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Nutritional Status Classification of Children Using a Decision Tree Method (Case Study at RS AN-NISA) Based on a Web Application

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Keyword

Classification; Decision Tree; Flask; Machine Learning; Nutritional Status

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Abstract

This study develops a web-based classification model for the nutritional status of children aged 0–5 years using the Decision Tree (C4.5) algorithm applied to anthropometric data obtained from RS AN-NISA Tangerang during the period of January–December 2024. The attributes utilized include age (in months), gender, weight, and height, with nutritional status categorized into three classes: undernutrition, normal nutrition, and overnutrition. The dataset underwent a preprocessing phase consisting of data cleaning, removal of extreme values, attribute selection, categorical encoding, normalization, and dataset splitting with an 80% training and 20% testing ratio. The model was constructed using entropy-based splitting criteria with hyperparameter tuning to minimize the risk of overfitting, and its performance was evaluated using accuracy, precision, recall, and F1-score metrics, with Logistic Regression employed as a baseline model for comparison. The results demonstrate that the Decision Tree achieved an accuracy of 96.12% and a macro recall of 89.49%, outperforming the baseline model. The trained model was subsequently serialized and integrated into a Flask-based web application to enable real-time data input and nutritional status prediction. Black-box testing and User Acceptance Testing (UAT) yielded a user satisfaction rate of 88%, indicating that the system is feasible as a practical tool for early detection of child nutritional status in healthcare services.

1. Introduction

Early childhood nutritional status remains a critical concern in public health due to its strong association with physical growth, cognitive development, and long-term health risks. The toddler period (0–5 years) represents a crucial developmental stage, often referred to as the “golden age,” which significantly determines physical growth quality, cognitive development, and overall health resilience in later life. Nutritional imbalance during this period may result in serious consequences such as stunting, wasting, obesity, and long-term developmental disorders that ultimately affect human capital quality [1].

According to the 2022 Indonesian Nutritional Status Survey (SSGI), the national prevalence of stunting remains at 21.6%, although it has decreased compared to previous years. This figure is still considerably higher than the national target of 14% as stated in the National Medium-Term Development Plan (RPJMN). In Banten Province, the prevalence of stunting also remains above 20%, indicating that systematic and continuous efforts in early detection and monitoring of child nutritional status are still required [2].

Clinically, child nutritional status assessment follows the WHO Child Growth Standards, which have been nationally adopted through Regulation of the Minister of Health of the Republic of Indonesia Number 2 of 2020 concerning Child Anthropometric Standards [3]. Assessment is conducted using anthropometric indicators such as age, weight, height, and gender, which are converted into Z-scores to determine nutritional categories, including undernutrition, normal nutrition, and overnutrition [4]. Although this method is medically validated, assessment processes in healthcare facilities are often performed manually, which may lead to inconsistencies, input errors, and longer analysis time, particularly in facilities with high patient volume.

Advancements in machine learning technology offer opportunities to automate the classification process of child nutritional status more efficiently and accurately [5]. The Decision Tree algorithm is widely applied in healthcare classification tasks due to its interpretability and ability to generate clear if–then decision rules, making it suitable for use by non-technical healthcare professionals [6]. Specifically, the C4.5 algorithm is widely recognized for its ability to handle both numerical and categorical data, using entropy and information gain for attribute selection, as well as pruning mechanisms to reduce overfitting. However, practical implementations in modern machine learning libraries may only approximate these characteristics rather than fully replicate the original formulation. [7].

Previous studies have applied the C4.5 algorithm to classify child nutritional status using community or public health center datasets [8], [9]. However, most of these studies primarily focused on algorithmic performance evaluation and did not utilize hospital-based clinical data, which tend to be more complex and reliable. Furthermore, limited studies have conducted comparative evaluations with baseline models such as Logistic Regression to objectively assess the effectiveness of the Decision Tree algorithm [10].

Based on this research gap, this study proposes the development of a Decision Tree-based classification model inspired by the C4.5 algorithm using clinical data of children aged 0–5 years from RS AN-NISA Tangerang for the period January–December 2024. The model employs key anthropometric attributes—age, gender, weight, and height—with nutritional status labels determined by hospital nutritionists according to WHO standards. To evaluate model effectiveness, performance comparison is conducted against Logistic Regression as a baseline model using standard evaluation metrics.

