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Child Nutrition Prediction for Stunting Prevention Using the K-Nearest Neighbor (K-NN) Algorithm

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Abstract. Stunting is a significant public health issue in Indonesia, affecting both children's physical growth and cognitive development. This study aims to develop a child nutritional status prediction application using the K-Nearest Neighbor (K-NN) algorithm as an early detection tool for stunting prevention. The model classifies nutritional status into five categories: good nutrition, poor nutrition, undernutrition, overnutrition, and obesity, using anthropometric data such as age, weight, height, and gender. The dataset comprises 49,766 samples of children aged 0–5 years from the Bangka Belitung Islands Provincial Health Office. The data processing included normalization, feature selection, and k-value testing to optimize model performance. Evaluation results showed that K-NN with k = 2 achieved 92% accuracy, with the best precision and recall in the good nutrition category (0.94 and 0.99). However, performance in minority categories like malnutrition remains low due to data imbalance. The weighted averages for precision, recall, and F1-score were 0.90, 0.92, and 0.90, respectively. This research's novelty lies in integrating the K-NN model into a mobile application, enabling real-time nutritional status assessment for health workers, improving fieldwork efficiency, and facilitating early detection and monitoring.

Keywords: K-Nearest Neighbor, child nutrition prediction, stunting prevention, classification, artificial intelligence

1. INTRODUCTION

Stunting is one of the chronic nutritional problems that is still a major health issue in Indonesia and other developing countries. The government pays serious attention to this problem, as stated in the 2020-2024 National Medium-Term Development Plan (RPJMN) through Government Regulation No. 18 of 2020 which targets a reduction in stunting prevalence by 24% by 2024 [1], [2]. According to UNICEF (2023), around 22.3% of children under five in the world are stunted, and Indonesia ranks fifth highest globally [3]. Stunting is generally caused by chronic malnutrition from pregnancy to the age of two, which impacts physical growth, brain development, and long-term productivity [4],[5],[6]. Therefore, monitoring children's nutritional status through anthropometric indicators such as weight and height is an important step in early prevention [7],[8],[9]. However, the manual monitoring mechanism in posyandu or health facilities still faces limitations, especially in the speed and accuracy of data interpretation.

In addition, challenges related to data quality and consistency are the main issues in stunting risk detection and classification of nutritional status in general. Variations in data sources, different recording methods, inaccuracies during anthropometric measurements, and imbalances in the distribution of samples per nutritional category can reduce model performance [10]. This challenge is exacerbated by the high potential for human error in manual assessments by health workers, such as misreadings of measuring instruments, inaccurate recording, or misinterpretation of growth charts. This condition shows the urgent need for a more objective, consistent, and adaptive system in managing large-scale data, so that machine learning can be a strategic solution in supporting the evaluation of nutritional status more accurately and efficiently [11].

Advances in information technology encourage the use of machine learning in the classification and prediction of the nutritional status of toddlers. Previous studies have adopted algorithms such as Naïve Bayes, Support Vector Machine (SVM), Decision Tree, and Random Forest, but each has its limitations. The Naïve Bayes algorithm is sensitive to data imbalances resulting in less stable accuracy [12],[13],[14]. SVM offers high performance, but requires large computations, especially on large-scale datasets [15],[16]. Decision Tree is easy to interpret, but its performance degrades when dealing with data that has high noise levels [17]. Meanwhile, Random Forest is relatively powerful but less efficient when implemented on small datasets or environments with computational limitations [18],[19]. Looking at these conditions, there is a fairly clear research gap: most of the previous models are too complex, require large resources, are less stable under varying field data conditions, and are not optimal for direct use by health workers at the basic service level.

In this context, the K-Nearest Neighbor (K-NN) algorithm is a relevant alternative because it is simple, easy to implement, does not require a heavy model training process, and has high interpretability in decision-making [20], [21]. K-NN works based on the proximity of feature values to similar data, so it is suitable for monitoring nutritional status with anthropometric data that is numerical and easily collected regularly [22]. In addition, the flexibility of K-NN allows direct integration into mobile applications without requiring high computing capabilities, making it practical to use in posyandu environments, health centers, and by parents at home [23].

