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Detection of Nutritional Status using K-Nearest Neighbors on a Mobile Based Platform

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Abstract

In recent decades, health issues related to nutritional status have become a major concern for the Indonesian government. Malnutrition or overnutrition can severely impact individual health, especially in children and adolescents. If left unaddressed, these issues can lead to various diseases, ranging from malnutrition to obesity and their associated complications. Despite the recognized importance of monitoring nutritional status, several challenges remain. Manual monitoring systems require significant time and resources. Moreover, access to healthcare services and qualified medical personnel for regular nutritional assessments is limited, particularly in remote or underserved areas. Indonesia's geographical complexity, consisting of thousands of islands, further complicates the equitable distribution of healthcare services. As a result, many cases of malnutrition or overnutrition go undetected early, causing delayed interventions. This research proposes the development of a K-NN-based mobile application to detect nutritional status. The application provides an initial diagnosis based on the user's physical parameters, such as weight, height, age, and gender. The dataset includes 120,999 samples, with 70% used for training and 30% for testing. Implementation of K-NN with k=7 achieved an accuracy of 91% on the test data, with the best performance in the normal category (F1-score 0.950), followed by stunted (0.889) and severely stunted (0.863). This platform has the potential to contribute to sustainable health systems, particularly in low-resource settings, by reducing reliance on energy-intensive infrastructure and minimizing the need for long-distance travel for healthcare. It could also support public health initiatives by enabling efficient large-scale population monitoring and reducing the environmental impact of traditional health services.

Keywords: Healthcare; K-Nearest Neighbors (KNN); Mobile Application; Nutritional.

1. Introduction

Nutritional status is an important indicator in assessing individual health and development, especially in children and adolescents (R. Rewane and P. M. Chouragade, 2019). Nutritional problems are a global health challenge that has a significant impact on the quality of life and human development (Utami et al., 2023). In Indonesia, nutritional problems such as malnutrition, stunting and obesity are serious issues that require special attention. According to data from the Ministry of Health of the Republic of Indonesia, the prevalence of stunting among toddlers has reached an alarming figure, while cases of obesity in children and adults are also showing an increasing trend. This condition requires immediate and appropriate intervention to reduce the negative impacts that may occur in the future (Mansouri et al., 2023).

In recent decades, health problems related to nutritional status have become a major concern for the Indonesian government (Mutammimul Ula, Ananda Faridhatul Ulva, Mauliza, et al., 2022). Malnutrition or excess nutrition can have a negative impact on individual health, especially children and adolescents (Yanto et al., 2024). Unbalanced nutritional status can cause various diseases, ranging from nutritional deficiencies to obesity and the complications that accompany it. Considering the importance of monitoring nutritional status, developments in information technology offer more efficient solutions in detecting nutritional status quickly and accurately via mobile devices (Yuliana et al., 2024).

Although the importance of monitoring nutritional status has been recognized, several problems still pose obstacles to its implementation. Manual monitoring of nutritional status often requires a lot of time and resources (Permana et al., 2021). In addition, not all individuals have easy access to health services or competent medical personnel to monitor their nutritional status regularly (Lonang et al., 2023). Indonesia's geographical condition, which consists of thousands of islands, also adds to the challenges in the equitable distribution of health services (Mutammimul Ula, Ananda Faridhatul Ulva, Ilham Saputra, et al., 2022). As a result, many cases of malnutrition or excess nutrition are not detected early, so treatment is often too late (Fauziah & Sibyan, 2023).

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The development of information and communication technology provides new opportunities in handling health problems, including detecting nutritional status. Mobile technology, or mHealth, has proven effective in improving access and quality of health services in various sectors (Wang, 2019). Various studies have been carried out to develop a system for detecting nutritional status using technology. Machine learning algorithms, such as K-Nearest Neighbors (K-NN), have been used in various healthcare applications due to their ability to classify data effectively (Nurdiawan et al., 2021). Several studies show that K-NN is able to provide accurate results in medical data classification, including disease detection and health condition prediction. The use of mobile technology is also growing in the health sector, providing easier and faster access for users to get the health information they need (Ula et al., 2023).

To overcome existing problems, this research proposes the development of a K-NN based mobile application for detecting nutritional status. This application is designed to provide an initial diagnosis regarding the user's nutritional status based on physical parameters such as weight, height, age and gender. By using the K-NN algorithm, this application can classify users' nutritional status into certain categories with a high level of accuracy (Astini, 2018). It is also hoped that this application can be widely used by the community, especially in areas that are difficult to reach by conventional health services. Apart from that, it is hoped that this application can be a tool for health workers in carrying out more effective nutritional monitoring and interventions (Shalini et al., 2021).