As an additional contribution, the trained classification model is implemented into a Flask-based web interface to display classification results. This web implementation is not intended to serve as a full hospital information system but rather as a simplified interface for running the trained model and presenting prediction results in a practical manner.

2. Research Method

2.1 Research Design

This study is classified as applied research employing a quantitative approach, focusing on the development of a child nutritional status classification model using a Decision Tree model with entropy-based splitting inspired by the C4.5 algorithm. A quantitative approach was selected because the study processes numerical anthropometric data, including age, weight, and height, to construct and evaluate the classification model. The primary objective of this research is to produce an accurate, interpretable, and applicable classification model. The web-based implementation serves solely as a medium to display classification results rather than as a comprehensive hospital information system.

2.2 Dataset and Respondent Characteristics

The dataset used in this study consists of secondary data obtained from the Nutrition Department of RS AN-NISA Tangerang. The data include medical records of children aged 0–5 years who underwent health examinations during the period of January to December 2024. Each data entry represents one child and includes the following primary attributes: age (in months), gender, weight (kg), and height (cm).

The nutritional status labels were determined by hospital nutritionists based on the WHO Child Growth Standards and categorized into three classes: undernutrition, normal nutrition, and overnutrition [4]. The use of hospital-based clinical data ensures that the dataset reflects real-world healthcare conditions and provides a reliable foundation for developing the classification model.After the preprocessing stage, a total of 361 valid records were retained and used for model development and evaluation.

2.3 Data Collection

Data collection was conducted through the retrieval of secondary medical record data from RS AN-NISA Tangerang with official authorization from the hospital. All data had been clinically recorded by professional healthcare personnel. In addition to the primary dataset, this study was supported by a literature review of scientific journals, official WHO documents, and regulations issued by the Ministry of Health of the Republic of Indonesia to strengthen the theoretical foundation and methodological framework.

2.4 Data Preprocessing

The preprocessing phase was carried out to ensure data quality prior to model training. This process included several steps, namely data cleaning by removing missing values, duplicate entries, and inconsistent data to improve dataset reliability. Outlier handling was performed by filtering extreme values in anthropometric measurements using a percentile-based approach (p1–p99) to eliminate unrealistic or clinically invalid data. Furthermore, attribute selection was applied by retaining only relevant variables, including age, gender, weight, and height.

Categorical data, particularly gender, were encoded into numerical format (male = 1, female = 0) to enable algorithmic processing. Subsequently, numerical features were normalized using Min-Max normalization to ensure consistency across attributes. Finally, the dataset was divided into training and testing sets using an 80:20 ratio to evaluate the model's generalization capability [11]. After preprocessing, the dataset consisted of 361 valid records, indicating that all retained data met the required quality criteria [12].

2.5 Decision Tree C4.5 Algorithm

The primary model employed in this study is a Decision Tree classifier inspired by the C4.5 algorithm. The model was implemented using the Scikit-learn library, which provides a DecisionTreeClassifier based on the CART algorithm. To approximate the behavior of C4.5, the entropy criterion was used as the splitting measure, allowing the model to select attributes based on information gain [13]. However, it is important to note that Scikit-learn does not fully implement the original C4.5 algorithm, particularly in terms of gain ratio and pruning mechanisms [14].To control model complexity and reduce overfitting, several hyperparameters were configured, including max_depth, min_samples_split, and min_samples_leaf. which were tuned experimentally using the training dataset. Therefore, the model used in this study should be interpreted as an entropy-based Decision Tree that approximates the characteristics of C4.5 rather than a strict implementation of the original algorithm [9].

2.6 Baseline Model: Logistic Regression

For comparative purposes, Logistic Regression was employed as a baseline model. The baseline model was trained using the same dataset and preprocessing procedures as the Decision Tree model to ensure fairness in performance comparison. The use of Logistic Regression provides an objective benchmark for evaluating the effectiveness of the proposed Decision Tree algorithm [10].

