Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 7 No. 6 (2023) 1378 - 1386 ISSN Media Electronic: 2580-0760

Optimization of Machine Learning Classification Analysis of Malnutrition Cases in Children

Musli Yanto[1], Febri Hadi[2], Syafri Arlis[3]
[1,2]Department Informatics Engineering, Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang, Padang, Indonesia
[3]Department Information System, Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang, Padang, Indonesia
[1]musli_yanto@upiyptk.ac.id

Abstract

Malnutrition is one of the problems that occurs in children caused by a lack of nutritional intake. Indonesia contributed 36%, making it the fifth country with the largest cases of malnutrition in the world. Based on this, a solution is needed to reduce the growth rate of malnutrition cases. This research aims to carry out classification analysis to determine nutritional status by optimizing Machine Learning (ML) performance. The ML classification analysis process will later utilize the performance of the Artificial Neural Network (ANN) method with the Multilayer Perceptron (MLP) algorithm. ML performance can be optimized using the Pearson Correlation (PC) method to produce optimal classification analysis patterns. This research dataset uses child nutrition case data of 576 patients sourced from the M. Djamil Padang Province Regional General Hospital (RSUP). The dataset is divided into 417 training data and 159 test data. Based on the tests that have been carried out, the performance of the PC method can provide precise and accurate analysis patterns. This analysis pattern has also been able to provide a fairly good level of accuracy, namely 95%. Not only that, this research is also able to present analysis patterns with the best ANN architectural model in classifying nutritional status. Based on the overall results, this research can be used as an alternative solution to handling nutritional problems in children.

Keywords: *analysis of classification; malnutrition, artificial neural network (ANN); multilayer perceptron (MLP); west sumatra province*

1. Introduction

The growth and development of children are something that needs to be considered by all parties, especially parents[1]. The 5-year-old child age period is a period that is very influential on the child's development[2]. This development focuses on the perspective of changing the form or maturation of individual organs, including the social and emotioSumatranal transformation caused by the environment[3]. Child growth and development can also be interpreted as 2 things where growth is closely related to the size or size of the child, while development can be defined as an increase in body composition and function[4].

The growth and development of children at an early age can also be affected by the influence of nutrition[5]. In essence, nutrition is something that must exist and be fulfilled because its existence is needed by the body, especially in the process of physical growth and development, the brain and nervous system, and even intelligence and human intellectual level[6]. The nutritional needs of children at an early age are vital to the growth and development of the human brain[7]. Several facts have explained that slowed physical growth, less agility, less intelligence, and low immune power are the result of not meeting nutritional needs[8]. This is based on the relationship between child growth and development and unbalanced nutritional needs and intake, where when a child gets sufficient and fulfilled nutrition, his growth and development will take place optimally[9]. Thus, nutritional problems can cause several diseases in children, one of which is malnutrition[10].

Malnutrition is a public health problem that can increase the risk of morbidity, death, and obstacles to both motor and mental growth[11]. Malnutrition is also a result of the problem of lack of nutrition over a long period so growth is stunted[12]. To prevent this, several efforts have been made such as prevention by carrying out situation analysis, activity plans, malnutrition consultations, making regulations, cadre training,

Accepted: 17-07-2023 | Received in revised: 21-12-2023 | Published: 26-12-2023

malnutrition management systems, measurement and publication of malnutrition data, and annual performance reviews[13].

The fact is that several regions still have problems dealing with malnutrition. One of these areas is in West Sumatra Province. The problem that arises is that the local Health Service is still having difficulties in handling malnutrition cases. Thus, in an effective analysis process, it is necessary to carry out analytical calculations on the development of the malnutrition problem that occurs in each period.

The step in overcoming this problem is that the analysis process by adopting the Machine Learning (ML) concept using the performance of the Artificial Neural Network (ANN) method is expected to be able to present precise and accurate analysis results in handling malnutrition problems. ANN is basically a branch of science that is capable of processing information in solving problems by training on large amounts of data[14]. The performance of ANN is analogous to knowledge that adopts the work of the human brain in learning[15]. The working structure of ANN can be described by a model consisting of several neurons arranged in certain layers and interconnected[16].

ANN performance in several studies has had an impact as well as solutions to problems in the analysis proces[17]. It can be seen that ANN has optimal analysis output [18]. ANN also presents a fairly minimal error rate and provides a model for solving a problem[19]. This model can be presented for solving problems such as identification, prediction, and classification [20] - [22].

