JINAV: Journal of Information and Visualization *ISSN: 2746-1440 (online)*
Vol. 6 No. 1 (2025)
https://doi.org/10.35877/454RI.jinav4100

Classification of Stunting Status Using the Naive Bayes Classifier Algorithm with Backward Elimination Feature Selection

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Abstract

Stunting is one of the major health issues affecting toddlers that can influence their physical growth and developmental progress, ultimately impacting their quality of life. It is characterized by a child's height being below the standard for their age. To address this issue, a method is needed to classify the stunting status in toddlers. This study aims to classify stunting status in toddlers using the Naive Bayes Classifier algorithm, with feature selection performed using the Backward Elimination method to improve classification accuracy.The dataset used in this research was collected in 2023 from the Lueng Daneun Public Health Center, located in Peusangan Simblah Krueng Subdistrict, Bireun District. The dataset includes several features such as age, gender, family income, height, weight, sanitation, clean water access, and formula milk consumption. The application of the backward elimination feature selection method is intended to identify the most significant and relevant features for the target variable. The Naive Bayes Classifier was implemented using the Python programming language. The analysis results indicated that the remaining feature, namely the sanitation condition, had a significant contribution to the classification process. The dataset consisted of 244 entries, divided into 195 training data and 49 testing data with an 80:20 ratio. The initial classification results showed an accuracy of 77.55%, a precision of 60.00%, a recall of 64.29%, and an F1-score of 62.07%. After feature selection, the accuracy increased to 81.63%, precision to 63.16%, recall to 85.71%, and the F1-score slightly improved to 72.73%. These results indicate that feature selection in the Naive Bayes model demonstrates good performance.

Keywords: Classfication, Stunting, NBC, Backward Elimination.

Received: 9 January 2025 Revised: 30 April 2025 Accepted: 18 June 2025

1. Introduction

Technological advancements in this era have progressed rapidly. One of the critical areas that requires attention is the health sector. An important initiative in improving healthcare involves addressing the issue of stunting in children under five. Stunting remains a major public health concern in Indonesia. In recent years, stunting or impaired growth and development in children has become a widely discussed topic, with the government actively promoting public awareness and intervention efforts (Sari et al., 2023). Stunting is a manifestation of chronic malnutrition, characterized by a height for age that falls below the standard deviation based on the World Health Organization (WHO) growth standards. This condition results from prolonged inadequate nutritional intake during both the prenatal period and early childhood (Yuwanti et al., 2021). Based on the 2022 Indonesian Nutritional Status Survey (SSGI) conducted by the Ministry of Health, the stunting rate in Indonesia was recorded at 21.6%. This figure reflects a decrease of 2.8% from 2021. The government has set a target to reduce the stunting rate to 14.2% by 2029. Therefore, continuous efforts are necessary to further reduce the prevalence of stunting (Kementrian Kesehatan RI, 2022).

The recording of stunting status at the Lueng Daneun Community Health Center, Peusangan Simblah Krueng Subdistrict, Bireuen Regency, has traditionally been carried out manually by midwives or nurses, which is time-consuming. A common issue in the collection and evaluation of stunting data is the lack of accuracy and consistency on a monthly basis, as assessments are often based only on estimates of cases handled by the health center. Therefore, support in the form of information technology, particularly data mining technology, is needed. Data mining refers to the process of extracting important and relevant information from large-sized databases (Nurdin et al., 2023). Data

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mining, also known as Knowledge Discovery in Databases (KDD), is a process that involves the collection and utilization of historical data to identify patterns, relationships, or trends within large datasets (Qamal et al., 2023). The results of the data mining process can be utilized to improve the quality of decision-making in the future.

In a study conducted by Syahrani Lonang and Dwi Normawati in 2022, titled *"Classification of Stunting Status in Toddlers Using K-Nearest Neighbor with Backward Elimination Feature Selection"*, a total of 1,000 data records were used, consisting of 243 stunted toddlers and 757 non stunted toddlers. The study concluded that the K-Nearest Neighbor (KNN) algorithm achieved an accuracy rate of 91.90% using 9 attributes. When combined with the backward elimination feature selection method, the accuracy increased to 92.20% with 8 attributes. The results of this study indicate that the KNN method with backward elimination feature selection is effective for classifying stunting status in toddlers (Lonang & Normawati, 2022).

