

# Prediction of Stunting in Toddlers Using Bagging and Random Forest Algorithms

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**Abstract:** Stunting is a condition of failure to thrive in toddlers. This is caused by lack of nutrition over a long period of time, exposure to repeated infections, and lack of stimulation. This malnutrition condition is influenced by the mother's health during pregnancy, the health status of adolescents, as well as the economy and culture and the environment, such as sanitation and access to health services. To find out predictions of stunting, currently we still use a common method, namely Secondary Data Analysis, namely by conducting surveys and research to collect data regarding stunting. This data includes risk factors related to stunting, such as maternal nutritional status, child nutritional intake, access to health services, sanitation, and other socioeconomic factors. This secondary data analysis can provide an overview of the prevalence of stunting and the contributing factors. To overcome this, the right solution is needed, one solution that can be used is data mining techniques, where data mining can be used to carry out analysis and predictions for the future, and provide useful information for business or health needs. Based on this analysis, this research will use the Bagging method and Random Forest Algorithm to obtain the accuracy level of stunting predictions in toddlers. Bagging or Bootstrap Aggregation is an ensemble method that can improve classification by randomly combining classifications on the training dataset which can reduce variation and avoid overfitting. Random Forest is a powerful algorithm in machine learning that combines decisions from many independent decision trees to improve prediction performance and model stability. By combining the Bagging method and the Random Forest algorithm, it is hoped that it will be able to provide better stunting prediction results in toddlers. This research uses a dataset with a total of 10,001 data records, 7 attributes and 1 attribute class. Based on the test results using the Bagging method and the Random Forest algorithm in this research, the results obtained were class precision yes 91.72%, class recall yes 98.84%, class precision no 93.55%, class recall no 65.28%, and accuracy of 91.98%.

**Keywords:** Bagging; Prediction; Random Forest; Stunting

## INTRODUCTION

Stunting is a condition of failure to thrive in toddlers. This is caused by lack of nutrition over a long period of time, exposure to repeated infections, and lack of stimulation. This malnutrition condition is influenced by the mother's health during pregnancy, the health status of adolescents, as well as the economy and culture and the environment, such as sanitation and access to health services. Referring to the Global Health Organization (WHO) report, around 149.2 million or 22% of children under the age of 5 worldwide are estimated to experience stunting in 2020 (Asian Development Bank, 2021). Basic Health Research data shows that the prevalence of stunted toddlers in 2018 reached 30.8 percent, which means one in three toddlers experienced stunting. Indonesia itself is the country with the 2nd highest burden of stunted children in the Southeast Asia region and 5th in the world (Ramadani, 2021).

To find out predictions of stunting, currently we still use a common method, namely Secondary Data Analysis. This technique is implemented by conducting surveys and research to collect data regarding stunting (Adityaningrum et al., 2023). This data includes risk factors related to stunting, such as maternal nutritional status, child nutritional intake, access to health services, sanitation, and other socioeconomic factors. This secondary data analysis can provide an overview of the prevalence of stunting and the factors that contribute. Although secondary data analysis can provide insight into the prevalence of stunting and associated risk factors, this approach has several weaknesses that need to be considered, namely data limitations, inconsistencies in definitions and methods,

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and the impossibility of including certain variables so that this results in the prediction data obtained being inconsistent, accurate and representative. To overcome this, the right solution is needed, one solution that can be used is data mining techniques using the Bagging and Random Forest Algorithms to get better accuracy of prediction results.

The Bagging algorithm used in this research functions to balance the stunting dataset used, because the dataset has class labels that are not balanced between yes and no stunting sufferers. On the use of data mining many optimization techniques have been developed to overcome class imbalance problems which are grouped into three types of approaches, namely data level approaches, algorithm level approaches, and hybrid approaches with ensemble techniques (Kotsiantis et al., 2006). One ensemble method that has been widely used is bagging (Sewell, 2007). Bagging or Bootstrap Aggregation is an ensemble method that can improve classification by randomly combining classifications on the training dataset which can reduce variation and avoid the occurrence of overfitting (Pan & Tang, 2014).

Meanwhile, the Random Forest algorithm is a powerful and popular machine learning method used for classification and regression tasks. Random Forest combines the concept of a decision tree with the concept of randomization to build a set of independent decision trees that work collectively.

