Klover Multidisciplinary Journal of Engineering
Volume 11 Issue 2, April-June 2023
ISSN: 2995-4118
Impact Factor: 7.36
http://kloverjournals.org/journals/index.php/Engineering

MACHINE LEARNING APPROACHES TO CHILD STUNTING PREDICTION

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Abstract
Children's growth and development are crucial for their well-being and future success, making nutrition a critical aspect of their early years. Malnutrition poses significant risks to children's health, particularly undernutrition, which remains a global concern. Adequate nutrition knowledge is essential for parents to ensure proper food intake for their children, thereby promoting brain development and memory retention. This study aims to address the high prevalence of stunting among children under five in East Aceh, Indonesia, a national priority for evaluating child growth. We employ the random forest method, a supervised machine learning model, to predict stunting in East Aceh and explore its potential as a valuable tool for assessing children's nutritional status.
Aceh ranks third in Indonesia for the number of children under five suffering from stunting, a condition closely linked to malnutrition and inadequate nutrition knowledge among parents. Malnourished children are more susceptible to various illnesses compared to their healthier counterparts. Past studies have investigated under-five malnutrition and associated risk factors, primarily relying on classical regression models. However, these traditional models present challenges in handling multicollinearity and a large number of covariates, limiting their accuracy.
In contrast, machine learning (ML) methods offer numerous advantages, such as using a larger number of predictors, requiring fewer assumptions, and accommodating multi-dimensional correlations. ML models provide more flexibility in establishing relationships between predictor and outcome variables, making them superior for handling classification problems and prediction tasks.
Our study's findings indicate an improvement in the nutritional status of under-five children in East Aceh over the last decades. The prevalence of underweight, stunting, and wasting has decreased significantly. We calculated the Composite Index for Anthropometric Failure (CIAF), which aggregates different forms of anthropometric failure to assess children's nutritional status comprehensively. ML models, particularly the random forest, prove effective in predicting stunting in East Aceh, potentially enabling early intervention to prevent malnutrition.
In conclusion, this study highlights the importance of nutrition knowledge among parents in ensuring children's healthy growth. Machine learning techniques offer promising opportunities to predict stunting and undernutrition, aiding public health efforts to combat malnutrition in children.

Keywords: Children's Growth, Nutrition Knowledge, Malnutrition, Stunting, Undernutrition, Machine Learning, Random Forest, East Aceh, Composite Index for Anthropometric Failure.

1. Introduction

Children's growth is an essential focus for every parent because at this age, food intake must be considered for brain development and memory. When feeding children do not meet their nutritional needs, they can be at risk of experiencing malnutrition. Therefore, information about nutrition knowledge is needed in children who can inform and meet the knowledge needs of the community, especially in this case, parents. Thus, to have the ability to have this knowledge, one must have

knowledge and understanding of nutrition to be able to provide initial action to be taken when their child is experiencing symptoms of malnutrition.

Aceh is in the third-highest national ranking for the number of children under five with stunting, behind East Nusa Tenggara (NTT) and West Sulawesi [1]. The leading case of this study is how to predict the stunting in East Aceh as a national priority to evaluate the growth of children. We used the random forest method's supervised model to predict the East Aceh stunting [2] [3].

Proper nutrition is so crucial to leading a healthy lifestyle. Malnutrition, particularly undernutrition, is a global concern for children's health conditions and survival [2] [3]. Almost half of the deaths of children in developing countries were directly or indirectly linked to malnutrition. Malnourished children are more vulnerable to different illnesses compathanr counterparts [5] [6]. A considerable number of studies investigating the issue targeting under-five children malnutrition and the risk factors associated with this age group. These studies employed classical models such as generalized linear (mixed) models [7]. The finding from the investigations, among others, showed that the nutritional status of children of this age group has gradually improved over the last decades in East Aceh. Particularly, it has been found that the prevalence of under-five children under-weight in East Aceh was 20.56% in 2019, while the majority of stunting was 36.9% in 2019. Similarly, 10.7% of under-five children were wasted in 7% in 2019. The prevalence of having at least one of the under-nutrition indicators was measured in terms of the composite index for anthropometric failure (CIAF) 42.4 in 2019. Moreover, the CIAF is computed by grouping different forms of anthropometric failure as such: B-wasting only, C-wasting and underweight, D-wasting, stunting and underweight, E-stunting and underweight, F-stunting only, and Y-underweight only. The CIAF was calculated by aggregating these six (B–Y) categories [7] [8]. Most of such studin in this country depicted the effects of socio-economic and demographic covariates ere associated with under-five children's undernutrition status using the classical regression models [5] [9]. Those traditional models are widely used for causal inferences and with the selection of built-in features, with a relatively small number of covariates. Correlations between covariates (multicollinearity) and a large number of factors are the common analytical challenges in traditional modeling [8] [9]. Moreover compared to those classical models, the machine learning (ML) methods have the qualities of using a lmore significant number of predictors, requiring fewer assumptions, incorporating "multi-dimensional correlations," and producing a more flexible relationship among the predictor variables and the outcome variables. In addition, the ML models can create models for prediction purposes that show superiority in handling classification problems when compared with the classical approaches [10] [11].

