

Implementation of ANN for Toddler Nutrition Classification Using Feature Selection

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ABSTRACT

The nutritional status of toddlers is an important indicator in assessing the health and growth quality of children. In Indonesia, nutritional problems such as malnutrition and obesity are still serious issues that require rapid and accurate identification strategies. Using the Artificial Neural Network (ANN) algorithm, this study classified the nutritional status of toddlers based on anthropometric data collected from the Tanjungharjo Community Health Center, Kapas District, Bojonegoro Regency. This study combines ANN with several feature selection and reduction methods, including Chi-Square, Pearson Correlation (PC), and Principal Component Analysis (PCA). In addition, it compares the performance of the model under data conditions with data without Min–Max Scaler normalization. The dataset was processed through preprocessing, encoding, normalization, and division stages using 80% training data and 20% test data. The results showed that ANN+PC with pearson correlations without normalization provided the best performance, with an accuracy value of 0.9809, precision of 0.9827, recall of 0.9809, and F1 score of 0.9815. These results indicate that data normalization does not always improve ANN performance; on the contrary, the PC method showed a significant improvement in performance after applying Min–Max without normalization. These results show that the feature selection method used is highly dependent on the method used. This study found that ANN+PC is an effective way to classify the nutritional status of toddlers, provided that the preprocessing and feature selection techniques are chosen correctly. The results of this study are expected to assist in decision-making regarding how to monitor and prevent nutritional problems in toddlers.



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I. INTRODUCTION

The nutritional status of toddlers is one of the main indicators in assessing children's health, especially in the early age group who are in a critical growth period. Nutritional problems in toddlers, such as malnutrition, overnutrition, and stunting, remain a serious challenge in Indonesia and have a direct impact on physical and cognitive development, as well as the quality of human resources in the future [1]. Long-term nutritional imbalance can cause permanent growth disorders [2]. Therefore, accurate and continuous monitoring and assessment of the nutritional status of toddlers is very important in the context of national health. Nutritional status

is usually assessed through body measurements (anthropometry), specifically by comparing height for age (HFA) against the growth standards set by the World Health Organization (WHO) [3]. This study specifically examines the nutritional status of toddlers in Kapas Subdistrict, Bojonegoro Regency.

Efforts to address nutritional status in a targeted manner require effective nutrition programs and the ability of the health system to identify children at risk early on [4]. Therefore, the use of data mining and machine learning approaches is a relevant solution to assist in the process of classifying the nutritional status of toddlers objectively, quickly, and consistently, as well as supporting early

detection of nutritional problems [5]. This approach enables more optimal utilization of anthropometric data in producing accurate and reliable classification models as a basis for decision-making in the health sector [6].

Several previous studies have examined the classification of toddler nutritional status using various machine learning algorithms. The first study applied the Naïve Bayes method to classify toddler nutritional status based on anthropometric indices according to World Health Organization (WHO) standards [7]. The case study classifies the nutritional status of toddlers using the K-Nearest Neighbor (K-NN) algorithm applied using the Euclidean Distance method to measure the proximity of toddler data based on the attributes of age, weight, height, and head circumference [8]. Other researchers applied the C4.5 algorithm in classifying the nutritional status of toddlers by constructing a decision tree model based on anthropometric attributes [9]. However, previous studies have focused on the application of a single algorithm without optimizing feature selection.

Based on the limitations of previous studies, this study chose Artificial Neural Network (ANN) as the main method in classifying the nutritional status of toddlers. Artificial Neural Network (ANN) has superior capabilities in modeling non-linear and complex relationships between anthropometric variables. Artificial Neural Network (ANN) has been widely used and proven effective in various classification studies in different fields, especially in the health sector. According to research on a case study of heart disease classification using ANN, it shows good ability in recognizing complex patterns. The ANN method can produce an accuracy value of 73,77%, precision of 80,43%, recall of 84,09%, and an F1-score of 82,22%, which indicates that ANN is capable of performing disease classification well [10]. In addition, ANN is also applied in the field of public opinion sentiment analysis related to Covid-19 by utilizing text data from Twitter social media. The study used ANN with the Backpropagation method and produced high performance [11]. Other studies have also implemented ANN in classification based on blood vessels with high accuracy results [12]. Various research results show that ANNs have flexibility and good generalization capabilities in solving classification problems with diverse data characteristics.

In addition to selecting the appropriate classification method, the application of feature selection in this study is also very important. Besides helping to determine the most important variables, feature selection plays an important role in the process of classifying the nutritional status of toddlers. Therefore, this method can improve accuracy and reduce model complexity. Furthermore, the data normalization stage using the Min-Max Scaler method is also used to convert feature values into a specific range, usually 0 to 1, so that there is no dominance of values in certain features. This normalization process is carried out with the aim of equalizing

