Journal of Artificial Intelligence and Software Engineering
Vol. 6, No. 2, Maret 2026, pp. 86~94
E-ISSN: 2777-001X, DOI: 10.30811/jaise.v6i2.8655

Application of the Random Forest Algorithm for Classifying Children's Nutritional Status

Rahma Jihan Ananta[1], Nurdin[2], Lidya Rosnita[3*]
[1,3]Department of Informatics, Faculty of Engineering, Malikussaleh University, Lhokseumawe, 24353, Indonesia
[2] Department of Information Technology, Faculty of Engineering, Malikussaleh University, Lhokseumawe, 24353, Indonesia

Article Information

Accepted	:	12 Januari 2026
Revision	:	04 Mei 2026
Publication	:	30 Juni 2026

Keyword:

Classification
Nutritional Status
Data Mining
Random Forest
Health Office

ABSTRAK

Status gizi yaitu suatu kondisi terkait gizi yang bisa diukur dan merupakan hasil dari adanya keseimbangan kebutuhan gizi pada tubuh dengan asupan gizi dari makanan. Klasifikasi yaitu teknik yang digunakan dalam data mining, untuk menganalisis data yang kemudian dijadikan kedalam beberapa kategori sesuai dengan variabel-variabel yang terkait. Pada Metode yang akan digunakan merupakan Algoritma *Random Forest* digunakan untuk klasifikasi klasifikasi status gizi anak berdasarkan data Dinas Kesehatan Lhokseumawe. Tujuan penelitian adalah untuk menerapkan Algoritma *Random Fores*t untuk melakukan klasifikasi status gizi anak serta mengetahui tingkat akurasi dan efektivitas *Random Forest* dalam melakukan klasifikasi status gizi anak. Metode penelitian yang digunakan dalam penelitian ini adalah metode pengumpulan data dan metode perancangan sistem, dalam metode pengumpulan data penulis mengumpulkan sample data, observasi, wawancara, dan studi literatur, kemudian dalam metode perancangan sistem penulis melakukan analisa kebutuhan sistem, dan analisa metode perancangan sistem. Sistem klasifikasi status gizi balita di Dinas Kesehatan Kota Lhokseumawe menggunakan algoritma *Random Forest* berhasil dikembangkan dengan dataset antropometri 2185 sampel yang terdiri dari variabel jenis kelamin (L0, P1), usia bulan, berat badan, tinggi badan, dan indeks massa tubuh (IMT) yang telah melalui *preprocessing* lengkap berupa label *coding* dan normalisasi *Min-Max Scaling* ke rentang, menghasilkan kinerja sebesar 97,89% pada *dashboard* produksi yang konsisten dengan perhitungan manual 75,51% menggunakan *bootstrap sampling* dan mayoritas voting dari 3 pohon ansambel. Tahapan pemodelan data mencakup transformasi kategorikal status_gizimenjadi numerik (*obesitas*0, *stunting*1, *underweight*2, *wasting*3) serta pembagian dataset 80:20 (350 data latih, 87 data uji) dengan *stratified sampling* yang mempertahankan proporsi kelas realistis sesuai prevalensi gizi buruk di Indonesia, di mana *underweight* dominan diikuti *stunting* dan *wasting* minoritas.

ABSTRACT

Nutritional status is a measurable condition related to nutrition that results from the balance between the body's nutritional needs and nutritional intake from food. Classification is a technique used in data mining to analyze data and then categorize it according to related variables. The method used is the Random Forest Algorithm to classify the nutritional status of children based on data from the Lhokseumawe Health Office. The purpose of this study is to apply the Random Forest Algorithm to classify the nutritional status of children and to determine the accuracy and effectiveness of Random Forest in classifying the nutritional status of children. The research methods used in this study are data collection and system design methods. In the data collection method, the author collects sample data, observations, interviews, and literature studies. Then, in the system design method, the author conducts a system requirements analysis and a system design method analysis.

