Jurnal Teknik Informatika (JUTIF)
Vol. 5, No. 4, October 2024, pp. 1327-1336

DOI: https://doi.org/10.52436/1.jutif.2024.5.5.2421
p-ISSN: 2723-3863
e-ISSN: 2723-3871

ENSEMBLE MACHINE LEARNING WITH NEURAL NETWORK STUNTING PREDICTION AT PURBARATU TASIKMALAYA

Muhammad Al-Husaini[1], Hen Hen Lumana[2*], Randi Rizal[3], Luh Desi Pusspareni[4], Irani Hoeronis[5]

[1,2,5]Faculty Engineering , Informatics Department, Siliwangi University, Tasikmalaya, Indonesia
[3]Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, Malaysia
[4]Faculty Health Science, Public Health Department, Siliwangi University, Tasikmalaya, Indonesia
Email: [1]alhusaini@unsil.ac.id, [2]henhenlukmana@unsil.ac.id, [3]p031910039@student.utem.edu.my ,[4]luhdesi@unsil.ac.id, [5]iranihoeronis@unsil.ac.id

(Article received: July 2, 2024; Revision: August 8, 2024; published: October 25, 2024)

Abstract

This research uses an ensemble model and neural network method that combines several machine learning algorithms used in the prediction of stunting and nutritional status children in Purbaratu Tasikmalaya. This ensemble method is complemented by a combination of the prediction results of several algorithms used to improve accuracy. The data used is anthropometry-based calculations of 195 toddlers with 39% of related stunting from 501 total data in Purbaratu Tasikmalaya City; high rates of stunting this research urgent to make a stable model for prediction. The results of this study are significant as they provide a more accurate and efficient method for predicting stunting and nutritional status in children, which can be crucial for early intervention and prevention strategies in public health and nutrition. The best accuracy value for some of these categories is 98, 21% for the Weight/Age category with the xGBoost algorithm, 97.7% of the best accuracy results with the Random Forest and Decision Tree algorithms for the Height/Age category, the Weight/Height category with the best accuracy of 97.4% for the Random Forest and xGBoost algorithms, and the use of neural network models resulted in an accuracy of 99.19% for Weight/Age and Height/Age while for Weight/Height resulted in an accuracy of 91.94%..

Keywords: *ensemble model, machine learning, neural network, Weight/Age, Height/Age, Weight/Height*

1. INTRODUCTION

Stunting is one of the global health problems, especially in developing countries including Indonesia. The Indonesian Nutrition Status conducted by the Ministry of Health in 2022 indicated that stunted toddlers in Indonesia were around 21.6% of the total 30.73 million toddlers [1],[2].

Stunting can occur in children who experience chronic malnutrition, especially at the age of 0-23 months [3]. Stunting is influenced by various things, namely poor nutrition of pregnant women, nutrition in infants, family economic factors, and the environment. [4]. The impact of stunting can affect adulthood such as lowering IQ, reducing work productivity, and increasing the risk of chronic diseases.

Public Health Center is a primary health facility that has an important role in preventing and overcoming stunting in children. Public Health Center can conduct early detection of stunting in children through anthropometric examinations and provide appropriate nutritional interventions. According to the toddler weighing report in February 2023 at the Purbaratu Health Center, data collection was conducted on 195 toddlers related to stunting from 501 or 39% of total data at this place.

Parents have to bring their children directly to the posyandu or Public Health Center to find out whether the child is stunted or not because the Public Health Center do not provide facilities for parents to diagnose stunting independently. Parents must be aware of the importance of early detection of stunting and pay attention to their child's growth [5]. Longitudinal studies in research by Hubbard, in this study uses machine learning to identify the most influential factors and estimate the impact on the population of these factors, beside that research with implementation information system that application web-based for stunting detection for Purbaratu Public Health Center. The system would be complemented with machine learning and neural network models to improve the information system to detect stunting with data collected.

Based on this study using the ensembled algorithm method, especially the use of machine learning algorithms. This method is a combination and process of classifying new data by voting or taking value evaluations from several algorithms to make predictions. In this method, voting classification is used for meta-classification and combining predictions from various machine-learning algorithms and semi-supervised learning[6]. The other research conducted by [7] Conclude that the used ensemble random forest has zero impact, adding more features that do not give overfitting results, but the built model can identify underweight, obese, and other risk nutrition.

A study conducted by [8] to build an information system used an artificial neural network for the prediction of stunting with anthropometric data.. The results of the study represent the use of several algorithms such as random forest, support vector machine, decision tree, logistic regression, and the use of gradient boosting shows the highest level of accuracy with a value of 68.47%, this value is based on an assessment of the parameters of parenting characteristics, nutrition and the environment, besides research related to the use of several machine learning models in research on malnutrition prediction in Bangladesh explaining that the application of machine learning models can be an option to predict the risk of malnutrition more accurately, in addition to the ability to use ordinary clinical tools, risk prediction can use several models combined, namely, Linear Discriminat Analysis (LDA), k-Neare, and k-Nears, in this study complemented predict with neural network related to research that the research aims to identify children who are stunted, underweight, or wasting based on trained data, and the neural network technique yields the greatest results, with an accuracy of around 86.0%, 70.0% and 67.30%, in that order, with waste. Based on training and test validation, research indicates that using deep learning with neural networks compared with ensembled achieved higher accuracy than random forest model without stacking and combination, related to that research conducted by [9] that combined ensemble Support Vector Machine (SVM), Gradient Boosting (GB) and Extreme Gradient Boosting (XGB) achieved properly training and testing validation accuracy that indicated not overfitting and underfitting. Model for prediction ensemble conducted by [10][11] implemented machine learning algorithms that include deep learning algorithm Artificial Neural Networks (ANN) developed with valuable steps help to prevent overfitting and underfitting properly stable imbalance target variable for suitable validation.

