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Toddler nutritional status identification: Support vector machine (SVM) algorithm adoption

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ABSTRACT

Inadequate nutrition in toddlers can lead to health issues and adversely affect their growth, development, and cognitive capabilities. Consequently, it is essential to assess the nutritional status of toddlers to ascertain their health level. This study seeks to ascertain the nutritional health of toddlers utilizing the support vector machine (SVM) methodology, taking into account body weight (BB), height (TB), age, BB/TB ratio, Z-scores for BB/U, Z-scores for TB/U, and Z-scores for BB/TB. The data of 1458 toddlers were evaluated using the knowledge data discovery methodology. This study effectively categorized toddler nutrition into six classifications including malnutrition, undernutrition, adequate nutrition, overnutrition, risk of overnutrition, and obesity. Utilizing the confusion matrix methodology with an 80% training data to 20% test data ratio yields an accuracy of 89.04%. The SVM method is effectively utilized to ascertain the nutritional condition of toddlers, hence enhancing their growth and development.

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1. INTRODUCTION

Checking the nutritional status of toddlers is very important to know the health of toddlers so that they do not easily experience malnutrition. Nutritional status shows the amount of food a person eats over a long period of time [1-3]. Thus, the availability of nutrients in a person's body, especially in infants and toddlers, is determined by the state of nutrition whether it is in good, balanced or poor condition [4]. According to Article 141 of Law No.36 of 2009 concerning Health, the basis of nutrition development aims to improve individual and community nutrition through improving the pattern of food consumed, which is in accordance with the 13 Messages of Balanced Nutrition (PUGS) and improving the behavior of Nutrition Aware Families (Kadarzi) [5-7].

Based on the Pekanbaru City Health Office report, the nutritional status of toddlers in Riau Province has a W/A index of 78 (39.4%) data with the results of nutritional status underweight, overweight 7 (3.5%) data and 113 (57.1%) data with nutritional status of toddlers in the normal category [8]. Based on the results of the anthropometric index assessment by comparing the value of H / Age (A), the amount of data obtained is 83 (41.9%) with the nutritional status of short H (Stunted) and 116 (58.6%) data of toddlers with normal status [9]. Based on the W / H index, the amount of data obtained was 61 (30.8%) data of toddlers with nutritional status less (Wasted) and 116 (58.6%) data of toddlers with normal status [10]. The study of the nutritional status of toddlers is carried out using anthropometric indices, which are made by measuring body weight and height, age, and gender as a comparison [11-13].

This Health Office report categorizes four types of data based on the assessment of the nutritional status or nutritional index of a toddler. The anthropometric indices used are Height for Age (H/A), Weight for Age (W/A), Weight for Height (W/H), and Body Mass Index for Age (BMI/A) [14-16]. Health workers, program managers and policy makers have made these anthropometric indices the reference standard since 2020 in assessing the nutritional status of children under five. Anthropometric indices are very commonly used as an assessment of the size, proportion, and composition of the human body [17]. However, the calculation of the anthropometric index has shortcomings such as insensitivity because it only cannot detect nutritional status in a short time, then several external factors can reduce the sensitivity of anthropometric measurements and field conditions both from officers and measurement tools [18-20].

Some previous research related to the support vector machine (SVM) algorithm such as research by Supriyono and Erida (2022) in a case study of diagnosing hypertension disease resulted in training data accuracy of 85% of 247 data and test data accuracy of 91.89% [21]. Then from Abidin et al. (2025) in a case study of hypertension disease produced an accuracy value of 77% using a linear kernel and 76% using a polynomial kernel [22]. Finally, Indri Monika in 2018 in a case study of child growth and development deviations produced an accuracy value of 63.11% with $\lambda = 10$, $C = 1$, itermax = 200 using a polynomial kernel [23]. For this reason, it is necessary to develop an analysis with more in-depth data processing in identifying the classification of nutritional status of toddlers based on anthropometric indices [24-26].