In a study conducted by Haditsah Annur in 2022, titled *"Implementation of the Naive Bayes Algorithm Based on Backward Elimination for Hotel Room Booking Prediction"*, the research achieved an accuracy of 89.67% using the Naive Bayes algorithm and an improved accuracy of 97.83% when applying the Naive Bayes algorithm with Backward Elimination feature selection, based on a dataset of 1,000 hotel room booking customers. The findings of this study concluded that the Naive Bayes algorithm combined with Backward Elimination feature selection is effective for predicting hotel room bookings (Annur, 2022).

This study will implement the Naive Bayes Classifier method with Backward Elimination feature selection for classification in determining the stunting status of toddlers.

2. Methods

2.1 Data and Variables

This study utilizes a dataset recorded at the Lueng Daneun Community Health Center, Peusangan Simblah Krueng Subdistrict, Bireuen Regency, in 2023. The dataset consists of 244 data entries, comprising 8 independent variables (X) and 1 dependent variable (Y). The dependent variable (Y) is the stunting status (1 = stunted, 0 = not stunted). The following is a description of the independent variables (X) included in the dataset:

Table 1. Dataset Variables

No	Variable	Description
X1	Age	Age of the toddler (0–59 months)
X2	Gender	0: Male, 1: Female
X3	Income Level	1: Very poor, 2: Poor, 3: Fair, 4: Good, 5: Very good
X4	Height	Toddler's height (cm)
X5	Weight	Toddler's weight (kg)
X6	Sanitation Condition	1: Very good, 2: Good, 3: Fair, 4: Poor, 5: Very poor
X7	Availability of Clean Water	1: Very good, 2: Good, 3: Fair, 4: Poor, 5: Very poor
X8	Formula Milk Provision	1: Given, 2: Not given

2.2 Data Preprocessing

1) This stage aims to perform data cleaning by addressing missing values, smoothing noise when identifying outliers, and correcting inconsistencies within the data (Yunus et al., 2023).
2) Encoding the data, in which the data is transformed into an appropriate format to be processed in data mining. This process enables the data to be read, transmitted, or interpreted by the system.

Table 2. Encoding Resutl

No	X1	X2	X3	X4	X5	X6	X7	X8	Y
1	21	1	3	73,08	13,90	1	0	1	1
2	31	1	4	78,71	10,68	0	1	1	0
3	56	1	4	51,76	7,53	1	1	1	0
4	16	1	3	73	10,62	1	0	1	1
5	7	0	3	71,24	7,24	0	0	1	1
....	…	…	…	….	…	…	…	…	…

No	X1	X2	X3	X4	X5	X6	X7	X8	Y
240	6	0	4	50,07	55,35	1	1	1	0
241	50	1	4	90,96	17,92	1	1	0	0
242	11	1	3	54,9	15,63	0	0	1	1
243	22	0	3	71,64	12,18	0	0	0	0
244	27	1	4	51,06	10,45	0	0	1	0

3) The process involves dividing the data into two subsets: training data and testing data. This division is performed randomly with an 80% ratio for training data and 20% for testing data, resulting in 195 training data points and 49 testing data points.

2.3 Feature Selection using Backward Elimination

Feature selection impacts the outcome of classification by enhancing the effectiveness and accuracy of classification algorithms. Backward Elimination is a method for feature selection that begins by testing all features and then progressively eliminates insignificant features based on a comparative evaluation of the obtained test results (Achmad Saiful Rizal & Moch. Lutfi, 2020).

Backward Elimination possesses the capability to identify attributes that, while individually exhibiting low classification performance, yield high accuracy when combined with other attributes (Gamadarenda & Waspada, 2020). Backward Elimination is a feature selection method that begins with all features and iteratively removes the least significant feature based on its p-value, until all remaining features have a p-value of less than 0.05. In real-world practice, p-values are typically calculated using statistical software such as Python (statsmodels) or R. However, for manual purposes, we will calculate them using simple logistic regression. Manually computing p-values for logistic regression involves complex statistical calculations. The following is the multiple linear regression equation:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \varepsilon_i \quad (1)$$

Explanation:
Y : Dependent variable
X : Independent variable
β : Regression parameter
ϵ : Error term/standard error of the estimate

2.4 Implementation of Naïve Bayes

The Naive Bayes Classifier algorithm is a probabilistic and statistical classification method used to categorize data into classes. Naive Bayes is a method proposed by British scientist Thomas Bayes in the 18th century, in which classification is carried out using a probability-based approach (Rahman Hakim & Sugiyono, 2024). This method offers several advantages, including the ability to handle both quantitative and discrete data, as well as resistance to isolated noise points. For instance, those that are averaged during the estimation of conditional probabilities. Additionally, it requires only a small amount of training data to estimate the necessary parameters, such as the mean, variance, and variables (Agustian, 2022).