2. RESEARCH METHOD

The method used is an ensemble model to combine several algorithms to predict a case, especially here related to early detection of stunting. Ensemble itself is one of the techniques used based on different algorithms with a combination of several models of these algorithms to make a prediction. [12].

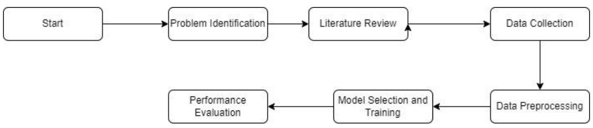

Fig. 1. *Research Method Stages*

2.1 Problem Identification

The problem is the prevalence of stunting among children in Purbaratu Tasikmalaya. Stunting is a significant health issue that affects children's growth and development. The objective is to develop a reliable method for early detection of stunting using machine learning and neural network models. This involves predicting stunting based on anthropometric data, which will help in taking timely actions to prevent it.

2.2 Literature Review

Machine learning has emerged as a tool in healthcare for predicting various health conditions and diseases. Its ability to analyze datasets and uncover hidden patterns makes it ideal for early detection and intervention strategies. Several algorithms can do it, like ensemble learning and neural network.

Decision Tree

A machine learning model for decision-making is to be used in an expert system or ensemble mode. This method creates a decision tree consisting of several branches, each branch representing a decision result or recommendation. This algorithm provides accurate accuracy for prediction consistency in a model [13].This algorithm can certainly be utilized to rank predictors that have different patterns from various data groups for data identification.

There are several steps to form a classification tree, one of which is:.Splitting the predictor space by adjusting the possible values for X1, X2, ... with the following equation:

$$E = 1 - \text{maxk} [\text{pmk}] \qquad (1)$$

On observations belonging to region Rj the same prediction is made and is the value of the observation at $\sqrt{p}$.

Random Forest

Supervised algorithm in Random Forest used for classification, regression or dimension reduction [14]. Random Forest performs feature selection to select the most important features.

This algorithm calculates entropy which is able to determine information gain or information gain with the equation:

$$\text{Entropy } (Y) = -\sum p\ (c|Y)\ i\ \log 2\ p\ (c|Y) \qquad (2)$$

Information Gain is calculated based on Y and p(C|Y) with the following equation:

$$\text{Information Gain } (Y,\alpha) = \text{Entropy}(Y) - \sum |Yv| \qquad (3)$$

Gradient Boosting

The gradient Boosting algorithm applies equal weights to all observations and sequentially builds classifiers based on re-weighting the observations.

In gradient boosting, the weights are updated from the negative gradient of the error between the original data and the prediction or loss function, gradient boosting can be combined with other algorithms such as decision trees, or linear models such as regression, one of the gradient boosting that can be used is Extreme Gradient Boosting combined with a decision tree or xgbTree.This framework has better control to overcome overfitting,.

Here is the equation for calculating training loss and regularization:

$$o(\theta) = L(\theta) + \Omega(\theta) \qquad (4)$$

The training loss function used in predictive models is related to the accumulated mean square error.

$$(\theta) = \sum(\mathcal{Y}i - \mathcal{Y}\, i)\ 2 \qquad (5)$$

Support Vector Machine (SVM)

This algorithm is a supervised learning method or learning system with the use of various linear functions on a feature with the use of high dimensions, this algorithm applies bias to perform an optimization in accordance with the theory of statistical learning[15].

This algorithm focuses on separating the space for specific feature variables so that the target variable becomes more objective or clearer. It aims to provide vector visualization with lower dimensions so as to provide good prediction performance. [16]. Here is the equation of this algorithm to calculate the kernel basis:

$$\exp\ (\ -\mathcal{Y}\ x|\ u - v|2) \qquad (6)$$

In this equation, $\gamma = 1/d$, where d is the predictor variable in the data. This algorithm can be used in linear or non-linear problems with linear functions such as the following:

$$f(x) = w.\, xi + b \qquad (7)$$

In this algorithm, w is identified as a weight vector as in the following equation:

$$b = -\,1.\,2\ (\ .\ x+ + w.\ x-) \qquad (8)$$

The above equation is equipped with a positive class identified as x+, which is a positive class support vector and x-, which is included in the negative class support vector, that in this algorithm, there is a function for data classification with the following equation:

$$f\,(x) = \sum \alpha i\ yiK\ (x,xi) + b \qquad (9)$$

This SVM algorithm aims to perform hyperplane separation or n-dimensional space that separates positive data from negative data.

Neural Network

The neural network model is a computational system inspired by the workings of the human brain.Here is an overview of the main components and how neural networks work. Neurons (Nodes) are the fundamental units of a neural network, similar to neurons in the brain. Each neuron receives input, processes it, and produces output.

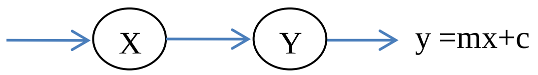

Fig.1. Input Output Neural Network

The way it works is that starting at this initialization stage, weights and biases are initialized randomly to provide a starting point for the neural network in the learning process. Next, the input data is passed through the network from the input layer to the output layer.