Several previous studies have been carried out using Bagging techniques, such as research conducted by Fitriyani, Implementation of Forward Selection and Bagging for Forest Fire Prediction The resulting accuracy is 98,40% (Fitriyani, 2022). Research carried out by Eka Rahmawati, Candra Agustina namely Implementation of Bagging Techniques to Improve J48 Performance and Logistic Regression in Predicting Online Purchase Interest The resulting accuracy is the resulting accuracy of 89,68% and 88,50% (Rahmawati & Agustina, 2020). Based on the background that has been described, the problem formulation in this research is how to get higher accuracy results regarding stunting predictions in toddlers using the Bagging and Random Forest algorithms using the Rapid Miner Tools.

## LITERATURE REVIEW

Stunting is a condition where a person's height is shorter than the height of other people in general (of the same age). Stunted (short stature) or low height/length for age is used as an indicator of chronic malnutrition which describes the history of under-nutrition in toddlers over a long period of time. Usually, stunting occurs during the early growth period, especially in children under five years of age. Stunting is considered a major indicator of chronic malnutrition in children. Stunting is caused by prolonged chronic malnutrition, especially during vulnerable childhood years. The main factors contributing to stunting include lack of adequate nutritional intake, especially protein and energy, recurrent infections, poor care and sanitation, as well as environmental and social factors.

In conditions of stunting, a child's physical growth is hampered and occurs at a slower rate than normal growth. The impact of stunting can have long-term impacts on children's health and development. Children who experience stunting tend to have a higher risk of infectious diseases, cognitive problems and delayed mental development, lower productivity in later life, and the risk of chronic diseases as adults.

Stunting prevention involves comprehensive efforts, including adequate nutritional intake, good feeding practices, quality health services, good sanitation and hygiene, as well as public education and awareness about the importance of balanced nutrition. This effort involves cross-sector collaboration, including the health, nutrition, agriculture, education and sanitation sectors, as well as support from the government, community and international institutions.

Bagging is an ensemble learning technique used to improve the performance of prediction models. Ensemble learning refers to the use of several models to make predictions, the results of which are then combined to produce a better final prediction.

Basically, Bagging involves creating a new sample dataset from an initial training dataset using random sampling with replacement (bootstrap sampling). Each of these new samples is used to train the same prediction model. Because each new sample has variations in data composition, the resulting models will also have variations. Then, the predictions from all these models are combined (for example, through voting or averaging) to produce a final prediction. The main benefit of Bagging is that it reduces the variance of the model, as it introduces variation in the training samples. This helps in reducing overfitting and improving overall model performance.

The bagging (bootstrap aggregating) algorithm is an ensemble learning method used to improve the performance of predictive models by combining predictions from several different models. This algorithm involves a resampling technique using the bootstrap method to generate several new training data sets, and then training a model on each of these training data sets. The predictions from each model are then combined to produce the final prediction (Kuhn & Johnson, 2013).

Following are the general steps in the Bagging algorithm:

a. Data Preparation

Collect available datasets. Divide the dataset into two parts: training data (training set) and test data (test set).

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- b. Formation of a New Training Data Set  
Utilizing the bootstrap resampling strategy, make a few new preparation datasets that are a similar size as the first preparation dataset. In each new preparation informational collection, the information is tested arbitrarily with inversion from the first preparation informational collection. This implies that a few examples might seem on numerous occasions and some may not be chosen by any means.
- c. Training the Model  
For each new training data set, train the same predictive model using the selected learning method. For example, you can use decision trees, logistic regression, or other methods.  
Each model is trained on a different training data set, resulting in different models.
- d. Combining Model Predictions  
Once all models are trained, use each model to make predictions on test data. For regression problems, predictions can be combined by taking the average of all model predictions. For classification problems, predictions can be combined using majority voting. For example, if there are 5 models and 3 models predict class A and 2 models predict class B, then the prediction result will be class A.  
Evaluation of Results
- e. Evaluate the performance of the resulting ensemble model using appropriate evaluation metrics, such as accuracy, precision, recall, or Mean Squared Error (MSE) in the case of regression. The advantages of the Bagging algorithm are that it reduces model variance or error, increases prediction accuracy, and can be used with a variety of different machine learning algorithms. Langkah-langkah di atas adalah konsep umum dalam algoritma Bagging, dan implementasinya dapat bervariasi tergantung pada algoritma atau platform yang digunakan.