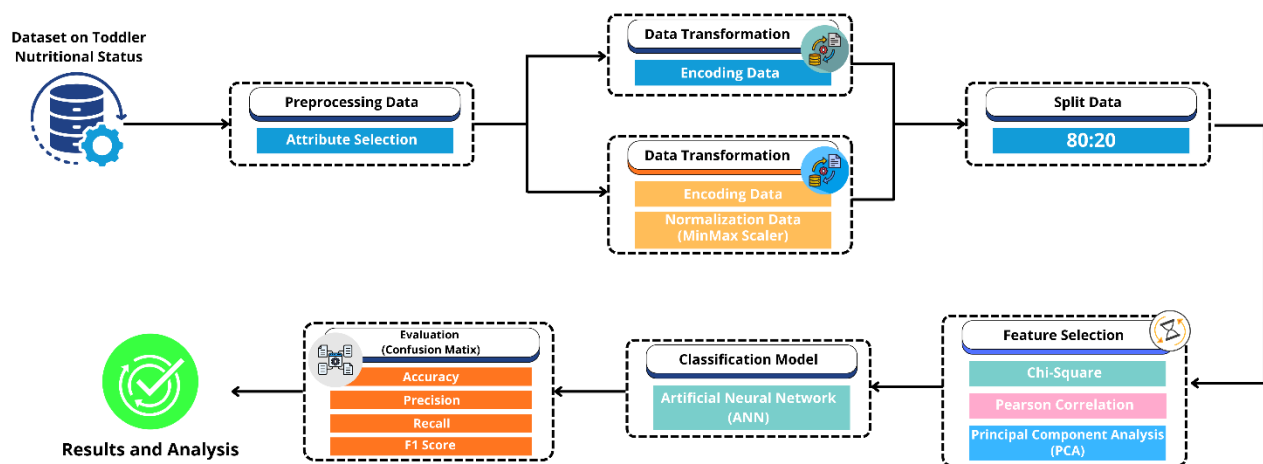
the scale between variables so that there is no dominance of values in certain features and to help improve the efficiency and stability of the model training process. It is expected that the classification model will work more optimally, be more stable, and have better generalization capabilities with the combination of Min-Max Scaler normalization and feature selection.

Although various machine learning methods have been successfully applied in classification, several previous studies show that the performance of classification models is greatly influenced by feature selection and data selection processes [13]. Using all attributes without considering the relevance of each feature to the target variable can increase model complexity and cause a decrease in accuracy and generalization ability. Therefore, applying feature selection techniques is an important step to simplify the model and improve classification efficiency and performance [14]. The Artificial Neural Network (ANN) method was used in this study to classify the nutritional status of toddlers. ANN was chosen because of its ability to model non-linear relationships between variables and identify complex patterns in health data. By applying a weight-based learning process and activation functions to each neuron, the ANN model is expected to produce a more optimal model, reduce the risk of overfitting, and improve accuracy in determining the nutritional status category of toddlers.

This study specifically aims to examine how the Artificial Neural Network (ANN) algorithm works in classifying the nutritional status of toddlers based on anthropometric data. Combining ANN with various feature selection methods, such as Chi-Square, Pearson correlation (PC), and Principal Component Analysis (PCA), was used in several testing scenarios. In addition, the effects of using Min-Max Scaling normalization and without normalization were compared. To determine the accuracy and stability of the model created, performance evaluation was carried out using confusion metrics and classification f1-scores to assess the accuracy and stability of the resulting model. The results of this study are expected to provide a comprehensive overview of the influence of data normalization and feature selection methods on the performance of the Artificial Neural Network (ANN) algorithm in classifying the nutritional status of toddlers. In addition, these results will enrich methodological research on how to optimize classification models in health data.

II. RESEARCH METHODOLOGY

This study aims to create an accurate classification system for toddler nutritional status based on an optimized Artificial Neural Network (ANN) algorithm. This system was developed to facilitate early detection of nutritional status in toddlers.



A. Dataset Collection

The data used in this study is secondary data that was collected through observation and interviews at the Tanjungharjo Community Health Center, Kapas District, Bojonegoro Regency. The data collected included include Name, JK (Gender), Age at Measurement, BB (Weight), TB (Height), BB/U (Weight for Age), MM (Measurement Method), ZS BB/U (Z-Score Weight for Age), TB/U (Height for Age), ZS TB/U (Z-Score Height for Age), BB/TB (Weight for Height), ZS BB/TB (Z-Score Weight for Height), and WG (Weight Gain). The data will be used to identify and analyze the nutritional status patterns of toddlers. If this study is replicated or applied in other locations, the features or variables used must remain the same so that the resulting models can be compared consistently and the validity and reliability of the research results can be maintained. Feature consistency is also necessary to ensure that the feature selection process, model training, and classification performance evaluation can be carried out with uniform standards.

B. Preprocessing Data

The data preprocessing stage is an important step that is carried out before the data analysis or modeling process. Preprocessing aims to ensure that the data is in the appropriate format and ready to be used by machine learning algorithms. Converting categorical data into a numerical form that can be processed by machine learning algorithms is known as encoding. The encoding process is carried out by assigning numerical labels to each existing category [15]. To standardize the range of values in numerical attributes, Min-Max Scaler is a normalization method that transforms data values into a specific range, usually between 0 and 1, because each feature in the dataset has different units and scales [16]. By using the Min-Max Scaler, all numeric features have a uniform scale, which improves performance and stability [17]. This normalization also helps the algorithm learn data

patterns better and prevents features with larger values from dominating.

C. Splitting Data

In the machine learning process, training data and test data are very important. Training data is used to build and train models, while test data is used to evaluate the accuracy of the models created. The percentage comparison between training data and test data greatly affects model performance [18]. In this study, the data was divided into two parts, with 80 percent as training data and 20 percent as test data. This division was chosen because it provides a balance between a sufficient amount of data to train the model optimally and a sufficient amount of data to test the model's ability to generalize to previously unseen data.

D. Feature Selection

The Chi-Square (χ^2) feature selection method is a statistics-based approach used to measure the level of dependence between features and class labels. This method calculates the chi-square value to determine whether there is a significant relationship between the independent variable and the target variable; a larger chi-square value indicates that the feature has a greater influence in distinguishing between classes [19]. Pearson correlation (PC) is a new variable generated from the results of linear transformation of the original features. Each Pearson correlation (PC) is a linear combination of the initial variables and is arranged based on the largest variance contribution in the data. The first PC explains the largest data variance, and the subsequent PCs explain smaller data variances. By using principal components, important information from the data can still be retained even though the number of features is reduced [20].