2.7 Model Evaluation

Model performance was evaluated using a confusion matrix and standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of model performance, particularly in healthcare datasets that may exhibit class imbalance. Evaluation was conducted on the testing dataset to measure the model's ability to classify previously unseen data [7].

2.8 System Implementation

The trained classification model was integrated into a Flask-based web interface to allow users to input anthropometric data and obtain real-time nutritional status predictions. The web implementation is intentionally designed to be simple and does not represent a full hospital information system. Instead, it functions as a practical visualization tool for displaying model predictions in an accessible and user-friendly manner for healthcare professionals and general users [15].

3. Result and Discussions

3.1 Dataset Description

The dataset used in this study consists of clinical records of children aged 0–5 years obtained from RS AN-NISA Tangerang for the period January–December 2024. After the preprocessing stage, the dataset includes all valid records that meet the data quality criteria. The nutritional status labels were categorized into three main classes, namely undernutrition, normal nutrition, and overnutrition. The distribution of these classes is not perfectly balanced, where one class dominates the dataset. This imbalance reflects real-world clinical conditions and introduces challenges in ensuring that minority classes are adequately recognized by the classification and introduces challenges in ensuring that minority classes are adequately recognized by the classification model. After preprocessing, the dataset consists of 361 valid records used for model training and evaluation.

3.2 Decision Tree Model Performance

The training results demonstrate that The Decision Tree model successfully generated a clear and interpretable decision tree structure. The model produced classification rules based on combinations of age, weight, height, and gender, which conceptually align with anthropometric assessment mechanisms defined by WHO standards. The resulting decision rules are logical and transparent, supporting their applicability in clinical contexts.

Model evaluation on the testing dataset was conducted using a confusion matrix and standard classification metrics. The Decision Tree achieved an accuracy of 96.12%, with macro precision, macro recall, and macro F1-score values of 89.49%. The weighted averages for precision, recall, and F1-score were each 96%, indicating consistent performance despite class imbalance [16].

Based on the confusion matrix analysis, in the normal nutrition class, the model correctly classified 50 out of 57 instances, with 3 instances misclassified as undernutrition and 4 as overnutrition (recall = 0.88). In the undernutrition class, the model demonstrated excellent performance, correctly identifying 279 out of 282 instances (recall = 0.99). For the overnutrition class, 18 out of 22 instances were correctly classified, with 4 misclassified as normal nutrition (recall = 0.82).

Overall, these results indicate that the Decision Tree model achieves high classification performance and maintains relatively stable recognition across all nutritional status categories, including minority classes. However, further validation using larger and more diverse datasets is required before confirming its applicability in real clinical decision-support scenarios.