This research uses the SVM algorithm in solving the problem of classification of nutritional status of toddlers. The data to be researched is the nutritional status data of toddlers in Pekanbaru City in 2022 obtained from the Pekanbaru City Health Office. The results obtained will contribute to the comparison between the SVM classification results and the anthropometric index. So that the community in this case is the Health Institution can identify more precisely and accurately the nutritional status of toddlers. Of course, the health level of toddlers in Pekanbaru city can be known for early treatment actions based on the results of the classification of the nutritional status of toddlers.

2. RESEARCH METHODS

The research methodology describes a series of systematic processes used so that the research objectives can be achieved. Figure 1 shows the stages of the research method discussed in this chapter:

Figure 1. Flow of research stages.

2.1. Problem Formulation

Problem Formulation is the initial stage of the research methodology, at this stage a search will be carried out from various sources of past research or news that is currently being discussed. After getting a problem, it will then be studied to get a solution to the problem. The formulation of the problem is how to use the SVM algorithm in determining the nutritional status of toddlers in Pekanbaru city.

2.2. Data Collection

There are two stages in data collection consisting of literature study and data collection, the first is a literature study which is considered to be helpful in collecting data so that it is relevant to the research. This method uses a search for references from various sources, including books, journals, and others that are considered relevant to the research. Second, data collection is the data that will be used in the form of secondary data obtained from the health department of the city of Pekanbaru with a total of 1458 data. The data is a report on the results of the nutritional status of toddlers from all health centers in the city of Pekanbaru in 2022. Table 1 shows some of the parameters that are needed in the study.

2.3. Modeling

In the modeling stage, the data will go through a process of cleaning, feature selection, and data transformation. The purpose of this process is to make the raw data formal and easy to process so that it is more efficient for the next stage. First, data selection is where relevant data is selected for analysis. This involves identifying important attributes and removing irrelevant attributes. In addition, selection criteria are determined and subsets of data that meet those criteria are selected. Next is data transformation by changing the data from its previous format to one that is more suitable or meets the needs of the analysis. This includes normalization, discretization, logarithmic transformation, dimension reduction, binning, and variable coding. Finally, data normalization where data that has passed the transformation stage will be normalized. Normalization aims to equalize the value of each attribute so that it is balanced and the results obtained become higher.

Table 1. Data parameters of toddler nutritional status.

No	Parameters	Description
1	Name	Toddlers who took measurements
2	Gender	To determine the Z score value
3	Weight	Toddler's weight when weighed
4	Height	Toddler height when measured
5	W/A	Under-five status of weight-for-age
6	ZS W/A	Score value of W/A
7	W/H	Toddler status from weight to height
8	ZS W/H	Score value of W/H
9	H/A	Toddler status from height to age
10	ZS H/A	Score value of H/A

2.3.1. Cleaning Data

The initial stage is data cleaning, the newly obtained initial data must be checked for blanks, duplicates and errors. In the toddler nutritional status data, the cleaning process has been carried out and no errors have been found so that this stage can be skipped and proceed to the next stage.

2.3.2. Feature Selection

The selection of basic features aims to determine the features needed for research. The nutritional status of toddlers is determined by the weight and height of toddlers, so the related features will be selected as basic features. The basic features selected are weight, height, W/H and Z score W/H.

2.3.3. Feature Enrichment

Feature enrichment is the utilization of several features that can be used to support the basic features. Some of the features added are:

a. Gender, the sex of the toddler is needed because the basic birth weight of males and females is different.
b. Date of birth, date of birth is needed as a starting number to add up the age of the toddler in days.
c. Measurement date, the measurement date is used as the last number for summing the age of toddlers in days.
d. Z Score W/A, numeric values of weight and height added to support basic features.
e. Z Score H/A, the values of height and age are also added.

Table 2. Data selection results.