Based on previous research, the application of ML with the performance of the ANN method can be used to determine nutritional status by presenting a classification model in determining nutritional status optimally[23]. ANN also has a major contribution in analyzing the effects of malnutrition using input variables such as age, weight, height, muscle circumference, head circumference, and arm circumference[24]. The application of ANN was also successful in predicting the Body Mass Index (BMI) for toddlers to calculate the number of cases of malnutrition in toddlers[25]. In other cases, ANN was also able to take into account the risk factors for malnutrition in toddlers with reported results that there was a relationship between the mother's knowledge and the incidence of malnutrition with an OR value of 95%[26].

Based on several previous results, the classification analysis process in determining the nutritional status of children in the city of Padang will be presented in the ML performance. ML classification analysis involves the performance of the ANN method using the Multilayer Perceptron (MLP) algorithm to obtain optimal results. The performance of the MLP algorithm has basically been able to present a fairly good analysis model in carrying out the classification process[27]. The concept of the MLP algorithm can present a Supervised Learning learning model to present network outpu [28]. MLP can present quite good values of accuracy, precision, and recall[29]. MLP was also able to obtain accuracy, sensitivity, and specificity values of 91.67%[30].

The implementation of the MLP algorithm performance in previous research optimally carried out the diabetes classification process with an accuracy rate of 86%[31]. Other research also explains that the performance of the MLP algorithm can provide a predictive process with an analytical model that produces optimal output[32]. Research on malnutrition cases with a prediction process using the MLP algorithm can classify malnutrition cases with an accuracy of 82.4%[33].

Some of the results of previous studies explain that MLP performance can be expected to provide maximum classification results in handling malnutrition cases. MLP performance will also be optimized later using the Pearson Correlation (PC) method in measuring variables that affect nutritional growth in the analysis of malnutrition cases. The process of measuring variable performance based on the performance of the PC method can provide new knowledge to see the factors that influence malnutrition cases. The performance of the PC method is expected to provide optimal analysis results in the classification process[34]. The PC method is also able to take into account the level of accuracy of classification analysis variables[35]. Previous studies have explained that the PC method provides a precise and accurate analytical model[36]. The PC method has also provided quite good performance in classification analysis based on the level of accuracy[37]. Furthermore, the PC method is able to evaluate data analysis pattern[38].

Based on the previous explanation, this research will carry out an optimized ML classification analysis process using the PC method to determine nutritional status. The ML classification analysis process can be developed by optimizing the correlation measurement process to present precise and accurate analysis patterns. The process of optimizing ML performance in classification analysis will also be something new and different from the previous classification analysis process. Overall, the classification analysis process with ML performance based on the MLP method optimized with the PC method can provide a new classification analysis model for determining nutritional status. This novelty is presented in the nutritional status classification analysis model. The resulting analysis model can also be used as an alternative solution in the process of determining nutritional status. The contribution of this research can have an impact on the

DOI: https://doi.org/10.29207/resti.v7i6.5278

West Sumatra Provincial Health Service in handling malnutrition problems in children.

2. Research Methods

In carrying out the classification analysis process for determining malnutrition cases in children, the concept of Machine Learning (ML) is adopted to provide maximum output. ML has a pretty good performance in dealing with classification analysis problems[39].. ML also provides a fairly good description of the analytical model in the case of classification[40]. Thus ML can be applied in a model of this research framework in carrying out the process of analyzing malnutrition cases. The description of the research framework can be presented in Figure 1.