2. Methods

To study stunting in East Aceh, we used the stunting survey data set selected to be used in this study [14]. This data set was collected in 2019 by surveying 143 Somerville residents about their stunting and satisfaction with city services. There are six attributes in Table 1, X1 to X6, with values 1 to 5 and a binary decision attribute.

D = decision attribute (D) with values 0 (unhappy) and 1 (happy)

- X1 = the weight

- X2 = the Height
- X3 = the head circumference
- X4 = the Upper arm circumference
- X5 = the fathom length
- X6 = the Knee Height

No missing values have been observed in this data set, so no further action is needed to deal with them. Table 2 describing with method statistic, and show the stunting survey data in East Aceh [15].
Your paper must be in two-column format with a space of 0.5cm between columns.

Table 1. Stunting Survey Data

	D	X1	X2	X3	X4	X5	X6
0	0	2	5	3	2	1	4
1	0	4	1	3	3	4	3
2	1	3	2	4	3	4	4
3	0	5	3	4	5	4	5
4	0	5	1	4	3	4	5

Based on the described methods in Table 2, we can calculate the statistic for calculating some statistical data like percentile, mean and std of the numerical values of the Series or DataFrame. It analyzes both numeric and object series and also the DataFrame column sets of mixed data types.

Table 2. Describe Methods Statistic

	D	X1	X2	X3	X4	X5	X6
count	143	143	143	143	143	143	143
mean	0.538462	4.307692	2.447552	3.244755	3.657343	3.615385	4.223776
std	0.500271	0.849447	1.085619	1.001525	0.864845	1.106467	0.825812
min	0	1	1	1	1	1	1
25%	0	4	2	3	3	3	4
50%	1	5	2	3	4	4	4
75%	1	5	3	4	4	4	5
max	1	5	5	5	5	5	5

In this study Random Forest (RF) method were used for training classification model to predict normal and abnormal [16]. Model building the ML models have shown superiority in taking care of classification problems when compared with the traditional models (like generalized linear mixed models) [17]. The raw data are usually not found in the form and shape that is required for optimal performance of the machine learning algorithms. The algorithms that would be implemented in ML are only numerical values and therefore it is important to transform the categorical variables into numerical

values. Hence, the preprocessing step is the most important aspect in the ML model applications [14] [16] [17]. The categorical features of the dataset are encoded to transform these features into numerical values and the continuous data in this study were normalized. For ML approaches, the dataset is randomly split into two: a training dataset which trains the model, and a test dataset where we predict the response variable and check whether the predicted outcome is similar to the actual outcomes, and the validation dataset is considered for the parameter estimates to be incorporated in the training models [20].

3. Result and Discussion

This analysis consisted of data from 143 children of age 0–59 months. Of these, 15,281 (52.09%) had at least one form of the undernutrition indicators (stunting, wasting, and underweight) measured in terms of CIAF. We examined the prevalence of CIAF of U5C experience across different child and mother-household level covariates. The prevalence of CIAF was more common among parents with no formal education compared to parents with secondary and post-secondary levels of educations. Most of the undernourished children were from rural areas. Also, the prevalence of undernourished children was reported from the lower wealth index of households, from mothers having no media exposure, from unimproved toilets and sanitation compared with their counterparts. Covariates that were significant in the statistics were used to develop the ML algorithms on the training dataset (Table 2).