ID	G	Age	Weight	Height	ZS W/A	ZS H/A	ZS W/H	W/H
1	L	1237	4.3	48	-0.73	-1	2.38	Risk of overnutrition
2	P	1510	3	49	-0.52	-0.08	-0.56	Good nutrition
3	L	1685	3	50	-0.24	-0.5	-1.7	Good nutrition
4	P	1531	3	49	-0.52	-0.08	-1.04	Good nutrition
5	P	1835	3	50	-0.62	-0.09	-1.74	Risk of overnutrition
6	L	1708	3	48	-1.12	-1.82	-0.27	Good nutrition
7	L	1749	4	53	1.12	1.17	-0.54	Good nutrition
8	P	1419	3	50	-1.04	0.01	-1.25	Good nutrition
9	L	1792	3	49	-0.79	-1.37	-0.97	Good nutrition
10	L	1079	3	48	-1.11	-1.81	-0.27	Risk of overnutrition
...	...	...	...	...	...	...	...	...
1458	P	1047	3	49	-4.36	-5.74	-0.97	Risk of overnutrition

2.3.4. Tranformasion Data

The transformation stage is to change the data from its previous format to one that is more suitable or meets the needs of the analysis. In the features of gender and BW, the data that was originally categorical will be transformed into numerical data with number labeling.

a. Gender, gender consisting of male and female will be labeled with 2 for male and 1 for female.
b. W/H, for each status will be sorted from less to more status by labeling number 1 for malnutrition, number 2 for undernutrition, number 3 for good nutrition, number 4 for risk of overnutrition, number 5 for overnutrition and number 6 for obesity.

2.3.5. Normalization Data

At this stage, the data will be normalized using Featur Scaling so that the attributes in the dataset are normalized and each value is equalized so that it is uniform. Normalized attributes include all attributes of the data selection, the resulting average value is 0 with a range of about -1 to 1. In table 3 the normalization results of some attributes are as follows.

Table 3. Data after normalization.

Gender	Age	Weight	Height	…	W/H
0.646752	0.427909	1.107983	0.700065	…	4
-1.546188	0.951344	1.292718	1.093430	…	3
0.646752	1.286880	1.292718	1.093430	…	3
-1.546188	0.991609	1.292718	1.093430	…	3
-1.546188	1.574482	-1.091241	-1.179345	…	4
-1.546188	-0.559525	-1.179210	-1.179345	…	4
-1.546188	-1.752114	-1.175691	-1.223053	…	4
-1.546188	-0.417641	-1.179210	-1.179345	…	4
0.646752	0.215083	-1.179210	-1.179345	…	4
-1.546188	0.115381	-1.179210	-1.179345	…	4

2.4. Testing

In the testing stage, appropriate data mining algorithms are selected and applied to the data. Some common techniques to be used in this stage include regression, classification, clustering, association, and others. The algorithm that will be used in the research is the SVM algorithm, the SVM modeling stage is to choose a kernel that matches the characteristics of the data. This research will use the RBF (Radial Basis Function) kernel as modeling and then add various parameters C = (1, 10, 100), Gamma = (0.1, 0.01, 0.001) and Cross Validation (CV) = 5 to get the best value. Next is the calculation using the SVM algorithm and the trained model can be classified with new data. After modeling, an assessment of the performance of the classification model is carried out after training the training data. This assessment will use the accuracy score and classification report which aims to show the number of percentages or ratios made by the model for each class. In addition, the values of precision, recall and F1-Score will also be obtained to evaluate the performance of the SVM algorithm.

2.5. Conclusion

Conclusion is the stage of explaining all the results of the whole research and also explaining the errors or shortcomings in the research. The results of the application of the SVM algorithm will explain the accuracy and F1-Score values. And it will also explain the prediction results of each class from the average weight and age of toddlers.

3. RESULTS AND DISCUSSIONS

The results and discussion of the research on the nutritional status of toddlers using the SVM algorithm in Pekanbaru City can find out the accuracy and F1 - Score value of each selected feature and the prediction results of each class to determine the average weight and height values for the age of each class toddler.

The dataset obtained comes from the Pekanbaru City Health Office with data totaling 1458 data which will be processed based on selected features which are divided into 2 processes. Before processing, data normalization will be carried out which can be seen in table 3 and continued to train data using the SVM algorithm.