Each neuron in the layer receives the input, multiplies the input by its weight, adds a bias, and applies an activation function. This process produces an output to be the basis for further calculations. The difference between the resulting output and the target value is calculated using a specific loss function. For example, Mean Squared Error is used for regression, while Cross-Entropy is usually for classification.

2.3 Data Collection

This research discusses early detection of stunting in the Purbaratu sub-district area based on data collection from 6 villages and 195 toddlers who have been recorded.

Table 1. Dataset Feature

Feature	Category
Gender	Male Female
Age	0-4 Year
Birth Weight	1-4 kg
Birth Height	0-70 cm
Measurement Weight	5-9,9 kg
Measurement Height	46-97,3 cm
BB/U	Normal Weight Adequate Low
TB/U	Short Very Short
BB/TB	Good Nutrition Obesity Risk Over Nutrition

Data collection for stunting is based on anthropometric measurements from WHO which are based on anthropometric measurements. These measurements are also used to check the nutritional status of toddlers.

2.4 Data Preprocessing

Prepare the collected data for modeling. There are several steps one of steps is handling missing values for Address any gaps in the dataset to ensure completeness. Missing values were imputed using the mean value for numerical features or the most frequent value for categorical features. For example, if the 'birth weight' feature had missing values, they were replaced with the mean birth weight of the dataset. Other steps encoding categorical data to change the 'gender' feature, which is categorical, was converted to numerical labels. For instance, 'male' was encoded as 0 and 'female' as 1, and the next splitting data was to create separate datasets for training the model and testing its performance. The dataset was divided into training (80%) and testing (20%) sets to evaluate the model on unseen data. This helps in assessing the generalizability of the model.

2.5 Model Selection and Training

These models are trained on the training dataset to learn patterns that distinguish stunted children from non-stunted ones. The study employs both ensemble models and a neural network. Ensemble model includes Decision Tree, Random Forest, Gradient Boosting (xGBoost), Support Vector Machine (SVM), and Neural Network using A multi-layer perceptron (MLP) with two hidden layers, softmax activation function, Adam optimizer, and categorical cross-entropy loss function. The model selection and training process involves appropriate algorithms, training on the preprocessed data, tuning hyperparameters, and evaluating their performance. Ensemble methods like Random Forest and Gradient Boosting, along with a neural network model, were employed to predict stunting status in children. Each model was trained and optimized to ensure high accuracy and reliability in predicting stunting, ultimately aiding early detection and intervention efforts.

2.6 Performance Evaluation

The methods used for evaluation of the ensemble model used from the algorithm are precision, recall, and F-score. Here is the equation for the three as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (10)$$

The method used for performance evaluation is the confusion matrix, which is used to identify the distribution of true and false predictions for adjustment of the two classes, namely the positive class and the negative class and is useful for the distribution of predictions represented in True Positive (TP) which refers to the number of actually positive data that has been correctly predicted by the model, True Negative (TN) based on the number of samples or data that are actually negative that the model has correctly predicted[17][18], False Positives (FP) based on data or the number of samples that are actually negative but have been incorrectly predicted as positive by the model, then False Negative (FN) based on the number of data or samples that are actually positive but incorrectly predicted as negative by the model.

The performance evaluation matrix extracted by the confusion matrix includes precision, recall, and F-Score, which is used to measure the overall performance of a model classifier [19]. In this study, the confusion matrix used uses 0 to 4 class dimensions, which will be extracted to calculate precision, and F1-Score, which has been accumulated for precision and recall.

In the performance evaluation matrix, the confusion matrix performance is equipped with visualization to facilitate interpretation in identifying prediction accuracy and reducing the risk of misinterpretation and interpretation of the results for a case to be used, in getting optimal results from the dataset owned and when tuning or adjusting the classification process, cross-validation is used to test the model used with each of the validation tests that produce evaluation metrics that can be used to evaluate the overall performance of the model in this confusion matrix [20].

3. RESULT AND DISCUSSION

This data has 3 (three) categories based on anthropometric data that adjust to the z-score value as a reference for predicting stunting in children and toddlers, The anthropometry was conducted for 195 toddlers in the Purbaratu Tasikmalaya area regarding stunting detection.

3.1 Implementation of Weight/Age Category Model

The results of implementing the classifier for several ensemble machine learning algorithms and Neural Network Model for BB/U for the data are as follows:

Table 2. Dataset Feature

No	X1	X2	X3	X4	X5	X6	X7	Y1
1.	0	3	4.83	50	11.9	96	-3	1
2.	1	3.5	4.5	50	12.4	95.7	-2.64	1
3.	1	2.9	1.25	50	6.8	70	-3.74	2
4.	1	2.8	3.41	49	10.9	89	-2.73	1
5.	1	3	4.67	50	12.2	97	-2.88	1
6.	1	3	1.25	50	7	71	-3.48	2
7.	1	3.1	0.75	49	6.8	66.5	-2.47	1
8.	1	3.2	3.25	50	10.4	89.6	-2.95	1
9.	1	2.6	1.91	48	8.8	80	-2.76	1
..								
195	0	3	2.16	49	9	80	-2.41	1

In the data table 2 from dataset, the target for prediction (y) is adjusted or preprocessed by encoding into values 0 to 2 for the results of nutritional status detection, respectively normal weight, less, and very less. The data is divided into 80:20 for split training data and test data with random state 42 times to increase prediction accuracy. The training data is then subjected to data scaling implementation with standarscaller to normalize the data so as not to produce a large standard deviation.