The equation of the Naive Bayes theorem is as follows:

$$P(Y|X) = \frac{P(X|Y).P(Y)}{P(X)} \quad (2)$$

Explanation:
X : Data with an unknown class
Y : Hypothesis that data X belongs to a specific class
P(Y|X) : Probability of hypothesis Y given condition X (posterior probability)
P(Y) : Probability of hypothesis Y (prior probability)
P(X|Y) : Probability of X given the condition of hypothesis Y
P(X) : Probability of X

For numerical features, the following equation is used:

$$P(Xi = xi|Y = yj) = \frac{1}{\sqrt{2\pi\sigma ij}} e^{-\frac{(xi-\mu ij)^2}{2\sigma^2 ij}} \quad (3)$$

Explanation:
P : Probability
Xi : The i-th attribute
Xi : Value of the i-th attribute
Y : Target class
Yi : Subclass of the target class
μ : Mean (average of all attribute values)
σ : Standard deviation (variance of all attribute values)

2.5 Model Evaluation

Model evaluation refers to the process of testing and calculating accuracy using a confusion matrix to assess whether the proposed hypothesis has been achieved. This matrix presents the number of correct and incorrect predictions made by the model compared to the actual values (true labels). It provides a detailed understanding of the model's prediction errors and successes. Precision (or confidence) is the proportion of cases predicted as positive that are actually positive in the real data. Recall (or sensitivity) is the proportion of actual positive cases that are correctly predicted as positive (Muktafin et al., 2020).

Table 3. Confusion Matrix

		Prediction	
		Positive	Negative
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Explanation of the Confusion Matrix table above:

1) True Positive (TP) refers to the number of positive data records that are correctly classified as positive.
2) False Positive (FP) refers to the number of negative data records that are incorrectly classified as positive.
3) False Negative (FN) refers to the number of positive data records that are incorrectly classified as negative.
4) True Negative (TN) refers to the number of negative data records that are correctly classified as negative.

The confusion matrix produces outputs such as accuracy, recall, and precision, which are formulated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$F1 - Score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (7)$$

Accuracy is the percentage of data records correctly classified by an algorithm during testing, compared to the total number of records. It can also be described as a measure of how accurately the model performs classification.

Precision is the number of predicted positive cases that are actually positive in the data, and it is interpreted as the degree of correctness between the requested data and the prediction results generated by the model.

Recall is the number of actual positive cases that are correctly predicted as positive, representing the model's ability to successfully retrieve relevant information.

3. Result and Discussion

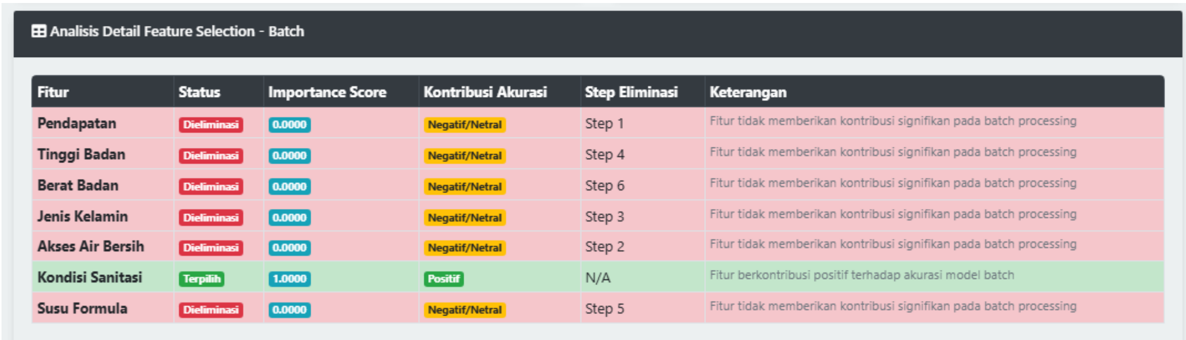
At the initial stage, the Naive Bayes Classifier algorithm was implemented without feature selection. All variables were included in the model training process. The system was developed using a Python-based web application with the Flask framework. The evaluation results of the classification model using all features are as follows:

Table 4. Naive Bayes Evaluation

Metric	Naïve Bayes Classifier
Accuracy	77,55%
Precision	60,00%
Recall	64,29%
F1-Score	62,07%

The evaluation results of the Naïve Bayes Classifier model demonstrate a reasonably good performance in classifying stunting cases. The model achieved an accuracy that indicates the majority of its predictions align with the actual conditions. The precision value shows that among all cases predicted as stunted, only 60% were truly stunted. Meanwhile, the recall value suggests that the model successfully identified approximately 64% of all actual stunting cases. The F1-Score, as the harmonic mean of precision and recall, reflects the model's balanced performance in accurately and comprehensively detecting positive cases.

Subsequently, the classification was carried out using feature selection through backward elimination combined with the Naïve Bayes algorithm, implemented via a web-based application developed using Python and the Flask framework. The results are as follows:



Analisis Detail Feature Selection - Batch

Fitur	Status	Importance Score	Kontribusi Akurasi	Step Eliminasi	Keterangan
Pendapatan	Dieliminasi	0.0000	Negatif/Netral	Step 1	Fitur tidak memberikan kontribusi signifikan pada batch processing
Tinggi Badan	Dieliminasi	0.0000	Negatif/Netral	Step 4	Fitur tidak memberikan kontribusi signifikan pada batch processing
Berat Badan	Dieliminasi	0.0000	Negatif/Netral	Step 6	Fitur tidak memberikan kontribusi signifikan pada batch processing
Jenis Kelamin	Dieliminasi	0.0000	Negatif/Netral	Step 3	Fitur tidak memberikan kontribusi signifikan pada batch processing
Akses Air Bersih	Dieliminasi	0.0000	Negatif/Netral	Step 2	Fitur tidak memberikan kontribusi signifikan pada batch processing
Kondisi Sanitasi	Terpilih	1.0000	Positif	N/A	Fitur berkontribusi positif terhadap akurasi model batch
Susu Formula	Dieliminasi	0.0000	Negatif/Netral	Step 5	Fitur tidak memberikan kontribusi signifikan pada batch processing

Figure 1. Backward Elimination feature selection in the system

Thus, through this iterative process, features such as age, gender, income, height, weight, sanitation, clean water, and formula milk were gradually eliminated. The final result indicated that only the feature 'sanitation condition' met the significance criteria. The evaluation results of the classification model using Naive Bayes with backward elimination are as follows:

Table 5. Evaluation After Selection

Metric	Naïve Bayes Classifier + Backward Elimination
Accuracy	81,63%
Precision	63,16%
Recall	85,71%
F1-Score	72,73%

The use of Backward Elimination for feature selection has successfully improved the model's performance, particularly in terms of recall, which is crucial for the detection of stunting cases. The other evaluation metrics also demonstrate satisfactory results, indicating that this model is suitable for scenarios where early detection of stunting is essential.

3.1 Model Evaluation

The Naive Bayes model was executed twice: first using all features, and second after applying feature selection. The comparative evaluation results are as follows:

Table 6. Evaluation Metrics Before and After Feature Selection

Metric	Initial (All Features)	After Selection (Height Only)	Change (%)
Accuracy	77,55%	81,63%	+4,08%
Precision	60,00%	63,16%	+3,16%
Recall	64,29%	85,71%	+21,43%
F1-Score	62,07%	72,73%	+10,66%

The evaluation results indicate that the feature selection process using Backward Elimination, which retained only the sanitation condition feature, led to an improvement in the performance of the classification model. The most significant enhancement was observed in the recall value, which increased by 21.43%, indicating that the model became more effective in detecting stunting cases. Additionally, the accuracy, precision, and F1-score metrics also showed improvements, reflecting an overall enhancement in model performance.

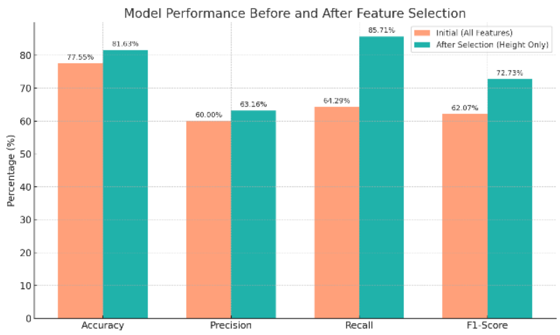


Figure 2. Model comparison

The model was trained using the test data consisting of a total of 49 records.