*** *Correspondent Writer***

Email: rahmajihananta4@gmail.com

How to cite IEEE::

R. J. Ananta, N. Nurdin, dan L. Rosnita, "Application Of The Random Forest Algorithm For Classifying Children's Nutritional Status" *Journal of Artificial Intelligence and Software Engineering (J-AISE)*, vol. 6, no. 2, p. 86-94, Juni 2026. doi:10.30811/jaise.v6i2.8655

1. INTRODUCTION

Nutritional status is a measurable condition related to nutrition that results from the balance between the body's nutritional needs and nutritional intake from food. In Indonesia, nutritional problems are still widely found, such as malnutrition and other nutritional problems. Nutrition refers to the nutrients needed to support the growth and development of a toddler [1]. The nutritional status of an infant is largely influenced by their intake. In Indonesia, many infants experience nutritional problems, including double burden, where they are obese or overweight on one hand, but on the other hand, they experience stunting, thinness, anemia, and malnutrition [2].

Based on the 2018 Basic Health Research, 17.7% of toddlers experience nutritional problems, with 3.9% experiencing malnutrition and 13.8% experiencing undernutrition. To address the problem of stunting in Indonesia, the government has divided regions based on the prevalence of stunting cases [3]. A child's nutritional status is an important indicator for assessing whether their daily nutritional needs are being met and utilized optimally. Good nutritional status is essential for supporting children's physical, mental, and overall health growth and development [4].

Data mining is a series of systems that aim to explore and extract values in the form of information and complex relationships stored in a data set. By analyzing information patterns in the data, the goal is to process the data into new, more useful information through a process of extraction and discovery of valuable or interesting patterns contained in the database [5]. Classification is a process of grouping or categorizing objects, data, or information based on similar characteristics or properties. The main purpose of classification is to facilitate the understanding, analysis, and management of complex data [6].

Classification is a technique used in data mining to analyze data, which is then categorized into several categories according to related variables. The method used is the Random Forest algorithm, which is used to classify the nutritional status of children based on data from the Lhokseumawe Health Office [7]. Random forest is a collection of unpruned regression or classification trees, which are constructed from random data samples. Predictions are made by combining the prediction results from all regression or classification trees in the group [8]. The advantages of random forest include the ability to identify relatively large errors, superior classification performance, processing of data with relatively small samples, and an efficient method for estimating the amount of missing data [9].

Based on the problems and important results of previous research described above, the author will develop a system using Random Forest for classification [10]. Based on the above background, the author intends to create "Application of the Random Forest Algorithm for Classifying Children's Nutritional Status."

2. METHOD

The research methods used in this study were data collection and system design methods. In the data collection method, the author collected sample data, observations, interviews, and literature studies. Then, in the system design method, the author conducted a system requirements analysis and a system design method analysis [11].

2.1 Random Forest Algorithm

Leo Breimean created the random forest algorithm. Random forest is a collection of unpruned regression or classification trees, built from random data samples [12]. Predictions are made by combining the prediction results from all regression or classification trees in the group [13]. The advantages of random forest include the ability to identify relatively large errors, superior classification performance, processing of data with relatively few samples, and an efficient method for estimating the amount of missing data [14]. The following is the procedure for applying the Random Forest approach in problem solving [15]:

1. Training data preparation can be done by utilizing recordings or records of events that have occurred previously. This historical data provides an important foundation for building accurate predictive models.

2. The root of the tree is determined by calculating the maximum gain of each attribute or based on the lowest entropy value. The initial stage of this process involves calculating the entropy index using a specific formula that has been predetermined with the following formula:
$I(S1S2 \dots Sm) = -\Sigma pi\ mi = 1log2(pi)$……………………………...(2.1)
3. Gain calculation is performed using the symbol S for the set of m cases as the sample size and Pi representing the class proportion. The gain information method is applied through a standardized mathematical equation to determine the gain value of each attribute as follows:
$E(A) = \Sigma S1j + \cdots + SmjSyj = 1\, I(S1j \dots Smj)$……………….…(2.2)
4. The calculation of information gain involves dividing the number of subsets j by the total sample S. The specific mathematical equation for calculating information gain is listed in equation 4 as follows:
$Gain\ (A) = I(S1S2 \dots Sm) - E(A)$………………………………..…..(2.3)
5. The entropy and gain calculation process is repeated for each attribute with A as the attribute and S as the set of cases until all attributes are partitioned. The process stops when all records in the N sample have the same class, there are no attributes left to partition, and there are no empty records in the branch. Next, a Gini index search is performed. If it reaches 0 (pure), the split is stopped, but if it is not yet pure, the split will continue until it produces a pure leaf. After the looping process is complete for each Random Forest algorithm tree, it ends with the word "End" in the flowchart [16].