This research aims to develop a child nutrition status prediction system based on the K-NN algorithm which is integrated in an interactive mobile application as an aid for early detection of stunting risk. The novelty of this study lies in three main aspects: (1) the utilization of large-scale datasets from 49,766 samples of children aged 0–5 years; (2) integration of the K-NN model into mobile applications that enable real-time prediction without special computing devices; and (3) focus on providing solutions that are balanced between accuracy, efficiency, and ease of implementation in the field. Thus, this research is expected to increase the effectiveness of early detection of stunting and strengthen nutrition interventions at the level of public health services.

2. METHODS

This study uses a supervised machine learning approach based on the K-Nearest Neighbor (K-NN) algorithm to predict the nutritional status of children as part of efforts to detect the risk of stunting early. K-NN was chosen because it is able to perform intuitive distance-based classification, does not require data distribution assumptions, and works effectively on numerical and small to medium-sized anthropometric data. The model is also easy to implement in mobile applications because the computation structure is simple and does not require complex training processes. The dataset used

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was obtained from the Bangka Belitung Islands Provincial Health Office in 2024, consisting of 49,766 data on children aged 0–5 years with age, gender, weight, height, and nutritional status features as labels. The data then goes through a pre-processing process before being tested using k-value variations to get the best performance based on accuracy, precision, recall, F1-score, and confusion matrix metrics. The stages of the research can be seen in Figure 1.

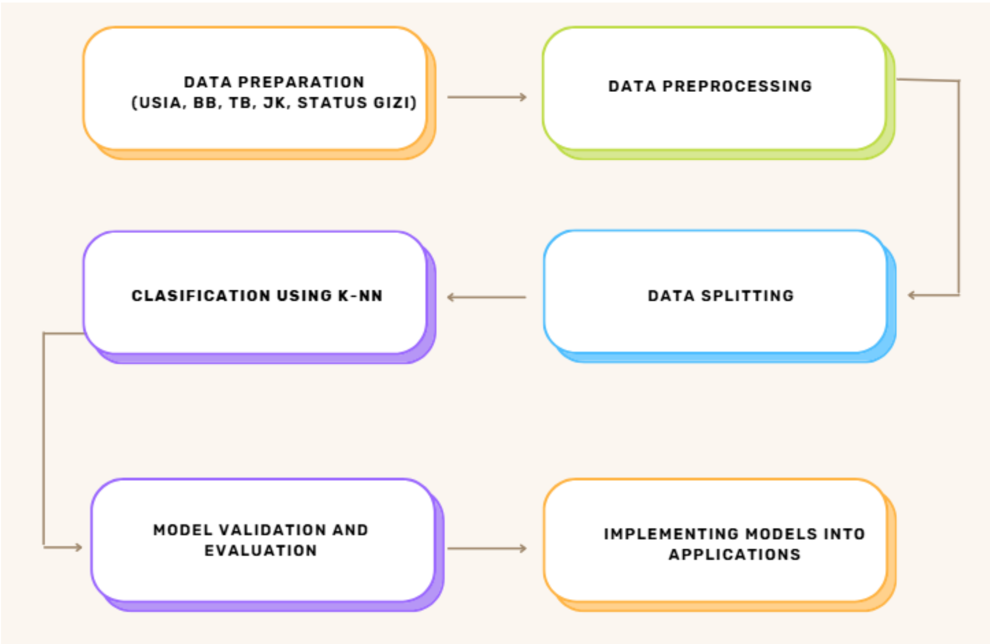

Figure 1. Research Stages

2.1 Data Preparation

This stage includes the collection and initial examination of the dataset to ensure the completeness and validity of the data. The variables used (age, weight, height, gender) were examined to detect duplication, entry errors, as well as the distribution of nutritional status labels. At this stage, initial data exploration was also carried out to understand the characteristics of the dataset and the conditions of class imbalance.

2.2 Data Preprocessing

Pre-processing is carried out to produce clean, structured, and ready-to-use data in the K-NN model. The process includes: Data cleaning, Normalization of numerical features, and Encoding gender and nutritional status.

