Multiclass classification of toddler nutritional status using support vector machine: A case study of community health centers in Bangkalan, Indonesia

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Abstract. Monitoring child development is vital in Indonesia due to its large child population and varying socio-economic and geographical conditions. Malnutrition adversely affects children's growth and development, with ongoing challenges in remote areas despite government efforts. This study addresses the need for accurate nutritional status classification to improve intervention strategies. This study applies the Support Vector Machine (SVM) classification method to analyze and classify nutritional status of toddlers using data from 473 samples collected from health centers in Bangkalan Regency. The classification includes categories such as Good Nutrition, Excess Nutrition, Obesity, and Risk of Excess Nutrition. The SVM model achieved an accuracy of 76% in predicting nutritional status.

1 Introduction

Child development is a fundamental aspect of human growth that includes physical growth, cognitive, social, emotional, and language development [1, 2]. In Indonesia, attention to child development is crucial given the large child population and the diverse socio-economic and geographical conditions that affect their development [3]. Monitoring child development is key to ensuring that every child can reach their full potential and to detecting early any developmental disorders that may arise [4].

In general, there are two main factors that influence child growth and development, namely genetic and environmental factors. Genetic factors are the basic capital in achieving the final results of the child's growth and development process. This factor is also a child's innate factor, namely the child's potential that is his or her characteristic. Environmental factors are factors that greatly determine whether or not innate potential is achieved.

The nutrition consumed by children has a significant impact on their nutritional status [5]. Differences in nutritional status among toddlers also affect their development in various ways. If the nutrition consumed is insufficient, the toddler's development will be hindered. Malnutrition at this age can lead to restricted growth, increased susceptibility to infections, and skin inflammation, and can impede cognitive, motor, language, and personal-social development compared to toddlers with good nutritional status [6]. The condition of child development in Indonesia still faces various challenges. Data from various surveys indicate that many Indonesian children still experience nutritional problems, such as stunting (short stature) and wasting (underweight), which can affect their physical and cognitive development [7]. In addition, access to quality healthcare and education services is still uneven across Indonesia. In remote and underdeveloped areas, healthcare and educational facilities are often inadequate, putting children in these regions at risk of developmental issues.

The Indonesian government has addressed child development issues through various programs and policies. However, the implementation of these programs still needs improvement, especially in terms of monitoring and evaluation. Information and communication technology can play a crucial role in supporting these efforts by providing tools for more effective and efficient monitoring and analysis of child development data.

In the context of monitoring child development, the use of machine learning-based classification methods can be an appropriate solution. One commonly used method is Support Vector Machine (SVM), which offers a different approach to processing and analyzing child development data. By utilizing data collected from various sources, this method can help identify developmental patterns, detect early developmental disorders, and provide appropriate intervention recommendations.

The series of data mining stages are as follows: Data cleaning (to remove inconsistent data and noise) Data integration (combining data from multiple sources) Data

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transformation (data is transformed into a form suitable for mining).

Child development research uses the Extreme Learning Machine (ELM) method and determines its level of accuracy for classifying deviations. The criteria used for classification are statements related to the criteria for the type of child development deviation as many as 38 pieces and the system output is the type of deviation experienced. This system produces poor accuracy due to data imbalance [8].

Support Vector Machine (SVM) is a classification method that uses the concept of hyperplanes to separate data into different classes [9]. This method is renowned for its ability to handle large and complex datasets and provides accurate results even with a limited amount of available data. This machine learning method is commonly used as a problem-solving tool due to its high accuracy, and it is widely applied in various fields, such as healthcare, where information technology is used for early analysis and diagnosis of patients. For example, a study conducted in 2023 utilized machine learning to classify stunting in children under 5 years old in Papua New Guinea, achieving an accuracy of 72.8% [10].

Additionally, research on classifying appendicitis in children also utilizes one of the machine learning methods known as SVM, along with the application of imputation processes to improve the accuracy of the classification model, achieving an accuracy of 89.69%. By using this method, a learning model can be produced that effectively classifies data with high accuracy [11].