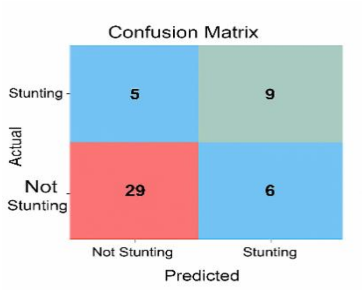


Figure 3. Confusion Matrik

Explanation of the Confusion Matrix:

a. True Positive (TP) = 5; Cases of children who are actually stunted and correctly predicted as stunted by the model.
b. False Negative (FN) = 9; Cases of children who are stunted, but the model incorrectly predicted them as not stunted.
c. False Positive (FP) = 29; Cases of children who are not stunted, but the model incorrectly predicted them as stunted.
d. True Negative (TN) = 6; Cases of children who are not stunted and correctly predicted as not stunted by the model.

3.2 System implementation

3.2.1. Dashboard interface

Based on the dashboard display shown in the provided image, the following are the main features available on the dashboard page:

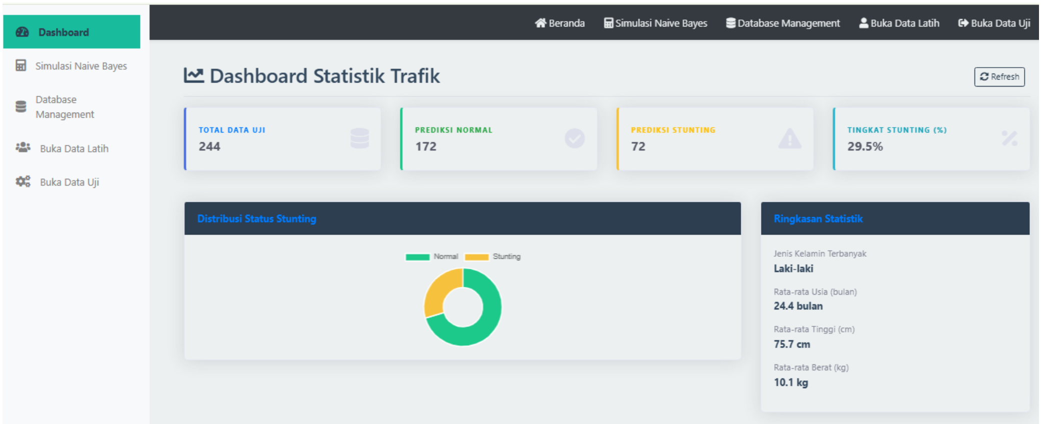


Figure 4. Dashboard Interface

1. Sidebar Navigation: The navigation menu on the left side allows users to switch between pages such as the dashboard, Naïve Bayes simulation, database management, training data viewer, and testing data viewer.
2. Dashboard Overview: Presents a summary of stunting-related information, including the total number of records, prediction results, and the distribution of stunting status.
3. Stunting Prediction Summary: Displays static summaries of stunting predictions based on gender, average age, average height, and average weight.
4. Training Data Table: Shows the training data consisting of columns such as family name, gender, age, height, weight, income, clean water access, sanitation condition, formula milk, and stunting status.
5. Testing Data Table: Displays the testing data with the same attributes as the training data, along with an additional column showing the predicted stunting status.
6. Data Access Buttons: Options at the top of the page allow users to directly open the training and testing data files.