Based on data analysis by using the person correlation we can devide the

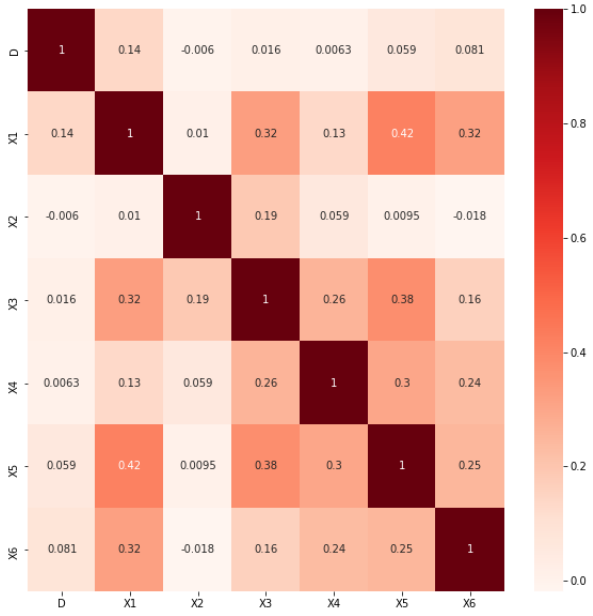

Fig 1. Data analysis using person correlation

By looking at results, we can say that attribute X1 in Fig 1 has the most correlation with the target among other features.

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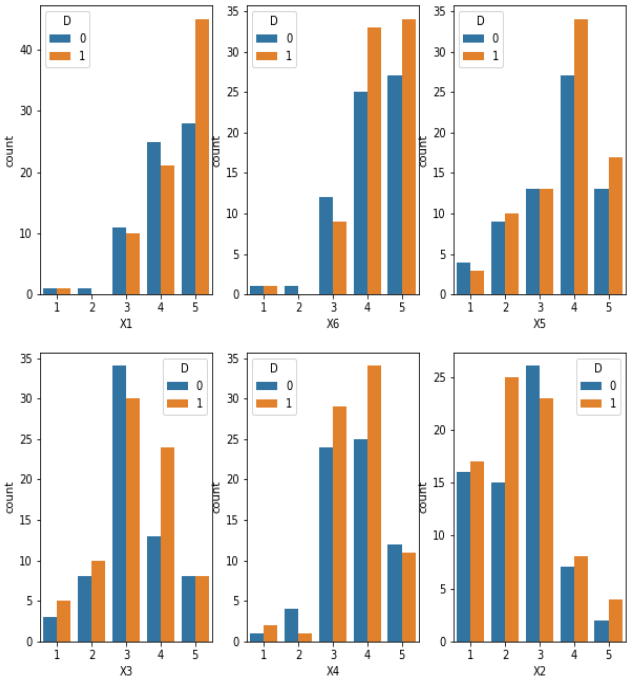

Fig 2. Multiple Count Plot of Correlation with Output Varible

Table 3. Dataset into Training and Testing Sets

	X1	X2	X3	X4	X5	X6
0	2	5	3	2	1	4
1	4	1	3	3	4	3
2	3	2	4	3	4	4
3	5	3	4	5	4	5
4	5	1	4	3	4	5

Based on the split in Table 3, we got the x_train.shape is (114, 6) x_test.shape is (29, 6), y_train.shape is (114,), (y_test.shape is (29,). The continuous data in this study were normalized and the categorical variables were encoded. The machine learning models are known as advanced approaches and techniques for quick and accurate prediction of real world problems. In this paper, the ML techniques are analyzed by investigating the influence of training/testing ratio on the performance of the six popular ML models to predict the undernutrition of underfive children. The performance of the ML models was slightly changed under the two different ratios. The result revealed that the ratio 70/30 was the most suitable ratio for the training and validating ML models. This study is in line with previously published studies [18, 23, 30–44, 83–86]. The ML tool can offer insight into the identification of novel

factors associated with under-five undernutrition that can serve as targets for intervention. Among the six predictive models built using these techniques, the Random Forest (RF) model reveals a higher predictive power as compared to other ML models including the logistic regression. The RF model reveals that urban rural settlement ratio, the literacy level of parents, under five populations, BMI of mothers, locations (zones, place of residence), and rainfall distributions were the top important predictors of under-five undernutrition in East Aceh.

According to the Random Forest we have the accuracy Random Forest's Accuracy 58.62 % and the confusion matrix as show in fig 3. In Fig 3 shows the confusion matrix results of Random Forest algorithm. It is a summary of the prediction results of this algorithm in classifying stunted and non-stunted children. Both correct and incorrect classes are represented in the table below.