3.1. Baseline Testing

In the initial stage of testing, the SVM data training process is carried out using the basic features that have been selected in the table. The division of training and test data in this study is 80: 20, then run and obtain an accuracy result of 62% with an F1 - Score value of 13%. The results obtained were very low because only class 3 (good nutrition) was successfully predicted while other classes were not detected. The test results can be seen in table 4.

Table 4. Baseline testing results.

	Precision	Recall	F1-score	Support
1	0.00	0.00	0.00	4
2	0.00	0.00	0.00	22
3	0.62	1.00	0.77	181
4	0.00	0.00	0.00	75
5	0.00	0.00	0.00	6
6	0.00	0.00	0.00	4
Accuracy			0.62	292
Macro average	0.10	0.31	0.13	292
Weighted average	0.38	0.84	0.47	292
SVM accuracy		61.99		

3.2. Testing with Feature Enrichment

In the next test, testing was carried out with additional feature enrichment which can be seen in table 2. After testing, the accuracy results obtained were 89% with an F1 - Score value of 74%. The results of testing with feature enrichment show a fairly high increase, especially in the F1 - Score value and for the value of each class successfully detected even though class 5 (Over Nutrition) gets a fairly low value. The results of the test can be seen in table 5.

Table 5. Test results with feature enrichment.

	Precision	Recall	F1-score	Support
1	1.00	0.50	0.67	4
2	0.88	1.00	0.94	3
3	0.99	0.89	0.94	181
4	0.75	0.95	0.84	75
5	0.25	0.17	0.20	6
6	1.00	0.75	0.86	4
Accuracy			0.89	292
Macro average	0.81	0.71	0.74	292
Weighted average	0.90	0.89	0.89	292
SVM accuracy		89.04%		

3.3. Class Prediction Results

The next test enters the predicted value into the data to find out whether the class prediction results match the class in the data. After the data is matched with the prediction results, the data will be divided according to each class and will be calculated the average value of weight and height for toddler age so that a diagram of each class can be displayed.

3.3.1. Malnutrition Class

The prediction results in class 1 (malnutrition) with 15 data get the average value of weight at the age of 0 – 600 = 5.87 kg, 601 – 1200 = 11.11 kg and 1201 – 1800 = 10.36 kg while the average value of height is 0 – 600 = 60.89 cm, 601 – 1200 = 83.50 cm and 1201 – 1800 = 78.07 cm. The average weight and height results can be seen in Figure 2.

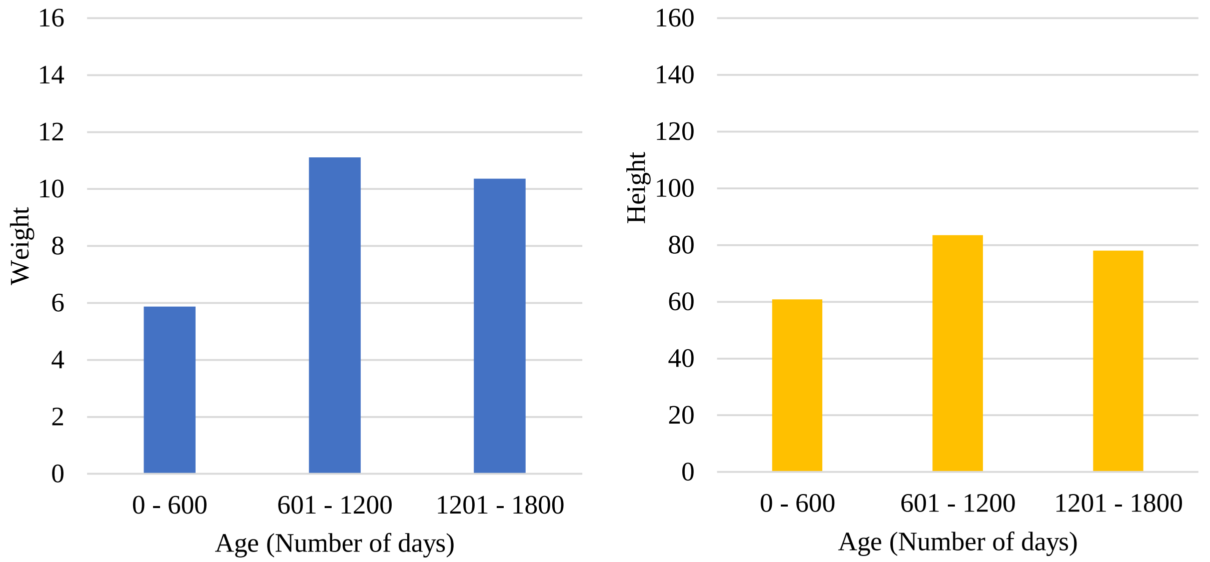

Figure 2. Prediction of malnutrition class.