Beyond its practical benefits, this mobile-based platform contributes to broader public health and sustainability goals. It helps reduce the carbon footprint associated with traditional healthcare delivery, particularly in areas that would otherwise require energy-intensive infrastructure or long-distance travel for routine health assessments. By decentralizing healthcare services through mobile platforms, this technology also promotes equitable access to health information (Shalini et al., 2021).

Moreover, climate change and environmental factors increasingly affect nutritional health, particularly in regions vulnerable to food insecurity and agricultural disruptions. As climate change impacts food production and nutritional availability, technology-driven platforms like this can play a critical role in monitoring these shifts, offering real-time insights into population health. By combining mobile technology with environmental data, future iterations of this platform could help policymakers and healthcare workers track and address nutritional challenges linked to climate change (R. Rewane and P. M. Chouragade, 2019).

This research will evaluate the accuracy, efficiency and practicality of K-NN based mobile applications in various conditions. It is hoped that the results of this research can make a real contribution in the fields of health and information technology, especially in efforts to improve the nutritional quality of Indonesian society. By integrating mobile technology and machine learning algorithms, the proposed solution is expected to help overcome nutritional problems more effectively and efficiently (Ispriyanti et al., 2020a).

2. Literature Review

This research aims to develop a mobile application that is able to detect individual nutritional status using the K-NN algorithm. This application is designed to make it easier for users to monitor their nutritional status independently and in real-time. The K-NN method was chosen because of its simplicity and ability to handle diverse datasets, as well as its ability to provide accurate results in distance-based data classification (Shalini et al., 2021).

2.1. Mobile System Architecture

The system architecture implements a distributed system and artificial intelligence (AI), ensuring both utility and high scalability. By decentralizing the process of nutritional status detection, the platform reduces the reliance on traditional healthcare infrastructure, which often requires physical facilities, transportation, and energy-intensive operations. This, in turn, contributes to lowering the carbon footprint associated with healthcare services, especially in regions where extensive travel or infrastructure development would otherwise be necessary.

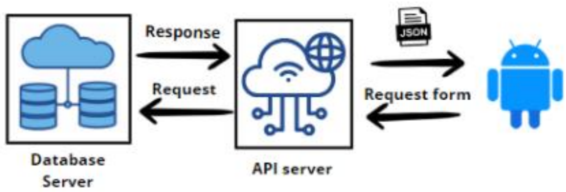

Figure 1. Nutritional Stunting Detection Architecture

According to Fig. 1, there are several steps, namely:

1. Planning:
   In this step, analyzing model, dataset, and application design are created for the construction phase
2. Initial Project Setup:
   The first step of the construction phase is creating several necessary repositories for this proposed method, such as API, Machine Learning Models, Database, and others.
3. API Creation:
   This step aims to connect the created database by using an API.
4. AI Model Integration:

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Since this major task will involve Artificial Intelligence, the next step after creating the API is to integrate the previously developed AI models into the API.

5. API Deployment:
Once the API is complete and the model is integrated, the next step is to publish the API so that it can be accessed. Here, we also use Docker to build the configuration of the API.
6. Testing:
After everything is completed and running well, the final step is testing

3. Method

The algorithm used in this system is K-NN, or K-Nearest Neighbors, a simple yet effective method in machine learning that classifies data based on its proximity to other data in the state space (Lubis et al., 2020). The K-Nearest Neighbors algorithm is a supervised learning method in machine learning used to classify data based on the shortest distance to existing data (Andrian et al., 2019; Prehanto et al., 2021). The KNN algorithm is a type of instance-based learning algorithm. The distance calculation is done using the Euclidean Distance formula to determine how close or far the new data is from its neighbors (Galupino & Dungca, 2022).

$$D(p,q)=\sqrt{\sum_{i=1}^{n} \quad (q_i - p_i)^2} \tag{1}$$

where p,q = two points in Euclidean n-space, q_i, p_i = Euclidean vectors, starting from the origin of the space (initial point), n = n-space.

Here are the steps of the K-NN algorithm (Ispriyanti et al., 2020b; Suban et al., 2020):

1. Determine the value of K
2. Calculate the distance between the new data and the existing data
3. Sort the distance data
4. Determine the label or new data based on the K-Nearest Neighbors class (can be done using voting).