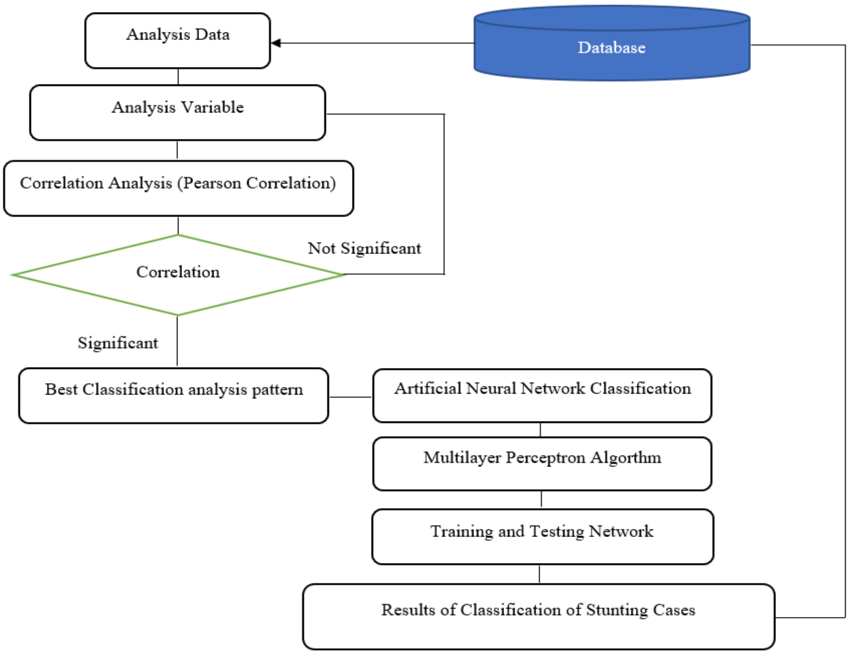

Figure 1. Research Framework

Figure 1 illustrates the process of classification analysis by adopting ML performance. The ML performance process in the classification analysis presented in the research framework uses the MLP-optimized PC method. The PC method will test the correlation of variables (X) with classification outputs (Y). Based on these tests will produce an optimal analysis pattern in the classification.

MLP performance in the classification process is also presented in the training and testing stages. The training process will test the training dataset to see the performance of the previously generated analysis pattern model. The results of the training process with the MLP algorithm will provide an overview of the testing process in conducting classification analysis. As a whole, the stages of this research will present a precise and accurate analysis process in the classification of malnutrition cases.

2.1. Pearson Correlation (PC) Method

Pearson Correlation (PC) is a technique used in the branch of statistics in measuring the correlation of relationships in each data[41]. PC can be adopted in[42]. PC can be combined with several other concepts and methods in conducting analysis[43]. The PC method can be described in Formula 1 and 2[41].

$$PX,Y=\left(\frac{\text{cov (X,Y)}}{\sigma X.\sigma Y}\right)=\left(\frac{\text{E ((cov (X}-\mu\text{X)(Y}-\mu\text{Y))}}{\sigma X.\sigma Y}\right) \quad (1)$$

$$=\frac{\text{E (XY)}-\text{E (X)E (Y)}}{\sqrt{\text{E (X.X)}-E.E(X)}\,\sqrt{B\,(Y.Y)-E.E\,(Y)}} \quad (2)$$

Formula 1 and 2 explains that cov(X,Y) is a covariance value of X and Y. The variable value of X,Y is measured using the standard deviation value. Meanwhile, the value of E(X,Y) can also be referred to as the expected value of the variables X,Y[36].

2.2. Multilayer Perceptron (MLP) Algorithm

The concept of the MLP algorithm consists of an input layer, a hidden layer, and an output layer [44]. The performance of the MLP algorithm presents calculations that adopt the performance of the feedforward algorithm[45]. The working principles of MLP include (1) each neuron has a non-linear activation function, (2) MLP has one or more hidden layers, (3) the analysis process goes through the input layer to the output layer, and (4) the MLP model has weights (synaptic)[46]. As for calculating the output of the MLP analysis results, it can be seen in Formula 3 and 4[47].

DOI: https://doi.org/10.29207/resti.v7i6.5278

$$Y_{j(p)} = sigmoid\left(\sum_{i=1}^{n} X_{i(p)}.w_{ij(p)} - \theta_j\right) \quad (3)$$

$$Y_{k(p)} = sigmoid\left(\sum_{i=1}^{n} X_{jk(p)}.w_{jk(p)} - \theta_k\right) \quad (4)$$

Formula 3 explains that the actual output in the hidden layer can be obtained by using the sigmoid activation function on the weight of each hidden layer. Formula 4 also explains how the output value Yk is obtained. The Yk value is obtained by the sum of all inputs in the input layer, multiplied by the weight of each input that enters the hidden layer, and reduced by the threshold value. After the output results are obtained, the MLP algorithm repairs the weight values starting from the output layer and continues to the input layer.