Based on the issues and previous research, the researcher is interested in examining this method. Using data obtained from research conducted at the health center in Bangkalan Regency, the data consists of nutritional status samples of toddlers based on anthropometric indices from each Health center in every district of Bangkalan Regency. This study aims to classify the nutritional status of toddlers into appropriate categories. A total of 473 samples are used, with attributes including No, Name, Gender, Date of Birth, Province, Regency, District, Health center, RT, RW, Address, Age at Measurement, Date of Measurement, Weight, Height, Weight-for-Age (BB/U), Z-score Weight-for-Age (ZS BB/U), Height-for-Age (TB/U), Z-score Height-for-Age (ZS BB/TB), and label. The label column contains 4 classes: Good Nutrition, Excess Nutrition, Obesity, and Risk of Excess Nutrition. The nutritional status data used is from measurements taken between 2021 and 2023.

This study aims to evaluate the performance of the method in classifying child development. By applying the SVM performance, this research hopes to identify the most effective and efficient method for application in child development monitoring systems. Performance evaluation will be conducted based on several metrics, including accuracy, precision, recall, F1-score, and computation time, providing a comprehensive view of the strengths and weaknesses of each method. The results of this study are expected to make a significant contribution to enhancing child development monitoring in Indonesia. With a more accurate and reliable monitoring system, healthcare professionals and educators can more easily detect potential developmental issues early and provide timely interventions. The implementation of this technology is expected to help create a generation of Indonesian children who are healthy, intelligent, and high-quality, ready to face future challenges. The implementation of the research results is hoped to help create an environment that supports healthy and balanced child development, and provide a strong foundation for their future.

2 Methods

This study aims to identify children at risk of health or developmental problems and take appropriate steps for intervention and necessary care by building a learning model that can classify the dataset into three categories: good nutrition, excess nutrition, and risk of excess nutrition, using machine learning with the Support Vector Machine method. It is hoped that this approach will optimize the potential of child development data.

Data mining classification is the process of finding definitions of similar characteristics in a group or class. Classification is one of the most common methods used in data mining. This method is carried out with the aim of estimating the unknown class of child growth and development.

The stages of this research are illustrated in Fig. 1 below.

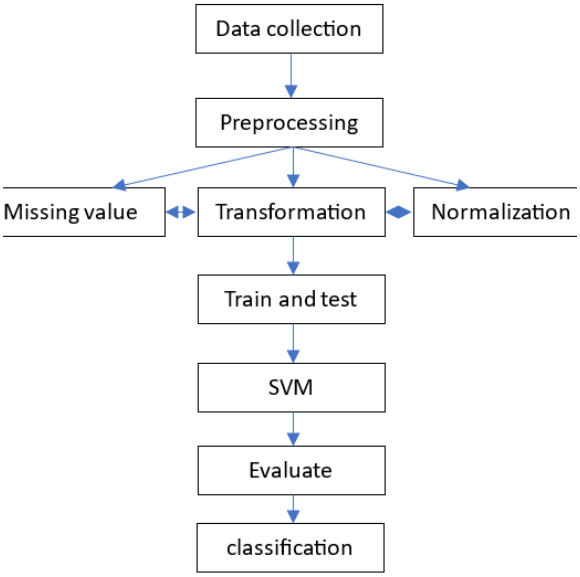

Fig. 1. Stages of data mining.

2.1 Dataset

Child development is a complex process influenced by various factors, including gender, age, weight, and height. Research on the relationship between these factors and child development has been a major focus in the field of child health [12]. This subsection will outline

relevant literature on the relationship between gender, age, weight, and height with child development.

SVM uses hypotheses in the form of linear functions in a high-dimensional feature space, by implementing learning bias derived from statistical learning theory. Data in a dataset is given a variable xi, while for the class in the dataset is given a variable yi.