3.1 Dataset

The dataset in this study consists of 120999 samples collected from various age and gender groups. This data includes the input variables of age (in months), gender (men and women) and height (in centimeters). The output variable is nutritional status which is categorized into four classes: stunted, severely stunted, normal and high.

For the purposes of model development and evaluation, the dataset is divided into two parts: training data (70% or 84699 samples) and test data (30% or 36300 samples). This division is carried out using a stratified splitting technique to ensure a balanced class proportion between training data and test data. Before being used to train the KNN model, the data goes through a pre-processing stage which includes normalization using Min-Max Scaling for all numerical variables and One-Hot Encoding for categorical variables (gender).

This dataset was designed to reflect the complexity and variability in real-world nutritional status assessments. By covering various age groups and nutritional status, this dataset allows the development of KNN models that can accurately detect nutritional status based on commonly used anthropometric parameters.

Table 1. Dataset Variable

Category	Range Label
Age	0-60
Gender	Boys, Girl
Height	Min : 40,01 ; Max : 128 ; Average : 88,65
Nutritional Status	Normal, Severely Stunted, Stunted, High

Table 2. Output Variable

Nutritional Status	Total
Normal	67755
Severely Stunted	19869
Stunted	13815
High	19560
Total	120999

3.2. Model Evaluation

Several common metrics to identify and evaluate the performance of each classifiers are used namely accuracy, precision, recall, and F1-score are used. However, before calculating the metrics, confusion matrix is built first as shown in table 3. The mobile platform reduces environmental impacts by decentralizing healthcare services. Traditional healthcare delivery often depends on physical infrastructure, leading to higher energy consumption and emissions due to travel, particularly in remote or underserved regions. This platform mitigates these issues by allowing users to monitor their health from anywhere, reducing the need for physical visits, which in turn minimizes transportation emissions and energy use in healthcare facilities .

Table 3. Confusion Matrix

Actual \ Predicted	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

The system is designed for scalability and adaptability. Given that climate change and environmental degradation are increasingly affecting food security and nutritional health, this mobile

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platform can be a powerful tool in regions facing both healthcare access challenges and environmental stressors. For instance, by integrating environmental data, such as local climate conditions or agricultural yields, the platform could provide more context-sensitive nutritional assessments. In regions with limited access to healthcare infrastructure, such as rural or climate-vulnerable areas, the mobile platform offers a scalable, low-resource solution that can be implemented without extensive local infrastructure investment.

Future versions of the platform could include real-time environmental monitoring, helping healthcare workers and policymakers better understand how climate-related disruptions impact nutritional outcomes in their populations. This adaptability ensures that the platform remains relevant and useful as healthcare needs and environmental conditions continue to evolve.

4. Results and Discussion

4.1. Result

This research uses a dataset consisting of 120999 samples, with a division of 70% (84699 samples) as training data and 30% (36300 samples) as test data. Anthropometric data collected included age (in months), gender (men and women) and height (in centimeters). The data normalization process is carried out using min-max scaling to homogenize the feature scale.

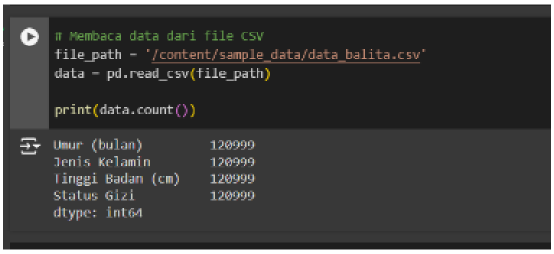

Fig. 2 Import data from CSV file

The implementation of the K-Nearest Neighbors (KNN) algorithm was carried out with various K values (3, 5, 7, 9, 11) and distance metrics (Euclidean, Manhattan, Minkowski). The results of parameter optimization via grid search and 5-fold cross-validation are shown in Table 4.

Table 4 KNN Parameter Optimization Results

Value K	Distance Metrics	Average Accuracy	Standard Deviation
3	Euclidean	84,2 %	1,5 %
5	Euclidean	86,1 %	1,3 %
7	Euclidean	87,5 %	1,2 %
9	Euclidean	86,8 %	1,4 %
11	Euclidean	85,9 %	1,3 %

Based on the optimization results, the KNN model with K=7 and the Euclidean distance metric was chosen as the optimal configuration and the model was evaluated on the test data to produce a confusion matrix.