The following neural network model architecture complements the prediction process with an ensemble process using 2 hidden layers, the Softmax activation function for the output and the use of Adam optimization.

Table 3. Neural Network Model Architecture

No	Hidden Layer	Activation Output	Optimation	Loss Function
1	2 (32, 64)	Softmax	Adam	Categorical Entropy

Performance evaluation on the algorithms used using confusion matrix for classification problems, the following are the results for the Decision Tree algorithm, Random Forest, Support Vector Machine, Extreme Gradient Boosting (xGBoost) for each algorithm containing 3 (three) classes that have been adjusted to the categories of normal weight, less, and very less, the following image for the matrix:

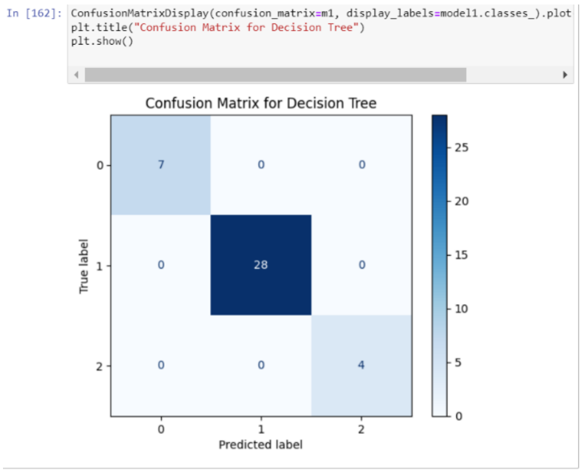

Fig. 2. *Decision Tree*

In Fig. 2. The Decision Tree model achieved perfect classification .This means that every instance was correctly classified, with no false positives or false negatives.

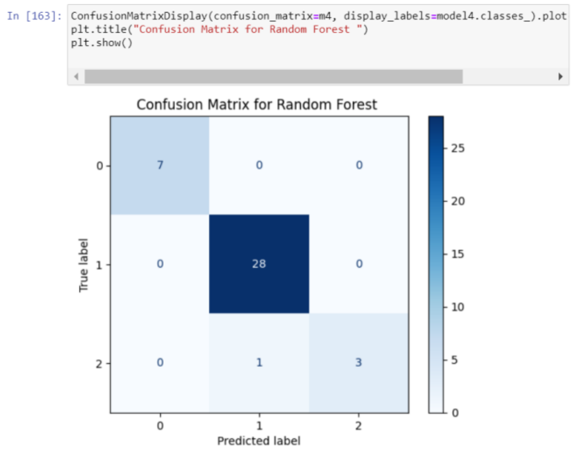

Fig. 3. *Random Forest*

The Random Forest model shows high predictive power with an accuracy of 97.20% based in Fig.3.. It correctly classified almost all instances, with only a single false positive and three false negatives.

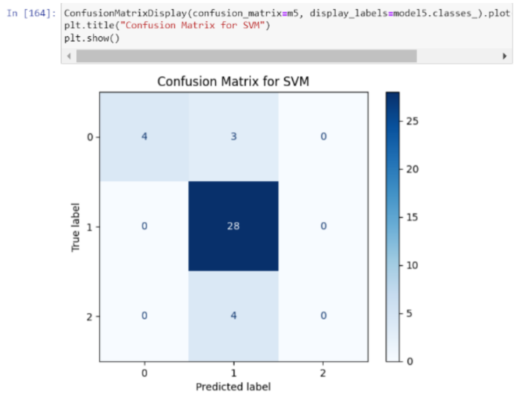

Fig. 4. *SVM*

The SVM model had moderate predictive capabilities with an accuracy of 84% based in Fig. 4. There were more misclassifications compared to other models.

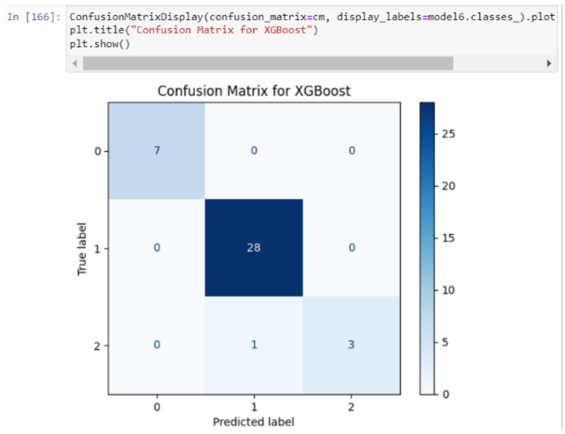

Fig **5**. *xGBoost*

The xGBoost model performed very well and was properly accurate. It had zero false positives and only four false negatives, indicating strong classification performance.

Table 4. Evaluation Performance Ensemble

No	Jenis	TP	TN	FP	FN	Akurasi (%)
1.	DT	7	28	0	0	100
2.	RF	7	28	0	1	97,20
3.	SVM	4	28	3	4	84
4.	xGB	7	28	0	1	98,21

Table 5. Neural Network Performance BB/U

No	Activation Output	Optimation	Iteration	Accuracy (%)	
1	Softmax	Adam	15	95,97	96,80
2	Softmax	Adam	30	99,19	96,80

Evaluation of the performance of the model using Neural Network on datasets with a simple level of complexity produces high accuracy, namely with an epoch or iteration of 30 has reached an accuracy of 99.19% with a validation accuracy of 96.80, stable model performance is at an epoch with a number of 15, which produces accuracy and validation accuracy according to 95.97% and 96.8%.