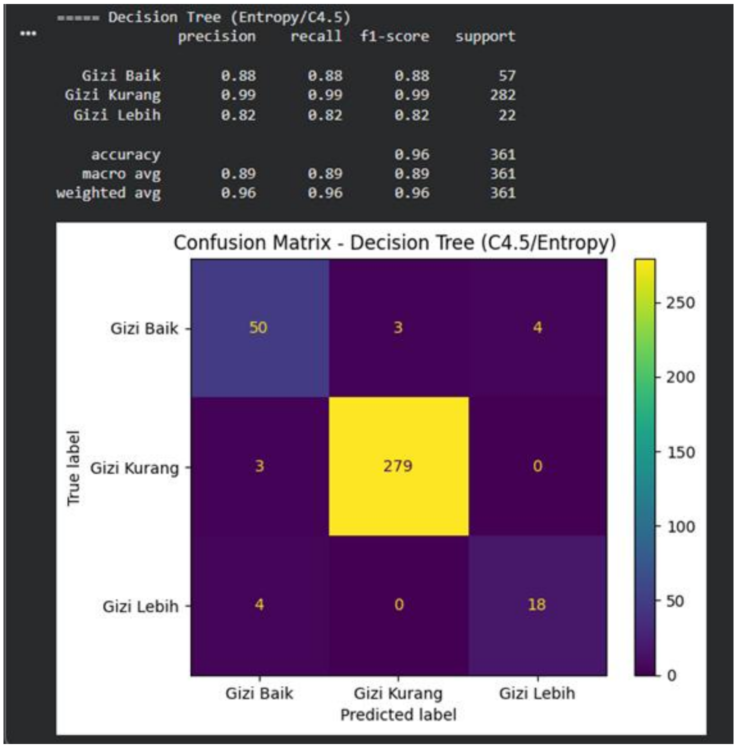


Figure 1. Hasil Confusion Matrix Decision Tree

3.3 Baseline Model Performance: Logistic Regression

For comparison, Logistic Regression was trained using the same dataset and preprocessing procedures [17]. The evaluation results show that Logistic Regression achieved an accuracy of 80.61%, with macro precision of 71.46%, macro recall of 46.05%, and macro F1-score of 50.12%. The relatively low macro recall indicates that the model struggled to recognize all nutritional status classes proportionally.

The confusion matrix reveals that Logistic Regression tended to predominantly predict instances as undernutrition. In the normal nutrition class, only 7 out of 57 instances were correctly classified, while 49 were misclassified as undernutrition and 1 as overnutrition, resulting in a recall of approximately 0.12. This demonstrates the model's limitation in distinguishing normal nutritional status from other categories.In the overnutrition class, only 6 out of 22 instances were correctly classified, with 12 misclassified as undernutrition and 4 as normal nutrition (recall = 0.27).Conversely, Logistic Regression performed very well in the undernutrition class, correctly identifying 278 out of 282 instances (recall = 0.99). However, this dominance in predicting a single class led to significant imbalance in class-level performance and directly reduced the macro-average metrics.

When compared to the Decision Tree model, the performance difference is substantial, particularly in macro recall, where Decision Tree achieved 89.49% compared to 46.05% for Logistic Regression a difference of 43.44%. These findings indicate that Decision Tree is more effective in proportionally recognizing all nutritional status classes, including minority classes, and is more suitable for anthropometric data that exhibit non-linear patterns compared to linear models such as Logistic Regression.

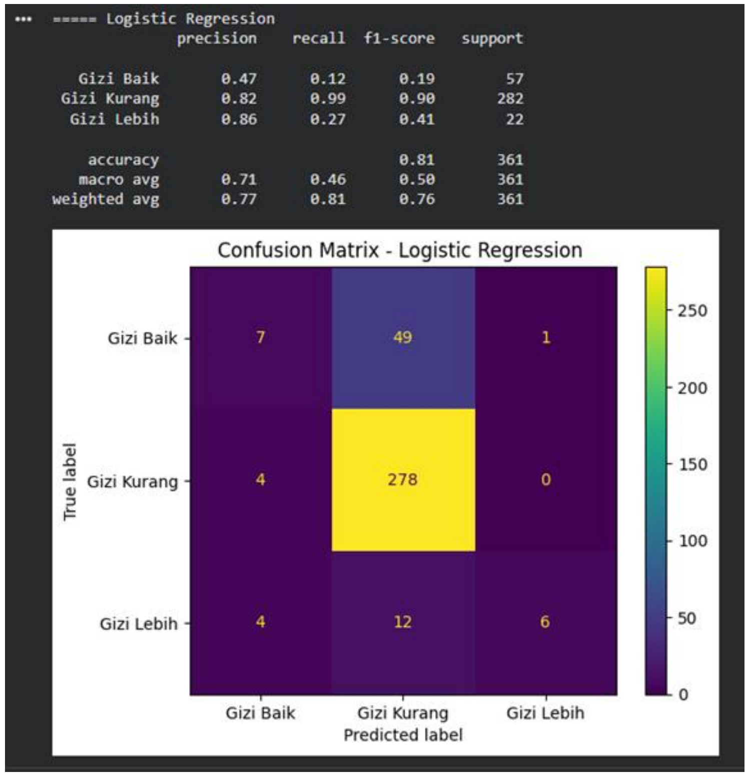


Figure 2. Hasil Confusion Matrix Logistic Regression

The strong performance of the Decision Tree model in this study can be explained by the characteristics of child anthropometric data. The relationships among age, weight, height, and nutritional status are inherently complex and do not always follow linear patterns. Decision Tree algorithms partition the data space into flexible and adaptive decision rules, enabling the model to capture non-linear relationships and interactions among variables more effectively Similar results have been reported in previous C4.5-based studies [18] .

