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Optimization of Support Vector Machine Algorithm Using Stunting Data Classification

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Abstract

Several studies from Indonesia reveal that malnutrition and stunting are still severe concerns to be addressed in the future. The complexity of the problem of stunting or nutritional status requires the responsibility of all parties, including science and technology. The issue of monitoring and data collection related to stunting or the nutritional status of children in Indonesia, especially Medan City, North Sumatra Province, is an essential factor in determining the calculations carried out by each Community Health Center with many attributes. Currently, the Support Vector Machine method is a solution to increase government intervention's effectiveness in classifying malnutrition and stunting. However, the Support Vector Machine algorithm still needs to improve, namely the difficulty of selecting the right and optimal features for the attribute weights, causing a low prediction accuracy. Therefore, researchers aim to optimize the Support Vector Machine Algorithm with Particle Swarm Optimization using Linear, Polynomial, Sigmoid, and Radial Basic Function kernels. The results were obtained from research utilizing nutritional status data, that performance in improving the Support Vector Machine algorithm based on Particle Swarm Optimization using four kernel tests, namely Linear, Polynomial, Sigmoid, and Radial Basic Function obtained different results, not all kernels in this study can improve accuracy well. The best performance is using the Radial Basic Function kernel with an Accuracy value of 78%, Precision of 89%, Recall of 66%, and F1-Score of 72%, so it is feasible for accurate information regarding the classification of nutritional status.

Keywords: SVM, PSO, Linear, Polynomial, Sigmoid, Radial Basic Function, Stunting

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INTRODUCTION

Several studies from Indonesia explained that malnutrition and stunting are still serious concerns to be addressed in the future (Ohyver et al., 2017). In 2020, Indonesia ranked 5th highest among all countries experiencing stunting based on data from the World Health Organization (WHO) (Kusumaningrum et al., 2020). Stunting is a condition disorder where toddlers have less length or height when compared to their age (Desyanti & Nindya, 2017) and lack nutritional intake in infants (Perdana et al., 2021). One of the impacts of malnutrition on babies can result in a slowing posture during growth (Titimeidara & Hadikurniawati, 2021). This condition is measured by a length or height more than minus two standard deviations of the median child growth standard from the World Health Organization (WHO) (Rachmi et al., 2016).

The community is the most influential factor in the problem of stunting itself (Beal et al., 2018). The complexity of the stunting problem demands the responsibility of all parties, including science and technology (Wiraguna et al., 2022). Using Machine Learning algorithms to identify and predict the main risk factors for stunting, wasting, and being underweight can identify potential risks from malnutrition (Rahman et al., 2021).

In terms of stunting or nutritional status, there are three categories: weight according to age, body length according to age, and weight according to body length. This research discusses stunting or nutritional status in weight-for-age data. The problem of monitoring and data collection related to stunting, especially the nutritional status of children in Indonesia, especially in the city of Medan, North Sumatra Province, is an essential factor in determining the calculations carried out by each health center which has many attributes. The Support Vector Machine needs to improve in selecting appropriate and optimal features for the attribute weights, causing the prediction accuracy to be low (Byna & Anisa, 2018). Research (Wijaya & Muslim, 2018) explains that the Support Vector Machine is challenging to use on large-scale data, and it is difficult to distinguish between influential and non-influential attributes in the prediction process.

Meanwhile, Eliyati et al., (2019) conducted a study to predict the classification of low birth weight in Indonesia using a linear kernel-based Support Vector Machine algorithm and compared it to Binary Logistic Regression as the most commonly used model for classifying low birth weight data. Research by Eliyati et al., (2019) found that the Support Vector Machine method using Linear, Radial, Polynomial, and Hyperbolic Tangent kernels can be applied to predict the classification of low birth weight.

Using the Radial Basic Function kernel with the Particle Swarm Optimization algorithm can significantly increase the accuracy of the Support Vector Machine algorithm classification method. The Radial Basic Function kernel optimization method provides an average accuracy of 71.55%, while the Support Vector Machine algorithm without optimization provides an average accuracy of 66.06% (Indraswari et al., 2017). The kernel functions to transform data into high-dimensional space and separate non-linear data linearly (Awad & Khanna, 2015). Non-linear problems can be overcome by modifying the kernel trick into a Support Vector Machine which will separate the class or hyperplane into two classes in the vector space (Isnain et al., 2021). Not all data can be separated linearly, while the Support Vector Machine is basically only able to separate data linearly, so a development is needed to make the Support Vector Machine able to separate non-linear data, one of which is by adding a kernel function (Athoillah, 2018). In this study, we will test the Support Vector Machine and Particle Swarm Optimization algorithms using the Radial Basic Function, Linear, Poly, and Sigmoid kernels to compare the best performance for use in the classification data of the nutritional status category of Weight by Age.

