Journal of Applied Engineering and Technological Science
Vol 6(2) 2025: 1135-1147

NAIVE BAYES ANALYSIS FOR NUTRITIONAL FULFILLMENT PREDICTION IN CHILDREN

Satrio Agung Wicaksono[1*], Satrio Hadi Wijoyo[2], Fatmawati[3], Tri Afirianto[4], Diva Kurnianingtyas[5], Mochammad Chandra Saputra[6]
Faculty of Computer Science, Universitas Brawijaya, Malang, Indonesia[12456]
Faculty of Medicine, Universitas Brawijaya, Malang, Indonesia[3]
satrio@ub.ac.id[1], satriohadi@ub.ac.id[2], fatmawati@ub.ac.id[3], tri.afirianto@ub.ac.id[4], divaku@ub.ac.id[5], andra@ub.ac.id[6]

Received: 14 September 2024, Revised: 21 January 2025, Accepted: 18 March 2025
**Corresponding Author*

ABSTRACT
Stunting in children remains a significant global health challenge, particularly in low- and middle-income countries. Addressing this issue requires an effective approach to predicting and preventing inadequate nutritional fulfillment. This study uses the Naïve Bayes approach to forecast nutritional needs for children's growth and development, providing practical information for stunting prevention efforts. The data used were sourced from 174 infant and toddler examinations at the Puskesmas Lawang, involving eight key attributes: gender, age, weight, height, head circumference, pre-screening, vision tests, and nutritional status. Key performance metrics were evaluated to validate the model's predictive capabilities, including accuracy, precision, recall, and F1-score. Six test scenarios were conducted using different percentages of training data (90%, 80%, 70%, 60%, 50%, and 40%) to evaluate the reliability of the Naïve Bayes method. Results indicated that the highest accuracy of 78.84% was achieved in the sixth test scenario. The third test scenario produced the highest precision at 97.5%, while the highest recall (100%) was observed in the first three scenarios. The highest F-measure of 90.3% occurred in the fourth scenario. These results suggest the algorithm's potential for early detection to decrease the number of stunting children. The study's implications are twofold: practically, the model can be integrated into health monitoring systems to assist healthcare professionals and policymakers in designing more effective nutrition programs; theoretically, it highlights the adaptability of Naive Bayes for handling complex, multi-dimensional health data.
Keywords: *Artificial Intelligence, Machine Learning, Early Detection Of Child Physical Growth, Nutritional Fulfillment, Health Issues.*

1. Introduction

Child malnutrition remains a critical global issue, with millions of children affected by undernutrition and its severe consequences. According to recent data, in 2022, about 148.1 million children under five years old experienced stunting, reflecting 22.3% of this age group worldwide (Unicef, 2023). While stunting prevalence has declined globally from 33% in 2000 to 22.3% in 2022, significant disparities persist, especially in regions like South Asia and sub-Saharan Africa, which house the majority of stunted children (Organization, 2023). In addition, malnutrition and stunting are currently considered global problems (Raiten & Bremer, 2020). Based on data from the World Health Organization (WHO), more than half of all stunted children under five years old live in Asia, Eastern and Southeastern Africa, West and Central Africa, Middle East, and North Africa. By 2022, the stunting prevalence rates in Africa, Eastern Mediterranean, and South-East Asia will be 31, 25, and 31.10.

Stunting results from prolonged nutritional deficiencies, often exacerbated by socio-economic factors, poor maternal health, and inadequate infant feeding practices. The first 1,000 days of a child's life, from conception to their second birthday, are critical for preventing stunting, as this period significantly influences physical and cognitive development. Early detection involves identifying children at risk of malnutrition before they develop stunting. This can be achieved through regular monitoring of growth parameters such as weight and height. Studies have shown that anthropometric measurements are effective tools for early identification of stunted growth (Ayukarningsih et al., 2024). By conducting periodic assessments, healthcare providers can recognize deviations from expected growth patterns and implement timely interventions. Several screening tools have been developed to predict malnutrition and assess the risk of stunting in children. For instance, a study in rural Zambia introduced a practical screening tool that evaluates various risk factors, including birth weight and maternal education level, to identify children at high risk of stunting (Hasegawa et al., 2017). Similarly, the "Stunting Tool for Early Prevention" identifies key predictors of stunting risk based on easily measurable factors such as maternal height and infant weight at six months (Hanieh et al., 2019). These example tools enable healthcare workers to make rapid assessments and initiate preventive strategies effectively.

Early prediction involves assessing various risk factors associated with stunting to identify at-risk children before they exhibit signs of growth faltering. Research has demonstrated that predictive models can effectively forecast the likelihood of stunting based on easily measurable indicators. For instance, a study developed a scorecard for early detection of stunting risk, which utilized factors such as maternal height, infant weight, and gestational age to predict outcomes accurately. This scorecard achieved a sensitivity of 80% and specificity of 75%, indicating its effectiveness in identifying children who may require intervention (Mardiyana et al., 2022). Stunting also can be prevented by early detection or early screening to predict malnutrition. By making early predictions, stunting prevention programs can be optimized. Prediction and integration of health data can be used as supporting data in decision-making and strategic plans in the health sector (Arumi et al., 2023; Muflikhah et al., 2023). Therefore, another approach is required to utilize artificial intelligence technology, especially machine learning to provide accurate prediction of stunting in children. This study aims to predict children's nutritional needs to prevent stunting in Indonesia. In addition, this study analyzes the Naïve Bayes method regarding data usage in more detail. This analysis will make a scientific contribution to preventing children's stunting by using the Naïve Bayes algorithm.