2.2 Research Steps

The waterfall method is the process that the author used to create this final product, where literature review is the first step before system evaluation. System literature, requirements analysis, system design, system implementation, system testing, and system evaluation are some of the phases that make up this waterfall process. Figure 3.1 below illustrates the steps in the sequence of the method:

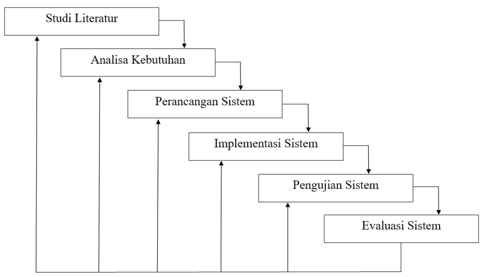

Figure 1. Flowchart of Research Steps

2.3 Data Collection Techniques and System Design

Data collection techniques are methods used to obtain information or data in a study. Choosing the right technique is very important so that the data collected is accurate and in line with the research objectives. In this study, the author used the following techniques to collect data:

1. Sample Data
2. Observation
3. Interview
4. Literacy Study

Techniques or procedures applied in the design process to facilitate designers in creating a design. The specific methods used vary depending on the type of design. Some examples of design techniques are as follows:

1. System Requirements Analysis
2. System Design Method Analysis

2.4 Random Forest Algorithm Scheme

The Random Forest Algorithm scheme can be seen in the image below:

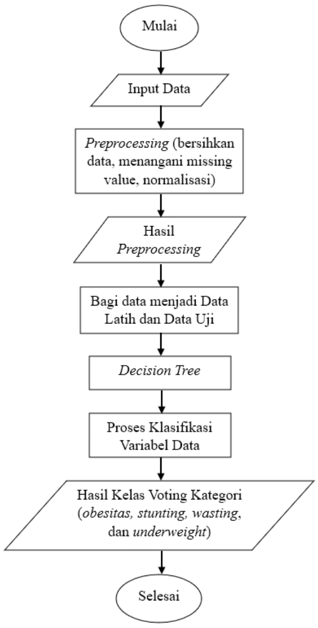

Figure 2. Random Forest Algorithm Diagram

Description:

1. Start the process by inputting child nutritional status data in the form of variables such as gender, age, weight, height, and body mass index.
2. Perform data preprocessing, which involves cleaning the data, handling missing values, and normalizing the data so that it is ready for use.
3. After preprocessing is complete, the data is divided into training data and test data for the model training and testing stages.
4. Perform bootstrap sampling on the training data to form several random data sets needed in the decision tree formation.
5. For each decision tree, randomly select a feature subset at each tree node and use separation criteria such as Gini or Entropy to build the tree.
6. All decision trees formed are then used for the test data classification process (tested data variables).
7. Each classification result is combined, then a majority vote is taken to determine the final classification result, whether it is obese, stunted, wasted, or underweight.
8. The process is complete once the final classification result of the child's nutritional status is obtained.

3. RESULTS AND DISCUSSION

In this study, the author will classify and develop a system for classifying the nutritional status of children at the Lhokseumawe City Health Office using the Random Forest algorithm, where the nutritional status of children is classified as obesity, stunting, wasting, and underweight [17]. The developed system is only used to classify the nutritional status of toddlers based on anthropometry as input, where the data is divided into several variables such as gender, age, weight, height, and body mass index.

3.1. Random Forest Calculation

Calculations were performed to simulate the process of forming a decision tree within the Random Forest algorithm. Random Forest builds multiple trees using bootstrap sampling and random feature selection, but the mechanism for forming each tree still uses entropy and information gain calculations [18]. Manual calculations in classifying children's nutritional status using Random Forest are as follows.