E. Dimensionality Reduction

Principal component analysis (PCA) is a dimension reduction technique used to simplify data while retaining most of the important information it contains. PCA works by transforming a number of correlated variables into a set of new variables called principal components. These

components are uncorrelated (orthogonal) and are arranged based on the amount of data variation they can explain. The first principal component has the largest contribution to the variation in the data, followed by the second component, and so on. By selecting several principal components that have the largest contribution to the variation, the data dimension can be reduced without losing significant information. This technique is very effective for overcoming multicollinearity problems, improving computational efficiency in the modeling process, and facilitating the process of data visualization in lower-dimensional space [21][22].

F. Artificial Neural Network

Artificial Neural Networks (ANN) were first created by McCulloch and Pitts in 1943 [23]. A simple mathematical model to show how biological neurons work in the human brain [24][25]. This model design became the basis for the development of various artificial neural network designs that are still in use today. This can be seen in Figure 2.

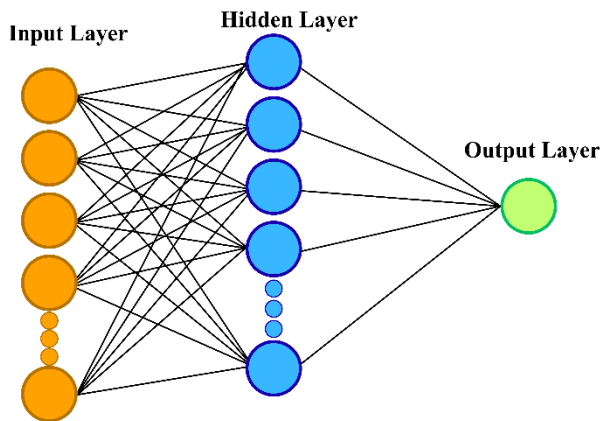


Figure 2 Artificial neural network with hidden 1 layer

An Artificial Neural Network (ANN) consists of many artificial neurons that are interconnected in various layers. The input layer, hidden layer, and output layer are the layers that make up an ANN. By multiplying the input by a certain weight, summing it, and using an activation function, each neuron produces an output. Mathematically, the output of a neuron can be written as :

$$y = f\left(\sum_{i=1}^n w_i X_i + b\right) \quad (1)$$

Where x_i is the input value i , w_i is the connection weight, b is the bias, and f is the activation function. The output value of the neuron is determined by this function. To reduce prediction errors, ANNs adjust weights and biases using optimization algorithms during the training process. ANNs can be used effectively for various tasks such as classification, prediction, and regression due to their ability to learn non-linear relationships.

In this study, the Multi-Layer Perceptron (MLP) algorithm was used to implement the Artificial Neural Network (ANN) model. The network consisted of four layers: one input layer, two hidden layers, and one output layer. The first hidden layer consisted of 64 neurons, while the second hidden layer consisted of 32 neurons. The input layer was adjusted to the number of features generated from each scenario, including principal component analysis (PCA), Pearson Correlation, and Chi-Square. Both hidden layers used Rectified Linear Unit (ReLU) as the activation function, and the output layer used the Softmax activation function to handle the classification of nutritional status of various classes based on the BB/TB index. The model training process was carried out with a maximum number of iterations of 500 epochs. The stratified sampling method was used to divide the data with a ratio of 80% training data and 20% test data to maintain the class distribution proportion in the.

G. Evaluation

Model performance is evaluated using commonly used classification metrics: accuracy, precision, recall, and F1 score. Each metric is evaluated separately to provide a comprehensive overview of the model's ability to perform classification. While precision indicates the model's ability to provide accurate predictions for each class, recall measures the model's ability to recognize correct data in each class, and F1 Score is used as a balance between precision and recall.

III. RESULT AND DISCUSSION

This study uses an Artificial Neural Network (ANN) algorithm to classify the nutritional status of toddlers. The results are based on anthropometric data from the Tanjungharjo Community Health Center, provided by the Bojonegoro Regency Health Office. The data used in this study covers the period from December 2024 to August 2025, thus representing the growth conditions of toddlers during that time period. Table I shows the data used in this study, which serves as the basis for the analysis and modeling of toddlers' anthropometric attributes. Using anthropometric indicators commonly used to assess nutritional status, this dataset provides a measurable and systematic depiction of toddlers' nutritional status based on the observation period.

The dataset used in this study consisted of 1.835 data points on toddlers with varying nutritional status labels. Good nutritional status dominated with 1.553 data points, followed by 141 data points for nutritional risk, 91 data points for malnutrition, 41 data points for overnutrition, and 9 data points for obesity. As shown in Table 1, the original attributes in this research dataset include Name, JK (Gender), Age at Measurement, BB (Weight), TB (Height), BB/U (Weight for Age), MM (Measurement Method), ZS BB/U (Z-Score Weight for Age), TB/U (Height for Age), ZS TB/U (Z-Score Height for Age), BB/TB (Weight for Height), ZS BB/TB (Z-Score Weight for Height), and WG (Weight Gain).