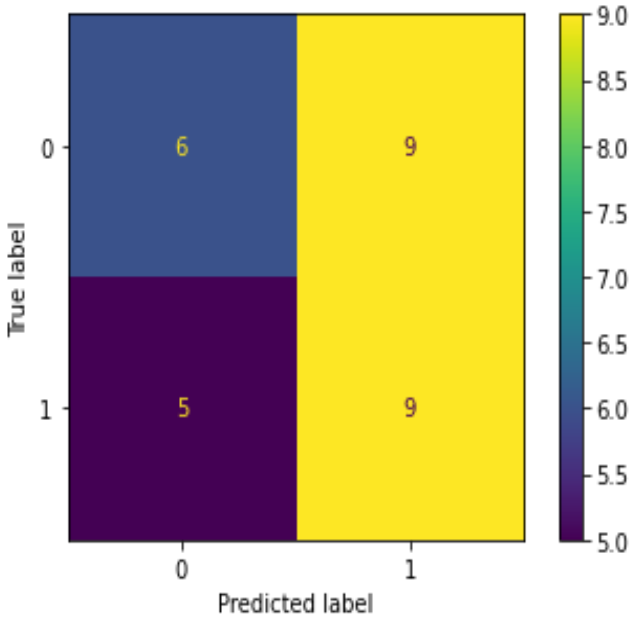

Fig 3. Confusion Matrix

For the graphical view based on the random forest we can get the visual as show in fig 4.

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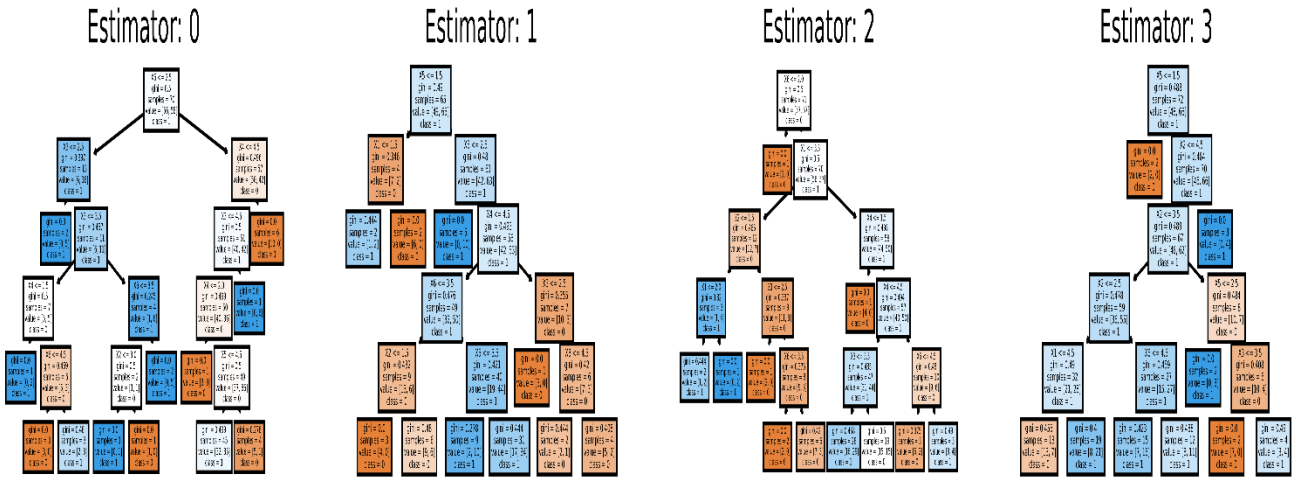

Fig 4. Graphical view based on random forest model

In Fig 4, showing a random forest, every tree will be built differently. We used these images to display the reasoning behind a decision tree (and subsequently a random forest) rather than for specific details. It's helpful to limit maximum depth in your trees when you have a lot of features. Otherwise, the end up with massive trees, which look impressive, but cannot be interpreted at all. To access the single decision tree from fig 4 the random forest in scikit-learn use estimators_ attribute. In Fig 4 covered how to visualize decision trees using Graphviz and Matplotlib. The way to visualize decision trees using Matplotlib is a newer method so it might change or be improved upon in the future. Graphviz in sunting dataset is currently more flexible as you can always modify your dot files to make them more visually appealing like did using the dot language or even just alter the orientation of your decision tree

4. Conclusion

The main objective of this study was to predict and evaluate the performance of Random forest machine learning (ML) algorithms considering the influence of two train-test splits ratios in predicting the stunting classification. Popular statistical indicators, such as accuracy and area under the curve were employed to evaluate the predictive power of the ML models under different testing and training ratios. The accuracy the model had, the better was the performance of the model. Our results confirm that ML models can effectively predict the stunting status and hence may be useful for concerned body decision tools. The best model of the RF, with accuracy of 58.6% respectively. The findings from this paper showed that considerable zonal disparities in the stunting status persist in the east part of Aceh.

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