3.2 Implementation of Heigh/Age Category Model

The data for the implementation of the ensemble model uses data entries related to height based on age in the following Table 2. In the data Table 2 above, the x variable will be used as an independent variable for the prediction of y, which includes the age of the toddler, weight, height at birth and at the time of measurement, and the z-score results based on the World Health Organization (WHO) standard values, in addition to the y2 prediction target, data scaling is carried out to 0 to 1 for short and very short categories.

Based on the results of existing data on child nutritional status data collection in the Purbaratu sub-district of Tasikmalaya. Performance on predictions for the TB / U category on anthropometric data using a confusion matrix that calculates accuracy and F1-score based on the results in the matrix elements related to the correct and incorrect predictions for several algorithms used.

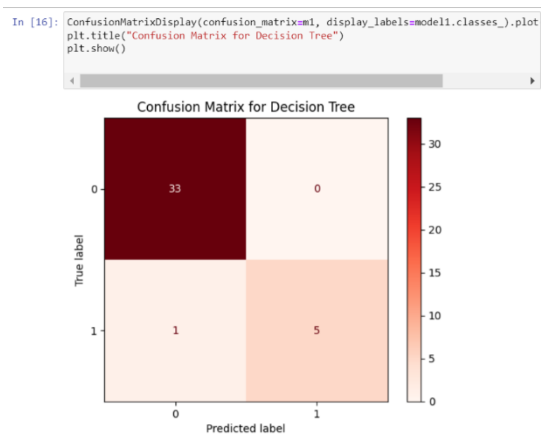

Fig. 6. *Decision Tree*

The Decision Tree model in this instance Fig. 6. achieved an accuracy of 97.37%. It correctly classified most instances, with a few misclassifications.

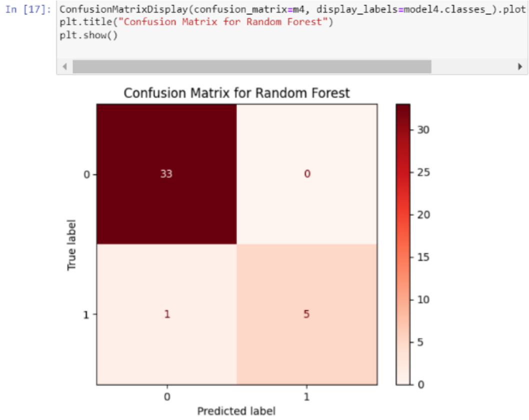

Fig. **7**. *Random Forest*

The Random Forest model demonstrated strong predictive power with an accuracy properly. It correctly classified nearly all instances, with only zero false positives and single false negatives.

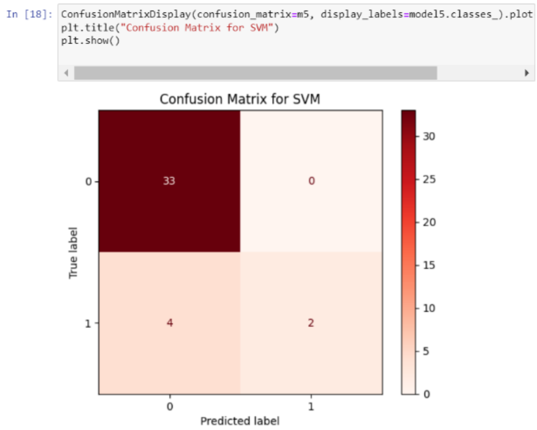

Fig. 8. *SVM*

The SVM model achieved an accuracy properly. It had a significant number of misclassifications compared to other models, with zero false positives and four false negatives.

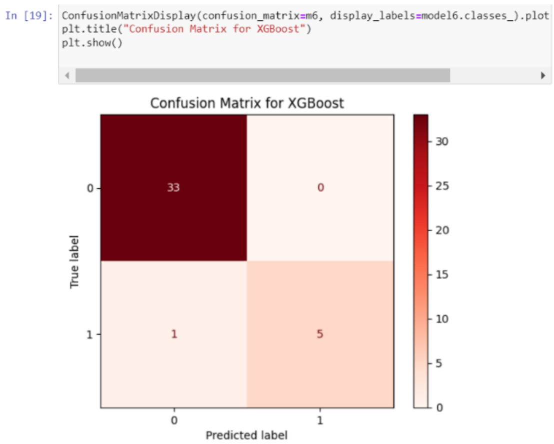

Fig. 9. *XGBoost*

The XGB model achieved perfect accuracy based in Fig.9.. It had a significant number of misclassifications compared to other models, with zero false positives and single false negatives.

Table 6. Performance Ensemble Model TB/U

No	Jenis	TP	TN	FP	FN	Accuracy (%)
1.	DT	33	5	0	1	97,70
2.	RF	33	5	0	1	97,70
3.	SVM	33	2	0	4	87,50
4.	XGB	33	5	0	1	97,50

Table 7 Performance Neural Network TB/U

No	Activation Output	Optimation	Iteration	Accuracy (%)
1	Softmax	Adam	15	94,35
2	Softmax	Adam	30	99,19

The prediction results using several algorithms indicate that the performance of the Decision Tree, Random Forest, and Extreme Gradient Boosting algorithms produce equally good performance for prediction related to TB/U anthropometric data with accuracy and F1- Score as in table 7 above. Neural network model resulted from suitable accuracy from 15 iterations with 94,35% and 96,8% validation accuracy. The activation output used is softmax, and optimation the model used by Adam.