3. Results and Discussions

The process of analyzing nutritional status classification using optimized ML can begin by analyzing research datasets. The research dataset comes from patient history data at the M. Djamil Provincial General Hospital (RSUP), Padang City and the West Sumatra Provincial Health Service. The research dataset consists of 576 patients for the 2018-2022 period. The dataset will later be divided into 417 training data and 159 test data. The research dataset sample in ML classification analysis can be seen in Table 1.

Table 1. Sample Research Dataset

No	Gender	Age (Month)	Tall Body (Cm)	Weight (Kg)	Malnutrition Case
1	F	19	47.1	4.4	Malnutrition
2	F	6	32	3.6	Normal
3	M	7	30	4.2	Normal
4	F	4	36	2.8	Malnutrition
5	F	11	51	5.6	Malnutrition
6	M	3	41	3.6	Normal
7	M	10	35	3.3	Normal
…	…..	…..	…….	……..	……….
…	…..	…..	…….	……..	……….
17	M	36	60	4.2	Normal
18	F	38	67.9	8.1	Malnutrition
19	M	50	66	59	Normal
20	M	35	60	62	Normal

Table 1 is an example of a research dataset in conducting classification analysis to determine nutritional status. There are at least 4 (four) input variables (X) and 1 (one) output variable (Y) that form a classification analysis pattern. These variables include gender (X1), height (X2), child's age (X3) and weight (X4). The output variable is taken from the value of the Malnutrition Case variable (Y). After the analysis variables are determined, the initial process is to test ML performance before optimizing the classification analysis. The classification analysis process will begin with the formation of an analysis network architecture which can be seen in Figure 2.

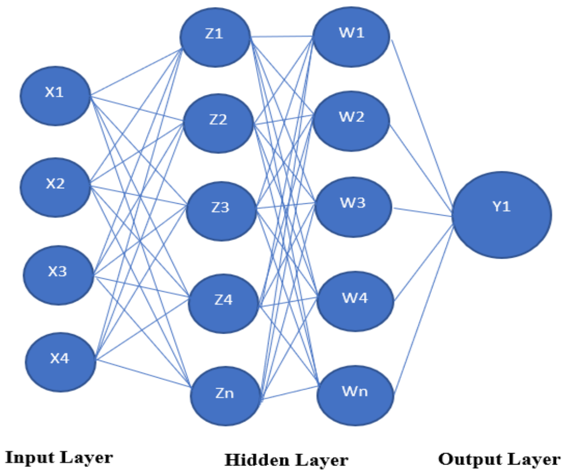

Figure 2. Analysis of ANN Network Architecture Malnutrition Classification

Figure 2 shows the MLP network architecture for ML nutritional status classification. The architectural pattern consists of 3 layers, namely the input layer consists of 4 input units, the hidden layer consists of 4 units and the output layer consists of 1 output unit. This architectural pattern will involve 417 training data and

DOI: https://doi.org/10.29207/resti.v7i6.5278

159 test data in the classification analysis process. The results of ML learning on MLP performance can be presented in Table 2.

Table 2. Comparison of MLP Classification Analysis Network Patterns

Single Hidden Layer						
Architecture	Training Accuracy	MSE	Performance	Testing Accuracy	MSE	Performance
(4-5-1)	99,730700	0,269300	0,002693	99,366950	0,633050	0,006331
(4-8-1)	99,998400	0,001600	0,001000	99,998400	0,001600	0,001000
(4-10-1)	99,717400	0,282600	0,002826	99,988600	0,011400	0,003300
(4-15-1)	99,693400	0,306600	0,001000	99,988500	0,011500	0,007200
(4-20-1)	98,420400	1,579600	0,001000	99,999446	0,000554	0,003700
Multi Hidden Layer						
Architecture	Training Accuracy	MSE	Performance	Testing Accuracy	MSE	Performance
(4-5-5-1)	99,944100	0,055900	0.0016	99,997600	0,002400	0,001600
(4-5-8-1)	99,444500	0,555500	0,000845	99,998600	0,001400	0,000845
(4-5-5-8-1)	99,893900	0,106100	0,006300	99,997100	0,002900	0,003800
(4-5-8-8-1)	99,995800	0,004200	0,001400	99,998200	0,001800	0,001400
(4-5-8-10-1)	99,959600	0,040400	0,008600	99,959600	0,040400	0,004100

Table 3 is the result of the ML learning process on MLP performance in the classification analysis process for determining malnutrition. The best ML performance was obtained on MLP architectural with 4-5-8-1 providing an accuracy rate of 99.44%. This architecture will later be adopted in ML analysis testing which can be presented in Figure 3.

