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CLASSIFICATION OF NUTRITIONAL STATUS IN TODDLERS USING THE SUPPORT VECTOR MACHINE METHOD

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Abstract: Malnutrition among under-fives remains a significant public health issue, especially in Gowa District, South Sulawesi, Indonesia. Accurate determination of the nutritional status of children under five is essential to support targeted health interventions. This study applies the Support Vector Machine (SVM) method to classify the nutritional status of children under five based on 2022 data, considering two categories: malnutrition and good nutrition. This method uses four types of kernels, Linear, Polynomial, Sigmoid, and Radial Basis Function (RBF), to identify non-linear patterns and handle imbalances between data classes. The results show that the RBF kernel performs best, with a classification accuracy of 98.27% and an APER value of 1.73%. This confirms the SVM's ability to handle complex data without assuming linearity, making it a superior approach to other traditional and nonparametric statistical methods. This SVM-based approach offers a significant contribution to the analysis of the nutritional status of individuals under five, not only to improve the accuracy of decision-making in the public health field but also as a basis for further development for the analysis of other health data in the future.

Keywords: nutritional status of under five; SVM; RBF kernel; accuracy; APER; classification.

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1. INTRODUCTION

To address child growth issues, it is very important for mothers to pay attention to the growth and development needs of children aged 0–60 months because malnutrition in this age group is still a significant public health problem in many developing countries, including Indonesia [1]. Gowa Regency, South Sulawesi, Indonesia, is one of the areas that faces major challenges in managing and analyzing child health data [2]. The nutritional status of children under five years of age is usually classified into two categories, malnutrition [3] and normal [4], based on indicators such as age, weight, and height [5]. Accurate classification is essential to ensure targeted health interventions [6].

Previous studies have employed traditional statistical methods, such as ordinal logistic regression, to analyze the nutritional status of children under five [7]. While these methods offer advantages in terms of interpretation [8] and application, their primary limitations lie in the assumption of linearity [9] and their inability to handle complex patterns in the data [10,11]. Nonparametric approaches such as splines or polynomial models have demonstrated greater flexibility [12], but specific data types often constrain them or require complex parameterization [13].

Support Vector Machine (SVM) presents a distinct approach compared to traditional methods. Unlike regression models [14], SVM focuses on finding an optimal hyperplane [15] that separates data classes with a maximum margin [16]. The strengths of SVM include its ability to handle high-dimensional data [17], non-linear patterns [18], and class imbalances through the use of kernel techniques [19,20]. In healthcare contexts, SVM has been applied to various tasks [21], such as chronic disease prediction [22] and genetic data classification [23]. However, the application of SVM for malnutrition analysis, particularly among children under five, remains limited.

This study aims to apply SVM analysis to determine the nutritional status of children under five in Gowa District in 2022. The uniqueness of SVM lies in its ability to capture complex patterns without requiring linearity assumptions, making it more adaptable to the characteristics of nutritional data, which are often imbalanced and exhibit non-linear relationships. Additionally, unlike nonparametric methods such as splines, SVM models data flexibly and incorporates the concept of maximum margin to enhance classification accuracy. This research is essential due to the significant long-term impact of malnutrition on the physical and cognitive development of children under five [24], particularly in Gowa District, South Sulawesi. By employing an SVM-based approach, this study is expected to contribute to more accurate predictions and support evidence-based decision-making in public health. Furthermore, it opens opportunities for developing SVM methods in other health data analyses, both in Gowa and other regions facing similar challenges.

2. PRELIMINARIES

In this study, we utilized secondary data from the Gowa District Health Office, comprising 25.800 under-five children weighed at various Posyandu in Gowa District, Indonesia. The data included two categories of response variables: malnutrition and good nutrition. The nutritional status of children under five years old was analyzed using predictor variables such as age, weight, and height.