2. Literature Review

Nutritional data is often high-dimensional and complex, encompassing various factors that influence dietary habits and health outcomes. Machine learning excels in analyzing such data due to its ability to identify patterns and relationships among multiple variables simultaneously. For example, studies have shown that ML techniques like Random Forest and Artificial Neural Networks can effectively predict malnutrition by analyzing diverse datasets that include socio-economic factors, dietary intake, and anthropometric measurements (Osco et al., 2020). The predictive accuracy of machine learning models has been demonstrated in various studies focused on nutrition. For instance, a study utilizing machine learning to predict nutrient content based on hyperspectral imaging achieved high accuracy rates for several essential nutrients, showcasing ML's capability to derive insights from complex spectral data (Qasrawi et al., 2024). The robust theoretical framework supporting the use of machine learning models for predicting nutritional needs encompasses statistical learning theory, effective feature engineering, and rigorous model evaluation metrics. The ability of ML to handle high-dimensional data, its predictive accuracy across various contexts, and its adaptability make it an invaluable tool in nutrition research. By anchoring studies within this clear academic framework, researchers can leverage machine learning to enhance our understanding of nutritional needs and improve public health interventions aimed at reducing stunting cases.

Several researchers have applied machine learning to predict nutritional needs, as shown in Table 1. Chilyabanyama et al. (2022), Rahmi et al. (2022), and Yunus et al. (2023) have predicted stunting based on nutritional needs with C4.5, Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and XGBoost methods. However, no one has used the Naïve Bayes method for stunting prediction. However, Putri et al. (2020) researchers have implemented Naïve Bayes on toddler nutrition prediction with satisfactory accuracy results of 100%. The study conducted by Putri et al. (2020) became the basis for this study to implement the Naïve Bayes method. Using the Naïve Bayes method can consider the results and accuracy of information with a small amount of data. In addition, classification using Naïve Bayes is most widely used for prediction, especially in data sets with many categorical or nominal type attributes (Bours, 2021).

Table 1 – Previous Studies About Nutrition Fulfillment Prediction

Research	Object	Method	result
Putri et al. (2020)	Toddler Nutrition	Naïve bayes	Accuracy = 100%
Hemo & Rayhan (2021)	Malnutrition	Classification tree, Random Forest	Classification tree - Accuracy for Stunting prediction = 70.10% - Accuracy for Underweight prediction = 72.40% Random forest - Accuracy for Stunting prediction = 68.70% - Accuracy for Underweight prediction = 70.50%
Nazir et al. (2022)	Toddler Nutrition	C4.5 and Particle Swarm Optimization	Accuracy = 94.49%
Yunus et al. (2023)	Stunting	C4.5	Accuracy = 61.82%
Rahmi et al. (2022)	Stunting	SVM	Accuracy = 100%
Syahrial et al. (2022)	Stunting	SVM-RBF	Accuracy = 78%
Shen et al. (2023)	Stunting (Papua New Guinea)	LASSO-XGBoost	Accuracy = 0.728 Precision = 0.715 Recall = 0.628 F1 scores = 0.669
Chilyabanyama et al. (2022)	Stunting	LR, RF, SVM, XGBoost	Accuracy for Stunting prediction - LR = 45.9% - RF = 61.62% - SVM = 55.83% - XGBoost = 58.51%

3. Research Methods

Indonesia is one of the countries paying attention to the problem of stunting. The prevalence of stunting in Indonesia in 2018 reached 30.5%, which can be categorized as very high (Raiten & Bremer, 2020). According to the results of the Indonesian Nutrition Status Survey in 2022, there are three provinces with stunting prevalence in Indonesia, namely East Nusa Tenggara, West Sulawesi, and Papua provinces at 35.3%, 34%, and 35% (Arumi et al., 2023). The Indonesian government has been working to reduce the prevalence of stunting. The government conducts monitoring in 34 provinces, especially in 514 districts. Based on the Medium-Term Development Plan, the government targets the prevalence of nutrition problems to decrease to 14% by 2024. In addition, the government designed 11 specific interventions, namely, anemia screening, consumption of blood supplement tablets for adolescent girls, antenatal care, consumption of blood supplement tablets for pregnant women, provision of supplementary food for pregnant women with chronic energy deficiency, monitoring of toddler growth, exclusive breastfeeding, provision of animal protein-rich complementary food for under-fives, management of toddlers with nutritional problems, increasing coverage and expansion of immunization, education of pregnant women and families, including triggering open defecation-free. This program focuses on the period before birth and children aged 6-23 months because stunting prevention is much more effective than stunting treatment (Indonesia, 2022). However, stunting can be prevented by prediction using machine learning.

This study implements Naïve Bayes in predicting nutritional needs in children. The research stages are divided into five: gathering, data preprocessing, naïve Bayes modelling, and evaluation. Fig. 1 shows the following stages of this research.

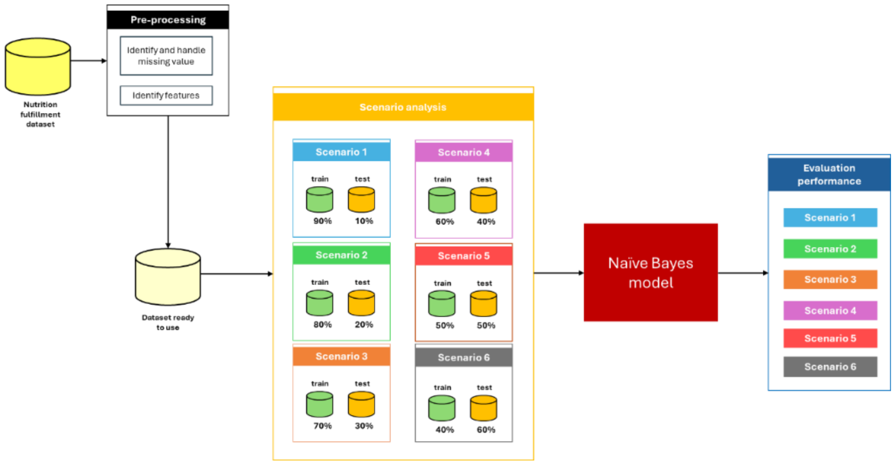

Fig. 1. Research Flow in This Study

A. Data Collection

This study collected data from primary data by interviewing the head of the health center (*Puskesmas)*, midwife coordinators, and pregnant women at *Puskesmas* Lawang in Malang, Indonesia. The interview participants consisted of children aged between 1-5 years old and had been visited within the last six months to the health center. In addition, during the interviews always ensured that the data obtained was consistent and in-depth. In primary data collection, this study used purposive sampling method to ensure the representation of social and economic backgrounds.