TABLE I
ORIGINAL DATASET

No	Name	JK	Age at Measure	BB	TB	MM	BB/U	ZS BB/U	TB/U	ZS TB/U	BB/T B	ZS BB/TB	WG
1	AHMAD RIFAT LAZUAR DI	L	4 Years - 6 Months - 14 Days	23	111,4	Stand	MR	2,07	Normal	1	MN	2,07	N
2	AZRIEF RAFARDAN S. A	L	3 Years - 11 Months - 27 Days	16,7	103,2	Stand	NOR	0,17	Normal	-0,02	GN	0,29	N
3	THORIQ UL MUTAQ QIN	L	0 Years - 3 Months - 22 Days	11,7	97,2	Supine	NOR	-2,31	Normal	-0,84	M	-2,84	N
4	MUHAMMAD HUSEIN ALKHAFIDS	L	1 Year - 1 Month - 7 Days	15,8	96,6	Supine	NOR	-0,07	Normal	-1,3	RO	1,08	N
5	KHALIS A AQHNIA ALMAH YRA	P	0 Years - 4 Months - 14 Days	20	96	Supine	NOR	3,73	Normal	1,6	O	4,02	T
...
1835	M DAMAR	L	3 Years - 3 Months - 28 Days	15,2	98,5	Stand	NOR	0,1	Normal	-0,03	GN	0,21	N

These attributes are used to describe the growth characteristics of toddlers and are the main input in the process of classifying nutritional status. For the JK attribute, the code L indicates male and P indicates female. Meanwhile, for the WG attribute, the code N indicates weight gain and the code T indicates no weight gain. In the BB/U attribute, the code MR indicates More Risk, NOR indicates Normal, and NE indicates Not Enough. Furthermore, in the BB/TB attribute, the code MN indicates More Nutrition, GN indicates Good Nutrition, M indicates Malnutrition, RO indicates Risk of Overnutrition, and O indicates Obesity.

A. Preprocessing

At this stage, it is an important first step in this study to ensure that the data used in Artificial Neural Network (ANN) modeling is clean, consistent, and suitable for analysis. Preprocessing begins with attribute selection, which is the

selection of relevant and numerical features to support the nutritional status classification process. The attributes used include gender, weight, height, weight-for-age, weight-for-age z-score, height-for-age, height-for-age z-score, weight-for-height z-score, weight gain, and weight-for-height as the target variable. Other categorical attributes such as weight gain status and non-numerical information were not included because they did not contribute directly to ANN modeling. The results of this attribute selection stage are shown in Table II, which describes the final attributes used in the study. This selection process aims to reduce data complexity so that the model can learn more effectively. By using only relevant features, the risk of noise and irrelevant information affecting the model performance can be minimized. As a result, the ANN model is expected to produce more accurate and reliable nutritional status classification results.

TABLE II
AFTER PREPROCESSING MINMAX SCALER

No	JK	BB	TB	BB/U	ZS BB/U	TB/U	ZS TB/U	ZS BB/TB	WG
1	0.0000	0.0067	0.9609	0.6666	0.0014	0.0000	0.6390	0.0006	0.3333
2	0.0000	0.0046	0.8422	0.3333	0.0010	0.0000	0.5198	0.0004	0.3333
3	0.0000	0.0017	0.2836	0.3333	0.0011	0.0000	0.5946	0.0005	1.0000
4	0.0000	0.0011	0.2720	0.3333	0.0007	0.0000	0.5595	0.0001	1.0000
5	1.0000	0.0015	0.2416	0.3333	0.0008	0.0000	0.3200	0.0005	1.0000
...
1835	0.0000	0.0041	0.7742	0.3333	0.0010	0.0000	0.5186	0.0004	0.3333

At this stage, categorical attributes have been encoded so that they can be processed by the ANN. The encoding process is applied to gender (JK), TB/U category, BB/U category, and the target variable BB/TB, which was originally categorical, is encoded. This process aims to enable the data to be processed by ANN, which only accepts numerical inputs. Nutritional status categories are converted into numerical values, namely 0 for good nutrition, 1 for malnutrition, 2 for overnutrition, 3 for obesity, and 5 for risk of overnutrition.

After encoding is complete, normalization is performed using the Min–Max Scaler method to equalize the scale of all numerical features into a range of values from 0 to 1, as shown in Table II. This is important because the data has significant differences in units and a wide range of values between features. Each feature can contribute equally to the model learning process by equalizing the data scale. During the Artificial Neural Network (ANN) training process, the use of Min–Max Scaler also increases stability and convergence speed and reduces the potential for weight bias caused by large-scale features. As a result, this allows the model to learn data patterns more efficiently and optimally.

Finally, the dataset was divided using stratified sampling techniques with a ratio of 80% training data and 20% test data to ensure that the distribution of each class remained balanced in both subsets. Of the total 1.835 data used in this study, 1.468 data were allocated as training data, while 367 data were used as test data. Thus, the preprocessing stage produced a selected, normalized dataset that was ready to be used in the ANN model training and evaluation process. In addition, to ensure the quality of the data used in ANN modeling, a data distribution verification process was carried out after the preprocessing stage was completed. This verification included re-examining the suitability of the range of normalization results, the balance of data in each nutritional status class, and the consistency between the training data and the test data. This step aimed to ensure that the processed data did not experience distortion due to the encoding and normalization processes, so that the ANN model could learn data patterns optimally.

B. Evaluation and Comparison of Classification Models

Support Vector Machine (SVM) was used as a comparison model to evaluate the performance of classifying the nutritional status of toddlers. The optimal hyperplane, which separates data between classes with maximum margin, is how SVM works. In this study, SVM was used with a Radial Basis Function (RBF) kernel and a dataset that produced Pearson Correlation feature selection without normalization. This study also uses stratified sampling to divide the training and test data by 80:20. The test results show that the SVM model has an accuracy of 84,74%, indicating that although SVMs can perform classification quite well, they still fail to capture complex patterns in infant nutritional status datasets that are more complex than ANN and Random Forest models.