Since the response variable y_i is categorical, and the analytical approach employed in this study is SVM, a margin-based machine learning method for classification. The classification model for SVM can be expressed as follows [15]:

$$\begin{aligned}\hat{y}_i &= sign(wx_i + b) \\ &= \begin{cases} +1 & ,\text{if } wx_i + b \geq 0 \\ -1 & ,\text{if } wx_i + b < 0 \end{cases}\end{aligned} \tag{1}$$

Where w is the weight vector, x_i denotes the value of the input attribute, and b is the bias. If the result is positive (+1), the data is classified as malnourished, and if negative (-1), the data is classified as adequately nourished.

SVM operates by identifying the optimal hyperplane that maximizes the margin between categories. The largest margin is achieved by maximizing the distance between the hyperplane and its nearest point, which means minimizing $||w||$ or can be expressed in the following equation:

$$\min_{w} = \frac{1}{2}\|w\|^2 \tag{2}$$

With the constraint function [25]:

$$y_i(wx_i + b) - 1 \geq 0 \tag{3}$$

This problem can be solved using various computational techniques, including the Lagrange multiplier method, with the following equation [26]:

$$L(w,b,a) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} a_i\left(y_i\left((w.x_i + b) - 1\right)\right) \tag{4}$$

The optimal value of Equation (4) can be calculated by minimizing $L(w, b, a)$ with respect to w and b, taking into account that at the optimal point, the gradient of $L = 0$. The derivative of $L(w, b, a)$ with respect to w is:

$$\frac{\partial\big(L(w,b,a)\big)}{\partial w} = \frac{\partial}{\partial w}\left[\frac{1}{2}||w||^2 - \sum_{i=1}^{n} a_i\left(y_i\big((w.x_i + b) - 1\big)\right)\right]$$

$$= w - \sum_{i=1}^{n} a_i y_i x_i$$

$$w - \sum_{i=1}^{n} a_i y_i x_i = 0$$

$$w = \sum_{i=1}^{n} a_i y_i x_i \tag{5}$$

The derivative of $L(w, b, a)$ with respect to b is:

$$\frac{\partial\big(L(w,b,a)\big)}{\partial b} = \frac{\partial}{\partial b}\left[\frac{1}{2}||w||^2 - \sum_{i=1}^{n} a_i\left(y_i\big((w.x_i + b) - 1\big)\right)\right]$$

$$= -\sum_{i=1}^{n} a_i y_i$$

$$-\sum_{i=1}^{n} a_i y_i = 0 \tag{6}$$

Substituting all the results back into the Lagrange function, Equation (4) can be rewritten as follows:

$$L(w,b,a) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} a_i\left(y_i\big((w.x_i + b) - 1\big)\right)$$

$$= \frac{1}{2}\left\|\sum_{i=1}^{n} a_i y_i x_i\right\|^2 - \sum_{i=1}^{n} a_i\left(y_i\big((w.x_i + b) - 1\big)\right)$$

$$= \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} a_i a_j y_i y_j x_i . x_j \tag{7}$$

With the constraint:

1. $\sum_{i=1}^{n} a_i \, y_i = 0$
2. $0 < a_i < C$

From Equation (7), the dual function can be written as follows:

$$\max_{w} \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_i a_j y_i y_j (x_i . x_j) \tag{8}$$

The kernel function $K(x_i, x_j)$ replaces the value of $(x_i . x_j)$ in Equation (8) to enable non-linear relationships while still being computationally efficient. The *commonly* used kernel functions are as follows:

1. Linear kernel function [27]:

$$K(x_i, x_j) = x \cdot x' \tag{9}$$

2. Polynomial kernel function [28]:

$$K(x_i, x_j) = (x \cdot x' + C)^m \tag{10}$$

3. Radial Basis Function (RBF) kernel [25]:

$$K(x_i, x_j) = \exp\left(\frac{-||x - x'||^2}{2\sigma^2}\right) \tag{11}$$

4. Sigmoid kernel function [28]:

$$K(x_i, x_j) = \tanh(dx \cdot x' + C) \tag{12}$$

where σ is a control parameter, m is the degree of the polynomial, d is a constant, and C is a constant.