Random Forest is a development of Bagging which is used especially in the context of decision trees. The basic idea of Random Forest is to use Bagging to train many decision trees, which are then combined to make better predictions. In contrast to regular Bagging, Random Forest introduces additional randomness in the formation of each decision tree. When creating each decision tree, the algorithm selects a random subset of the available features. This aims to introduce additional variation between decision trees, which helps reduce correlation between them and increase diversity. Finally, the predictions from all these decision trees are combined, usually through voting for classification or averaging for regression.

The main advantage of Random Forest is its ability to handle large datasets with many features without requiring complex parameter tuning. In addition, Random Forest can also provide estimates of feature importance, which is additional information that is useful in modeling and interpretation. By combining the prediction results from a number of independent decision trees, Random Forest can produce a more stable, accurate and robust model against overfitting. This algorithm has proven successful in various modeling tasks and has become one of the popular algorithms in the field of machine learning.

Precision is a proportion of how close the forecasts of a model or framework are to the genuine qualities. With regards to AI, exactness is the capacity of a model to accurately foresee the objective worth or mark from the given information. Numerically, precision is determined by separating the quantity of right forecasts by the absolute number of expectations. Exactness is one of the most generally utilized arrangement execution assessment measurements by Hastie, Tibshirani, and Friedman. The following is the mathematical formula for determining accuracy:

$$\text{Akurasi} = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Prediction}}$$

For binary classification, accuracy can also be calculated in positive and negative terms as follows:

$$\text{Akurasi} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Where :

- TP : True Positif
- TN : True Negatif
- FP : False Positif
- FN : False Negatif

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## METHOD

Methodology is a process carried out to solve a problem raised in a research so that accurate results can be found and conclusions can be drawn. This research method explains in detail all the sequences in carrying out the research.

### A. Persiapan Data

In the initial stage of the research, data preparation was carried out. The dataset used in this research is public data taken from Kaggle.com regarding Stunting data. The stunting dataset consists of 10,001 data records, 7 attributes and 1 attribute class, with the method used being the Bagging Algorithm and Random Forest (<https://www.kaggle.com/datasets/muhtarom/stunting-dataset>, n.d.).

### B. Data processing

Data processing in this research uses data mining techniques, namely the Bagging and Random Forest algorithms. Data mining is the process of finding significant patterns or information from large datasets. In this context, research uses data mining techniques, which are a collection of algorithms and methods for extracting insights from data ("About the Authors," 2012). Bagging (Bootstrap Aggregating) and Random Forest are two ensemble learning techniques that use multiple models to improve predictive performance. They build several models and combine their prediction results to produce more stable and accurate predictions.

The stages in this research are as follows:

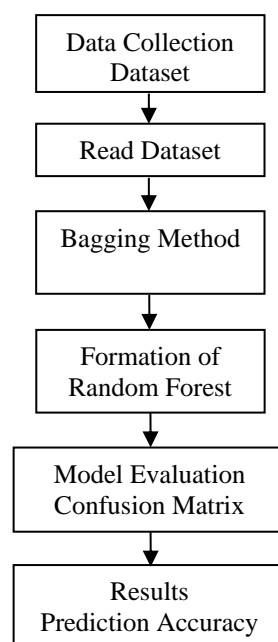


Figure 2. Research Stages

La steps in conducting research:

**Dataset Collection:** Collect a dataset containing information about toddlers, including relevant attributes such as nutritional status, environmental factors, eating patterns, health history, and others. This dataset must include information about whether toddlers are stunted or not.

1. **Read Dataset:** a step or operation that involves importing or reading a dataset from a file or external data source into the Rapidminer software.
2. **Bagging method:** creating an ensemble of models by combining several models generated from a random subset of the training dataset. By building models on random subsets of the dataset (bootstrap samples), the bagging method introduces variation among the resulting models. This helps reduce overfitting and improves model stability.
3. **Establishment of Random Forest Model:**
  - a. Determine the number of trees ( $n_{estimators}$ ) to be used in the Random Forest ensemble.
  - b. Define other parameters such as the maximum depth of the tree ( $max\_depth$ ), the number of features to be considered in each separator selection ( $max\_features$ ), etc.
  - c. Train a Random Forest model using the training set.
5. **Model Evaluation:**
  - a. Use test sets to test model performance. Calculate evaluation metrics such as accuracy, precision, recall, F1-score, to evaluate the extent to which the model can accurately predict stunting in toddlers.

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b. Results

Results are results obtained from data analysis carried out in order to answer research questions. Research results reflect findings or information found by researchers based on data that has been collected and analyzed.

**RESULT**

In this chapter the author will discuss the data calculations used. This data will be calculated using bagging using the random forest algorithm.