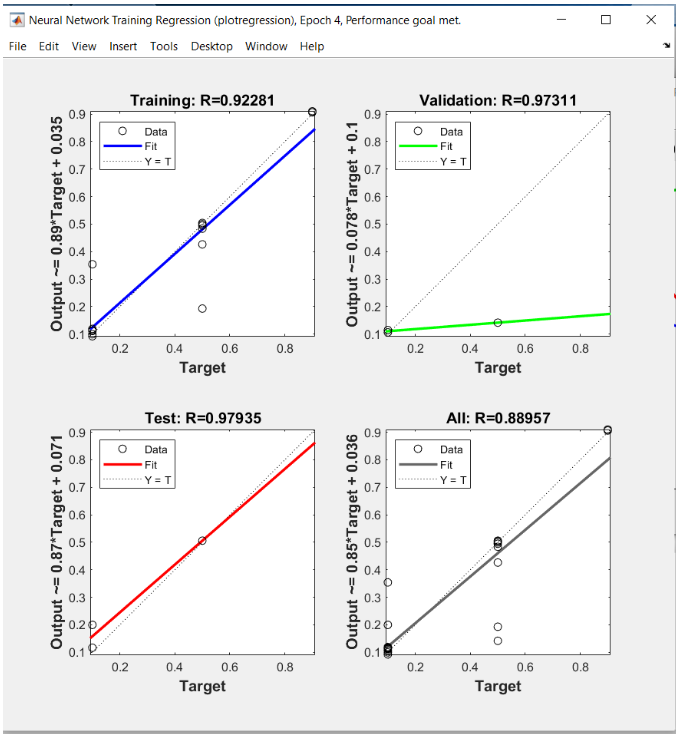

Figure 3. ML Testing Results Before Optimization

Figure 3 is the result of ML testing using the MLP method before optimization was carried out in carrying out classification analysis to determine nutritional status in children. The test results present a performance level value of 92.28%. Based on these results, ML performance is optimized to provide maximum results by measuring the correlation in the analysis patterns used. The optimization process for measuring correlation analysis patterns was carried out using the PC method. The PC method measurement results can be seen in Table 3. Table 3 explains the results of the variable correlation test in the classification analysis pattern for determining malnutrition status. The results of correlation measurements can be seen from the level

DOI: https://doi.org/10.29207/resti.v7i6.5278

of relationship between variables (X) and the analysis output (Y). Based on testing, the correlation between the Gender variable (X1) has a correlation level of 0.587 with case (Y). The measurement of the Age variable (X2) also has a correlation level of 0.707 with Case (Y). Furthermore, the Height variable (X3) also has a fairly good correlation of 0.773 with Case (Y). The High Variable (X4) in the analysis results was also able to provide a correlation of 0.715 to Case (Y).

Table 3. Pearson Correlation (PC) Analysis Results

Correlations		Gender	Age	Tall_Body	Month	Case
Gender	Pearson Correlation	1	0.625	0.654	0.792	0.587
	Sig. (2-tailed)		0.599	0.820	0.212	0.220
	N	20	20	20	20	20
Age	Pearson Correlation	0.625	1	0.749**	0.487*	0.707
	Sig. (2-tailed)	0.599		0.000	0.029	0.978
	N	20	20	20	20	20
Tall_Body	Pearson Correlation	0.654	0.749**	1	0.393	0.773
	Sig. (2-tailed)	0.820	0.000		0.087	0.244
	N	20	20	20	20	20
Month	Pearson Correlation	0.792	0.487*	0.393	1	0.715
	Sig. (2-tailed)	0.212	0.029	0.087		0.363
	N	20	20	20	20	20
Case	Pearson Correlation	0.587	0.707	0.773	0.715	1
	Sig. (2-tailed)	0.220	0.978	0.244	0.363	
	N	20	20	20	20	20

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Based on the results of the correlation level measurements carried out, the Gender variable (X1) has the worst correlation among the other variables. Thus, the ML classification analysis pattern used in determining nutritional status can be taken based on the variables Age (X2), Height (X3), and Body Height Variable (X4). After the analysis pattern is measured using the PC method, the classification analysis process will be carried out again using the ML performance of the MLP algorithm to determine malnutrition status. The results of the optimized ML analysis process can be seen in Figure 4.