1. Gender

Gender has been shown to play a role in child development. Some studies indicate that gender can affect physical growth, cognitive development, and behaviour in children. For example, research has found differences in height and weight between boys and girls at certain stages of development. Additionally, some studies also suggest differences in cognitive abilities and language development between genders [13].

2. Age

Age is also a crucial factor in child development. Each developmental stage has its own characteristics and challenges. The literature contains numerous studies identifying expected developmental milestones for each age range, such as increasing motor, language, and cognitive skills with age. Additionally, research shows that age can also influence a child's height and weight [13].

3. Weight

A child's weight also has a strong correlation with their development. Proper weight growth is an important indicator for monitoring a child's health and development. Research has shown that weight deviations from growth standards can indicate nutritional or other health problems. Additionally, weight is related to physical development, such as muscle and bone system development [13].

4. Height Relations

A child's height also plays an important role in their development. A child's height is influenced by both genetic and environmental factors. Research has found that normal height growth, in line with established growth curves, is crucial for optimal development. A child's height can also impact their health and psychosocial development [13].

2.2 Data mining

Data mining is the process of extracting valuable information from large and complex datasets [14]. Through various analytical techniques and algorithms, data mining aims to uncover patterns, trends, and relationships hidden in the data that may not be immediately apparent. This process is crucial in various fields, including business, healthcare, marketing, and science, as it provides deep insights and supports better decision-making.

One of the key steps in data mining is data preprocessing, which involves cleaning, normalizing, transforming, and dimensionality reduction of the data [15]. Data cleaning ensures that the data used is free from errors or inconsistencies, while normalization aligns the scale of features within the dataset. Data transformation, such as encoding categorical data, helps make the data more suitable for analysis.

Good preprocessing is crucial because low-quality data can reduce the effectiveness and accuracy of data mining results. After preprocessing, the next step is to apply data mining algorithms to identify patterns in the data. Various techniques used in data mining include clustering, classification, regression, and association rule learning. This study utilizes classification techniques to recognize patterns that can be used for early prevention of child development disorders. The following outlines the stages of the classification process.

Data mining classification is a process of finding definitions of similar characteristics in a group or class. Classification is one of the most common methods used in data mining. This method is carried out with the aim of estimating the class of an object whose label is not yet known.

2.2.1 Pre-processing

The preprocessing process is a crucial step in data classification aimed at improving data quality so that machine learning models can operate more effectively and accurately [16]. This process includes various techniques such as data cleaning, normalization, handling missing values, and data transformation. Data cleaning involves removing or correcting errors in the data, such as duplicates, inconsistencies, or outliers. For example, data with duplicate entries or invalid values must be removed or corrected to avoid bias in the model. This study involves several preprocessing steps to support the accuracy of the resulting model, including transformation, normalization, and data imputation.

2.2.2 Missing value imputation

Handling missing values is also an important step in data preprocessing as it can affect the resulting model. Raw data used in research often has some defects, one of which is the presence of missing values [17]. Missing values can occur for various reasons, such as measurement errors or incomplete data entry.

Therefore, the process of missing value imputation aims to maintain the integrity of the dataset so that data analysis or machine learning model training can proceed without disruption. Without imputation, missing data can cause bias, reduce model accuracy, or even obstruct the analysis process entirely. This technique involves various methods, ranging from simple imputation using the mean, median, or mode, to more complex methods such as k-Nearest Neighbors (k-NN) or other machine learning algorithms that predict missing values based on patterns in the available data.

2.2.3 Transformation

Data transformation is the process of changing the format, structure, or values of data to make it more suitable for analysis or machine learning model training

[18]. The main goal of data transformation in the classification process is to improve the quality and consistency of the data so that the model can learn more effectively and produce more accurate predictions. Data transformation includes various techniques such as normalization, standardization, encoding categorical data, and dimensionality reduction.

These preprocessing methods are widely applied in various studies due to their ability to standardize feature scales, reduce redundancy, and address issues with heterogeneous data. Through normalization or standardization, features with different scales can be transformed into a uniform scale, which is important for algorithms like SVM that are highly sensitive to feature scales. Encoding categorical data allows machine learning algorithms that work with numerical data to effectively use categorical data.