The data used in this research is a dataset from Kaggle, namely stunting data. The number of data records consists of 10,001 records, 8 attributes, namely gender, age, Birth Weight, Birth Length, Body Weight, Body Length, Breastfeeding, and Stunting. This data set is used to predict whether a patient is likely to suffer from stunting or not. Stunting data is in Figure 4.1 below:

	A	B	C	D	E	F	G	H	I	J	K	L	M
	Gender	Age	Birth Weight	Birth Length	Body Weight	Body Length	Breastfeeding	Stunting					
1	Male	17	3	49	10	72.2	No	No					
2	Female	11	2.9	49	2.9	65	No	Yes					
3	Male	16	2.9	49	8.5	72.2	No	Yes					
4	Male	31	2.8	49	6.4	63	No	Yes					
5	Male	15	3.1	49	10.5	49	No	Yes					
6	Female	11	2.8	49	8.5	65	No	No					
7	Male	35	2.8	49	10.5	72.2	No	Yes					
8	Female	17	2.8	49	8	63	No	Yes					
9	Female	10	2.7	49	8.4	73.5	No	No					
10	Female	16	2.8	49	8.5	65	No	Yes					
11	Female	11	2.8	49	10	68.3	No	Yes					
12	Male	13	2.9	50	10	69	No	Yes					
13	Male	44	3	49	7.1	72.2	No	Yes					
14	Male	18	2.8	50	7.2	65	No	Yes					
15	Male	13	2.8	48	7.7	65	No	Yes					
16	Female	13	2.8	49	10.5	72.2	No	Yes					
17	Male	7	2.3	50	6.4	68.3	No	No					
18	Male	16	2.7	50	2.9	69	No	Yes					
19	Female	17	2	49	8	92.7	No	Yes					
20	Female	13	3.1	49	7	65	No	Yes					
21	Male	8	2.9	49	6.4	68.3	No	Yes					
22	Male	17	2.9	49	9	69	No	Yes					
23	Male	17	2.9	49	9	69	No	Yes					

Figure 3. Stunting Dataset

The image above shows the character of the data in this research, the data has labels, which means this data is supervised data because it has labels. The tool used in this research is the Rapidminer application.

In carrying out analysis and looking for data patterns to be used as a dataset to facilitate research and be able to run systematically to meet the desired goals, a flow is created in the research stages that will be carried out as follows:

1. The business understanding phase can also be called the research understanding phase which includes clear project objectives and requirements in business terms or the research unit as a whole, translating objectives and limitations into formulating data mining problem definitions, preparing strategies beginning to achieve that goal.
2. Data understanding stage by collecting data using exploratory data analysis to familiarize yourself with data and discover initial insights, evaluate data quality, if desired select an interesting subset that may contain possible patterns followed up.
3. The data preparation stage is preparing the initial raw data collection final data that will be used for all subsequent stages. On this stage selects the desired cases and variables, analyzes them suitable for analysis. Perform transformations on certain variables, if necessary, clean the raw data so that it is ready for modeling tools. The data in this research consists of 10001 records, 8 attributes and target class is stunting with 2 class labels Yes/No stunting.
4. Modeling stage. This stage is carried out by selecting and implementing appropriate modeling techniques. Calibrate model settings for optimize results, several different techniques can be used for the same data mining problem, if necessary repeat Return to the data preparation stage to bring the data into an appropriate form with the specific requirements of a particular data mining technique.
5. The next stage is evaluation, namely the research stage to measure the performance of the prediction model that has been built. The evaluation provides insight into the extent to which the model is more effective at making predictions on never-before-seen data.
6. The final stage is preparing a report in the form of a report on the test results which refers to the problem formulation and research objectives.

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### DISCUSSIONS

Application of the Bagging method with the Random Forest algorithm. The implementation of methods and algorithms in rapidminer is shown in the image below:

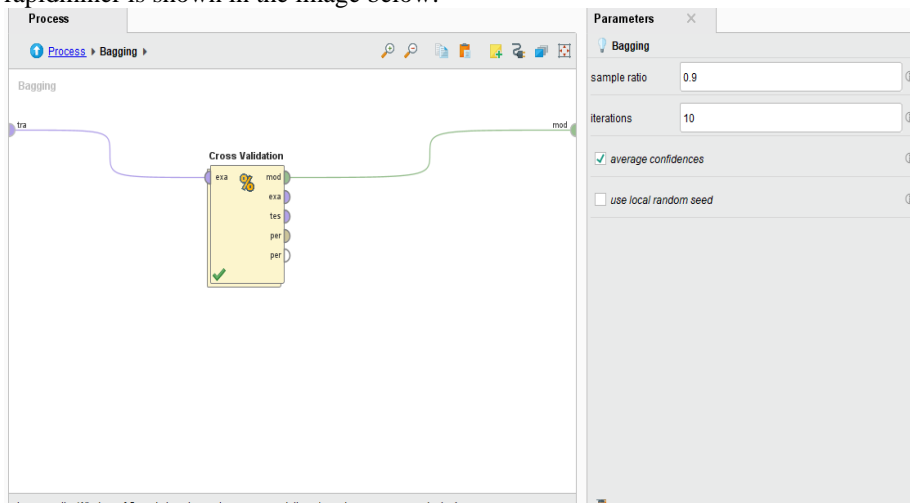


Figure 4. Split Data Menu Display

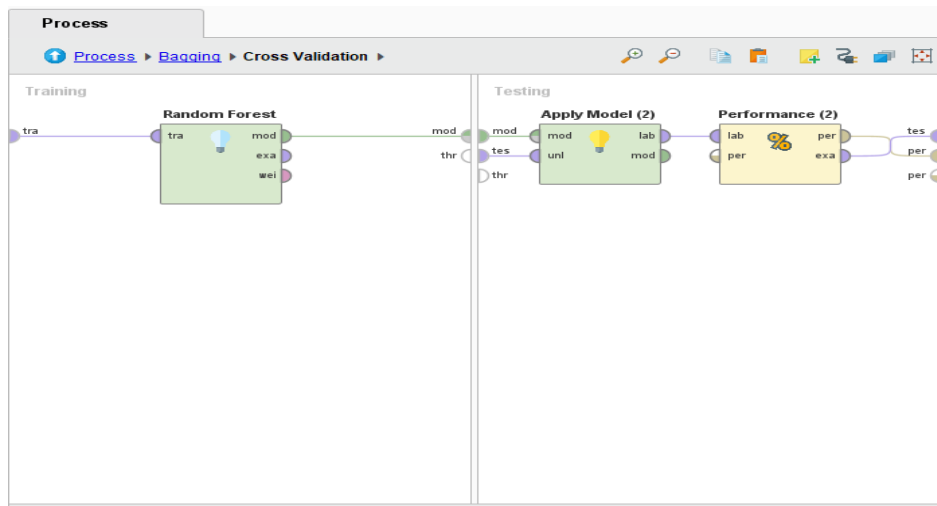


Figure 5. Application of Stunting Data Using the Bagging Method and Random Forest Algorithm in Rapidminer

In Figure 4.3, it can be seen that the data that has been prepared is used in the RapidMiner application to make predictions regarding stunting. In this process, a series of important experiments were carried out. First of all, a cross-validation technique was used to ensure the reliability of the model in predicting stunting cases. This technique involves testing the model on different subsets of the data to objectively measure performance.

In addition, experiments were carried out by applying the Bagging technique, which combines several different base models to increase prediction accuracy. During this experiment. The results of this experiment, which are key information for evaluating the quality of stunting predictions, can be seen in Figure 4.4.

Criterion	Table View	Plot View	
accuracy	accuracy: 91.98%		
precision			
recall			
AUC (optimistic)			
AUC			
AUC (pessimistic)			
	true No	true Yes	class precision
pred. No	1335	92	93.55%
pred. Yes	710	7883	91.72%
class recall	65.28%	98.84%	