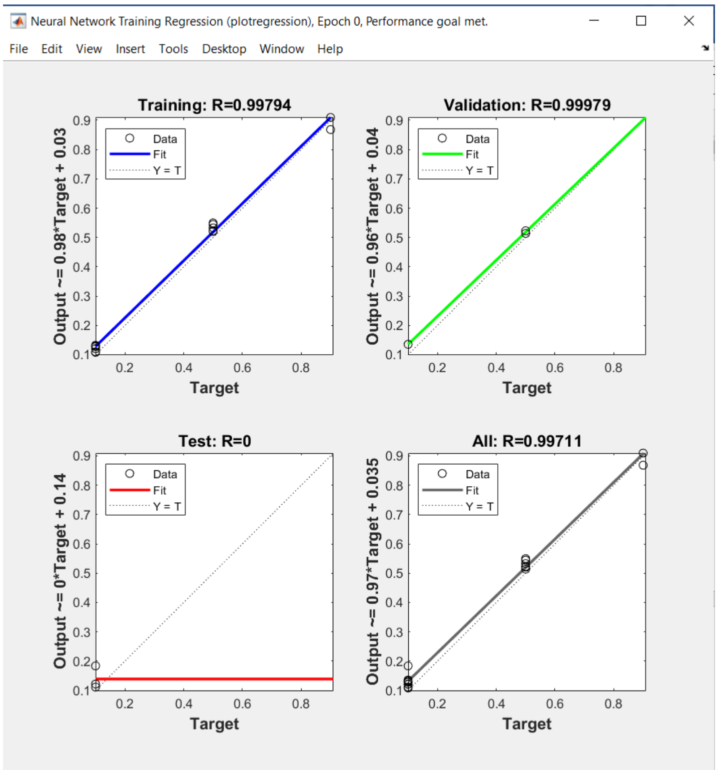

Figure 4. Results of The Optimized ML Analysis Classification Process

DOI: https://doi.org/10.29207/resti.v7i6.5278

Figure 4 is the result of ML testing which has been optimized using the PC method to produce optimal analysis patterns. The ML test results were able to show a performance level value of 99.97%. Based on these results, the optimized ML performance has provided maximum results in determining malnutrition in children. To see the difference in ML performance before optimization and after optimization, see the Table 4.

Table 4. ML Performance Before and After Optimization determining Malnutrition in Children

Gender (X1)	Age (X2)	Tall Body (X3)	Weight (X4)	Malnutrition Case (Y)	Accuracy ML
F	19	47.1	4.4	Malnutrition	
F	6	32	3.6	Normal	
M	7	30	4.2	Normal	
F	4	36	2.8	Malnutrition	
F	11	51	5.6	Malnutrition	
M	3	41	3.6	Normal	
M	10	35	3.3	Normal	
M	18	45	3.7	Normal	
M	40	55	5.1	Normal	
M	42	61	7.2	Malnutrition	92.28%
M	19	68.7	8.2	Malnutrition	
F	27	34.2	4.2	Normal	
F	36	57.9	5.1	Normal	
F	37	67.7	7.2	Malnutrition	
M	16	41	3.7	Malnutrition	
M	35	45	17	Malnutrition	
M	36	60	4.2	Normal	
F	38	67.9	8.1	Malnutrition	
M	50	66	59	Normal	
M	35	60	62	Normal	
Cor X1 - Y	Cor X2 - Y	Cor X3 - Y	Cor X4 - Y	Average Correlation	
0,587	0,707	0,773	0,715	0,6955	

Age (X1)	Tall Body (X2)	Weight (X3)	Malnutrition Case (Y)	Accuracy ML
19	47.1	4.4	Malnutrition	
6	32	3.6	Normal	
7	30	4.2	Normal	
4	36	2.8	Malnutrition	
11	51	5.6	Malnutrition	
3	41	3.6	Normal	
10	35	3.3	Normal	
18	45	3.7	Normal	
40	55	5.1	Normal	
42	61	7.2	Malnutrition	99.97%
19	68.7	8.2	Malnutrition	
27	34.2	4.2	Normal	
36	57.9	5.1	Normal	
37	67.7	7.2	Malnutrition	
16	41	3.7	Malnutrition	
35	45	17	Malnutrition	
36	60	4.2	Normal	
38	67.9	8.1	Malnutrition	
50	66	59	Normal	
35	60	62	Normal	
Cor X2 - Y	Cor X3 - Y	Cor X4 - Y	Average Correlation	
0,707	0,773	0,715	0,731666667	

