature review, this research aims to evaluate the effectiveness of machine learning algorithms, specifically Deep Neural Networks and Random Forests, in predicting multi-class stunting outcomes in toddlers. By comparing the performance of these two algorithms, this research can identify the most accurate and efficient model for stunting prediction, thus contributing to the development of data-driven interventions for early childhood health.

II. RESEARCH METHODOLOGY

This research adopts a systematic approach to compare the performance of two algorithm, Deep Neural Networks (DNN) and Random Forest (RF) in predicting multiclass stunting among toddlers. The methodology is segmented into several essential steps, including data collection, data preprocessing, model development, evaluation, and comparison of results.

Stages of the research methodology can be seen in Figure 1.

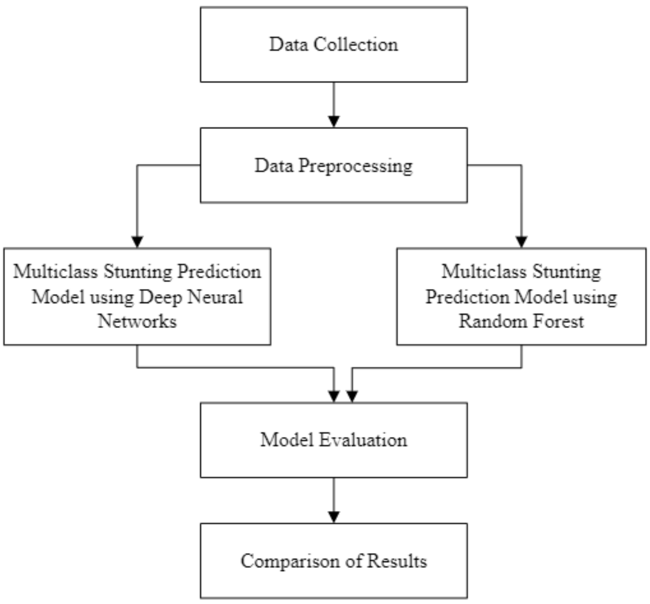

Figure 1. Research Methodology

A. Data Collection

The dataset employed in this research was sourced from the publicly accessible Kaggle platform. The "Stunting Toddler Detection" dataset was compiled using the WHO's z-score methodology to classify stunting in children under five [20]. This dataset contains 120,999 observations, with variables including age, gender, height, and nutritional status. The nutritional status is categorized into four classes: 'severely stunting', 'stunting', 'normal', and 'height', corresponding to different levels of growth deviation from the reference population. These categories help in the quick identification and intervention for children who are at risk or experiencing growth issues.

B. Data Preprocessing

Data preprocessing is a crucial step to ensure that the data is of high quality and suitable for the machine learning model to be used. During this stage, data cleaning is performed through several steps, such as checking for missing values, converting object data types to numeric, normalizing continuous variables, and transforming categorical features into a format that the model can understand. The processed dataset is then split into training and testing sets, ensuring that the class distribution for stunting remains balanced.

C. Model Development

In this stage, we build prediction models for multiclass stunting classification using two methods. The first model is created using the Random Forest method. The parameters for the Random Forest model are as follows:

a. RandomForestClassifier(): This function is used to construct the Random Forest model.
b. n_estimators=100: This parameter specifies the number of decision trees to be built in the forest. In this study, we use 100 decision trees.
c. random_state=42: This argument establishes the random number generator's seed. When the code is executed numerous times, setting this seed ensures that the results are repeatable.

In addition to the Random Forest model, this study also employs Deep Neural Networks for prediction model development. The parameters for the Deep Neural Networks are as follows:

a. Sequential(): This function defines a neural network model sequentially, adding each layer one by one.
b. Three hidden layers with 128 neurons each, a kernel_regularizer value of 0.01, and a dropout rate of 0.3 in each layer to reduce overfitting by preventing the model from becoming too reliant on specific neurons.
c. Two activation functions are used: the Rectified Linear Unit (ReLU) activation function, commonly used in hidden layers to address the vanishing gradient problem, and the softmax activation function, used for multiclass classification as it generates a probability distribution for each class.
d. The model weights are updated using the Adam optimizer in accordance with the gradient of the loss function. The Adam optimizer is used in this instance, and its learning rate is 0.00001.

e. The number of epochs is set to 100, meaning the model will be trained for 100 iterations over the entire dataset.
f. The batch_size=64 indicates that the model will be updated after processing 64 data samples at once (batch).