This study also uses secondary data obtained from the *Puskesmas* database. There were 200 child growth screening results data that had 12 attributes, namely child's name, date of birth, parent's name, parent's address, name of pre and postnatal health service center *(Posyandu/Pos Pelayanan Terpadu)* and information for mothers and children under five or Integrated Service Post), birth weight, birth height, birth order, weight measurement results, height, child's age every month, and history of vitamin intake. This data collection was undertaken to ensure that the data provided a comprehensive and representative overview of child growth and development. Thus, the sampling method and participant criteria can represent information that is expected to be more credible and valid.

B. Preprocessing

In this study, there are two stages of data preprocessing, namely the selection of attribute features and the removal or alteration of inconsistent and appropriate records. The data obtained has 12 attributes, namely child's name, date of birth, parent's name, parent's address, name of pre and postnatal health service center and information for mothers and children under five, birth weight, birth height, birth order, weight measurement results, height, child's age every month, and history of vitamin administration. However, eight attributes were used in the next stage: gender, age, weight, height, head circumference, pre-screening, vision test, and nutritional status. Other attributes such as demographic data needed to be removed as it was less relevant and did not contribute significantly to the model. The selection of attributes is important because it can help build a more robust, efficient, and easy-to-interpret model (Gosiewska et al., 2021). The characteristics of the data used in this study are shown in Table 2.

Table 2 – Data characteristics

Attribute	Range
Age	[0.50 … 64.50]
Body weight	[0.36 … 23.90]
Height	[11.40 … 110.05]
Head circumference	[36.00 … 51.00]
Gender	0 = Girl 1 = Boy
Pre-Screening	0 = Dubious 1 = Age-appropriate
Vision Test	0 = Not conducted

Nutrition Status	1 = Normal 1 = Good nutrition 2 = Malnutrition 3 = Over nutrition

Another preprocessing stage is the data cleaning process that aims to remove noise, inconsistent, and irrelevant data. Inconsistent data such as incomplete entries or inappropriate information needs to be removed to maintain the quality and accuracy of the data used in the analysis (Nandan Prasad, 2024). For example, there are several data records that have a value of 0, especially in the attributes of body weight, height, and head circumference, so these data records need to be removed because it has the potential to make the results invalid.

Moreover, preprocessing is also done by cleaning other data such as inconsistent attribute writing when filling in the data. This was found in the age attribute, for example the writing in one record was "35.5 *bulan*" but another record was "38.5". The inconsistency of data input in one record adds the word "*bulan*", but in another record without adding the word. In this research, inconsistent data like this example will be processed by removing the word "*bulan*". After preprocessing, the number of records obtained is 174 data. Furthermore, after identifying the data, this study only uses eight attributes.

C. Naïve Bayes

Naïve Bayes is a simple classification that applies Bayes' theorem by assuming all features are unrelated. Naïve Bayes users use the overall probability, which is the probability of the data against the category (prior). Afterwards, the data will be categorized based on the maximum probability (posterior). With other data, this method assumes that the availability of certain class features is not related to the availability of other features (Mansour et al., 2022). Naive Bayes assumes that the features in the dataset are independent of each other. Next, a posteriori probability calculation for each class is used to classify new instances (Alamer et al., 2023; Permatasari et al., 2023). The class with the highest probability is the predicted class.

In this study, the characteristics of the dataset and the challenges faced are in line with the advantages of Naïve Bayes. Compared to other classification methods such as Random Forest and Support Vector Machine (SVM), Random Forest (RF) is a flexible and robust method because it can handle large datasets with complex features without overfitting. However, RF tends to require more resources for training than Naïve Bayes (Bogdal et al., 2022; Stiawan et al., 2020). On the other hand, the SVM method is also very effective in high-dimensional spaces with kernels that can solve non-linear problems, but SVM works slowly on very large data with complex parameter tuning (Chauhan et al., 2019; Ghosh et al., 2019). Based on the comparison of the advantages and disadvantages of the methods, the selection of Naïve Bayes in this study provides a balance of efficiency and performance on limited sample size problems (Blanquero et al., 2021).

The Naive Bayes formula used as shown in Equation (1) is as follows

$$P(C_{k=3}|x_1, x_2, \dots, x_{n=9}) = \frac{P(C_3) \cdot P(x_1, x_2, \dots, x_9|C_3)}{P(x_1, x_2, \dots, x_9)} \quad (1)$$

where:

$P(C_{k=3}|x_1, x_2, \dots, x_{n=9})$ = probability of class $C_{k=3}$ given features $x_1, x_2, \dots, x_{n=9}$

$P(C_{k=3})$ = prior probability of class $C_{k=3}$

$P(x_i|C_{k=3})$ = probability of feature i given class $C_{k=3}$

In the Naïve Bayes implementation process, this study uses Weka to find the prediction results. Next, with these tools, we tested the test scenario six times.

D. Performance Evaluation

Testing the performance of the model aims to determine its performance. Testing is performed with six scenarios to determine how well Naïve Bayes classifies growth and development deviations in children. Each test in the scenario requires evaluation methods such as Accuracy, Precision, Recall, and F-measure (Jia et al., 2020; Peretz et al., 2024). Accuracy is used to calculate the percentage of correct predictions compared to the total predictions shown in Equation (2).

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \tag{2}$$

Afterwards, precision is calculated to find the proportion of correct optimistic predictions out of all positive predictions. Meanwhile, recall calculates the proportion of positive cases that Naïve Bayes detects out of all real positive cases. Finally, the F-measure is applied to balance precision and recall (Peretz et al., 2024; Sravani & Karthikeyan, 2023; Widyawati et al., 2023; Yudhana et al., 2022). The equations to calculate precision, recall, and F-measure, respectively, are shown in Equations (3)-(5).