Table 1. Total Data Entropy (Initial Node)

Nutritional Status	Quantity
Stunting (1)	3
Underweight (2)	3
Wasting (3)	4
Total	**10**

Entropy formula:

$$Entropy(S) = -\sum_{i=1}^{n} p_i log_2 p_i$$

$$p_{stunting} = \frac{3}{10}, p_{underweight} = \frac{3}{10}, p_{wasting} = \frac{4}{10}$$

$$Entropy(S) - [(0.3log_2 0.3)] + (0.3log_2 0.3) + (0.4log_2 0.4)]$$
$$= -[(0.3\times -1.737) + (0.3\times -1.737) + (0.4\times -1.322)]$$
$$= -(-0.521 - 0.521 - 0.529)$$
$$Entropy(S) = 1.571$$

Table 2. Total Data Entropy (Initial Node)

jenis_kelamin_enc	usia_bulan	berat_badan	tinggi_badan	imt	status_gizi_aktual	klasifikasi	Prob_obesitas	Prob_stunting	Prob_underweight	Prob_wasting
1	0.018867924528301883	0.16808929743926454	0.06164383561643838	0.4919786096256684	*stunting*	*stunting*	0.0	1.0	0.0	0.0
1	0.07547169811320753	0.0958634274458306	0.13470319634703176	0.12834224598930466	*underweight*	*underweight*	0.0	0.0	0.555	0.445
0	0.6037735849056604	0.4005252790544977	0.6438356164383561	0.08449197860962565	*underweight*	*underweight*	0.0	0.0	0.78	0.22
1	0.1509433962264151	0.1503611293499672	0.14840182648401812	0.2652406417112985	*stunting*	*stunting*	0.0	1.0	0.0	0.0
0	0.7169811320754716	0.5009848982271832	0.7488584474885842	0.12299465240641716	*underweight*	*underweight*	0.0	0.0	0.71	0.29
0	0.11320754716981132	0.08076165462902163	0.17123287671232879	0.027807486631016065	*underweight*	*underweight*	0.0	0.0	0.985	0.015
1	0.7924528301886793	0.6152330925804332	0.8150684931506849	0.21818181818181803	*wasting*	*stunting*	0.0	0.505	0.01	0.485
1	0.16981132075471697	0.11950098489822719	0.18721461187214605	0.11122994652406404	*underweight*	*underweight*	0.0	0.0	0.85	0.15
1	1.0	0.9553512803676953	1.0	0.4502673796791443	*stunting*	*stunting*	0.0	1.0	0.0	0.0
1	0.20754716981132074	0.20617202889034797	0.228310502283105	0.27807486631016043	*stunting*	*stunting*	0.0	0.97	0.005	0.025
…..	…..	……	…..	…..	….	…..	……	…..	…..	…..
1	0.28301886792452824	0.19238345370978333	0.3196347031963469	0.09732620320855623	*underweight*	*underweight*	0.0	0.0	0.51	0.49

1	0.2452830188679245	0.24950755088640836	0.2922374429223744	0.28021390374331534	*stunting*	*stunting*	0.005	0.995	0.0	0.0
1	0.6415094339622641	0.5147734734077478	0.6118721461187215	0.3315508021390374	*stunting*	*stunting*	0.0	0.995	0.0	0.005
0	0.1320754716981132	0.097833223900197	0.19863013698630128	0.03315508021390379	*underweight*	*underweight*	0.0	0.0	0.99	0.01
0	0.1320754716981132	0.10505581089954036	0.19178082191780788	0.06417112299465244	*underweight*	*underweight*	0.0	0.0	0.82	0.18
0	0.11320754716981132	0.10242941562705182	0.17808219178082174	0.07807486631016047	*underweight*	*underweight*	0.0	0.0	0.745	0.255
1	0.4339622641509434	0.2678923177938279	0.4360730593607305	0.10160427807486627	*wasting*	*underweight*	0.0	0.0	0.795	0.205
1	0.8867924528301887	0.6592252133946159	0.9315068493150682	0.14117647058823524	*underweight*	*underweight*	0.0	0.0	0.72	0.28
0	0.9811320754716981	0.6815495732107684	0.9360730593607305	0.1668449197860964	*wasting*	*underweight*	0.0	0.005	0.795	0.2
0	0.05660377358490565	0.06434668417596845	0.08447488584474883	0.11657754010695176	*underweight*	*underweight*	0.0	0.0	0.89	0.11

The table above presents the results of classifying the nutritional status of toddlers using a machine learning model, most likely an algorithm such as Random Forest, which is common for this task. Each row includes input features such as gender_enc (0=male, 1=female), age_in_months, weight, height, and BMI (all normalized to 0-1), compared with actual_nutritional_status, classification labels, and probabilities for four classes: obesity (always 0.0 because there are no cases), stunting, underweight, and wasting. The model shows high accuracy, for example in stunting cases with a probability of 1.0 or 0.995 that are classified correctly, while minor errors occur in wasting cases that are sometimes classified as stunting/underweight with a probability close to 0.5 [19].