Random Forest is used as an ensemble learning-based comparison algorithm that builds a number of decision trees

to improve classification stability and accuracy. This model is trained using the same dataset as ANN and SVM, namely the results of Pearson Correlation feature selection without normalization, with a training data and test data ratio of 80:20. The evaluation results show that Random Forest achieved an accuracy of 93,73%, which is higher than SVM but still below the performance of ANN. This shows that the ensemble method is able to capture non-linear patterns quite well, but is still unable to surpass the performance of ANN in this study. In addition, Random Forest demonstrates good robustness against overfitting due to the use of multiple decision trees. However, the model may require higher computational resources compared to simpler classification methods.

TABLE III
COMPARISON OF CLASSIFICATION MODEL ACCURACY

No	Model	Accuracy
1	SVM	84,74 %
2	Random Forest	93,73%
3	ANN + PC Nonnormalization	98,09%

Based on the comparison of the three models, the Artificial Neural Network (ANN) with Pearson Correlation feature selection without normalization showed the best performance with an accuracy of 98,09%, followed by Random Forest at 93,73%, and Support Vector Machine at 84,74%. The superiority of ANN in this study demonstrates its ability to model complex non-linear relationships between nutritional status variables. Meanwhile, Random Forest showed stable performance due to the ensemble approach used, and SVM had the lowest performance, which was likely influenced by the characteristics of the data distribution and sensitivity to feature scale. These results prove that the ANN model is the most optimal approach for classifying the nutritional status of toddlers in the dataset used in this study.

C. Feature Selection

At this stage, feature selection was performed to determine the effect of feature reduction on the classification performance of toddler nutritional status based on the BB/TB index using the Artificial Neural Network (ANN) method. Feature selection aims to select the most relevant original features to the target variable so as to improve model performance and reduce data complexity. The initial dataset consists of 9 features, namely gender (jk), weight, height, BB/U, ZS BB/U, TB/U, ZS TB/U, ZS BB/TB, and weight gain.

Based on the test results, the Chi-Square and Pearson Correlation methods produced different numbers of selected features from the initial dataset. The Chi-Square method produced 6 selected features, namely gender (jk), weight, height, BB/U, TB/U, and weight gain. This selection was based on the level of dependence of each feature on the target class, where features with a significant relationship to BB/TB nutritional status were retained.

Meanwhile, the Pearson Correlation method also produced 6 selected features, namely ZS BB/TB, ZS BB/U, weight,

BB/U, weight gain, and ZS TB/U. This method assesses the strength of the linear relationship between each feature and the target variable. The results obtained show that Z-score-based features have a fairly strong contribution in the process of classifying nutritional status based on the BB/TB index. Overall, the application of feature selection successfully reduced the number of features from the initial 9 features to 6 features in each method, making the model more efficient without losing relevant information.

D. Dimensionality Reduction

In addition to feature selection, this study also applied dimensionality reduction techniques using the Principal Component Analysis (PCA) method. Unlike feature selection, which selects specific original features, PCA transforms all initial features into new components that are linear combinations of those features.

The results of applying PCA show that the 9 initial features can be represented by 1 principal component that is able to explain most of the data variation. This principal component summarizes important information from all features in one dimension, thereby reducing redundancy due to correlations between features. The application of dimensionality reduction through PCA helps simplify the data structure, reduce calculation complexity, and improve the efficiency of the ANN training process without losing significant information in BB/TB nutritional status classification.

E. K-Fold Cross-Validation

This study uses the 5-Fold Cross-Validation method, which divides the dataset into five parts, with each part used as test data and training data, to evaluate the overall performance of the model and reduce bias caused by single data division. To evaluate the consistency and generalization ability of the ANN model with Pearson correlation feature selection, the evaluation was conducted using accuracy, precision, recall, and F1 score metrics. Table IV shows the test results for each fold.

TABLE IV
RESULTS OF 5-FOLD CROSS-VALIDATION OF ANN MODEL WITH PEARSON CORRELATION FEATURE SELECTION

Fold	Accuracy	Precision	Recall	F1-Score
1	0,8529	0,7571	0,8529	0,7982
2	0,8529	0,7711	0,8529	0,7895
3	0,8474	0,7201	0,8474	0,7786
4	0,8501	0,7528	0,8501	0,7910
5	0,8420	0,7131	0,8420	0,7722
Average	0,8490	0,7428	0,8490	0,7859

Based on Table IV, it can be seen that the accuracy value for each fold is in the range of 84%–85%, with an average of 84.90%. The relatively small difference in values between folds indicates that the model has a good level of stability and does not depend on a specific data division scenario. The consistently high recall value 84,90% indicates that the model

is able to detect positive classes well. However, the precision value, which is lower than the recall, indicates that there are still a number of false positive predictions. The average F1-Score value of 78,59% shows a fairly good balance between precision and recall.

When compared to the previous results, which achieved an accuracy of around 98% on a single data split (train-test split), these cross-validation results provide a more realistic picture of performance. The decrease in accuracy indicates that evaluation using K-Fold Cross-Validation is able to detect potential overfitting and provide a more reliable estimate of the model's generalization ability to new data.