3.3.2. Undernutrition Class

The prediction results in class 2 (malnutrition) with 90 data get the average value of weight at the age of 0 – 300 = 4.44 kg, 301 – 600 = 6.43 kg, 601 – 900 = 11.66 kg, 901 -– 1200 = 10.38 kg, 1201 – 1500 = 5. 72 kg and 1501 – 1800 = 11.95 kg while for the average height get a value at the age of age 0 – 300 = 56 cm, 301 – 600 = 63.06 cm, 601 – 900 = 85.34 cm, 901 – 1200 = 80.38 cm, 1201 – 1500 = 61.63 cm and 1501 – 1800 = 85.35 cm. The prediction results can be seen in Figure 3.

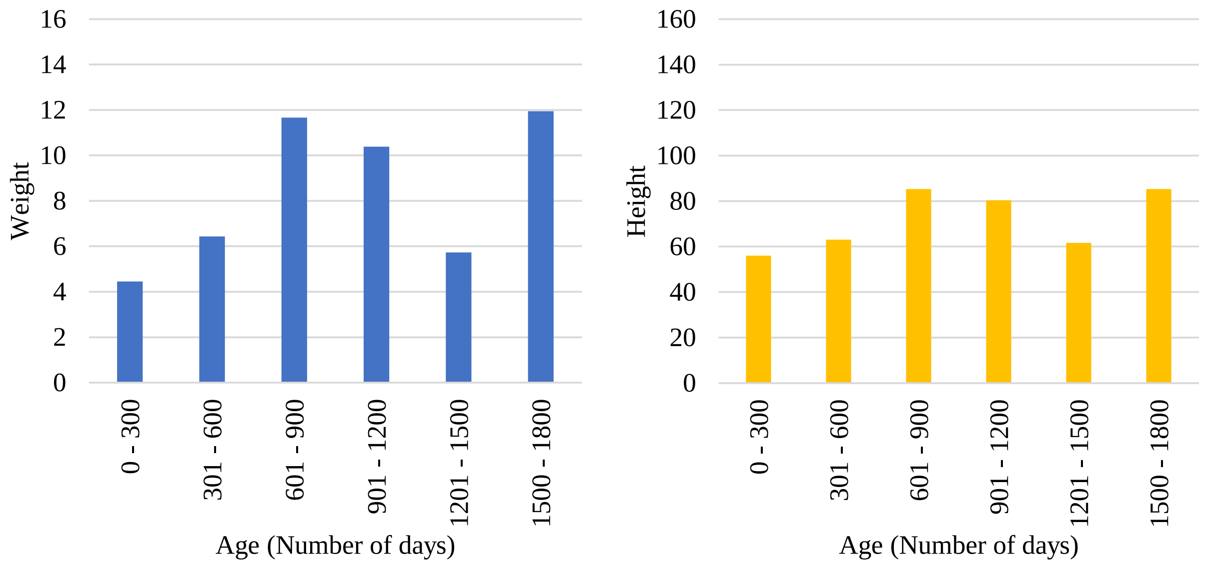

Figure 3. Prediction of undernutrition class.

3.3.3. Good Nutrition Class

Prediction results in class 3 (good nutrition) with 903 data getting the average value of weight at the age of 0 – 300 = 4.97 kg, 301 – 600 = 7.78 kg, 601 – 900 = 8.50 kg, 901 – 1200 = 12.25 kg, 1201 – 1500 = 10. 42 kg and 1501 – 1800 = 12.41 kg while for the average height get a value at the age of age 0 – 300 = 56.73 cm, 301 – 600 = 69.18 cm, 601 – 900 = 72.97cm, 901 – 1200 = 80.06 cm, 1201 – 1500 = 80.79 cm and 1501 – 1800 = 87.08 cm. The prediction results can be seen in Figure 4.