Table 4 is an analysis of ML performance before and after optimization in classifying malnutrition in children. ML performance can work optimally based on optimization that has been carried out previously. ML performance can be seen based on the accuracy level presented at 99.97%.. Based on these results, this research has been able to present a new classification analysis model on ML performance in determining nutritional status. The novelty presents a reliable classification analysis model based on multiple testing processes to produce optimal output. The application of the MLP algorithm to the ANN method also makes an active contribution to ML performance in presenting precise and accurate analysis results. Overall, this research has also provided output in the form of an analysis model for the classification of cases of malnourished children. Based on the results of this research, the West Sumatra Provincial Health Service will be able to carry out optimal treatment and become a benchmark for implementing strategies to overcome the problem of malnutrition in children..

4. Conclusion

Based on the discussion in this study, it can be concluded that the application of the MLP algorithm to ML can provide optimal analysis results. The analysis process is inseparable from the performance of the PC method which provides an overview of the level of measurement of classification analysis patterns. The results of the error rate analysis carried out are presented in a performance of 0.0491. The results show that the error rate of classification analysis is minimal and provides precise and accurate accuracy. Overall this study can provide an overview of the optimal classification pattern model for analyzing the classification of malnutrition cases in children.

Acknowledgements

Thank you for research addressed to Mrs. Dr. Hj. Zerni Melmusi, SE, MM, Ak, CA as Yayasan Perguruan Tinggi Komputer (YPTK) and Prof. Sarjon Defit, S.Kom, M.Sc as Chancellor of Universitas Putra Indonesia YPTK Padang who has provided full support for the implementation of this research. The research has been fully funded by Putra Indonesia University YPTK Padang with agreement Number: 124/UPI-YPTK/LPPM/P/KP/VII/2023 Simlitupi Research funding for 2023.

References

[1] S. A. Norris *et al.*, “Nutrition in adolescent growth and development,” *Lancet*, vol. 399, no. 10320, pp. 172–184, 2022.