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2.3 Data Splitting

The dataset is divided into 80% training data and 20% test data using the train_test_split function [24]. This separation aims to train the model on the majority of data while testing generalization capabilities on data that has never been seen before. The 80:20 ratio was chosen based on previous studies that showed optimal performance in distance-based models such as K-NN.

2.4 Clasification Using Model K-NN

The K-NN model was built using the scikit-learn library. The stages include:

1) Determination of the range of k values (1–15) to be tested systematically, This study uses a value range of k = 1 to k = 15 to determine the best configuration that produces optimal performance.
2) the use of Euclidean distance as a measure of proximity between data, The classification process in K-NN relies heavily on the calculation of the distance between samples. The Euclidean formula as shown in Equation 1.

$$d = \sqrt{\left\{\sum_{\{i=1\}}^{\{p\}}\left(x_{\{2i\}} - x_{\{1i\}}\right)^2\right\}} \qquad (1)$$

Where d = Euclidean distance, x2i = value on test data to -I, x1i = value in the training data to- 1, and p = number of attributes. K-NN is used to classify nutritional status into categories: Good nutrition, poor nutrition, undernutrition, overnutrition, obesity, and overnutrition risk.

2.5 Model Validation and Evaluation

Model performance was validated using the k-fold cross-validation technique to reduce evaluation bias. The model is evaluated using metrics such as Accuracy, Precision, Recall, F1-score, Confusion Matrix [25]. The hyperparameter optimization process is performed using GridSearchCV to determine the best k-value that provides the highest performance.

3. RESULTS AND DISCUSSION

The study consists of seven main stages: data preparation, pre-processing, breakdown of the data into training and testing sets, classification using the KNN model, hyperparameter optimization using the SearchCV Grid for the KNN model, and finally, obtaining the best classification results based on evaluation metrics such as accuracy.

3.1. Preparing Data

This research uses a 2024 data set sourced from the Provincial Health Office. Bangka Belitung District. The dataset contains some of the key features for predicting child nutrition which can be seen in Table 1.

Table 1. Child Nutrition Dataset

No	JK	Age	Weight	Height	Nutritional Status
1	P	9	8	70	Good Nutrition
2	L	55	18	109	Good Nutrition
3	L	46	15	101	Good Nutrition
4	L	57	18	105	Risk of Overnutrition
......	......	......	......	......	......
49764	L	55	18	110	Good Nutrition
49765	P	47	16	109	Good Nutrition
49766	L	48	18	105	Risk of Overnutrition

Table 2. Encoding Dataset

No	JK	Age	Weight	Height	Nutritional Status
1	1	9	8	70	0
2	0	55	18	109	0
3	0	46	15	101	0
4	0	57	18	105	5
......	......	......	......	......	......
49764	0	55	18	110	0
49765	1	47	16	109	0
49766	0	48	18	105	5

Based on Table 1, the Dataset consists of 5 features with a total of 49766 data. Out of the 5 features, one feature is selected as the target variable, while the other 4 features serve as inputs. The targeted feature is "Nutritional Status". After the dataset is

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determined, the next process is encoding, namely on the "Gender" and "Nutritional status" features as shown in Table 2. Based on the previous dataset, it can be seen that there has been a data imbalance in each class, so that data balancing is carried out with "SMOTE" as shown in figures 2 and 3.