The findings of this study are consistent with those reported by Mahpuz et al. [8] who stated that the C4.5 algorithm demonstrates strong classification performance in determining the nutritional status of toddlers using community health center (posyandu) data. Similarly, Pinaryanto et al. [9] emphasized that the Decision Tree method excels in terms of interpretability and performance stability in healthcare data classification. The results of the present study reinforce these previous findings, [19] by demonstrating that the C4.5 algorithm remains effective when applied to hospital-based clinical data, which typically exhibit higher levels of recording consistency and measurement reliability.

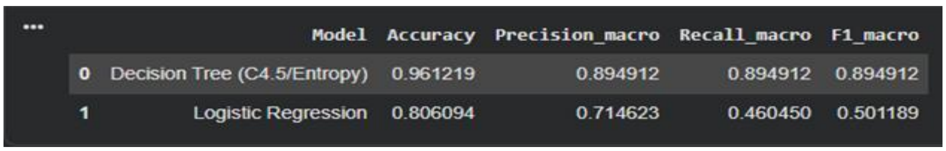
In comparison with the study conducted by Mawardi et al. [20] which compared C4.5 and Naïve Bayes, this research employs Logistic Regression as a baseline model to evaluate the capability of a linear model in handling anthropometric data. The relatively low macro recall achieved by Logistic Regression (46.05%) indicates the limitations of linear models in proportionally recognizing all classes, particularly minority classes. This finding suggests that non-linear approaches such as Decision Tree are more suitable for classifying child nutritional status based on anthropometric measurements.

Beyond predictive performance, interpretability represents a crucial consideration in healthcare contexts. The decision tree structure generated by the Decision Tree algorithm enables healthcare professionals to understand the basis of model decisions through transparent if–then rules. This supports the recommendation of Larose and Larose [6] who emphasized the importance of explainable models in decision-support systems.

Furthermore, the results of this study confirm that the use of hospital-based clinical data offers advantages over community or posyandu datasets due to better measurement quality and greater consistency in data recording. By leveraging real clinical data, the developed Decision Tree model demonstrates strong computational performance and shows potential as a supporting tool for early-stage nutritional status assessment for child nutritional status within healthcare service environments. These findings strengthen the conclusion that the Decision Tree (C4.5) approach is more appropriate than linear models such as Logistic Regression for anthropometric-based child nutritional status classification.

Tabel 1. Perbandingan Performa Model (Decision Tree vs Logistic Regression)

Model	Accuracy (%)	Precision Macro (%)	Recall Macro (%)	F1-Score Macro (%)
Decision Tree (C4.5/Entropy)	96.12	89.49	89.49	89.49
Logistic Regression	80.61	71.46	46.05	50.12



	Model	Accuracy	Precision_macro	Recall_macro	F1_macro
0	Decision Tree (C4.5/Entropy)	0.961219	0.894912	0.894912	0.894912
1	Logistic Regression	0.806094	0.714623	0.460450	0.501189

Figure 3. Hasil Perbandingan

3.4 System Testing and User Acceptance

The trained classification model was implemented into a Flask-based web interface to display real-time classification results. Functional testing was conducted using a black-box testing approach, and the results showed that all primary features, including input validation and the display of classification results, operated as expected.

In addition, User Acceptance Testing (UAT) conducted with healthcare professionals indicated a user satisfaction rate of 88%, which falls within the “good” category. These results suggest that the system is user-friendly, responsive, and capable of practically supporting the process of determining children’s nutritional status.