3.3 Implementation of the Weight/Height Category Algorithm

The last implementation in this research is related to the weight category based on height for anthropometric data in Purbaratu District. The following is the data for BB / TB, which is used to apply several ensemble algorithms to predict stunting detection and neural network model architecture.

The target is first normalized to a value of 0 to 4 for the categories of malnutrition, less, good, obesity, and risk of overnutrition. The implementation of the ensemble algorithm will be used to predict nutritional status based on the BMI status in the data. The algorithm's performance in predicting nutritional status is based on BB / TB data after going through the learning process with training data and test data using several combined categories of machine learning algorithms.

Data that has gone through the learning with the algorithm model is used to calculate accuracy and F1-Score to identify the balance of positive and negative classes in the suitability of target predictions. The following is a performance evaluation based on the elements in the confusion matrix as the basis for calculating accuracy and F1-Score.

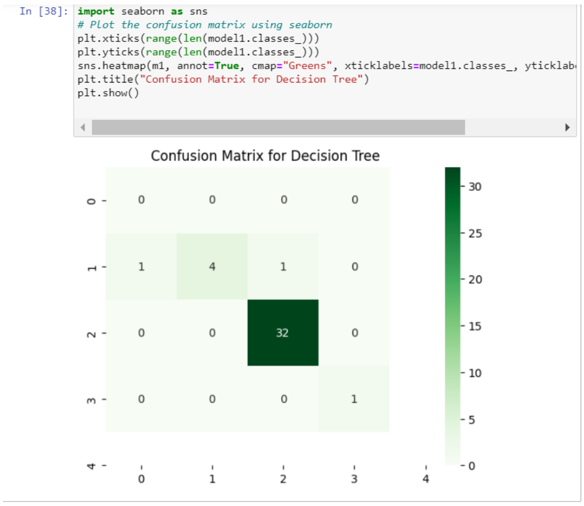

Fig. 10. *Decision Tree*

The accuracy of the Decision Tree in Fig. 10. model is properly good. This indicates that the model has a good balance between TP and TN, although there are a few errors (FP and FN).

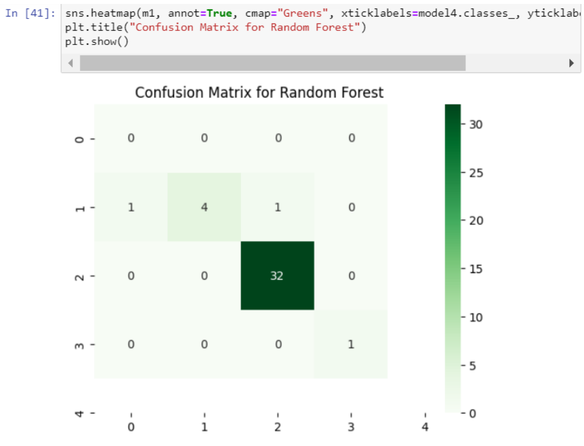

Fig. 11. *Random Forest*

The accuracy of the Random Forest model is 97.40% based in Fig.11. This model shows excellent performance with only one error (FP) and no FN.

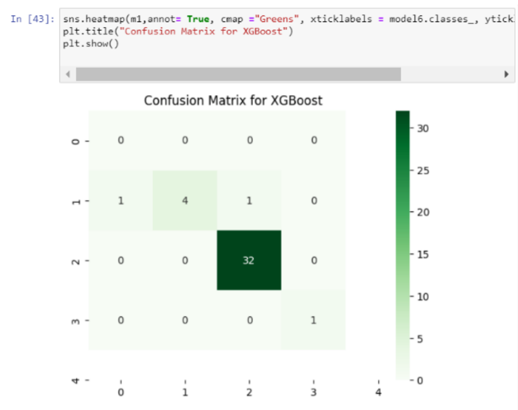

Fig. 12. *XGBoost*

The accuracy of the XGBoost model is 97.40%, the same as that of Random Forest. This model also shows excellent performance with only one error FP and no FN.

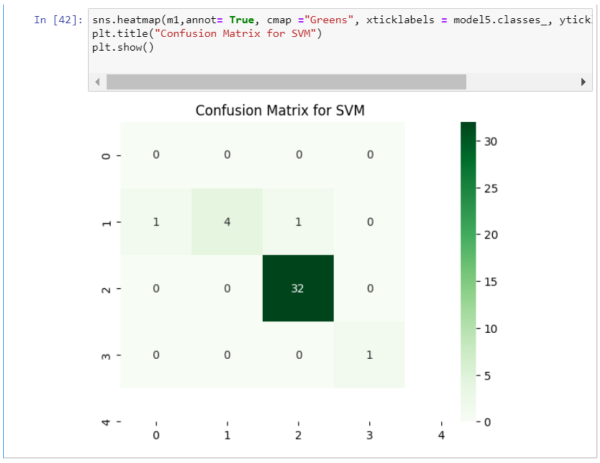

Fig. 13. *SVM*

The accuracy of the SVM model is 89.50%. This model has more errors (FP and FN) based in Fig.13. compared to the other models, indicating lower performance in correctly classifying compared to Decision Tree, Random Forest, and XGBoost.