F. Classification

At this stage, the Artificial Neural Network (ANN) method was used to classify the nutritional status of toddlers based on the BB/TB index. The classification process was carried out using six test scenarios, which were a combination of feature selection methods and data normalization applications, as shown in Table IV. The scenarios were as follows :

- ANN + PCA Non-Normalization
- ANN + PC Non-Normalization
- ANN + Chi-Square Non-Normalization
- ANN + PCA Normalization MinMax Scaler
- ANN + PC Normalization MinMax Scaler
- ANN + Chi-Square Normalization MinMax Scaler

TABLE IV
RESULT CLASSIFICATION

Algorithm	Accuracy	Precision	Recall	F1-Score
ANN+Chi-Square	0.8801	0.8587	0.8801	0.8622
ANN+PC	0.9809	0.9827	0.9809	0.9815
ANN+PCA	0.8474	0.7181	0.8474	0.7774
ANN+Chi-Square Normalization	0.8692	0.8325	0.8692	0.8370
ANN+PC Normalization	0.8801	0.8491	0.8801	0.8504
ANN+PCA Normalization	0.8583	0.8239	0.8583	0.8301

Based on the results of testing six classification scenarios using Artificial Neural Network (ANN), which can be seen in Table V, different accuracy, precision, recall, and F1-score values were obtained for each combination of feature selection and data normalization methods. These differences indicate that the selection of feature selection methods and the application of normalization have a significant effect on model performance. One of the normalization methods used in this study is Min-Max Scaler, which is a data transformation technique that converts the range of feature values into a specific scale, generally between 0 and 1. This process aims to reduce scale differences between features so that the ANN model can perform the learning process more

stably and optimally, considering that the ANN algorithm is sensitive to differences in the range of values in the input data.

To analyze model performance in greater depth, evaluation is not only based on accuracy, precision, recall, and F1-score values, but also through confusion matrix analysis. The confusion matrix is used to see the distribution of model predictions for each class, so that the number of correct predictions (true positives and true negatives) and classification errors (false positives and false negatives) can be determined. In this study, confusion matrix analysis focused on ANN models with Pearson Correlation (PC) feature selection, both without normalization and with Min-Max Scaler normalization, because this method showed significant differences in performance in previous tests.

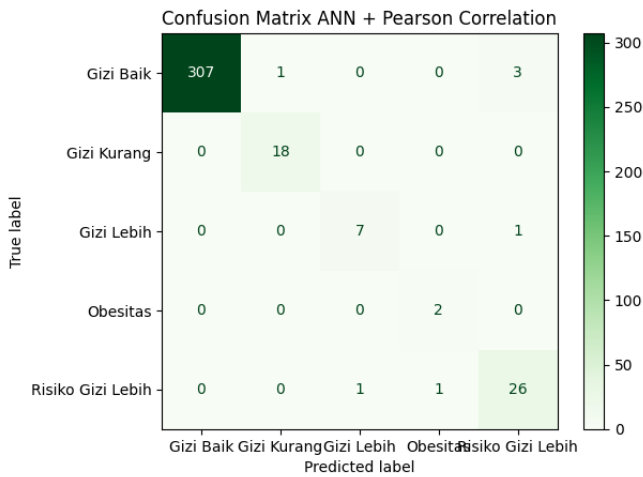


Figure 3 Confusion Matrix ANN + Pearson Correlation non-normalization

Based on the confusion matrix in the ANN + Pearson Correlation scenario without normalization, the classification performance showed excellent results. In the Good Nutrition class, 307 data points were correctly classified, with minimal errors, namely 1 data point incorrectly predicted as Poor Nutrition and 3 data points as Risk of Over Nutrition. In the Malnourished class, all 18 data points were correctly predicted without error, demonstrating the model's ability to optimally detect malnutrition. For the Overweight class, 7 data points were correctly predicted and only 1 data point was incorrectly predicted as at Risk of Overweight. In the Obese class, all 2 data points were correctly classified without error. Meanwhile, in the Overweight Risk class, 26 data points were classified correctly, with 1 error as Overweight and 1 as Obesity. Overall, the distribution of values on the main diagonal was dominant, indicating a very low classification error rate and the consistency of the model in distinguishing between classes, including classes with similar anthropometric characteristics.

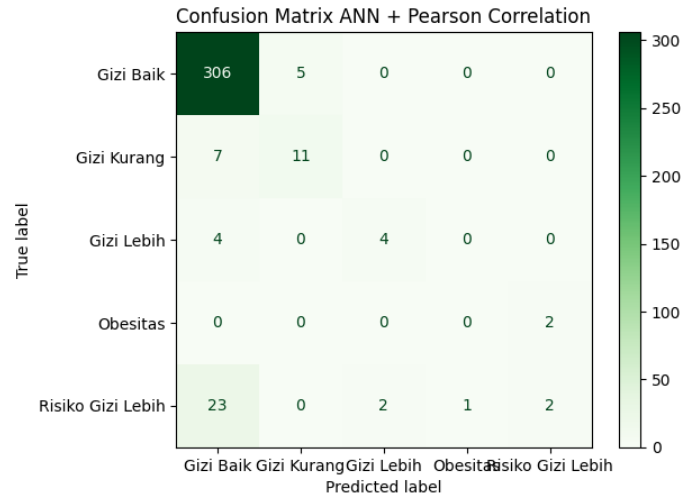


Figure 4 Confusion Matrix ANN + Pearson Correlation normalization

Conversely, in the ANN + Pearson Correlation scenario with normalization, there was an increase in the number of classification errors in several classes. In the Good Nutrition class, the number of correct predictions decreased slightly to 306 data points, with 5 data points incorrectly predicted as Poor Nutrition. In the Poor Nutrition class, only 11 data points were predicted correctly, while the other 7 data points were misclassified as Good Nutrition. In the Overweight class, only 4 data points were correctly classified, while the other 4 were incorrectly classified as Good Nutrition. For the Overweight class, there were no correct predictions, with all 2 data points incorrectly classified as Overweight Risk. A significant decline in performance was seen in the Overweight Risk class, where only 2 data points were predicted correctly, while 23 data points were incorrectly predicted as Good Nutrition, 2 data points as Overweight, and 1 data point as Obesity.