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Positive}} \tag{3}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive}+\text{False Negative}} \tag{4}$$

$$\text{F} - \text{measure} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}} \tag{5}$$

4. Results and Discussions

A. Exploratory Data Analysis

The data for this study has eight attributes consisting of seven independent attributes and one dependent attribute. Based on the correlation matrix presented, there are several results obtained from the relationship between variables in order to strengthen the exploratory analysis of the data shown in Figure 2. First, a significant positive correlation occurs between age and height (0.50) and head circumference (0.57). This means that children's physical growth increases with age. Similarly, the relationship between weight and height is 0.57, indicating that children who weigh more tend to have greater height. These two indicators are important factors for evaluating nutritional status because good and balanced nutrition is essential for optimal growth and development of children (Elgadal et al., 2024). Good nutritional status can be monitored through BMI, which is a growth standard derived from a child's weight and height (Reber et al., 2021). Adequate nutrition supports healthy physical growth (Mkhize & Sibanda, 2020; Zong et al., 2024). An important role in achieving good nutritional status in children comes from adequate nutrient intake, access to nutritious foods, and health interventions to improve child health (Heidkamp et al., 2021). However, there needs to be additional analysis of whether the relationship is linear or whether there is a significant non-linear pattern.

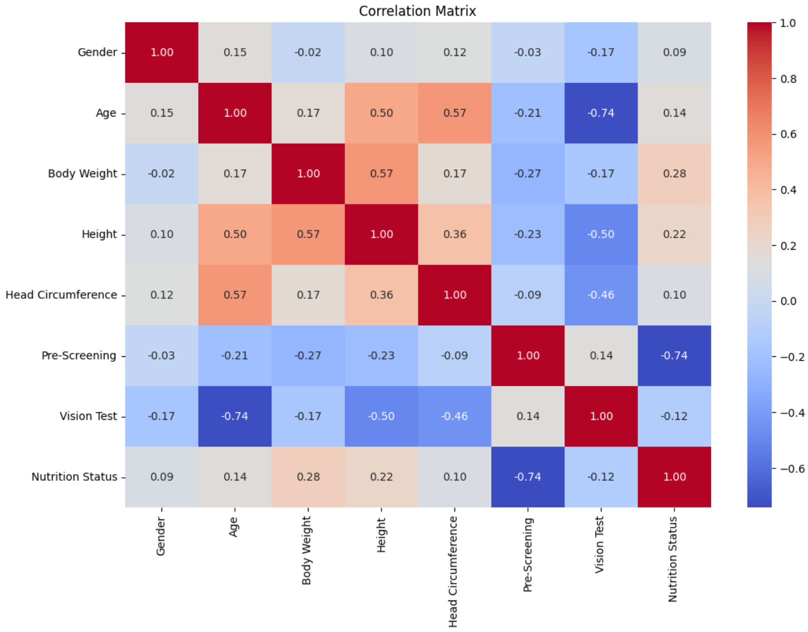

Fig. 2. Correlation Matrix Result

Meanwhile, there is a strong negative correlation between nutritional status and screening results, as indicated by a value of -0.74. This indicates that children with poorer pre-screening results tend to have lower nutritional status. Good nutritional status can reduce the risk of disease, leading to better screening results. A similar negative correlation was observed between vision test results and nutritional status at -0.12. This correlation could be interpreted as health problems such as vision occurring due to a lack of intake of certain nutrients such as vitamin A, but this needs to be investigated further (Tanumihardjo et al., 2016). However, overall, the exploratory analysis of the data provides interpretations that can make a significant contribution to understanding and addressing the risk of stunting.

B. Scenario Test Analysis

In this study, the model utilizes seven independent attributes, namely gender, age, weight, height, head circumference, pre-screening, vision test, and nutritional status, to detect the nutritional status of children. The attribute was selected based on the correlation matrix results. In contrast to other studies, Putri et al. (2020) used three attributes, namely age, weight, and height. Likewise, using three attributes, Ula, Ulva, Saputra, et al. (2022) applied sex, weight, and height for child nutrition status detection. Furthermore, Rozaq & Purnomo (2022) have four attributes, namely gender, age, height, and weight. Then, Darnila et al. (2022) also utilized six attributes, namely weight, height, head circumference, upper arm circumference, fathom length, and knee height. Gustriansyah et al. (2024) consider seven attributes, namely name, gender, age, weight, height, and BMI. The addition of attributes in this study allows for a more comprehensive and accurate analysis, considering various variables that can affect children's nutritional needs.

In addition, this study uses one dependent attribute, namely nutrition status, which is divided into three categories: good nutrition, malnutrition, and Overnutrition. In the study, Hemo & Rayhan, (2021), Rahmi et al. (2022), Talukder & Ahammed (2020), Ula, Ulva, Mauliza, et al. (2022), and Yunus et al. (2023) only two categories were used, namely Malnourished and Nourished. In contrast, the study of Nazir et al. (2022) utilized four classes, namely Very Short, Short, Normal, and High, and the study of Ula, Ulva, Ali, et al. (2022) also tried to use four classes namely Short, Tall, Thin, and Fat. Meanwhile, Ridwan & Sari (2021) applied to five classes, namely Very Thin, Thin, Normal, Fat, and Very Fat. The use of fewer class categories in this study was designed to improve efficiency and ease of interpretation of the results while still maintaining adequate prediction accuracy.

In the following study, the model was tested in six scenarios by sensitizing the training data from 90%, 80%, 70%, 60%, 50%, to 40%. The division of scenarios is based on the number of datasets used in the training and test process. The test aims to test the model or pattern obtained from the training data. In the first scenario, the training and test data were split by 90% and 10%. The scenario test results are shown in Table 3.

The first scenario test used 90% training, and 10% test data obtained an accuracy value of 76.47%. The highest precision value occurs in the Good Nutrition class, 92.3%; the most considerable recall value is in the Malnutrition class, 100%; and the largest F-measure is in the Good Nutrition class, 85.7%. When viewed from the output, the correct data from the Good Nutrition and Malnutrition classes are 12 and 1, respectively.

The second scenario was tested with 80% training data, obtaining an accuracy value of 77.14%. The most considerable precision value in the Good Nutrition class is 96.3%, the enormous recall value in the Malnutrition class is 100%, and the largest F-measure in Good Nutrition is 88.1%. The correct output results in the Good Nutrition and Malnutrition classes are 26 and 1, respectively.