3.2.2. Prediction Page

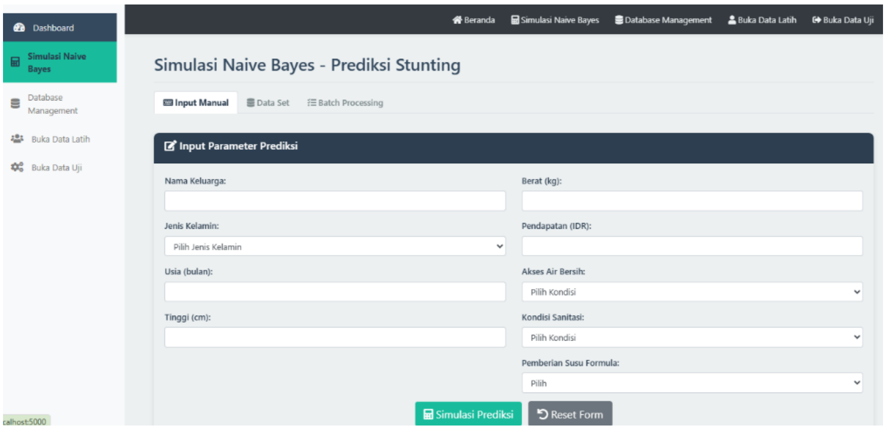


Figure 5. Prediction Page

On this page, users can input new data and check whether the newly entered child data falls into the stunted category or not. Users are required to complete all fields in the form below, including name, gender, age, height, weight, income, access to clean water, sanitation, and formula milk. If any of these fields are left blank, the result cannot be displayed, and the system will prompt the user to fill in the missing information.

3.2.3. Accuracy Page

This page is designed to compute the accuracy, precision, recall, and f1-score metrics.

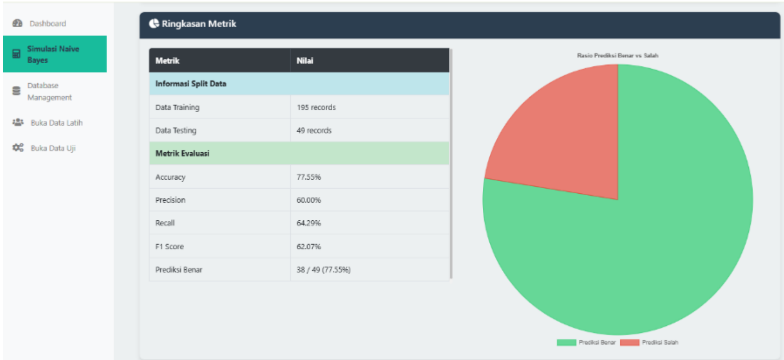


Figure 6. Accurasy Page

3.2.4. File Upload Page

On this page, users can upload data using a file with the `.xlsx` extension.

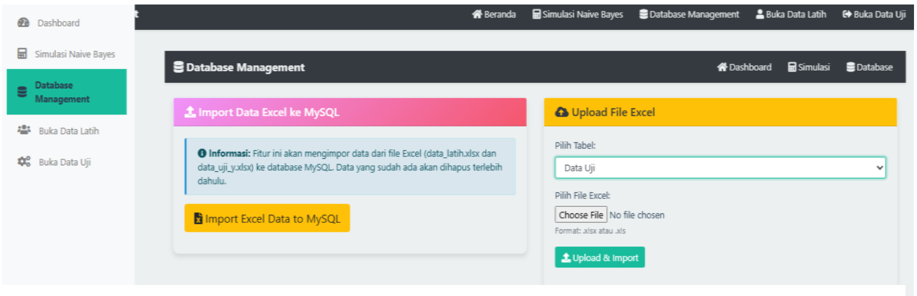


Figure 7. Data Upload

4. Conclusion

Based on the conducted research titled *"Classification of Stunting Status Using the Naïve Bayes Classifier Algorithm with Backward Elimination Feature Selection"*, it can be concluded that this study utilized 224 data records, resulting in 172 predictions of non-stunted and 72 of stunted children. The initial classification using all features achieved an accuracy of 77.55%, precision of 60.00%, recall of 64.29%, and an F1-score of 62.07%. Following the feature selection process, only the sanitation condition feature was found to be most significant. The application of the Backward Elimination method proved to enhance the overall performance of the model. The simplified model showed improved metrics with an accuracy of 81.63%, precision of 63.16%, recall of 85.71%, and an F1-score of 72.73%. The highest improvement was observed in the recall metric, which is crucial in the context of stunting detection, as it reflects the model's ability to correctly identify children who are actually stunted. This indicates that the model performs well in this classification task.

Recommendation for future research on similar topics include:

1) Hybrid Methods: Combining Naïve Bayes with other algorithms such as Random Forest to enhance the prediction accuracy of stunting.
2) Real-Time Monitoring Systems: Utilizing IoT technology for real-time monitoring of child growth integrated with predictive models.
3) Socio-Economic Analysis: Conducting deeper analyses of socio-economic factors such as parental education and access to healthcare to better understand the holistic risks of stunting.

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