The selection of parameters for both models was based on experimentation and analysis during the training phase. The model construction was performed using the preprocessed training data.

D. Model Evaluation

A critical phase in machine learning is model evaluation, which gauges a model's capacity to forecast outcomes accurately on fresh, unobserved data. This include computing different performance indicators and putting the model to the test on a holdout dataset. The overall accuracy of the model's predictions is measured by accuracy. Precision and recall assess the model's ability to identify positive examples without producing false positives (precision) and the number of true positive instances it detects (recall), with a focus on particular classes. The F1-score offers a fair evaluation of the model's performance by integrating recall and precision into a single statistic.

Here are the Equation 1-4 for calculating accuracy, precision, recall, and F1-score:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = 2\,x\,\frac{Precision\,x\,Recall}{Precision + Recall} \quad (4)$$

E. Comparison of Results

At this stage, both models that have been trained and evaluated are compared based on the defined performance metrics from point D. This comparison is conducted to determine which model performs better in multiclass stunting prediction for toddlers.

III. RESULT AND DISCUSSION

The following section presents the results obtained from this research.

A. Dataset

The present research employs a dataset entitled "Stunting Baby/Toddler Detection" that is grounded in the WHO's z-score formula for identifying stunting in children below the age of five. A detailed overview of the dataset is provided in Table 1.

Table 1. Dataset Details

No	Status	Total
1	Severely Stunted	19,869
2	Stunted	13,815
3	Normal	67,755
4	Tall	19,560
	Total	**120,999**

B. Data Processing Result

The subsequent section presents the outcomes of the data preprocessing phase. A visual representation of the missing value analysis is provided in Figure 2, which confirms the absence of missing data in the dataset.

```
#Missing value check
df.isnull().sum()

Umur (bulan)        0
Jenis Kelamin       0
Tinggi Badan (cm)   0
Status Gizi         0
```

Figure 2. Missing Value Check

The transformation of the data type from object to numeric is illustrated in Figure 3. This process involved converting the categorical variables "Gender" (coded as 1 for male and 2 for female) and "Nutritional Status" (coded as 3 for tall, 2 for stunted, 0 for normal, and 1 for severely stunted) into numerical representations.

	Umur (bulan)	Jenis Kelamin	Tinggi Badan (cm)	Status Gizi
0	0	1	44.591973	2
1	0	1	56.705203	3
2	0	1	46.863358	0
3	0	1	47.508026	0
4	0	1	42.743494	1
...	...	...	...	...
120994	60	2	100.600000	0
120995	60	2	98.300000	2
120996	60	2	121.300000	0
120997	60	2	112.200000	0
120998	60	2	109.800000	0

Figure 3. Convert Object to Numeric Results

Subsequent to data collection, data normalization was performed using StandardScaler to standardize the independent variables. This transformation scaled the data to possess a mean of 0 and a standard deviation of 1. The standardized dataset is presented in Table 2.

Table 2. Data Normalization Results

Age	Gender	Height
-1.7168548	-1.00834064	-2.54688462
-1.7168548	-1.00834064	-1.84673536
-1.7168548	-1.00834064	-2.41559775
		...

1.69707641	0.99172836	1.88686819
1.69707641	0.99172836	1.36088477
1.69707641	0.99172836	1.22216386

The categorical feature "Nutritional Status" was transformed into a numerical representation using LabelEncoder's fit_transform function as the final preprocessing step. Subsequently, the numerical labels were one-hot encoded using keras.utils' to_categorical function to facilitate multi-class classification. The outcomes of this transformation are visualized in Figure 4.

```
array([[0., 0., 1., 0.],
       [0., 0., 0., 1.],
       [1., 0., 0., 0.],
       ...,
       [1., 0., 0., 0.],
       [1., 0., 0., 0.],
       [1., 0., 0., 0.]])
```

Figure 4. Convert Categorical Features into Numerical Format Results

The processed data was subsequently partitioned into training and testing sets using an 80:20 split. A detailed breakdown of this random partition is presented in Table 3.

Table 3. Dataset Sharing Result

No	Status	Training	Testing
1	Severely Stunted	15,739	4,130
2	Stunted	11,025	2,790
3	Normal	54,373	13,382
4	Tall	15,662	3,898

C. Model and Evalution

This research involved the development of two predictive models:

a. A multi-class stunting prediction model based on the Random Forest algorithm.
b. A multi-class stunting prediction model utilizing Deep Neural Networks.