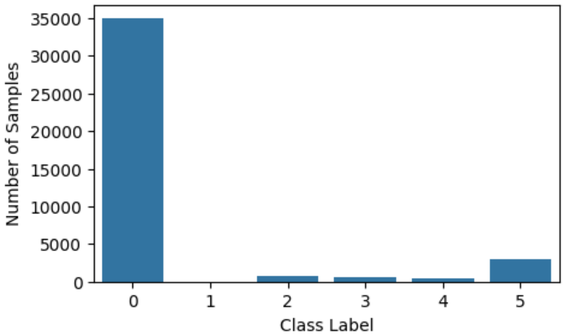

Figure 2. Class distribution before SMOTE

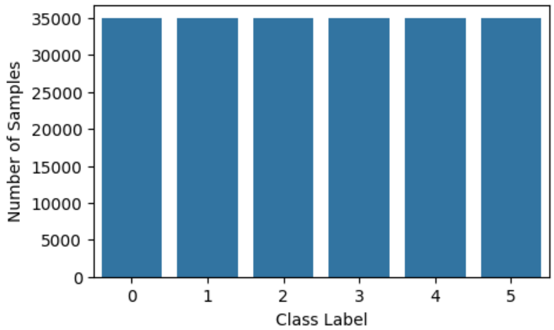

Figure 3. Class distribution after SMOTE

3.2. Data Splitting

The data in this study is divided into two parts, namely training data and testing data. This division is created so that the model can learn from training data and then test it with test data to evaluate its performance. The data separation is shown in Figure 4. Based on Figure 4, the input variable is stored in X, while the target variable is stored in y. The data is divided using an 80:20 ratio, 80% data for training and 20% for testing.

```
scaler = MinMaxScaler()
x_train_scaled = scaler.fit_transform(x_train_res)
x_test_scaled = scaler.transform(x_test)
```

Figure 4. Data Split Process

3.3. Classification Model K-NN

The confusion matrix in figure 4 shows that the K-NN model that has been optimized through Grid Search performs very well in the majority category, especially Good Nutrition, with 8,610 correct predictions and only a small number of errors to other classes. However, the model still has difficulty recognizing minority classes such as Malnutrition and Undernutrition, because the amount of data is very small. This can be seen from the Malnutrition class which was only detected 0 times correctly, while Malnutrition was only detected 46 times from all samples. A fairly frequent

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misclassification is the move to the Excess Nutrition Risk category, for example 309 samples of Excess Nutrition Risk were incorrectly predicted as Good Nutrition. Meanwhile, the Obesity category performed well, with 73 predictions correct and only a few misclassified to Nutritional Over. Overall, this confusion matrix confirms that the model works optimally in classes with large amounts of data, but there is still room for improvement in classes with a small sample count, so that data balancing techniques or the addition of additional features can be a solution in future studies. The results of the confusion matrix can be seen in Figure 5, while the classification report can be seen in Table 3.

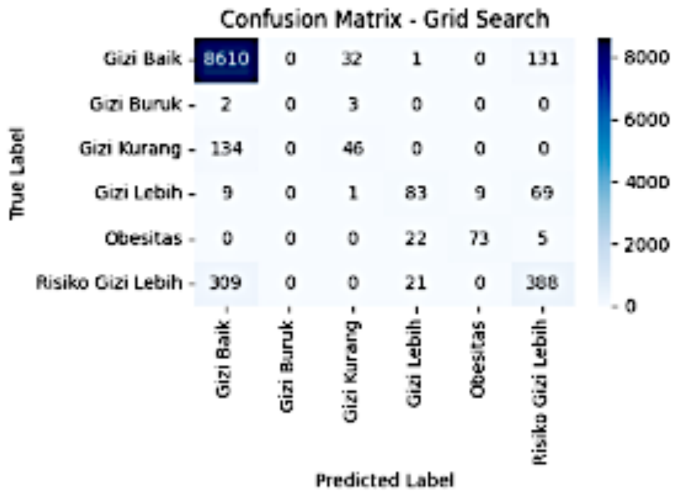

Figure 5. Confusion Matrik-Grid Search

Table 3. Classification Performance K-NN

Nutrition Status	Precision	Recall	F1-Score
Good Nutrition	0.95	0.98	0.97
Malnutrition	0.00	0.00	0.00
Undernutrition	0.56	0.26	0.35
Overnutrition	0.65	0.49	0.56
Obesity	0.89	0.73	0.80
Risks of Overnutrition	0.65	0.54	0.59

Based on table 3, the results of the evaluation in the classification table show that the K-NN model performs very well in the Good Nutrition category, with a precision of 0.95, recall of 0.98, and an F1-score of 0.97, indicating the model's strong ability to recognize