Tabel 1. Hasil Black Box Testing

No	Feature Tested	Testing Scenario	Expected Result	Test Result	Status
1	Input Page	Open the system web page	Input page is displayed with a complete form	Page displayed	Successful
2	Valid Data Input	Age ≤ 5 years, valid weight and height	Data processed and classification result displayed	Classification result displayed	Successful
3	Age Validation	Age > 5 years	System rejects input and displays an error message	Error message displayed	Successful
4	Numeric Format Validation	Input using comma/decimal format	System accepts and processes the data	Data processed	Successful
5	Classification Process	Valid data sent to the model	System displays nutritional status	Nutritional status displayed	Successful
6	Abnormal Data Warning	Weight/height outside training range	System still predicts and displays a warning	Warning displayed	Successful
7	Reset Form	Click reset button	Form returns to empty state	Form reset	Successful

Tabel 3. Keterangan

Score	Description
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

Tabel 2. Hasil UAT

No	Statement	User 1	User 2	User 3	Average
1	Ease of system use	4	5	4	4.33
2	System interface design	4	4	5	4.33
3	Classification processing speed	5	4	5	4.67
4	Clarity of classification results	4	5	4	4.33
5	Usefulness of the system for healthcare professionals	5	5	4	4.67

$$Maximum\ Score = 5\ (highest\ score) x\ 5\ statements\ x\ 3\ respondents = 75 \quad (1)$$

$$Total\ Score\ Obtained = (4.33 + 4.33 + 4.67 + 4.33 + 4.67)\ x\ 3 = 66 \quad (2)$$

$$Satisfaction\ Percentage : (1) \quad (3)$$

$$Satisfaction\ (\%) = \frac{66}{75} x\ 100\ (\%) = 88\ \% \quad (4)$$

The user satisfaction rate of 88% indicates that the system is generally well received in terms of usability, processing speed, and clarity of the displayed results. However, it is important to note that the User Acceptance Testing (UAT) involved only three respondents; therefore, the results should be interpreted as preliminary usability feedback rather than conclusive evidence of system effectiveness in healthcare practice. Accordingly, the system demonstrates potential as a supporting tool for early-stage nutritional status assessment, but further evaluation involving a larger number of users is required to validate its practical applicability.

4. Conclusions and Future Works

4.1 Conclusions

This study developed a classification system for the nutritional status of children aged 0–5 years using the Decision Tree C4.5 algorithm, utilizing clinical data from RS AN-NISA Tangerang during the period of January to December 2024. The model was constructed using key anthropometric attributes, namely age, gender, weight, and height, along with nutritional status labels determined by hospital nutritionists in accordance with World Health Organization (WHO) standards. Based on the evaluation results, the Decision Tree C4.5 algorithm demonstrated optimal classification performance on the testing dataset, with more stable evaluation metrics compared to Logistic Regression as the baseline model.

The superiority of the Decision Tree model in this study is reflected in its ability to handle non-linear relationships and complex interactions among anthropometric variables. The recall values indicate that the model was able to identify each nutritional status category proportionally, including categories with relatively fewer instances. Furthermore, the resulting decision tree structure is interpretable and easy to understand, making it suitable as a decision-support tool for healthcare professionals without requiring in-depth technical knowledge of machine learning.

These findings indicate that the application of the Decision Tree model to hospital-based clinical data demonstrates promising potential for supporting the assessment of child nutritional status. However, the system should be considered as a supporting tool rather than a replacement for professional medical assessment, and further validation is required before broader clinical implementation.

4.2 Future Works

Although this study demonstrates promising results, several limitations remain that provide opportunities for future research. The dataset used in this study was limited to a single healthcare institution and a specific time period; therefore, the generalizability of the model to broader populations has not been comprehensively evaluated. Future studies are recommended to incorporate data from multiple hospitals or healthcare facilities over longer time periods in order to enhance the robustness and external validity of the model.

In addition, the variables used in this study were limited to basic anthropometric parameters. Further development may consider incorporating additional supporting variables, such as medical history, dietary intake patterns, and environmental or socioeconomic factors that may influence child nutritional status. From a methodological perspective, the application of more rigorous validation techniques, such as k-fold cross-validation, as well as strategies for handling class imbalance, could be implemented to improve model performance stability.

From an implementation standpoint, the developed web-based system remains relatively simple and is not yet integrated with a database or a comprehensive health information system. Future enhancements may include the storage of classification history, automated report generation, and improvements to the user interface to make the system more informative and sustainable for long-term use in healthcare service environments.

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