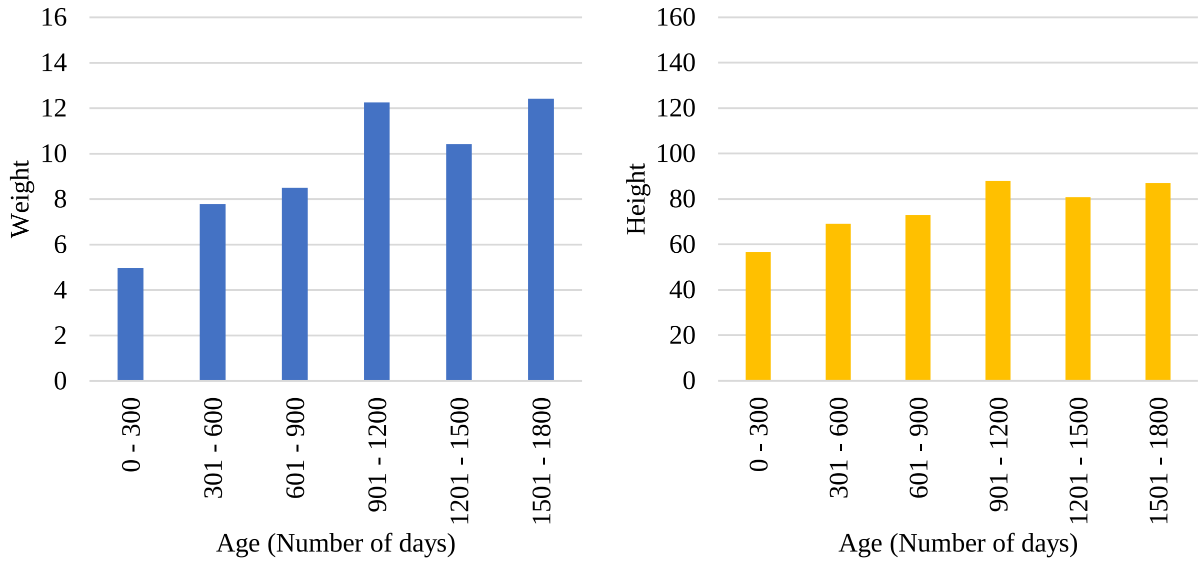

Figure 4. Good nutrition class prediction.

3.3.4. Class of Overnutrition

The prediction results in class 4 (risk of over nutrition) with 419 data get the average value of weight at age 0 – 300 = 4.82 kg, 301 – 600 = 9.18 kg, 601 – 900 = 9.18 kg, 901 – 1200 = 11.30 kg, 1201 – 1500 = 8. 89 kg and 1501 – 1800 = 12.97 kg while for the average height get a value at the age of age 0 – 300 = 55.80 cm, 301 – 600 = 57.87 cm, 601 – 900 = 75.62 cm, 901 – 1200 = 84.86 cm, 1201 – 1500 = 73.17 cm and 1501 – 1800 = 82.86 cm. The prediction results can be seen in Figure 5.