Table 8. Performance Model Evaluation

No	Jenis	TP	TN	FP	FN	Akurasi (%)
1.	DT	4	32	1	1	94,70
2.	RF	5	32	1	0	97,40
3.	SVM	2	32	4	0	89,50
4.	XGB	5	32	1	0	97,40

Table 9. Model Performance Neural Network Weight/Height

No	Activation Output	Optimation	Iteration	Accuracy (%)	Accuracy Validation (%)
1	Softmax	Adam	15	90,32	96,8
2	Softmax	Adam	30	91,94	96,8

Based on this data in Table 8, the Random Forest and XGBoost models have the same performance both for accuracy and F1-Score with both values being 97.4% and 90.9%. The calculation of F1-Score is influenced by the calculation of recall and precision, in addition to the value of the Decision Tree model also produces a fairly high level of accuracy and F1-Score value to identify the balance of target value predictions with an accuracy percentage of 94.7%.

Still, for F1-Score this model only reaches 77.1% in its prediction suitability, and the performance of the neural network model used for the TB / U category with 15 and 30 iterations produces a fairly stable accuracy of 90.32% and 91.94% in accuracy training and more high accuracy on validation accuracy of 2 scenario validation with 15 and 30 iteration resulted from 96, 8%..

Table 9 provides an overview of the performance metrics for a neural network model focusing on weight and height data. It compares two configurations of the model across several parameters including the type of activation output, the optimization algorithm used, the number of iterations, and the resulting accuracy percentages for both the test and validation datasets. Both configurations employ the Softmax activation function and utilize the Adam optimization algorithm, differing primarily in the number of iterations they are run for—15 and 30, respectively. The first configuration, with 15 iterations, achieves a test accuracy of 90.32% and a validation accuracy of 96.8%. On increasing the iteration count to 30 in the second configuration, there's a minor improvement in test accuracy to 91.94%, while the validation accuracy remains unchanged at 96.8%. This table succinctly demonstrates the impact of iteration count on the model's ability to accurately predict outcomes based on weight and height data, showing a direct correlation between increased iterations and improved test accuracy, without affecting the validation accuracy.

4. DISCUSSION

The methodology demonstrates the strength of combining multiple machine learning and including neural network algorithms to improve prediction accuracy. The ensemble method and neural network's success in this study reflect their capability to handle complex, multifactorial issues like stunting, which involves various anthropometric and nutritional variables. By integrating different algorithms, the model compensates for individual weaknesses and leverages their strengths, leading to more reliable and accurate predictions.

Comparing the results with similar studies, it is evident that ensemble machine learning models consistently show high accuracy and performance in predicting stunting. For example, Bitew et al. utilized machine learning algorithms to predict undernutrition among under-five children in Ethiopia, achieving significant predictive performance with their models . Similarly, demonstrated the effectiveness of machine learning classifiers in classifying stunting among under-five children in Zambia .

Furthermore, the study on childhood stunting in Bangladesh highlighted the importance of model and variable selection in achieving high prediction accuracy. They found that combining multiple machine learning methods, including Linear Discriminant Analysis (LDA) and k-Nearest Neighbors (k-NN), resulted in more accurate predictions . In another related study, Kusumaningrum[21] benchmarked multi-class algorithms for classifying documents related to stunting, further emphasizing the robustness of ensemble approaches in handling such tasks .

The research on Ensemble Machine Learning and Neural Network Stunting Prediction at Purbaratu Tasikmalaya provides compelling evidence of the efficacy and potential of these technologies in addressing complex public health issues. The high accuracy rates in prediction not only highlight the effectiveness of the ensemble and neural network methods but also open up new avenues for their application in the public health sector. As technology continues to advance, the integration of such innovative methods in health monitoring and intervention strategies holds significant promise for improving public health outcomes, especially in regions burdened by malnutrition and stunting.

5. CONCLUSION

The ensemble model used for stunting prediction has been implemented for nutritional status data based on anthropometry at Purbaratu, Tasikmalaya City. The model is applied to anthropometric category data adjusted for z-score. The test results show that the best model performance for the BB/U category is using the Random Forest algorithm, achieving 95% and a result F1-Score of 90.9%, while in the TB/U category, the model uses the Random Forest algorithm.

The best model performance from ensemble machine learning is using the xGBoost algorithm with an accuracy of 97% and F1-Score of 90.9%. This study uses the Confusion Matrix, which is used to identify the distribution of true and false predictions, which are divided into positive and negative classes. Based on other test results related to the use of several machine learning models such as in research that discusses the ensemble model [21], the test results from training and testing show that the performance of the model is different performance depending on the combination of feature extraction techniques and algorithms used for machine learning used Besides the model neural network is part of deep learning that can used for prediction stunting based on dataset at Purbaratu with suitable accuracy from architecture neural network model both of activation function and optimation model with high accuracy resulted stable on 15 until 20 iteration achieved 91,94 until 99,19 percentage on training test.

REFERENCES

[1] Katadata, “Daftar-prevalensi-balita-stunting-di-indonesia-pada-2022-provinsi-mana-teratas,” 2022. https://databoks.katadata.co.id/datapublish/2023/02/02/daftar-prevalensi-balita-stunting-di-indonesia-pada-2022-provinsi-mana-teratas

[2] Kementerian Kesehatan, “Cegah Stunting Itu Penting!,” *Cegah Stunting itu Penting*, vol. 4, no. 2, pp. 63–67, 2022, doi: 10.54339/jurdikmas.v4i2.417.

[3] E. Selviyanti, M. C. Roziqin, D. S. H. Putra, and M. S. Noor, “Intelligent Application of Stunting Monitoring and Mapping Systems (Smart Ting) in Toddlers Based on Android in Jember,” *Proc. 2nd Int. Conf. Soc. Sci. Humanit. Public Heal. (icosh. 2021)*, vol. 645, no. Icoship 2021, pp. 147–157, 2022, doi: 10.2991/assehr.k.220207.024.