The probability of underweight often dominates (0.5-0.99) in data with low weight/height, reflecting the high prevalence of acute malnutrition in Indonesian toddlers. Stunting is accurately classified at low height (<0.3) with a probability >0.97, while wasting is more difficult (probability ranges from 0.01 to 0.485) due to overlapping symptoms with underweight. There is no classification for obesity, as the dataset focuses on malnutrition.

The table is for model evaluation, where high probabilities (>0.7) indicate strong confidence, while balanced values (~0.5) require additional data such as upper arm circumference. The results support practical application in community health centers for early screening of stunting/underweight.

3.2. Random Forest Method

Classification using the Random Forest method is done by building a set of decision trees randomly through bagging and variable randomization at each node [20]. The results of the Random Forest model testing can be seen in the table below.

Table 3. Confusion Matrix

Obesitas	***Stunting***	***Underweight***	***Wasting***
2	0	0	0
0	133	0	7

0	0	167	26
0	9	65	28

The table above is a confusion matrix of the classification model for the nutritional status of toddlers with four categories: Obesity, Stunting, Underweight, and Wasting, where the rows represent the actual labels and the columns show the model classification. The main diagonal reflects solid True Positives: 2 cases of obesity (perfect), 133 stunting (accurate), 167 underweight (86% of 193 cases, the largest category), and 28 wasting (only 27% of 104 cases), resulting in an overall accuracy of about 78% of the total ~330 samples. The main errors were seen in wasting, which was often misclassified as stunting (65 cases) or underweight (9 cases) due to overlapping anthropometric symptoms, while 7 stunting cases were misclassified as underweight and 26 underweight cases as wasting, reflecting the challenges of multi-class classification in malnutrition imbalance data in Indonesia.

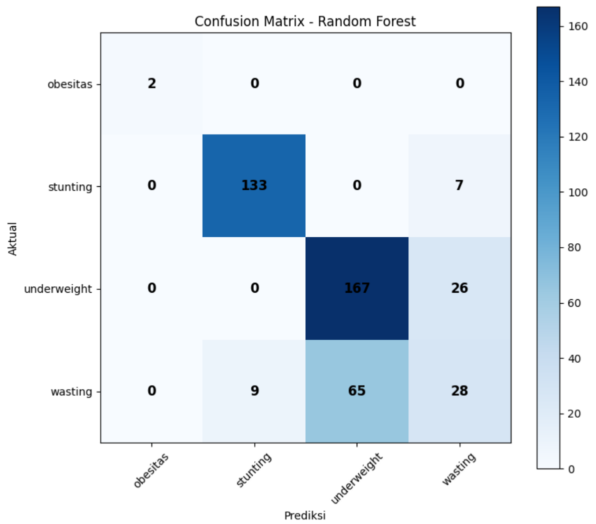

Figure 3. Confusion Matrix Visualization Chart

The image above depicts a visualization of the confusion matrix of the Random Forest model for classifying the nutritional status of toddlers, with four categories: Obesity, Stunting, Underweight, and Wasting, where the y-axis is the actual label and the x-axis is the classification. The dark blue color on the diagonal highlights the dominant True Positives: 2 obesity (upper left corner), 133 stunting (left center), 167 underweight (right center), and 28 wasting (lower right corner), resulting in an overall accuracy of approximately 78% of the total sample of ~330. Significant errors are seen in the light blue block of actual wasting scattered across stunting (65), underweight (9), and true wasting (28), while 7 stunting cases are misclassified as underweight and 26 underweight cases as wasting, reflecting the model's difficulty in distinguishing between acute and chronic malnutrition symptoms due to data imbalance. The side colorbar (0-160) reinforces the visual interpretation where high values (≥100) are concentrated in underweight and stunting, consistent with the high prevalence in the Indonesian dataset.