As a preliminary step, both models were trained on 80% of the dataset. The outcomes of the training phase are presented in Table 4 and Figure 5.

Table 4. Training Model Results

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	100	100	100	100
Deep Neural Networks	93.49	93.70	93.49	93.19

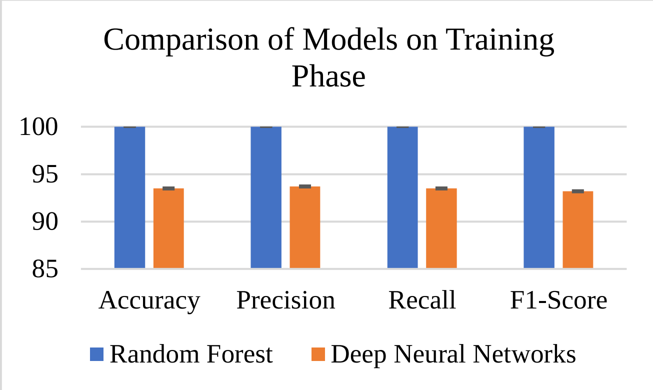

Figure 5. Comparison of Models on Training Phase

Subsequent models were evaluated on a held-out testing set. The outcomes of this evaluation are summarized in Table 5 and Figure 6.

Table 5. Evaluation Model Results

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	99.92	100	100	100
Deep Neural Networks	93.21	93.41	93.21	92.91

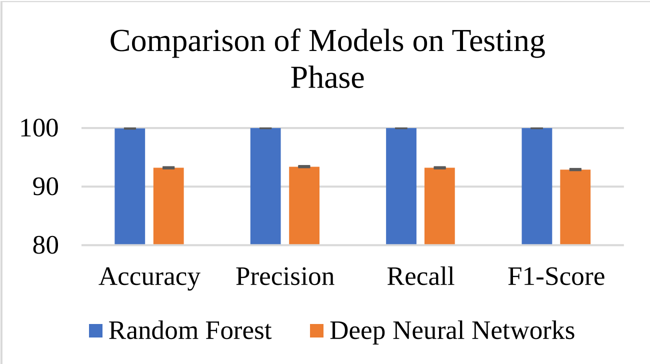

Figure 6. Comparison of Models on Testing Phase

As shown in Table 5 and Figure 5, the Random Forest model outperformed the Deep Neural Networks, achieving a significantly higher accuracy. Random Forest reached an accuracy of 99.92% on the testing set, compared to 93.21% for the Deep Neural Networks. This superior performance of Random Forest is likely due to its capability to handle complex datasets and define more precise decision boundaries, especially in multi-class classification tasks. While Deep Neural Networks are known for their ability to learn intricate patterns through layered architectures, in this case, they were unable to match the accuracy delivered by Random Forest.

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IV. CONCLUSION

This research compared the performance of Deep Neural Networks and Random Forest algorithms in predicting multi-class stunting status in young children. The results indicate that both models exhibited strong performance, with Random Forest achieving a superior accuracy of 100% in training and 99.92% in testing. In contrast, the Deep Neural Networks model attained an accuracy of 93.49% in training and 93.21% in testing. Collectively, these findings suggest that Random Forest is a more suitable algorithm for multi-class stunting prediction due to its higher accuracy and precision. Nevertheless, Deep Neural Networks remain a promising approach, particularly when further optimization or feature engineering is implemented. These results offer valuable insights for researchers and practitioners seeking to select the optimal algorithm for similar classification tasks.

This research has several limitations to consider. First, the possibility of data imbalance in the stunting prediction dataset could influence model performance, particularly for minority classes, where Random Forest may perform better due to its resilience to imbalanced data, while Deep Neural Networks (DNN) may require additional techniques such as class weighting or oversampling. Second, the perfect accuracy of 100% during the training phase for Random Forest indicates a potential risk of overfitting, although the testing accuracy remains high. For future research, it is recommended to explore hybrid models that combine the strengths of both Random Forest and DNN, conduct more extensive hyperparameter tuning for DNN, expand the dataset with additional features such as genetic or environmental data, and apply more robust cross-validation techniques to ensure the model generalizes well.

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