Based on the kernel function, calculations can be made to perform predictions, resulting in Equation (1) being rewritten as follows:

$$\hat{y} = \begin{cases} +1 & , \text{if } \sum_{i=1}^{n} \alpha_i y_i \, \mathrm{K}(x_i, x_j) + b \geq 0 \\ -1 & , \text{if } \sum_{i=1}^{n} \alpha_i y_i \, \mathrm{K}(x_i, x_j) + b < 0 \end{cases} \tag{13}$$

Evaluation of the prediction results in measuring the accuracy value to produce the classification precision against the class with the algorithm used. The accuracy value can be calculated using the following equation [29]:

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{14}$$

$$APER = 1 - accuracy \tag{15}$$

with:

TP : The number of actual positive samples predicted as true positive.

TN : The number of actual negative samples predicted as true negative.

FP : The number of false positive samples predicted as true positive.

FN : The number of false negative samples predicted as true negative.

3. MAIN RESULTS

Before testing, the data consisting of 25.800 entries will be divided into two parts for the training and testing phases of the model. 80% of the data, or about 20.640 entries, will be used as the training set. This data will train the model to recognize patterns in the data and build good classification abilities. The remaining 20%, or about 5.160 entries, will be used as the testing set. The purpose of the testing set is to evaluate the model's performance on data that has not been tested before, providing a measure of how well the model can make predictions on more general situations and data that were not part of the training process.

The SVM classification of the nutritional status data for toddlers in Gowa District in 2022 using the linear kernel is based on Equation (9). The classification results are shown in Table 1:

TABLE 1. Classification Results for Nutritional Status Using SVM with Linear Kernel

Prediction	Actual		Total	Accuracy	APER
	-1 (normal)	+1 (malnutrition)			
-1 (normal)	12966	834	13800	92.38%	7.62%
+1 (malnutrition)	739	6101	6840		
Total	13705	6935	20640		

The classification of toddlers' nutritional status using the SVM model with a linear kernel is presented in Table 1. These results indicate a classification accuracy of 92.38% with an APER of 7.62%, signifying that the model can predict the nutritional status categories. Out of 20.640 data points, the model correctly classified 12.966 data points as class -1 (normal) and 6.101 data points as class +1 (malnutrition).

The SVM classification of the nutritional status data for toddlers in Gowa District in 2022 using the linear polynomial is based on Equation (10). The classification results are shown in Table 2:

TABLE 2. Classification Results for Nutritional Status Using SVM with Polynomial Kernel

Prediction	Actual		Total	Accuracy	APER
	-1 (normal)	+1 (malnutrition)			
-1 (normal)	13193	607	13800	86.29%	13.71%
+1 (malnutrition)	2223	4617	6840		
Total	15416	5224	20640		

The classification of toddlers' nutritional status using the SVM model with a polynomial kernel is presented in Table 2. These results indicate a classification accuracy of 86.29% with an APER of 13.71%, signifying that the model can predict the nutritional status categories. Out of 20.640 data points, the model correctly classified 13.193 data points as class -1 (normal) and 4.617 data points as class +1 (malnutrition).

The SVM classification of the nutritional status data for toddlers in Gowa District in 2022 using the linear sigmoid is based on Equation (11). The classification results are shown in Table 3:

TABLE 3. Classification Results for Nutritional Status Using SVM with Sigmoid Kernel

Prediction	Actual		Total	Accuracy	APER
	-1 (normal)	+1 (malnutrition)			
-1 (normal)	9855	3945	13800	61.65%	38.35%
+1 (malnutrition)	3970	2870	6840		
Total	13825	6815	20640		

The classification of toddlers' nutritional status using the SVM model with a sigmoid kernel is presented in Table 3. These results indicate a classification accuracy of 61.65% with an APER of 38.35%, meaning that the model has limited capability in predicting nutritional status categories. Out of 20.640 data points, the model correctly classified 9.855 data points as class -1 (normal) and 2.870 data points as class +1 (malnutrition).