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the majority class. In contrast, the Malnutrition category scored 0 on all metrics, indicating that the model failed to detect these cases because the amount of data was so small and the patterns were difficult to study. In the Malnutrition category, the model's performance was still low (precision 0.56, recall 0.26, F1-score 0.35), indicating that there was often a misclassification of the dominant class. The Overnutrition category showed moderate performance (precision 0.65, recall 0.49, F1-score 0.56), illustrating the overlapping pattern with the Overnutrition Risk class. For Obesity, the model gave fairly good results with a precision of 0.89, a recall of 0.73, and an F1-score of 0.80, suggesting that this class has a clearer pattern. Meanwhile, the Overnutrition Risk category showed moderate performance (precision 0.65, recall 0.54, F1-score 0.59), which indicates that the model still faces challenges in distinguishing this borderline class from Overnutrition and Good Nutrition. Overall, this table shows that the performance of the model is greatly influenced by the class size and the proximity of patterns between nutritional status categories and supports the implementation of early detection of nutritional status through mobile applications.

3.4. Validation and Evaluation of the K-NN Model

The KNN model is built using the Kneighbors Classifier function from the sklearn.neighbors. library The classification process involves testing the value k, which is k=1-15. Hyperparameter optimization is done using GridSearchCV to determine the best k-value that provides the highest performance. The results of validation and evaluation of the model that have been optimized can be seen in Table 4 and Figure 6.

Table 4. k Value and Accuracy of Grid Search Model

k Value	Training Accuracy	Testing Accuracy	k Value	Training Accuracy	Testing Accuracy
1	0.949433	0.912545	**8**	0.964387	0.926116
2	0.959386	0.923703	**9**	0.964312	0.925111
3	0.961648	0.924809	**10**	0.964463	0.924608
4	0.963558	0.926819	**11**	0.964513	0.924507
5	0.963633	0.927322	**12**	0.964538	0.923703
6	0.964312	0.927322	**13**	0.964538	0.924005
7	0.964186	0.925915	**14**	0.964538	0.924005

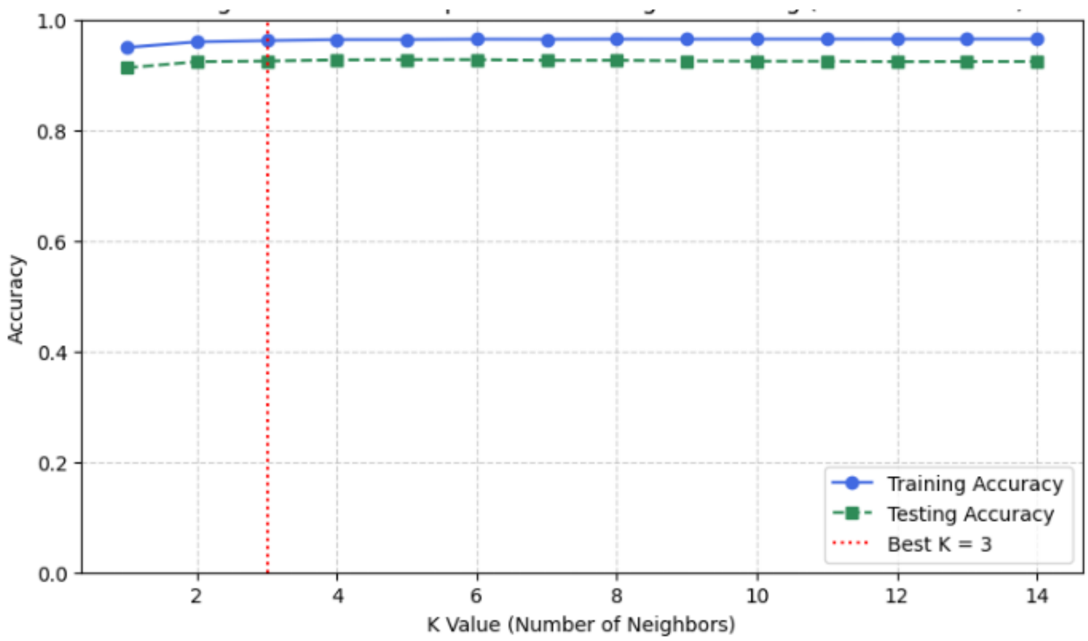

Figure 5. The relationship of K value to Training and Testing Accuracy (Grid Search K-NN)

The results of the accuracy test based on Table 4 show the K value with the smallest difference between training and testing, which is k=2 with a training accuracy value of 0.959386 and a testing accuracy of 0.923703, and a value difference of 0.035683. Meanwhile, Figure 5 shows that the accuracy test of the K-Nearest Neighbor algorithm for the nutritional status of children that has been optimized with Grid Search is 92% with the best k value of k = 3.