Table 3 - Result of precision, recall, and F-measure

Scenario	Class	Evaluation			Confussion Matrix		
		Precision	Recall	F-Measure	Good nutrition	Undernourished	Over nutrition
1	Good nutrition	92.3%	80%	85.7%	12	3	0
	Malnutrition	25%	100%	40%	0	1	0
	Over nutrition	NAN	0%	NAN	1	0	0
2	Good nutrition	96.3%	81.3%	88.1%	51	9	0
	Malnutrition	12.5%	100%	22%	0	2	1
	Over nutrition	NAN	0%	NAN	2	3	2
3	Good nutrition	97.5%	81.3%	88.6%	39	9	0
	Malnutrition	8.3%	100%	15.4%	0	1	0
	Over nutrition	NAN	0%	NAN	1	2	0
4	Good nutrition	96.2%	85%	90.3%	61	11	1
	Malnutrition	14.3%	66.7%	23.5%	0	3	3
	Over nutrition	66.7%	28.6%	40%	2	2	4
5	Good nutrition	96.8%	83.6%	89.7%	74	14	1
	Malnutrition	18.8%	50%	27.3%	0	4	2
	Over nutrition	50%	50%	50%	2	3	4
6	Good nutrition	97.4%	83.1%	89.7%	12	3	0
	Malnutrition	19%	66.7%	29.6%	0	1	0
	Over nutrition	57.1%	44.4%	50%	1	0	0

The third scenario test uses 70% and 30% of training and test data, respectively. It obtained an accurate value of 76.92%. The most significant precision value in the Good Nutrition class is 97.5%, the enormous recall value in the Malnutrition class is 100%, and the largest F-measure in Good Nutrition is 88.6%. Based on the test data, the correct data for the Good Nutrition class is 39, and the correct data for the Malnutrition class is one.

Furthermore, the fourth scenario was tested using 60% training data. The accuracy result obtained is 78.57%. Meanwhile, the most significant precision value occurs in the Good Nutrition class, which is 96.2%; the most considerable recall value in the Good Nutrition class is 85%, and the largest F-measure in Good Nutrition is 90.3%. In this test, the correct data results in the Good Nutrition class were 51 data, in the Malnutrition class there were two data, and in the Over Nutrition class there were 2 data. Next, the fifth scenario test with training data and test data of 50% and 50%, we obtained an accuracy value of 78.16%. The correct data obtained in the Good Nutrition class are 61 data, in the Malnutrition class are 3 data, and in the Over Nutrition class are four data. Finally, testing the sixth scenario with 40% training data and 60% test data, the accuracy obtained is 78.84% with correct data in the Good Nutrition class, as much as 74 data, in the Malnutrition class, as much as four data, and in the Over Nutrition class as much as four data.

Naive Bayes is a simple yet effective probability-based classification method for many classification tasks, especially those involving text data. Based on Table 4, Naive Bayes can be analyzed for performance characteristics and performance through testing six scenarios by sensitizing the training data from 90%, 80%, 70%, 60%, 50%, to 40%. Based on the evaluation results, the precision metric has high consistency especially in the “Good nutrition” class, while

Recall shows considerable variation results especially in the “Malnutrition” and “Over nutrition” classes. The high precision value in the “Good nutrition” class represents that the model's ability is good to ensure that individuals really have good nutritional status by meeting the appropriate criteria. Meanwhile, the recall value is low in some classes such as “Malnutrition”, for example in scenario 4, which obtained 66.7%, it can be said that the model often fails to detect so that it has a serious impact if individuals with malnutrition but are not immediately identified. the category is a record that avoids positive errors. The gap between precision and recall results represents a trade-off in model performance. In addition, scenario six is the best recommendation for this study because it has the highest accuracy of 78.84% compared to the others, considering that the dataset used is balanced for each category. However, when compared to other studies, such as the study of Qasrawi et al. (2024) using a comparison of 80% training data and 20% testing data, we can get 99.8% accuracy using the Random Forest method. Then, in the study of Shen et al. (2023) , using a comparison of 90% training data and 10% testing data, we obtained an accuracy of 72.8% using the XGBoost method. This comparison shows that although the methods and proportions of data used are different, the accuracy results can vary greatly, and the best choice depends on the specific dataset conditions and research objectives.

Table 4 – Test scenario comparison result

Scenario	Accuracy	Precision	Recall	F-Measure
1	76.47%	92.3%	100%	85.7%
2	77.14%	96.3%	100%	88.1%
3	76.92%	97.5%	100%	88.6%
4	78.57%	96.2%	85%	90.3%
5	78.16%	96.8%	83.6%	89.7%
6	78.84%	97.4%	83.1%	89.7%

The use of seven attributes allows for more comprehensive and accurate detection of children's nutritional status compared to previous studies that used fewer attributes. With one dependent attribute divided into three categories, this approach improves efficiency and ease of interpretation of results. Scenario six (40% training data and 60% testing data) is recommended as the best approach in this study, with the highest accuracy of 78.84%. Despite the different methods and data proportions, the variation in accuracy results show that the best choice depends on the specific dataset conditions and research objectives. Overall, Naive Bayes showed good resilience to changes in the proportion of training data. Despite a decrease in recall at a smaller proportion of training data, precision remains high, which helps keep accuracy and F-Measure reasonable. This method is very effective for some classification tasks, especially when dealing with text data or data with well-separated probability distributions, as seen from the constant high accuracy performance (Al Moubayed et al., 2020; Yaqoob et al., 2023). When faced with a large amount of training data, Naive Bayes may be prone to overfitting, as shown by the decrease in recall at a smaller percentage of the training set. This result is due to the method's basic feature independence assumption, which often needs to hold in real-world data. With proper customization, Naive Bayes performs better on datasets with features that are highly dependent on each other or with highly uneven class distributions.

The result of the experiment also confirms the strength of Naïve bayes algorithm for computational efficiency. In terms of computation, Naive Bayes has excellent efficiency. It is capable of processing huge datasets quickly since it determines the likelihood of each feature separately given the class label (Appasani et al., 2024). Since speed is essential in real-time applications, this efficiency makes it very helpful. When it comes to challenges on nutritional fulfillment prediction in children, Naive Bayes can deliver unexpectedly good results. It can do fairly well, especially when dealing with high-dimensional data, where other algorithms might not be as successful. The experiment confirms that Naive Bayes excels in situations where computational efficiency is paramount and where the data is high-dimensional, such as nutritional fulfillment prediction. This makes it a valuable tool in both research and real-world applications.