A comparison of the two confusion matrices shows that the ANN model with Pearson Correlation without normalization has a much more stable and accurate classification ability than the model using normalization. Without normalization, the model's predictions are concentrated on the main diagonal with minimal error, whereas in the normalization scenario there is an increase in error, especially in the Overweight and Underweight classes. This finding is in line with the results of previous performance evaluations, where the scenario without normalization obtained the highest accuracy and F1-score. Thus, it can be concluded that the combination of ANN and Pearson Correlation without normalization is the most optimal approach in classifying the nutritional status of toddlers based on the BB/TB index in this study.

G. Visualization of Feature Selection Results Using Pearson Correlation

The Pearson Correlation method is used to measure the strength and direction of the linear relationship between each feature and the target variable, namely nutritional status based on the BB/TB index. The Pearson correlation coefficient (r)

has a value range between -1 and +1. A value of r close to +1 indicates a strong positive relationship, a value close to -1 indicates a strong negative relationship, while a value close to 0 indicates a weak relationship or no linear relationship. In this study, correlation calculations were performed on training data (80%) to avoid data leakage. Six features with the highest absolute correlation values were selected for use in the Artificial Neural Network (ANN) model.

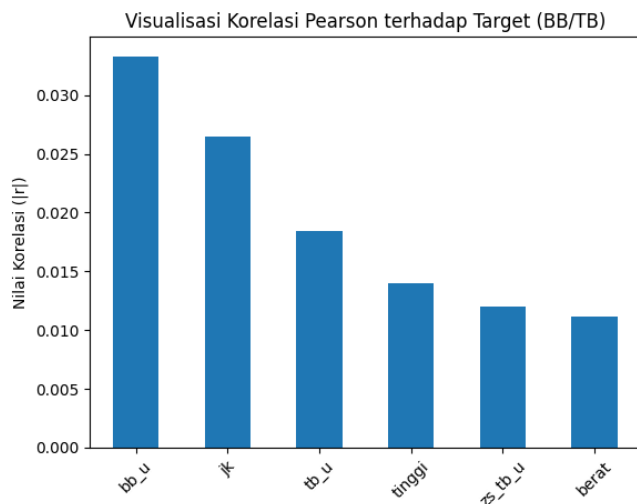


Figure 5 Visualization of Pearson Correlation Values against BB/TB Targets

Based on Figure 5, the *bb_u* feature has the highest correlation value with the BB/TB target of 0,0333, followed by *jk* (0,0264), *tb_u* (0,0184), height (0,0140), *zs_tb_u* (0,0120), and weight (0,0112). All correlation values obtained are positive, indicating that the relationship between variables is unidirectional.

However, all correlation coefficients are below 0,1 which means they are very weak. This indicates that the linear relationship between features and nutritional status based on the BB/TB index is not very strong. Therefore, an Artificial Neural Network model is used to capture non-linear relationship patterns that cannot be explained by a linear correlation approach alone.

IV. CONCLUSION

This study successfully implemented an Artificial Neural Network (ANN) algorithm to classify the nutritional status of toddlers based on the BB/TB index using anthropometric data from the Tanjungharjo Community Health Center, Kapas District, Bojonegoro Regency. This study also examined the effect of feature selection methods (Chi-Square, Pearson Correlation, and PCA) and the application of Min–Max Scaler normalization on the performance of the ANN model.

Based on six testing scenarios, the results showed that the combination of ANN + Pearson Correlation without normalization provided the best performance compared to other scenarios, with an accuracy value of 98,09%, precision

of 98,27%, recall of 98,09%, and F1-score of 98,15%. These results indicate that the features selected based on the highest linear correlation with the target variable are able to optimally represent the nutritional status characteristics of toddlers without requiring additional normalization processes.

Analysis of the confusion matrix in the best-case scenario shows that the model is able to classify almost all data in each nutritional status class with a very low error rate. All data in the Malnourished and Obese classes were correctly predicted, while classification errors only occurred in classes with closely related anthropometric characteristics, such as Overweight and At Risk of Overweight. This confirms that the ANN + Pearson Correlation model has excellent and stable class discrimination capabilities.

Furthermore, the results of this study prove that data normalization does not always improve ANN performance, especially for features that already have consistent scales and distributions. Instead, normalization only has a positive impact on dimension reduction methods such as PCA. Therefore, the selection of preprocessing techniques and feature selection must be tailored to the characteristics of the data in order to optimize model performance.

Overall, this study found that Artificial Neural Network (ANN) combined with Pearson Correlation (PC) feature selection without normalization is an effective and accurate method for classifying the nutritional status of toddlers based on anthropometric data. The model created by this study can identify nutritional status categories with high accuracy, indicating that it may be well suited for use in data-based systems where toddler nutrition is stored in a database.

In the context of public health, this study aims to support early detection of nutritional problems, especially stunting, wasting, and obesity in toddlers. Nutritional status classification is very important for conducting initial screening, determining intervention priorities, and monitoring child growth development in a more systematic and data-driven manner. The results of this study can be applied in health facilities such as community health centers and integrated health service posts as a decision support system. As a tool to assist in data-driven nutrition intervention planning, the system can help health workers identify malnourished or undernourished toddlers more quickly, reduce the possibility of manual classification errors, and support digital reporting and monitoring of nutrition improvement programs.