2.2.4 Normalization

Data normalization is a technique in data preprocessing aimed at aligning the scales of feature values within a dataset so that they fall within the same range, typically between 0 and 1 [19]. In the context of data mining, normalization is crucial because features in a dataset often have different scales. For example, one feature might have a range of values between 1 and 1000, while another feature has a range between 0 and 1. Without normalization, features with a larger range of values can dominate distance or similarity calculations in machine learning algorithms, thereby affecting the final analysis results.

The main goal of data normalization is to ensure that each feature contributes equally to machine learning models or data mining algorithms. This is important for algorithms sensitive to feature scales, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and neural networks. With normalization, the optimization process becomes more stable and faster, and it improves the model's prediction accuracy. Additionally, normalization helps reduce the impact of outliers by ensuring that extreme values do not dominate the analysis results. Thus, normalization is a crucial step in data preprocessing to ensure that machine learning models operate effectively and accurately.

When performing data normalization, the Min-Max Normalization technique can be used. This technique works by shifting and scaling the original values of each data point based on the minimum and maximum values within the dataset [20]. The formula used in the Min-Max normalization technique is as follows:

$$z = \frac{x - min\ (x)}{[max(x) - min\ (x)]} \quad (1)$$

Describes:
z : Normalized value,
x : Original value x,
min(x) : Minimum value for the variable x,
max(x) : Maximum value for the variable x.

2.3 Support vector machine

Support Vector Machine (SVM) is a machine learning method used for classification and regression. SVM was developed by Vladimir Vapnik and his colleagues at AT&T Bell Laboratories in the 1990s [21] This method works by finding the optimal hyperplane that separates data from two classes with a maximal margin. In the context of classification, SVM is highly effective for high-dimensional data problems and has been shown to provide good results in various applications, such as facial recognition, handwriting recognition, and text analysis. [22]

SVM has advantages including determining the distance using Support Vector Machine so that the computation process is fast. SVM operates on the concept of maximal margin, which is the closest distance between data points from both classes to the separating hyperplane. SVM aims to find the hyperplane that maximizes this margin, as a hyperplane with a larger margin tends to provide better generalization to unseen data. For data that cannot be linearly separated, SVM uses a technique called the kernel trick. This technique allows SVM to map the data into a higher-dimensional space where it can be linearly separated [23].

The way SVM works is based on SRM or Structural Risk Minimization which is designed to process data into a Hyperplane that classifies the input space into two classes. The theory of SVM begins with a grouping of linear cases that can be separated by a hyperplane and divided according to their classes.

Several types of kernels can be used in SVM, such as linear, polynomial, radial basis function (RBF), and sigmoid. Choosing the right kernel is crucial for SVM performance, as different kernels can produce different hyperplanes [24]. The linear kernel is suitable for data that can be linearly separated, while polynomial and RBF kernels are better suited for data with non-linear relationships. In practice, the RBF kernel is one of the most frequently used due to its flexibility in handling various types of data. Below are the formulas for each kernel.

1. Kernel Linear

$$K(x_i, x) = x_i^T x \quad (2)$$

2. Kernel Polynomial

$$K(x_i, x) = (\gamma x_i^T + r)^p, \gamma > 0 \quad (3)$$

3. Kernel Radial Basis Function (RBF)

$$K(x_i, x) = \exp(-\gamma||x - x_i||^2) \quad (4)$$

4. Sigmoid Kernel

$$K(x_i, x) = \tanh(\gamma x_i^T + \mathrm{r}) \quad (5)$$

In addition to its ability to handle high-dimensional data, SVM also has several other advantages. SVM is relatively resistant to overfitting, especially in cases

where the number of features exceeds the number of samples. This is due to the use of regularization in margin optimization. Additionally, SVM has good interpretability because the model relies only on a small subset of the training data known as support vectors. These support vectors are the data points located at the edge of the margin and are most influential in determining the position of the hyperplane.