5. Conclusion

Naive Bayes predicts child nutrition fulfillment based on 174 data with eight attributes. Based on the results of the analysis of the relationship between attributes, it was found that the factors of age, body weight, height, and head circumference significantly affect the growth and development of children in the *Puskesmas* area with a positive correlation of +0.57. When viewed from the results of data analysis, children with good nutritional status tend to have more optimal growth, which is determined by the social and economic background of the family. In addition, this study conducted six test scenarios involving the training data used. Based on this research, the highest accuracy value occurred in the sixth test scenario which amounted to 78.84%. Furthermore, the highest precision value occurred in the third test scenario which had a value of 97.5%. The highest recall value of 100% occurred in the first, second, and third test scenarios. Meanwhile, the highest F-measure value of 90.3% occurred in the fourth test scenario. Although recall decreased when the training data decreased, accuracy and precision still obtained high values. These results show that Naive Bayes is reliable even when the training data is small. The findings have significant practical and theoretical implications. Practically, the results obtained can be used to design more effective nutrition interventions that consider the nutritional status of children. Another finding is that social and economic variables need to be considered because they can help policy makers design more comprehensive nutrition intervention strategies. However, when viewed from some test results, the NAN value is due to data in one or more categories not being missing in the test data, so the data used between categories needs to be balanced. Therefore, it is necessary to increase the amount of data by taking primary and secondary data from other villages or searching for secondary data with the same characteristics on websites that provide datasets. In addition, it is necessary to use other machine learning methods to compare performance between methods. This can implement evolutionary methods to automate machine learning parameters so that the performance of the model is maximized, and stunting prevention efforts are achieved with the proposed model.

Acknowledgement

This work was supported by Universitas Brawijaya under the Strategic Research Grant Number 1665.24/UN.01/UB/2022.

References

Al Moubayed, N., McGough, S., & Hasan, B. A. S. (2020). Beyond the topics: how deep learning can improve the discriminability of probabilistic topic modelling. *PeerJ Computer Science*, *6*, e252. https://doi.org/10.7717/peerj-cs.252

Alamer, L., Alqahtani, I. M., & Shadadi, E. (2023). Intelligent Health Risk and Disease Prediction Using Optimized Naive Bayes Classifier. *J. Internet Serv. Inf. Secur.*, *13*(1), 1–10. https://doi.org/10.58346/JISIS.2023.I1.001

Appasani, D., Bokkisam, C. S., & Surendran, S. (2024). An Incremental Naive Bayes Learner for Real-time Health Prediction. *Procedia Computer Science*, *235*, 2942–2954. https://doi.org/10.1016/j.procs.2024.04.278

Arumi, E. R., Subrata, S. A., & Rahmawati, A. (2023). Implementation of naïve Bayes method for predictor prevalence level for malnutrition toddlers in Magelang City. *Jurnal Resti (Rekayasa Sistem Dan Teknologi Informasi)*, *7*(2), 201–207.

Ayukarningsih, Y., Sa'adah, H., Kusmayadi, M. A., & Ramadhan, M. Z. (2024). Stunting: Early Detection with Anthropometric Measurements and Management. *Journal of Health and Dental Sciences*, *4*(1), 91–104. https://doi.org/10.54052/jhds.v4n1.p91-104

Blanquero, R., Carrizosa, E., Ramírez-Cobo, P., & Sillero-Denamiel, M. R. (2021). Variable selection for Naïve Bayes classification. *Computers & Operations Research*, *135*, 105456. https://doi.org/10.1016/j.cor.2021.105456

Bogdal, C., Schellenberg, R., Höpli, O., Bovens, M., & Lory, M. (2022). Recognition of gasoline in fire debris using machine learning: Part I, application of random forest, gradient boosting, support vector machine, and naïve bayes. *Forensic Science International*, *331*, 111146. https://doi.org/10.1016/j.forsciint.2021.111146

Bours, M. J. L. (2021). Bayes' rule in diagnosis. *Journal of Clinical Epidemiology*, *131*, 158–160. https://doi.org/10.1016/j.jclinepi.2020.12.021

Chauhan, V. K., Dahiya, K., & Sharma, A. (2019). Problem formulations and solvers in linear SVM: a review. *Artificial Intelligence Review*, *52*, 803–855. https://doi.org/10.1007/s10462-018-9614-6

Chilyabanyama, O. N., Chilengi, R., Simuyandi, M., Chisenga, C. C., Chirwa, M., Hamusonde, K., Saroj, R. K., Iqbal, N. T., Ngaruye, I., & Bosomprah, S. (2022). Performance of machine learning classifiers in classifying stunting among under-five children in Zambia. *Children*, *9*(7), 1082. https://doi.org/10.3390/children9071082

Darnila, E., Maryana, M., Mawardi, K., Sinambela, M., & Pahendra, I. (2022). Supervised models to predict the Stunting in East Aceh. *International Journal of Engineering, Science and Information Technology*, *2*(3), 33–39. https://doi.org/10.52088/ijesty.v2i3.280

Elgadal, A. H., Elnour, A. A., Mohamed, R. M., Omer, Y. A. A., Saeed, A. A., Al-Kubaisi, K. A., Al Mazrouei, N., Beshir, S. A., Menon, V., & Al Amoodi, A. (2024). *Assessment of the Nutritional Status of a Hospitalized Children by Using Growth Parameters Ad Indicators: A Cross-Sectional Study*. https://doi.org/10.20944/preprints202411.1680.v1

Ghosh, S., Dasgupta, A., & Swetapadma, A. (2019). A study on support vector machine based linear and non-linear pattern classification. *2019 International Conference on Intelligent Sustainable Systems (ICISS)*, 24–28. https://doi.org/10.1109/ISS1.2019.8908018