METHOD

Support Vector Machine is one of the fields of science that studies numerical prediction and classification, and pattern recognition which is very effective for regression. Research (Susilowati et al., 2015) explained the meaning of SVM as a learning machine method that works with the principle of Structural Risk Minimization (SRM), aiming to find the best hyperplane that can separate two classes in input space. The following is equation of the Support Vector Machine is as follows (Nalatissifa et al., 2021).

$$\{(Xi, Yi)\}_{i=1}^{N}$$
(1)

Maximize functions:

$$Ld = \sum_{i=1}^{N} \alpha_i - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \, a_j \, y_i \, y_j \; K(x_i, j_j) \; syarat: 0 \le a_i \le C \; dan \; \sum_{i=1}^{N} \alpha_i \; y_i = 0$$
(2)

Calculating the values of w and b:

$f(x) = w.x + b \; atau \; f(x) = \sum_{j=1}^{N} \alpha_i \, y_i \, K(x, x_i) + b$
(3)

Feature space is a conversion method from input (dot product) that can only separate linear data into high-dimensional forms (feature space). The process of converting dot products into feature spaces results in long computational times because it creates kernel processes.

This study used four kernels: Radial Basic Function, Linear, Poly, and Sigmoid. Here's what some of those kernels have in common (Sasongko & Arifin, 2019).

Table 1. Kernels Formulas

No	Name	Kernel $K\,(x, y), i = 1, 2, \dots, N$
1	Linier	$K(x, y) = x^T y + c$
2	Radial (RBF)	$K(x, y) = exp(-g \, \|\| x - y \|\|^2$
3	Polinomial	$K(x, y) = (ax^T y + c)^d$
4	Sigmoid	$K(x, y) = tanh(ax.y + \beta)$
5	Linier	$K(x, y) = x^T y + c$

Particle Swarm Optimization this method for particle intelligence-based optimization is also referred to as behaviorally inspired algorithms, which can be an alternative to genetic algorithms, which are indeed popular with evolution-based procedures. Here is the Particle Swarm Optimization equation.

a. Velocity update formula

$v_{i,j}^{t+1} = w_{i.j}^{vt} + c1.r1\left(Pbest_{i,j}^{t} - x_{i,j}^{t}\right) + c_2.r_2\left(Gbest_{i,j}^{t} - x_{i,j}^{t}\right)$
(4)

b. Position update formula

$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t}$
(5)

The test stages carried out to obtain the results of the classification of Weight data according to Age, namely precision, recall, F1-Score, and accuracy using the Confusion Matrix test, are as follows (Isnain et al., 2021).

Table 2. Confusion Matrix Testing

No	Name	Kernel $K\,(x, y), i = 1, 2, \dots, N$
1	Precicion	$\frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}} * 100$
2	Recall	$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} * 100$
3	F1-Score	$2 * (recall * presisi) / (recall + presisi)$
4	Accuracy	$\frac{TP + TN}{TP + TN + FP + FN} * 100$

Data on Weight by Age consists of nutritional status categories that can be calculated by obtaining a value from the threshold (Z-Score). An explanation of the categories and thresholds for children's nutritional status is explained in the Regulation of the Minister of Health of the Republic of Indonesia No. 2 of 2020 concerning Child Anthropometric

Standards (*Peraturan Menteri Kesehatan Republik Indonesia Nomor 2 Tahun 2020 Tentang Standar Antropemetri Anak*, 2020) in Table 3. Nutrition Threshold Category.

Table 3. Nutrition Threshold Categories

No	Index	Nutritional Status Category	Threshold (Z-Score)
1	Weight by Age	Severe Underweight	<-3 SD
2	Recall	Underweight	-3 SD sd <-2 SD
3	F1-Score	Normal Body Weight	-2 sd SD +1 SD
4	Accuracy	Overweight Risk	<-3 SD

One nutritional status data consists of Weight according to Age. The stunting data collection is the primary data at the Medan City Health Office. The following details of the data used after deletion are found in Table 4. Data Cleaning Feature.