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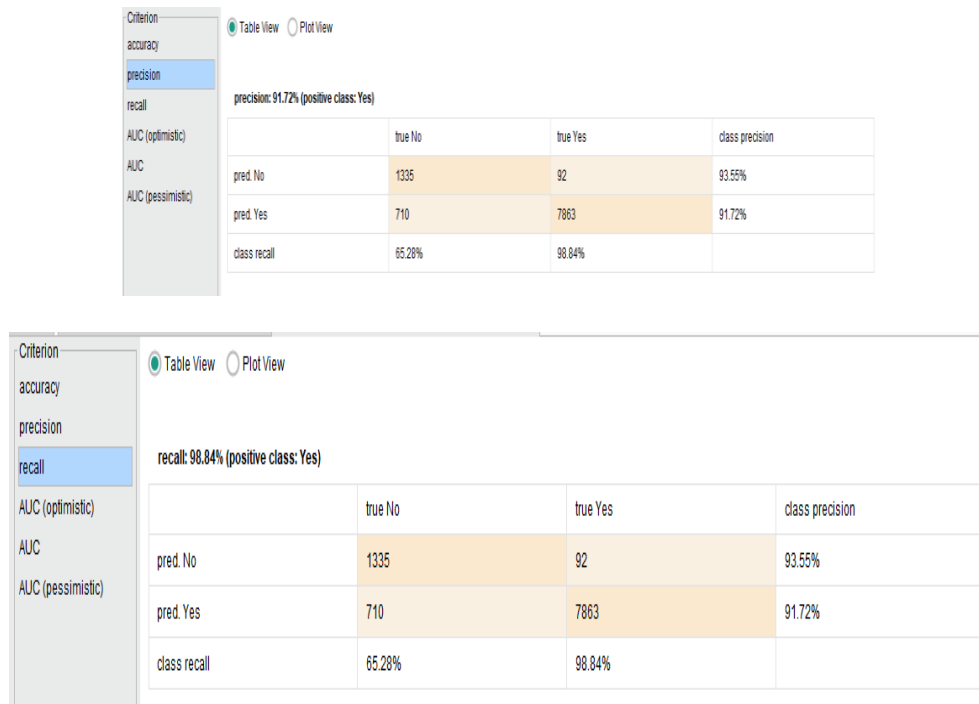


Figure 6. Confusion Matrix Stunting prediction results using the method Bagging and Random Forest Algorithms

### Evaluasi Dengan Confusion Matrix Model Bagging dan Random Forest

Confusion matrix is a performance evaluation method used to measure the extent to which a machine learning model can classify data correctly. Confusion matrices are generally used in classification tasks where we have known labels and want to measure the model's ability to predict those labels. A confusion matrix is a two-dimensional table that shows the amount of data that is classified correctly and incorrectly by the model.

Tabel 1. Confusion Matrix Algoritma Bagging dan Random Forest

	true No	true Yes	class precision
pred. No	1335	92	93.55%
pred. Yes	710	7863	91.72%
class recall	65.28%	98.84%	

Based on Table 1 above, Prediction for Class "No":

Class Prediction "No":

True Negative (TN): 1335

False Positives (FP): 92

So, the total number of "No" class predictions is 1427 (1335 + 92). This means that the model predicted the class "No" 1427 times, and of these predictions, 1335 were correct (True Negative) and 92 were incorrect (False Positive).

Class Prediction "Yes":

Class Prediction "Yes":

False Negative (FN): 710

True Positive (TP): 7863

So, the total number of "Yes" class predictions is 8573 (710 + 7863). This means that the model predicted the "Yes" class 8573 times, and of these predictions, 710 were false (False Negative) and 7863 were true (True Positive).

Recall (Sensitivity) for class "No" from the given Confusion Matrix Table:

$$\text{Recall (No)} = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Negative (FN)}}$$

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$$\text{Recall (No)} = \frac{1335}{1335 + 710}$$

$$\text{Recall (No)} = \frac{1335}{2045}$$

$$\text{Recall (No)} \approx 0.6528$$

So, Recall (Sensitivity) for class "No" is 65.28%.

Recall (Sensitivity) for class "Yes" from the given Confusion Matrix Table:

$$\text{Recall (Yes)} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}}$$

$$\text{Recall (Yes)} = \frac{7863}{7863 + 92}$$

$$\text{Recall (Yes)} = \frac{7863}{7955}$$

$$\text{Recall (Yes)} \approx 0.9884$$

So, Recall (Sensitivity) for the "Yes" class is 98.84%.

By testing using the confusion matrix, on the Stunting dataset it is known that the Bagging and Random Forest methods have an accuracy value of 91.98%. The model that has been formed can then be developed and implemented into an application so that it can help and make it easier for stakeholders in making decisions in predicting stunting in toddlers.

## CONCLUSION

This research succeeded in developing a prediction model for stunting in toddlers using the Bagging and Random Forest algorithms. This model can be used as a predictive tool to predict toddlers who are at risk of experiencing stunting. Based on the results of testing the Bagging and Random Forest algorithm models which were carried out through confusion matrix evaluation, it was proven that the tests carried out by the Bagging and Random Forest algorithms had a high accuracy value, the results obtained were class precision yes 91.72%, class recall yes 98.84%, class precision no 93.55%, class recall no 65.28%, and accuracy of 91.98%.

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