Gosiewska, A., Kozak, A., & Biecek, P. (2021). Simpler is better: Lifting interpretability-performance trade-off via automated feature engineering. *Decision Support Systems*, *150*, 113556. https://doi.org/10.1016/j.dss.2021.113556

Gustriansyah, R., Suhandi, N., Puspasari, S., & Sanmorino, A. (2024). Machine Learning Method to Predict the Toddlers' Nutritional Status. *JURNAL INFOTEL*, *16*(1), 32–43. https://doi.org/10.20895/infotel.v15i4.988

Hanieh, S., Braat, S., Simpson, J. A., Ha, T. T. T., Tran, T. D., Tuan, T., Fisher, J., & Biggs, B.-A. (2019). The Stunting Tool for Early Prevention: Development and external validation of a novel tool to predict risk of stunting in children at 3 years of age. *BMJ Global Health*, *4*(6), e001801. https://doi.org/10.1136/bmjgh-2019-001801

Hasegawa, J., Ito, Y. M., & Yamauchi, T. (2017). Development of a screening tool to predict malnutrition among children under two years old in Zambia. *Global Health Action*, *10*(1), 1339981. https://doi.org/10.1080/16549716.2017.1339981

Heidkamp, R. A., Piwoz, E., Gillespie, S., Keats, E. C., D'Alimonte, M. R., Menon, P., Das, J. K., Flory, A., Clift, J. W., & Ruel, M. T. (2021). Mobilising evidence, data, and resources to achieve global maternal and child undernutrition targets and the Sustainable Development Goals: an agenda for action. *The Lancet*, *397*(10282), 1400–1418. https://doi.org/10.1016/s0140-6736(21)00568-7

Hemo, S. A., & Rayhan, M. I. (2021). Classification tree and random forest model to predict under-five malnutrition in Bangladesh. *Biom Biostat Int J*, *10*(3), 116–123. https://doi.org/10.15406/bbij.2021.10.00337

Indonesia, S. U. N. (2022). Mengenal Studi Status Gizi Indonesia 2021. *Kementerian Perencanaan Pembangunan Nasional/Badan Perencanaan Pembangunan Nasional (BAPPENAS)*.

Jia, Z., Lin, S., Gao, M., Zaharia, M., & Aiken, A. (2020). Improving the accuracy, scalability, and performance of graph neural networks with roc. *Proceedings of Machine Learning and Systems*, *2*, 187–198. https://people.eecs.berkeley.edu/~matei/papers/2020/mlsys_roc.pdf

Mansour, N. A., Saleh, A. I., Badawy, M., & Ali, H. A. (2022). Accurate detection of Covid-19 patients based on Feature Correlated Naïve Bayes (FCNB) classification strategy. *Journal of Ambient Intelligence and Humanized Computing*, 1–33. https://doi.org/10.1007/s12652-020-02883-2

Mardiyana, E., Ambarwati, R., & Shifaza, F. (2022). The stunting scorecard for early prevention: Development and external validation of a novel tool for predicting stunting risk in children under 5 years of age. *International Journal of Advanced Health Science and Technology*, *2*(3), 137–144. https://doi.org/10.35882/ijahst.v2i3.2

Mkhize, M., & Sibanda, M. (2020). A review of selected studies on the factors associated with the nutrition status of children under the age of five years in South Africa. *International Journal of Environmental Research and Public Health*, *17*(21), 7973. https://doi.org/10.3390/ijerph17217973

Muflikhah, L., Mahmudy, W. F., & Kurnianingtyas, D. (2023). *Machine Learning*. Universitas Brawijaya Press. https://books.google.co.id/books/about/Machine_Learning.html?id=tu_uEAAAQBAJ&redir_esc=y

Nandan Prasad, A. (2024). Data Quality and Preprocessing. In *Introduction to Data Governance for Machine Learning Systems: Fundamental Principles, Critical Practices, and Future Trends* (pp. 109–223). Springer. https://doi.org/10.1007/979-8-8688-1023-7_3

Nazir, A., Akhyar, A., Yusra, Y., & Budianita, E. (2022). Toddler nutritional status classification using C4. 5 and particle swarm optimization. *Sci. J. Informatics*, *9*(1), 32–41. https://doi.org/10.15294/sji.v9i1.33158

Organization, W. H. (2023). *Levels and trends in child malnutrition child malnutrition: UNICEF/WHO/World Bank Group Joint Child Malnutrition Estimates: Key findings of the 2023 edition*. World Health Organization. https://www.who.int/publications/i/item/9789240073791

Osco, L. P., Ramos, A. P. M., Faita Pinheiro, M. M., Moriya, É. A. S., Imai, N. N., Estrabis, N., Ianczyk, F., Araújo, F. F. de, Liesenberg, V., & Jorge, L. A. de C. (2020). A machine learning framework to predict nutrient content in valencia-orange leaf hyperspectral measurements. *Remote Sensing*, *12*(6), 906. https://doi.org/10.3390/rs12060906

Peretz, O., Koren, M., & Koren, O. (2024). Naive Bayes classifier–An ensemble procedure for recall and precision enrichment. *Engineering Applications of Artificial Intelligence*, *136*, 108972. https://doi.org/10.1016/j.engappai.2024.108972

Permatasari, T., Sandy, Y., Pratiwi, C., Damanik, K., & Silitonga, A. (2023). Naive Bayes Classifier (NBC) application on the nutritional status of adolescents in Medan. *Proceedings of the 4th Annual Conference of Engineering and Implementation on Vocational Education, ACEIVE 2022, 20 October 2022, Medan, North Sumatra, Indonesia*. https://doi.org/10.4108/eai.20-10-2022.2328884

Putri, T. E., Subagio, R. T., & Sobiki, P. (2020). Classification System Of Toddler Nutrition Status using Naïve Bayes Classifier Based on Z-Score Value and Anthropometry Index. *Journal of Physics: Conference Series*, *1641*(1), 012005. https://doi.org/10.1088/1742-6596/1641/1/012005

Qasrawi, R., Sgahir, S., Nemer, M., Halaikah, M., Badrasawi, M., Amro, M., Vicuna Polo, S., Abu Al-Halawa, D., Mujahed, D., & Nasreddine, L. (2024). Machine Learning Approach for Predicting the Impact of Food Insecurity on Nutrient Consumption and Malnutrition in Children Aged 6 Months to 5 Years. *Children*, *11*(7), 810. https://doi.org/10.3390/children11070810

Rahmi, I., Susanti, M., Yozza, H., & Wulandari, F. (2022). Classification of Stunting in Children Under Five Years in Padang City using Support Vector Machine. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, *16*(3), 771–778. https://doi.org/10.30598/barekengvol16iss3pp771-778

Raiten, D. J., & Bremer, A. A. (2020). Exploring the nutritional ecology of stunting: new approaches to an old problem. *Nutrients*, *12*(2), 371.