[4] S. Sugiyanto and S. Sumarlan, “Analisa Faktor Yang Berhubungan Dengan Stunting Pada Balita Usia 25-60 Bulan,” *J. Kesehat. PERINTIS (Perintis’s Heal. Journal)*, vol. 7, no. 2, pp. 9–20, 2021, doi: 10.33653/jkp.v7i2.485.

[5] D. D. S. Fatimah, Y. Septiana, and G. Ramadhan, “Rancang Bangun Aplikasi Sistem Pakar Diagnosa Penyakit Stunting Berbasis Web Menggunakan Metode Certainty Factor,” *J. Algoritm.*, vol. 19, no. 2, pp. 547–557, 2022, doi: 10.33364/algoritma/v.19-2.1144.

[6] S. P. Manongga, H. Hendry, and D. H. F. Manongga, “Predicting a stunting prevalence using semi-supervised learning models in east nusa tenggara,” *Int. J. Innov. Comput. Inf. Control*, vol. 19, no. 4, pp. 1073–1086, 2023, doi: 10.24507/ijicic.19.04.1073.

[7] A. S. Iorhemen, “Random Forest Ensemble Machine Learning Model for Early Detection and Prediction of Weight Category,” *J. Data Sci. Intell. Syst.*, vol. 00, no. September, pp. 1–8, 2023, doi: 10.47852/bonviewjdsis32021149.

[8] H. H. Lukmana, M. Al-husaini, L. D. Puspareni, and I. Hoeronis, “Rancang Bangun Sistem Informasi Deteksi Dini Stunting dengan Metode Artificial Neural Network Development of an Early Detection Information System for Stunting Using the Artificial Neural Network Method,” vol. 12, no. 3, 2024, doi: 10.26418/justin.v12i3.80119.

[9] M. H. Kalayou, A. A. K. Kassaw, and K. B. Shiferaw, “Empowering child health: Harnessing machine learning to predict acute respiratory infections in Ethiopian under-fives using demographic and health survey insights,” *BMC Infect. Dis.*, vol. 24, no. 1, pp. 1–13, 2024, doi: 10.1186/s12879-024-09195-2.

[10] T. Z. Yehuala *et al.*, “Machine learning algorithms to predict healthcare-seeking behaviors of mothers for acute respiratory infections and their determinants among children under five in sub-Saharan Africa,” *Front. Public Heal.*, vol. 12, no. June, 2024, doi: 10.3389/fpubh.2024.1362392.

[11] B. Ogwel, V. H. Mzazi, A. O. Awuor, C. Okonji, R. O. Anyango, and ..., “Predictive Modelling of Linear Growth Faltering Among Pediatric Patients with Diarrhea in Rural Western Kenya: An Explainable Machine

Learning Approach," 2024, doi: https://doi.org/10.21203/rs.3.rs-4047381/v1.

[12] F. H. Bitew, C. S. Sparks, and S. H. Nyarko, "Machine learning algorithms for predicting undernutrition among under-five children in Ethiopia," *Public Health Nutr.*, vol. 25, no. 2, pp. 269–280, 2022, doi: 10.1017/S1368980021004262.

[13] S. M. Ahmed *et al.*, "Derivation and external validation of clinical prediction rules identifying children at risk of linear growth faltering," *Elife*, vol. 12, pp. 1–18, 2023, doi: 10.7554/eLife.78491.

[14] O. N. Chilyabanyama *et al.*, "Performance of Machine Learning Classifiers in Classifying Stunting among Under-Five Children in Zambia," *Children*, vol. 9, no. 7, 2022, doi: 10.3390/children9071082.

[15] I. Rahmi, M. Susanti, H. Yozza, and F. Wulandari, "Classification of Stunting in Children Under Five Years in Padang City Using Support Vector Machine," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 16, no. 3, pp. 771–778, 2022, doi: 10.30598/barekengvol16iss3pp771-778.

[16] J. R. Khan, J. H. Tomal, and E. Raheem, "Model and variable selection using machine learning methods with applications to childhood stunting in Bangladesh Model and variable selection using machine learning methods with applications to childhood stunting in Bangladesh," *Informatics Heal. Soc. Care*, vol. 00, no. 00, pp. 1–18, 2021, doi: 10.1080/17538157.2021.1904938.

[17] D. Chicco and G. Jurman, "An ensemble learning approach for enhanced classification of patients with hepatitis and cirrhosis," *IEEE Access*, vol. 9, pp. 24485–24498, 2021, doi: 10.1109/ACCESS.2021.3057196.

[18] A. A. Bakar, R. Hamdan, and N. S. Sani, "Ensemble learning for multidimensional poverty classification," *Sains Malaysiana*, vol. 49, no. 2, pp. 447–459, 2020, doi: 10.17576/jsm-2020-4902-24.

[19] M. Heydarian and T. E. Doyle, "MLCM : Multi-Label Confusion Matrix," pp. 19083–19095, 2022.

[20] A.J Lamer, *The 2x2 Matrix: Contingency, Confusion and the Metrics of Binary Classification*. Springer International Publishing, 2022.

[21] R. Kusumaningrum, T. A. Indihatmoko, S. R. Juwita, A. F. Hanifah, K. Khadijah, and B. Surarso, "Benchmarking of multi-class algorithms for classifying documents related to stunting," *Appl. Sci.*, vol. 10, no. 23, pp. 1–13, 2020, doi: 10.3390/app10238621.