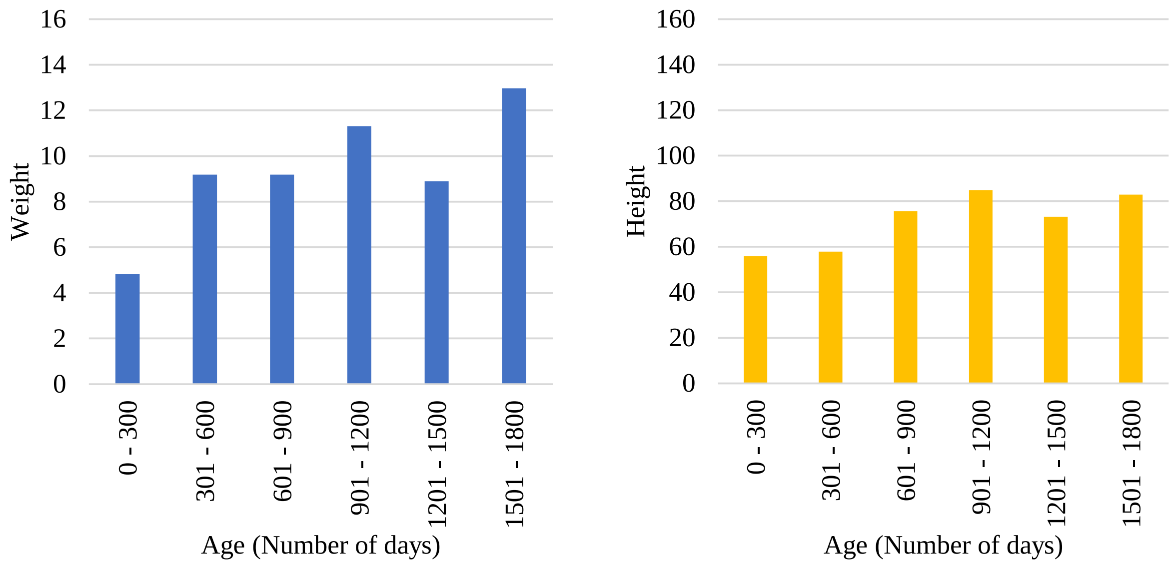

Figure 5. Predicted risk class of overnutrition.

3.3.5. Overnutrition Class

The prediction results in class 5 (over nutrition) with 20 data get the average value of weight at the age of 0 – 600 = 6.64 kg, 601 – 1200 = 11.31 kg and 1201 – 1800 = 11.05 kg while the average value of height is 0 – 600 = 64.26 cm, 601 – 1200 = 11.31 cm and 1201 – 1800 = 81.78 cm. The average weight and height results can be seen in Figure 6.

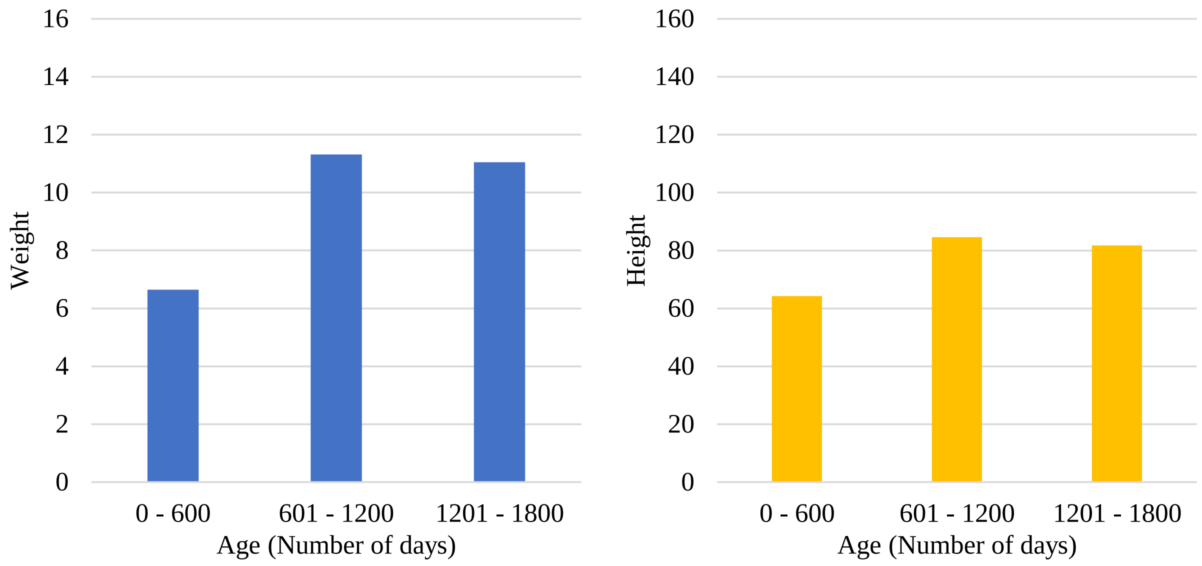

Figure 6. Prediction of overnutrition class.