Reber, E., Schönenberger, K. A., Vasiloglou, M. F., & Stanga, Z. (2021). Nutritional risk screening in cancer patients: the first step toward better clinical outcome. *Frontiers in Nutrition*, *8*, 603936. https://doi.org/10.3389/fnut.2021.603936

Ridwan, A., & Sari, T. N. (2021). The comparison of accuracy between naïve bayes clasifier and c4. 5 algorithm in classifying toddler nutrition status based on anthropometry index. *Journal of Physics: Conference Series*, *1764*(1), 012047. https://doi.org/10.1088/1742-6596/1764/1/012047

Rozaq, A., & Purnomo, A. J. (2022). Classification Of Stunting Status In Toddlers Using Naive Bayes Method In The City Of Madiun Based On Website. *Techno Nusa Mandiri*, *19*(2), 69–76. https://doi.org/10.33480/techno.v19i2.3337

Shen, H., Zhao, H., & Jiang, Y. (2023). Machine learning algorithms for predicting stunting among under-five children in Papua New Guinea. *Children*, *10*(10), 1638. https://doi.org/10.3390/children10101638

Sravani, S., & Karthikeyan, P. R. (2023). Detection of cardiovascular disease using KNN in comparison with naive bayes to measure precision, recall and f-score. *AIP Conference Proceedings*, *2821*(1). https://doi.org/10.1063/5.0177014

Stiawan, D., Idris, M. Y. Bin, Bamhdi, A. M., & Budiarto, R. (2020). CICIDS-2017 dataset feature analysis with information gain for anomaly detection. *IEEE Access*, *8*, 132911–132921. https://doi.org/10.1109/ACCESS.2020.3009843

Syahrial, S., Ilham, R., & Asikin, Z. F. (2022). Stunting Classification in Children's Measurement Data Using Machine Learning Models. *Journal La Multiapp*, *3*(2), 52–60. https://doi.org/10.37899/journallamultiapp.v3i2.614

Talukder, A., & Ahammed, B. (2020). Machine learning algorithms for predicting malnutrition among under-five children in Bangladesh. *Nutrition*, *78*, 110861. https://doi.org/10.1016/j.nut.2020.110861

Tanumihardjo, S. A., Russell, R. M., Stephensen, C. B., Gannon, B. M., Craft, N. E., Haskell, M. J., Lietz, G., Schulze, K., & Raiten, D. J. (2016). Biomarkers of Nutrition for Development (BOND)—vitamin A review. *The Journal of Nutrition*, *146*(9), 1816S-1848S. https://doi.org/10.3945/jn.115.229708

Ula, M., Ulva, A. F., Ali, M. A., & Said, Y. R. (2022). Application of Machine Learning in Predicting Children's Nutritional Status with Multiple Linear Regression Models. *Multica Science and Technology*, *2*(2), 42–48. https://doi.org/10.47002/mst.v2i2.363

Ula, M., Ulva, A. F., Mauliza, M., Ali, M. A., & Said, Y. R. (2022). Application Of Machine Learning In Determining The Classification Of Children's Nutrition With Decision Tree. *Jurnal Teknik Informatika (Jutif)*, *3*(5), 1457–1465. https://doi.org/10.20884/1.jutif.2022.3.5.599

Ula, M., Ulva, A. F., Saputra, I., Mauliza, M., & Maulana, I. (2022). Implementation of machine learning using the k-nearest neighbor classification model in diagnosing malnutrition in children. *Multica Science and Technology*, *2*(1), 8–13. https://doi.org/10.47002/mst.v2i1.326

Unicef. (2023). Stunting has declined steadily since 2000–But faster progress is needed to reach the 2030 target. *UNICEF, New York, NY*. https://data.unicef.org/topic/nutrition/malnutrition/#:~:text=Stunting%20has%20declined%20steadily%20since,target%20is%20to%20be%20achieved

Widyawati, D., Faradibah, A., & Belluano, P. L. L. (2023). Comparison Analysis of Classification Model Performance in Lung Cancer Prediction Using Decision Tree, Naive Bayes, and Support Vector Machine. *Indonesian Journal of Data and Science*, *4*(2), 78–86. https://doi.org/10.56705/ijodas.v4i2.76

Yaqoob, A., Musheer Aziz, R., & verma, N. K. (2023). Applications and techniques of machine learning in cancer classification: A systematic review. *Human-Centric Intelligent Systems*, *3*(4), 588–615. https://doi.org/10.1007/s44230-023-00041-3

Yudhana, A., Umar, R., & Saputra, S. (2022). Fish Freshness Identification Using Machine Learning: Performance Comparison of k-NN and Naïve Bayes Classifier. *J. Comput. Sci. Eng.*, *16*(3), 153–164. https://doi.org/10.5626/JCSE.2022.16.3.153

Yunus, M., Biddinika, M. K., & Fadlil, A. (2023). Classification of Stunting in Children Using the C4. 5 Algorithm. *Jurnal Online Informatika*, *8*(1), 99–106. https://doi.org/10.15575/join.v8i1.1062

Zong, X.-N., Li, H., & Zhang, Y.-Q. (2024). Height and body mass index trajectories from 1975 to 2015 and prevalence of stunting, underweight and obesity in 2016 among children in Chinese cities: findings from five rounds of a national survey. *World Journal of Pediatrics*, *20*(4), 404–412. https://doi.org/10.1007/s12519-023-00747-1