3.5. Implementation of the K-NN Model

The implementation of the K-NN model into a mobile-based application was carried out based on the validation and evaluation results. The user interface of the application, showcasing its functionalities, is illustrated in Figures 6, 7, 8, and 9. Figure 6 displays the Nutritional Status Page, which serves as the main screen for users to calculate or determine nutritional status based on three key indicators: BB/U (Weight-for-Age), TB/U (Height-for-Age), and TB/BB (Height-for-Weight). This page allows users to input the required data to evaluate the child's nutritional status using the K-NN model. Figures 7 to 9 demonstrate how the system facilitates real-time nutritional status assessment. These figures show the steps involved in selecting the desired nutritional category, processing the input data, and generating the results based on the K-NN classification.

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The intuitive layout and design of the application ensure that health workers can easily assess and monitor a child's nutritional status with minimal effort.

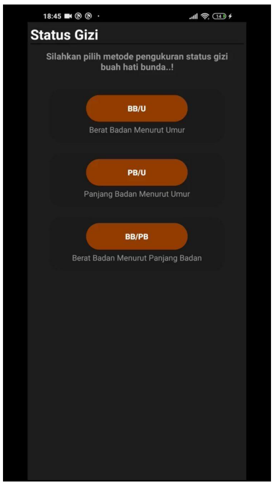

Figure 6. Nutritional Status Page

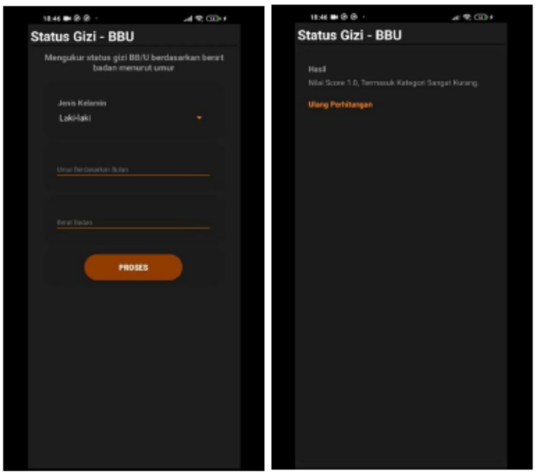

Figure 7 Nutritional Status Page BB/U

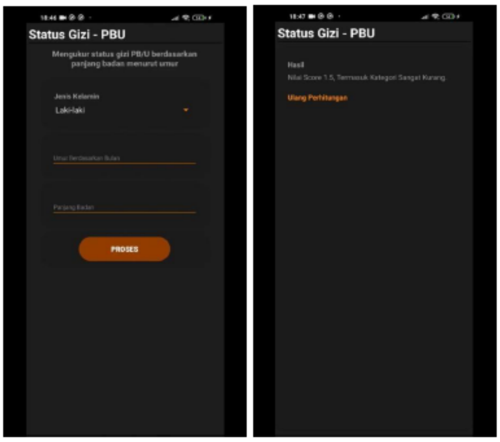

Figure 8. Nutritional Status Page TB/U

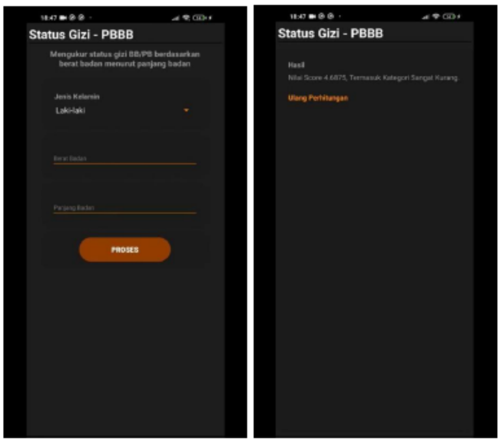

Figure 9. Nutritional Status Page TB/BB

3.6. Discussion

Stunting remains a significant public health challenge in Indonesia and other developing nations, with the Indonesian government committing to reducing stunting prevalence by 24% by 2024 through the National Medium-Term Development Plan (RPJMN). Globally, Indonesia ranks fifth in terms of stunting prevalence, with 22.3% of children under five being affected, according to UNICEF. Stunting, caused by chronic malnutrition, particularly in the critical first two years of life, has profound effects on both physical growth and cognitive development. Early and accurate detection of stunting is crucial to mitigate long-term consequences. However, traditional methods of nutritional monitoring in

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health centers face limitations, including data quality, human error, and inefficiency in interpreting anthropometric data.

This study aims to address these limitations by using machine learning, specifically the K-Nearest Neighbor (K-NN) algorithm, integrated into a mobile application for real-time nutritional status prediction. One of the key findings of this study is the effectiveness of the K-NN algorithm, which provides a simple yet powerful solution for classifying nutritional status using data that is easily collected, such as weight, height, and age. The model's simplicity, interpretability, and ability to function with minimal computational resources make it highly suitable for use in mobile applications, especially in community health settings like posyandu (integrated health posts).

Data quality and consistency, particularly the imbalance in nutritional status categories, remain a challenge. The K-NN algorithm performed well in identifying major categories like "Good Nutrition," achieving high accuracy in classification. However, the model struggled with minority categories, such as "Malnutrition" and "Undernutrition," due to the low frequency of these cases in the dataset. This challenge reflects a common issue in predictive modeling: the importance of addressing class imbalances to improve the model's ability to detect less-represented conditions. Future studies could explore advanced techniques such as data augmentation or the use of ensemble methods to enhance the model's performance on these minority classes.