Table 4. Data Cleaning Feature

No	Data Feature	Description
1	Body Weight (kg)	In Numeric Unit
2	Body Height (cm)	In Numeric Unit
3	Age in Month	In Numeric Unit
4	Income	Low Middle High
5	*Program Keluarga Harapan* (PKH)	Yes No
6	*Bantuan Pangan Non Tunai* (BPNT)	Yes No
7	*Jaminan Kesehatan Nasional* (JKN)	JKN Mandiri Mandiri BPJS PBI
8	House Ownership Status	Self-Owned Property Rent Staying Orphanage Parent's House
9	House Condition	Healthy Unhealthy
10	Sanitaion	Eligible Ineligible
11	Source of Drinking Water	Packaged Water Ground Water PDAM

After the data cleaning is obtained, then weighting is carried out. Weighting is the criterion that is considered the most important and is used to compute in applying algorithm performance. The results of the weighting can be seen in Table 5. Weight Data by Age.

Table 5. Data Cleaning Feature

No	Data Feature	Description	
1	Body Weight (kg)	In Numeric Unit	
2	Body Height (cm)	In Numeric Unit	
3	Age in Month	In Numeric Unit	
			Weight
4	Income	Low	0
		Middle	1
		High	2
5	*Program Keluarga Harapan* (PKH)	Yes	0
		No	1
6	*Bantuan Pangan Non Tunai* (BPNT)	Yes	0
		No	1
7	Jaminan Kesehatan Nasional (JKN)	JKN Mandiri	0
		Mandiri	1
		BPJS	2
		PBI	3
8	House Ownership Status	Self-Owned Property	0
		Rent	1
		Staying	2
		Orphanage	3
		Parent's House	4
9	House Condition	Healthy	0
		Unhealthy	1
10	Sanitaion	Eligible	0
		Ineligible	1
11	Source of Drinking Water	Packaged	0
		Water	1
		Ground Water	2
		PDAM	

RESULTS AND DISCUSSION

Results should be clear and concise. Discussion should explore the significance of the results of the work, not repeat them. A combined Results and Discussion section is often appropriate. Avoid extensive citations and discussion of published literature.

Tables and Figures are presented center and cited in the manuscript. The figures should be clearly readable and at least have a resolution of 300 DPI (Dots Per Inch) for good printing quality. Table made with the open model (without the vertical lines) as shown in Table 6.

Table 6. Data Classification Results.

Index	Nutritional Status Category	Gender	Amount
Body Weight	Underweight	Male	426
		Female	360

by Age	Normal Body Weight	Male	239
		Female	216
	Severe Underweight	Male	162
		Female	114
	Overweight Risk	Male	8
		Female	3
			1528

In Figure 1 shows results in testing Accuracy, Precision, Recall, and F1-Score Support Vector Machine algorithm data used as much as 1528 with 80% training and 20% testing data.

	precision	recall	f1-score
Berat Badan Kurang	0.65	0.97	0.78
Berat Badan Normal	0.92	0.61	0.73
Berat Badan Sangat Kurang	0.73	0.10	0.18
Resiko Berat Badan Lebih	1.00	0.56	0.71
accuracy			0.71

Figure 1. Accuracy, Precision, Recall, F1-Score SVM Results

In Table 7 until Table 14. Is the result of calculations from Precision, Recall, and F1-Score on the Support Vector Machine algorithm using the Linear, Polynomial, Sigmoid, and Radial Basic Function kernels getting different values after optimization using the Support Vector Machine algorithm based on Particle Swarm Optimization with Linear, Polynomial, Sigmoid, and Radial Basic Function kernels.

Table 7. Precision, Recall, F1-Score results with SVM + Linear.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	78%	93%	85%
Normal Body Weight	92%	88%	90%
Severe Underweight	88%	57%	69%
Overweight Risk	100%	50%	67%

In Table 7. Shown the results of Precision, Recall, and F1-Score using SVM Linear Kernel with the highest value in Precision obtained in the Overweight Risk category with a percentage of 100%, while the lowest value was obtained in the Underweight category with a percentage value of 78%. In the Recall evaluation metrics, the highest value was obtained in Underweight with a percentage of 93%, while the lowest score was obtained in the Overweight Risk category, which was 50%. The highest score in the evaluation metrics F1-Score results were obtained in the Normal Body Weight category with a value of 90%, while the lowest score was obtained in the Overweight Risk category with a value of 67%.