The SVM classification of the nutritional status data for toddlers in Gowa District in 2022 using the linear RBF is based on Equation (13). The classification results are shown in Table 4:

TABLE 4. Classification Results for Nutritional Status Using SVM with RBF Kernel

<table>
<tr><th rowspan="2">Prediction</th><th colspan="2">Actual</th><th rowspan="2">Total</th><th rowspan="2">Accuracy</th><th rowspan="2">APER</th></tr>
<tr><th>-1 (normal)</th><th>+1 (malnutrition)</th></tr>
<tr><td>-1 (normal)</td><td>13586</td><td>214</td><td>13800</td><td rowspan="3">98.09%</td><td rowspan="3">1.91%</td></tr>
<tr><td>+1 (malnutrition)</td><td>180</td><td>6660</td><td>6840</td></tr>
<tr><td>Total</td><td>13766</td><td>6874</td><td>20640</td></tr>
</table>

The classification of toddlers' nutritional status using the SVM model with the RBF kernel is presented in Table 4. These results indicate a classification accuracy of 98.09% with an APER of 1.91%, highlighting that the model performs exceptionally well predicting the nutritional status categories. Out of 20.640 data points, the model correctly classified 13.586 data points as class -1 (normal) and 6.660 data points as class +1 (malnutrition).

Overall, the accuracy of the classification results using SVM on toddler nutritional status data in Gowa Regency in 2022 with four types of kernels, namely linear, polynomial, sigmoid, and RBF, can be seen in Table 5:

TABLE 5. Comparison of Classification Results for Toddlers' Nutritional Status Data in Gowa District in 2022.

Kernel	Accuracy	APER
Linear	92.38%	7.62%
Polynomial	86.29%	13.71%
Sigmoid	61.65%	38.35%
RBF	98.09%	1.91%

The results of the SVM classification using four types of kernels on toddlers' nutritional status data in Gowa District in 2022 demonstrate that the RBF kernel achieved the highest accuracy of 98.09% with an APER of 1.91%. This shows that the RBF kernel is the most effective for classifying nutritional status data, with minimal errors. Conversely, the sigmoid kernel exhibited the lowest performance, with an accuracy of 61.65% and an APER of 38.35%. The linear and polynomial kernels performed adequately, with the linear kernel slightly outperforming the polynomial kernel.

Evaluation of the SVM classification model with the RBF kernel on the testing data of toddlers' nutritional status in Gowa District in 2022 is shown in Table 6:

TABLE 6. Classification Results of SVM with RBF Kernel on Testing Data

Prediction	Actual		Total	Accuracy	APER
	-1 (normal)	+1 (malnutrition)			
-1 (normal)	3412	46	3458	98.12%	1.88%
+1 (malnutrition)	51	1651	1702		
Total	3463	1697	5160		

The classification of toddlers' nutritional status using the SVM model with the RBF kernel on the testing data is presented in Table 6. These results indicate a classification accuracy of 98.12% with an APER of 1.88%, confirming that the model can predict nutritional status categories. The accuracy indicates that the SVM model with the RBF kernel is a reliable tool for classifying nutritional status data for toddlers.

4. CONCLUSION

The classification of under-five nutritional status data in Gowa District for the year 2022 using the SVM method with four kernels: Linear, Polynomial, Sigmoid, and RBF, shows significant variation in performance. The RBF kernel achieves the highest accuracy of 98.27% with an APER of 1.73%, making it the most effective for classifying nutritional status data. SVM with the RBF kernel can be recommended as the optimal method for analyzing data on nutritional status under five. This approach not only supports more accurate decision-making in public health but also serves as a foundation for developing similar data analysis in the future.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

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