3.3.6. Obesity

The prediction results in class 6 (Obesity) with 11 data get the average value of weight at the age of 0 – 600 = 9.01 kg, 601 – 1200 = 9.82 kg and 1201 – 1800 = 14.63 kg while the average value of height is 0 – 600 = 74.48 cm, 601 – 1200 = 76.08 cm and 1201 – 1800 = 98.40 cm. The average weight and height results can be seen in Figure 7.

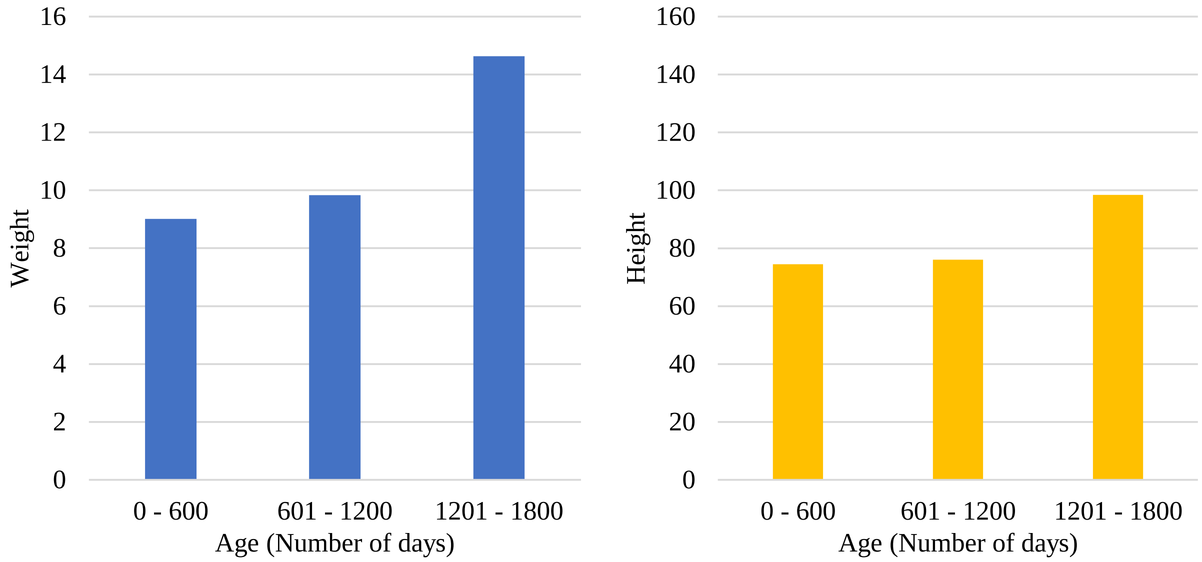

Figure 7. Predicted obesity class.

4. CONCLUSION

Based on the results of the research that has been done, testing the SVM algorithm on the nutritional status of toddlers processed with basic features of feature enrichment fiber results in a significant increase in accuracy value. Testing by adding feature enrichment is very effective on results, it can be seen that the accuracy value gets a value of 89.04% using the RBF kernel with the best parameters, namely C = 100, gamma = 0.01 with a ratio of 80% training data and 20% test data. Previously, data processed only with basic features produced very low values, the value of each class was not identified except in class 3 and the accuracy obtained was only 61.99%. The evaluation results of the classification report method work well with the F1 Score value obtained of 74% while without feature enrichment only gets a value of 13%. The results of the average value of weight and height of toddlers in each class are shown with a diagram picture so that it can be seen that the graph changes with the age of the toddler, The conclusion in this study can be drawn is that the more features used will get higher accuracy and F1-score results. In the prediction results obtained, it can be seen the average value of weight & height against the age of each class, this helps explain how much weight & height in a certain age range to the nutritional status of each toddler in Pekanbaru City.

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