Table 8. Precision, Recall, F1-Score results with SVM + PSO + Linear.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	78%	89%	83%
Normal Body Weight	91%	88%	90%
Severe Underweight	80%	59%	68%
Overweight Risk	100%	50%	67%

The results obtained on Precision, Recall, and F1-Score with SVM optimization using PSO with Linear kernels showed that the Risk of the More Weight category with a value of 100% and the lowest value in the Underweight category was 78%. Meanwhile, in the evaluation metrics, the highest score was obtained in the Recall category with a value of 89% and the lowest value in the Overweight Risk category with 50%. In the F1-Score, the highest score was obtained in the Normal Body Weight category with a value of 90% and the lowest score of 67% in the Overweight Risk category.

Table 9. Precision, Recall, F1-Score results with SVM + Polynomial.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	55%	97%	70%
Normal Body Weight	91%	88%	54%
Severe Underweight	43%	5%	9%
Overweight Risk	100%	50%	67%

Table 9. Precision, Recall, and F1-Score with SVM Polynomial kernel obtained the highest accuracy result in the Overweight Risk category with a value of 100%, while the lowest value was obtained in the Severe Underweight category with a percentage of 43%. In the Recall metrics evaluation, the highest value was obtained in the Underweight category with a percentage of 97%, and the lowest score was obtained in the Severe Underweight category with a value of 5%. Meanwhile, in the evaluation metrics F1-Score, the highest score was obtained in the Underweight category, namely 70%, and the lowest score of 9%.

Table 10. Precision, Recall, F1-Score Result with SVM + PSO + Polynomial.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	56%	98%	71%
Normal Body Weight	94%	36%	52%
Severe Underweight	62%	8%	14%
Overweight Risk	0%	0%	0%

In the Precision, Recall, F1-Score results with SVM optimization using PSO with Polynomial kernels showed that the Normal Body Weight category had the highest accuracy result with a value of 94%, while the Overweight Risk category had the lowest accuracy result of 0%, which was shown in the Precision evaluation metrics. In Recall, the highest value is shown in the Normal Body Weight category, which is 98%, and the lowest value of 0% is shown in the Risk of Weight Over 0% category. Meanwhile, the evaluation metrics F1-Score showed the highest value in the 71% category, namely Underweight, and the lowest value, namely 0%, in the Overweight Risk category.

Table 11. Precision, Recall, F1-Score Result with SVM + Sigmoid.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	61%	85%	71%
Normal Body Weight	67%	61%	64%
Severe Underweight	60%	14%	23%
Overweight Risk	0%	0%	0%

Precision, Recall, and F1-Score results using SVM with Sigmoid kernels showed the highest results in the Precision metrics evaluation, namely 67% at Normal Body Weight, and the lowest value of 0% was shown in the Overweight Risk category. Recall shows the highest value in the highest category, namely Underweight, with a value of 85%, and the lowest value of 0% in the Overweight Risk category. In the evaluation metrics, F1-Score got the highest score in the Underweight category 71%, and the lowest score in the Risk of Weight Category More 0%.

Table 12. Precision, Recall, F1-Score Result with SVM + PSO + -Sigmoid.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	53%	69%	60%
Normal Body Weight	54%	45%	49%
Severe Underweight	44%	25%	32%
Overweight Risk	0%	0%	0%

In the Precision, Recall, F1-Score results shown in Table 13 with SVM optimization using PSO with Sigmoid kernels showed that the Normal Body Weight category had the Highest accuracy result with a value of 54%, while the Overweight Risk category had the lowest accuracy result of 0% which was shown in the Precision evaluation metrics. In Recall, the highest value is shown in the Underweight category, which is 60%, and the lowest value of 0% is shown in the Risk of Weight Category, Is More is 0%. Meanwhile, the evaluation metrics F1-Score show the highest value in the 60% category, namely Underweight, and the lowest value, which is 0%, in the Overweight Risk category.

Table 13. Precision, Recall, F1-Score Result with SVM + Radial Basic Function.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	58%	95%	72%
Normal Body Weight	91%	55%	69%
Severe Underweight	25%	2%	3%
Overweight Risk	100%	50%	67%

In Table 13. Precision, Recall, and F1-Score results with SVM kernel Radial Basic Function obtained the highest accuracy results in the Overweight Risk category with a value of 100%, while the lowest value was obtained in the Very Underweight category with a percentage of 25%. In the Recall metrics evaluation, the highest value was obtained in the Underweight category with a percentage of 95%, and the lowest value was obtained in the Very Underweight category with a value of 2%. Meanwhile, in the evaluation metrics F1-Score, the highest score was obtained in the Underweight category, namely 72%, and the lowest value of 3% in Severe Underweight.