The results of the model's evaluation show an overall accuracy of 92%, with the K-NN model performing optimally with a k-value of 3, providing a good balance between training and testing accuracy. While the model excelled in major categories, there is room for improvement in identifying edge cases like "Malnutrition" or "Undernutrition." The introduction of synthetic data balancing methods such as SMOTE, or incorporating additional features, could help mitigate this issue. Additionally, incorporating expert knowledge into the fuzzy logic or refining the feature selection process may improve the classification of borderline categories.

Incorporating the K-NN model into a mobile application for real-time prediction is a significant step forward in the fight against stunting. The app allows health workers to monitor children's nutritional status efficiently, reducing the reliance on manual processes, and ensuring faster detection of potential stunting risks. The intuitive user interface, as demonstrated in the figures, allows for easy data entry and instant feedback on nutritional status, empowering health workers and parents alike to take timely actions to improve children's nutritional outcomes.

The study shows the feasibility and effectiveness of using the K-NN algorithm in mobile applications for early detection of stunting risk. By addressing the challenges related to class imbalance and incorporating advanced data handling techniques, future versions of the model could provide even more accurate predictions, supporting better decision-making in child health monitoring and intervention programs.

4. CONCLUSION

This research succeeded in achieving all the set objectives, namely developing a model for predicting children's nutritional status based on the K-Nearest Neighbor (K-NN) algorithm and integrating it into an interactive mobile application as a tool for early detection of stunting risk. The results of the experiment showed that K-NN was able to work effectively on a large dataset of 49,766 samples, with very good performance in the majority category such as Good Nutrition (precision 0.94; recall 0.99; F1-score 0.96) and Obesity (precision 0.90; recall 0.69; F1 score 0.78). The study also confirms that the integration of the model into mobile applications allows the prediction process to be carried out in real-time without the need for special computing devices, so that it can be used directly by healthcare workers in the field. In addition, the goal of providing a solution that balances accuracy, efficiency, and ease of implementation is also achieved through a lightweight system architecture, a fast classification process, and an easy-to-use interface. This research can be developed by adding other supporting features such as parental health history, daily diet, environmental factors, and immunization history to improve accuracy, especially in minority classes such as Malnutrition and Malnutrition. In addition, the mobile application can be improved with periodic monitoring features, an early warning system, and integration with the information system of health centers or regional health offices.

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