Despite its many advantages, SVM also has some drawbacks. One major disadvantage is its high computational complexity, particularly for large datasets with many features. The training process for SVM can be time-consuming and require significant computational resources.

For further research development, it is recommended to use a dataset with more complex attributes and use feature selection so that we can find out whether the performance of the SVM algorithm still produces high accuracy.

2.4 Evaluation

Evaluation in data mining is a crucial stage for measuring how well a model performs in classifying data. One commonly used evaluation method is the confusion matrix. A confusion matrix is a table that displays a comparison between the classifications predicted by the model and the actual classifications. This table helps in analyzing the model's performance by showing the number of correct and incorrect predictions for each class in the dataset [25].

The first step in using a confusion matrix is to identify the four main components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). True Positives are the number of correct predictions for the positive class, while True Negatives are the number of correct predictions for the negative class. False Positives and False Negatives indicate the number of prediction errors for the positive and negative classes, respectively [25]. By calculating these values, we can obtain various evaluation metrics such as accuracy, precision, recall, and F1-score.

The second step involves calculating the evaluation metrics from the confusion matrix. Accuracy measures how often the model is correct in its classifications overall, while precision indicates how accurate the model is in predicting the positive class from all positive predictions made. Recall, or sensitivity, measures how well the model identifies all actual positive examples. The F1-score is the harmonic mean of precision and recall, providing a balanced view of the model's performance [26]. By analyzing these metrics, we can assess the quality of the model and determine the necessary steps for improvement.

Based on the explanation above, the calculations for Accuracy, Recall, Precision, and F1-score can be formulated as follows [27]:

1. Accuracy represents the effectiveness of the overall classification process, calculated with the formula[17]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

2. Precision is the percentage of correctly classified positive labels, calculated with the formula:

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (7)$$

3. Recall is the effectiveness of the classification process in identifying positive labels, calculated with the formula:

$$Recall = \frac{TN}{TN + FN} \times 100\% \quad (8)$$

4. The F1-measure is the harmonic mean of precision and recall, with a range from 0 to 1:

$$F - measure = 2\,x\,\frac{Recall \times Precision}{Recall + Precision}\,x\,100\% \quad (9)$$

3 Result and discussion

The results obtained from applying the child development nutrition dataset using the Support Vector Machine method with a linear kernel, tested through several scenarios for the ratio of training to test data splits, are displayed in Table 1 below.

Table 1. Testing scenario.

	Splitting Data
Scenario 1	70:30
Scenario 2	80:20
Scenario 3	90:10

Based on the above criteria and test scenarios, the results of each test are detailed in Table 2 below.

Table 2. Results on SVM classification model.

Scenario	**Accuracy**	**Precision**	**Recall**	**F1-Score**
70:30	76%	58%	76%	66%
80:20	75%	56%	75%	64%
90:10	71%	50%	71%	59%
Running Time	0,15 s			

The results obtained from each test scenario show differences. However, overall, splitting the training and test data using a 70:30 ratio provides the best accuracy compared to the other two test scenarios, with an accuracy of 76%, an F1 score of 66%, precision of 58%, and recall of 76%.

4 Conclusion

Based on the research conducted, it was found that the Support Vector Machine (SVM) method can classify a child development dataset of 473 records.

1. The SVM method is particularly effective for this classification task due to its ability to handle non-

linear data separations and find optimal hyperplanes that maximize class margins.

2. While the SVM method achieved a 76% accuracy, comparing this performance with other machine learning techniques such as Decision Trees or Neural Networks could provide a more comprehensive understanding of its relative effectiveness
3. The classification relied on key features such as nutritional intake and developmental indicators, which were instrumental in accurately categorizing the child development data

The 70:30 ratio provided the most optimal results, indicating that this ratio strikes a balance between having enough data for training and sufficient data for testing, which is crucial for model generalization.

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