Table 14. Precision, Recall, F1-Score Result with SVM + PSO + Radial Basic Function.

Nutritional Status Category	Precision	Recall	F1-Score
Underweight	71%	95%	81%
Normal Body Weight	91%	79%	85%
Severe Underweight	93%	40%	56%
Overweight Risk	100%	50%	67%

In Table 14. Precision, Recall, and F1-Score results with SVM optimization using PSO and kernel Radial Basic Function showed the highest results in the Precision metrics evaluation, namely 100% on Overweight Risk and the lowest value of 71% shown in the Underweight category. Recall shows the highest value in the highest category, underweight, with a value of 95%, and the lowest value of 40% in the Very Underweight category. In the evaluation metrics, F1-Score got the highest score in the Normal Body Weight category of 85% and the lowest score in the Overweight Risk category, 56%.

Figure 2 shows that the results of Precision, Recall, and F1-Score in the Support Vector Machine algorithm using the Linear kernel get different values after optimization based on Particle Swarm Optimization.

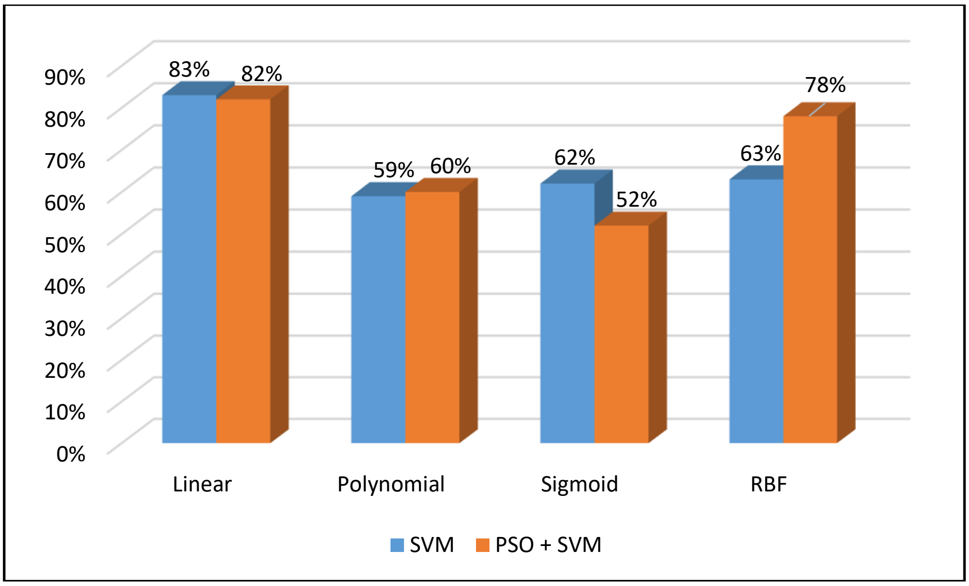

Figure 2. Data Graph Weight by Age SVM + PSO + Kernel Accuracy Results

The accuracy results of the Weight by Age nutritional status category using the Support Vector Machine algorithm with Radial Basic Function and Polynomial kernels are 63% and 59%, respectively. After optimization of the Support Vector Machine algorithm based on Particle Swarm Optimization with Radial Basic Function and Polynomial kernels, it experienced an increase in accuracy results by 78% and 60%, respectively. When using the Support Vector Machine algorithm with linear and sigmoid kernels, the accuracy results obtained were 83% and 62%, respectively. After optimization of the Support Vector Machine algorithm based on Particle Swarm Optimization with linear and sigmoid kernels, the accuracy results decreased by 82% and 52%, respectively.

CONCLUSION

This study used data on the nutritional status of Weight According to Age in the Medan City Health Office with a total of 1528 data. In classification performance with optimization of the Support Vector Machine algorithm based on Particle Swarm Optimization using the Radial Basic Function and Polynomial kernels proven to improve performance. The best performance results in increasing the Accuracy value by 78%, Precision by 89%, Recall by 66%, and F1-Score by 72% using the Radial Basis Function kernel. Of the four kernels that are used, such as Linear, Polynomial, Sigmoid, and Radial Basic Functions, the worst performance is sigmoid.

RECOMMENDATION

Further research is expected to use optimization algorithms and analyze other kernel types and can use stunting data classification as well as more features.

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