REFERENCES

- [1] B. Di, K. Simalungun, H. Hafizan, and A. N. Putri, "Penerapan Metode Klasifikasi Decision Tree Pada Status Gizi," vol. 1, no. 2, pp. 68–72, 2020.
- [2] R. Setiawan and A. Triayudi, "Klasifikasi Status Gizi Balita Menggunakan Naïve Bayes dan K- Nearest Neighbor Berbasis Web," vol. 6, no. 2, pp. 777–785, 2022, doi: 10.30865/mib.v6i2.3566.
- [3] S. Lestari and R. A. Amalia, "Penerapan Algoritma C . 45 Pada Klasifikasi Status Gizi Balita di Posyandu Desa Sukalilah Cibatu Kabupaten Garut Jawa Barat," vol. 5, no. 1, pp. 177–182, 2023.
- [4] O. A. For, "SUBMISSION Faktor yang Berhubungan dengan Status

- Gizi pada Anak Balita Penerbit : Edukasi Ilmiah Indonesia,” vol. 1, no. 2, pp. 99–106, 2023, doi: 10.61099/junedik.v1i3.24.
- [5] K. Penderita, D. Menggunakan, and M. L. D. A. N. Z-score, “Jurnal Teknologi Terpadu,” vol. 8, no. 2, pp. 94–99, 2022.
- [6] V. No, J. Hal, A. Wicaksono, and H. Lugo, “Perbandingan Teknik Klasifikasi Catatan Medis untuk Indeks Antropometri Status Gizi Balita,” vol. 6, no. 1, pp. 229–235, 2024.
- [7] E. Darnila and M. Azmi, “Aplikasi Klasifikasi Status Gizi Balita Menggunakan Metode Naïve Bayes Berbasis Android,” vol. 5, no. 2, pp. 135–141, 2021.
- [8] A. Fauzia, A. Sendar, and R. Maryana, “Penerapan Algoritma K-Nearest Neighbors pada Klasifikasi Status Gizi Balita (Studi Kasus Posyandu Desa Aras Kabu),” vol. 1, pp. 17–22, 2024.
- [9] J. Ilmiah and W. Pendidikan, “3 1,2,3,” vol. 8, no. July, pp. 116–125, 2022.
- [10] D. Pradana, M. Luthfi Alghifari, M. Farhan Juna, and D. Palaguna, “Klasifikasi Penyakit Jantung Menggunakan Metode Artificial Neural Network,” *Indones. J. Data Sci.*, vol. 3, no. 2, pp. 55–60, 2022, doi: 10.56705/ijodas.v3i2.35.
- [11] K. Opini and P. Terhadap, “Penerapan Algoritma Artificial Neural Network untuk,” vol. 5, no. 2, pp. 109–118.
- [12] C. Edge, “Klasifikasi Citra Glaukoma dengan ANN Berdasarkan Pembuluh Darah pada Citra Fundus Retina Menggunakan Perbandingan Metode Otsu- Thresholding dan Deteksi Tepi Canny,” vol. 6, no. 1, pp. 81–90, 2022.
- [13] E. Engineering, “Implementasi Seleksi Fitur Klasifikasi Waktu Kelulusan Mahasiswa Menggunakan Correlation Matrix With Heatmap,” vol. 4, pp. 169–174, 2022.
- [14] I. Pratama *et al.*, “Seleksi Fitur dan Penanganan Imbalanced Data menggunakan RFECV dan ADASYN,” pp. 38–49, 2021, doi: 10.30864/eksplora.v11i1.578.
- [15] H. N. Wismadi *et al.*, “Jurnal Optimasi Teknik Industri Klasifikasi Varietas Biji Kismis dengan Artificial Neural Network,” pp. 8–13, 2023.
- [16] M. Rizky and A. Pramuntadi, “Implementation of Deep Neural Network Method on Classification of Type 2 Diabetes Mellitus Disease Implementasi Metode Deep Neural Network pada Klasifikasi Penyakit Diabetes Melitus Tipe 2,” vol. 4, no. July, pp. 1043–1050, 2024.
- [17] S. H. Gulo, A. H. Lubis, T. Informatika, F. Teknik, and U. M. Area, “Penerapan Multi-Layer Perceptron untuk Mengklasifikasi Penduduk Kurang Mampu,” vol. 4, no. 2, pp. 51–59, 2024.
- [18] D. N. Ardelia, H. D. Arifin, S. Daniswara, and A. P. Sari, “Klasifikasi Harga Ponsel Menggunakan Algoritma Logistic Regression,” vol. 04, no. 01, pp. 37–43, 2024.
- [19] A. Mutiarachim, F. K. Fikriah, B. Ansor, and A. P. Ramdani, “Boosting Performance Classification KNN Customer Loyalty with Chi-Square and Information Gain,” vol. 22, no. 2, pp. 81–89, 2025.
- [20] V. No, J. Hal, F. Adi, R. Anggi, D. Puji, and E. Kartikadarma, “Optimasi Algoritma Random Forest menggunakan Principal Component Analysis untuk Deteksi Malware,” vol. 5, no. 3, pp. 217–223, 2023.
- [21] A. Dwi, M. A. Barata, and R. Rohmah, “Algoritme Jaringan Syaraf Tiruan pada Perangkat e-Nose untuk Klasifikasi Madu,” vol. 20, no. 1, pp. 28–48, 2025, doi: 10.61769/telematika.v20i1.722.
- [22] D. Reduction, U. Principal, C. Analysis, and F. S. Using, “i,” vol. 7, no. 1, pp. 154–166, 2025.
- [23] N. Kahar *et al.*, “Monitoring Perkembangan Anak Usia Dini Dengan Batanghari,” pp. 91–97, 2019.
- [24] A. Info, “Journal of Mathematics Education Machine Learning-Based Early Prediction Of Kidney Failure: A Comparative Study Of Artificial Neural Network And Random,” vol. 8, no. 2, pp. 202–215, 2025.
- [25] K. Kalirejo, K. Kokap, and K. K. Progo, “Pemodelan Artificial Neural Network (Ann) Untuk,” vol. 14, no. 1, pp. 9–18, 2024.