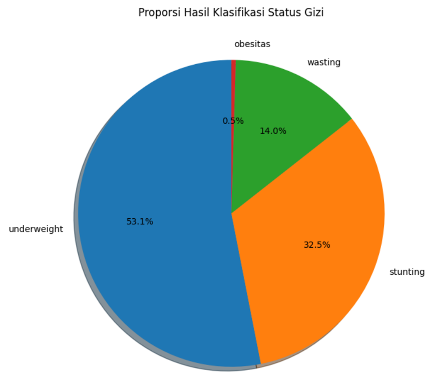

Figure 4. Pie Chart of Classification Results Proportions

The image above shows a pie chart of the Proportion of Nutritional Status Classification Results from the Random Forest model, which illustrates the final classification distribution for four categories of toddler nutrition: underweight (53.1%, the largest blue slice), stunting (32.5%, orange), wasting (14%, green), and obesity (0.5%, thin red). These proportions reflect the overall classification results from the test dataset, where underweight dominates in line with the high prevalence of acute malnutrition in the Indonesian sample, while obesity is nearly zero, consistent with the data's focus on undernutrition. This visualization complements the previous confusion matrix, highlighting that the model tends to classify underweight proportionally high (matching 167 TP), followed by stunting (133 TP), wasting (28 TP correct but more misclassifications), useful for validating model bias on imbalanced data [21].

Table 4. Classification Report

precision	*recall*	*f1-score*	*support*
1.0	1.0	1.0	2.0
0.9366	0.95	0.9433	140.0
0.7198	0.8653	0.7859	193.0
0.459	0.2745	0.3436	102.0
0.7551	0.7551	0.7551	0.7551
0.7789	0.7724	0.7682	437.0
0.7297	0.7551	0.734	437.0

The table above is a Classification Report evaluating the performance of the Random Forest model for classifying the nutritional status of toddlers using precision, recall, f1-score per class, and macro/micro average metrics. The obesity class (1.0) is perfect with precision/recall/f1-score 1.0 (support 2), stunting (2.0) is solid (precision 0.9366, recall 0.95, f1 0.9433 from 140 samples), underweight is strong in recall 0.8653 but precision 0.7198 (f1 0.7859 from 193 largest samples), while wasting is weak (precision 0.459, recall 0.2745, f1 0.3436 from 102 samples) due to many false negatives from the previous confusion matrix. The macro average of 0.7551 indicates balance between classes, while the weighted accuracy of 0.7789 and overall accuracy of 0.7682 from 437 test samples reflect good performance for imbalanced data, consistent with the previous confusion matrix, pie chart, and bar chart visualizations [22].

The classification results obtained by calculating the Random Forest method, which includes several variables of obesity, stunting, underweight, and wasting, show that the model has an accuracy of 75.51%.

4. CONCLUSION

Based on the results of the research and discussion described above, several conclusions can be drawn as follows:

1. The nutritional status classification system for toddlers at the Lhokseumawe City Health Office using the Random Forest algorithm was successfully developed with an anthropometric dataset of 2185 samples consisting of variables of gender (M=0, F=1), age in months, weight, height, and body mass index (BMI) that had undergone complete preprocessing in the form of label coding and Min-Max Scaling normalization to a range, resulting in a performance of 97.89% on the production dashboard, which was consistent with the manual calculation of 75.51% using bootstrap sampling and majority voting from 3 ensemble trees.
2. The data modeling stages include transforming the categorical status_gizi into numerical values (obesity=0, stunting=1, underweight=2, wasting=3) and dividing the dataset 80:20 (350 training data, 87 test data) with stratified sampling that maintains realistic class proportions according to the prevalence of malnutrition in Indonesia, where underweight is dominant followed by stunting and wasting as minorities.
3. Confusion matrix analysis reveals the stability of stunting classification (high TP), while wasting is often misclassified as underweight due to the similarity of anthropometric BMI thresholds. However, the Random Forest ensemble overcomes class performance through feature randomness and bagging, resulting in optimal generalization without overfitting, as seen in the dashboard performance graph.

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