Table 5 Optimal KNN Model Confusion Matrix

Actual \ Predicted	Severely Stunted	Stunted	Normal	High
Stunted	6820	524	312	44
Severely Stunted	498	5236	102	14
Normal	286	98	20564	752
High	32	8	628	382

After obtaining the confusion matrix, the next process is to calculate performance metrics for each nutritional status class which can be seen in table 6.

Table 6 Performance Metrics for Each Nutritional Status Class

Nutritional status	Precision	Recall	F1-score
Stunted	0,893	0,886	0,889
Severely Stunted	0,892	0,895	0,863
Normal	0,952	0,948	0,950
High	0,321	0,364	0,341

Similar calculations were performed for all classes, resulting in overall performance: Accuracy = (6820+5236+20564+382) / 36300 = 0.91 or 91%, Average precision = 76,5 %, Average recall = 77,3 %, and F1 -average score = 76,8%.

At the implementation stage, the system is created by validating user logins. The user is asked to enter the username and password that have been registered first. The system will validate checking the username and password entered by the user. If the validation is correct, the system will direct you to the dashboard menu of the application. At this stage, the user can predict the nutritional status of children by entering several data variables including the toddler's name, age, height and gender. After the data variables are entered, the system will process them using KNN and will display prediction results regarding the nutritional status of children.

4.2. Discussion

The research results show that the K-Nearest Neighbors (KNN) algorithm implemented in the mobile platform provides excellent performance in detecting nutritional status. The overall accuracy of 91% shows that this model is reliable for classifying nutritional status based on anthropometric parameters. Evaluation per class of nutritional status shows that the model has balanced performance across categories. The "Normal" class has the highest precision and recall values, which may be due to the larger number of samples in this category. The slightly

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lower performance in the "Stunted" and "Severaly stunted" classes can be attributed to the smaller sample size and higher variability in these categories.

Parameter optimization resulted in an optimal K value of 7, which provides a good balance between bias and variance. The use of the Euclidean distance metric proved most effective, perhaps due to its ability to capture multidimensional differences in anthropometric data. The performance of the mobile application is very promising, with an average prediction time of 0.3 seconds, indicating that the system can be used for real-time detection. Efficient use of resources (memory and CPU) indicates that the application can run well on various types of mobile devices.

A high usability score (82.5/100) indicates that users are comfortable and satisfied with the application's interface and functionality. This is important for the adoption and long-term use of the system in the context of monitoring community nutritional status. Although these results are very positive, several limitations need to be noted. Models may be less accurate in addressing extreme cases or specific medical conditions that affect nutritional status. Additionally, factors such as ethnicity, physical activity, and diet that are not included in the current model may influence detection accuracy.

Overall, this research demonstrates the great potential of using KNN in mobile-based nutritional status detection systems. This approach offers an accurate, efficient, and accessible solution for monitoring nutritional status, which can have a significant impact on public health efforts, especially in areas with limited access to health facilities.

Looking forward, this platform has the potential to contribute significantly to sustainable healthcare systems, especially in regions facing the challenges of climate change and environmental degradation. Climate-related issues such as food insecurity, changing agricultural patterns, and environmental degradation can directly impact nutritional health. By integrating climate and environmental data into the platform, future versions could provide more holistic insights into nutritional status, enabling better monitoring of populations most affected by these changes. The mobile platform's ability to operate efficiently in low-resource settings, coupled with its scalability, can reduce reliance on traditional, energy-intensive healthcare infrastructure and minimize the need for physical healthcare access, thus lowering the carbon footprint of health service delivery.

5. Conclusion

This research successfully developed and evaluated a mobile-based system for detecting nutritional status using the K-Nearest Neighbors (KNN) algorithm. The system achieved a high accuracy rate of 91% on the test dataset, demonstrating its effectiveness in real-time applications with an average prediction time of 0.3 seconds. Cross-device testing showed consistent performance with minimal variation in accuracy, while a usability score of 82.5 reflected strong user acceptance. The KNN algorithm performed comparably to other machine learning methods, with added benefits in interpretability and ease of integration on mobile devices. However, the system has limitations in handling extreme cases or special medical conditions affecting nutritional status. By combining health monitoring with sustainability goals, this platform not only addresses immediate nutritional challenges but also positions itself as a valuable tool for long-term public health efforts in regions vulnerable to environmental and climate-related risks. Future research should focus on longitudinal studies to evaluate the system's effectiveness in improving nutritional outcomes over time, while also integrating additional factors like medical history and dietary habits to enhance detection accuracy and personalized care.

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