[2] B. S. Zemel, "Body composition during growth and development," *Hum. growth Dev.*, pp. 517–545, 2022.
[3] J. Julizal, L. Lukman, and I. Sunoto, "Rancang Bangun Aplikasi Sistem Monitoring Pertumbuhan Anak sebagai Alat Deteksi Pertumbuhan," *STRING (Satuan Tulisan Ris. dan Inov. Teknol.*, vol. 4, no. 1, pp. 18–24, 2019.
[4] M. Shakhnoza, "IMPROVING THE PEDAGOGICAL AND PSYCHOLOGICAL COMPETENCE OF FIRST-YEAR CHILDREN IN PRESCHOOL EDUCATION," *Eur. Int. J. Multidiscip. Res. Manag. Stud.*, vol. 2, no. 05, pp. 121–124, 2022.
[5] R. A. Mahumud, S. Uprety, N. Wali, A. M. N. Renzaho, and S. Chitekwe, "The effectiveness of interventions on nutrition social behaviour change communication in improving child nutritional status within the first 1000 days: Evidence from a systematic review and meta-analysis," *Matern. Child Nutr.*, vol. 18, no. 1, p. e13286, 2022.
[6] F. Mayar and Y. Astuti, "Peran Gizi Terhadap Pertumbuhan dan Perkembangan Anak Usia Dini," *J. Pendidik. Tambusai*, vol. 5, no. 3, pp. 9695–9704, 2021.
[7] P. Rahmi, "Peran nutrisi bagi tumbuh dan kembang anak usia dini," *J. Pendidik. Anak Bunayya*, vol. 5, no. 1, pp. 1–13, 2019.
[8] A. Amirullah, A. T. A. Putra, and A. A. D. Al Kahar, "Deskripsi status gizi anak usia 3 sampai 5 tahun pada masa Covid-19," *Murhum J. Pendidik. anak usia dini*, vol. 1, no. 1, pp. 16–27, 2020.
[9] C. Setyorini and A. D. Lieskusumastuti, "Gambaran Status Gizi Bayi Dan Balita Pada Masa Covid-19 Di Kalurahan Jetis," *Avicenna J. Heal. Res.*, vol. 4, no. 1, 2021.
[10] S. Thurstans *et al.*, "The relationship between wasting and stunting in young children: A systematic review," *Matern. Child Nutr.*, vol. 18, no. 1, p. e13246, 2022.
[11] E. N. Hutabarat, "Permasalahan Stunting dan Pencegahannya," *J. Heal. Med. Sci.*, pp. 158–163, 2022.
[12] A. M. Arsyati, "Pengaruh penyuluhan media audiovisual dalam pengetahuan pencegahan stunting pada ibu hamil di Desa Cibatok 2 Cibungbulang," *Promotor*, vol. 2, no. 3, pp. 182–190, 2019.
[13] C. Lawaceng and A. Y. S. Rahayu, "Tantangan pencegahan stunting pada era adaptasi baru 'new normal' melalui pemberdayaan masyarakat di kabupaten pandeglang," *J. Kebijak. Kesehat. Indones. JKKI*, vol. 9, no. 3, pp. 136–146, 2020.
[14] M. H. Esfe, M. H. Kamyab, and D. Toghraie, "Statistical review of studies on the estimation of thermophysical properties of nanofluids using artificial neural network (ANN)," *Powder Technol.*, p. 117210, 2022.
[15] Y. I. Alatoom and T. I. Al-Suleiman, "Development of pavement roughness models using Artificial Neural Network (ANN)," *Int. J. Pavement Eng.*, vol. 23, no. 13, pp. 4622–4637, 2022.
[16] A. N. Bhatt and N. Shrivastava, "Application of artificial neural network for internal combustion engines: a state of the art review," *Arch. Comput. Methods Eng.*, vol. 29, no. 2, pp. 897–919, 2022.
[17] V. Gholami and H. Sahour, "Simulation of rainfall-runoff process using an artificial neural network (ANN) and field plots data," *Theor. Appl. Climatol.*, pp. 1–12, 2022.
[18] M. Ahmad, M. A. Al Mehedi, M. M. S. Yazdan, and R. Kumar, "Development of Machine Learning Flood Model Using Artificial Neural Network (ANN) at Var River," *Liquids*, vol. 2, no. 3, pp. 147–160, 2022.
[19] M. H. Alshayeji, H. Ellethy, and R. Gupta, "Computer-aided detection of breast cancer on the Wisconsin dataset: An artificial neural networks approach," *Biomed. Signal Process. Control*, vol. 71, p. 103141, 2022.
[20] M. Khan, Z. Ullah, O. Mašek, S. R. Naqvi, and M. N. A. Khan, "Artificial neural networks for the prediction of biochar yield: A comparative study of metaheuristic algorithms," *Bioresour. Technol.*, vol. 355, p. 127215, 2022.
[21] E. M. Rentería-Vargas *et al.*, "Neural network-based identification of a PSA process for production and purification of bioethanol," *IEEE Access*, vol. 10, pp. 27771–27782, 2022.
[22] T. Si, J. Bagchi, and P. B. C. Miranda, "Artificial neural network training using metaheuristics for medical data classification: an experimental study," *Expert Syst. Appl.*, vol. 193, p. 116423, 2022.
[23] T. Hidayat, "MODEL KLASIFIKASI JARINGAN SARAF TIRUAN UNTUK MENENTUKAN STATUS GIZI PADA BALITA DENGAN METODE LVQ (LEARNING VECTOR QUANTIZATION) STUDI KASUS PUSKESMAS DI KABUPATEN TANGERANG," 2020.
[24] M. Yanto, "Jaringan Syaraf Tiruan Analisa Pengaruh Gizi Buruk Terhadap Perkembangan Balita dengan Algoritma Perceptron," *J. Ilm. Media Sisfo*, vol. 12, no. 1, pp. 1003–1011, 2018.
[25] D. A. Simbolon, D. Hartama, and F. Anggraini, "Penerapan Jaringan Saraf Tiruan Dalam Memprediksi Gizi Balita Pada Puskesmas Siantar Utara Kota Pematangsiantar," *Brahmana J. Penerapan Kecerdasan Buatan*, vol. 1, no. 1, pp. 48–54, 2019.
[26] G. Pratama, A. Yusuf, S. Kasau, and A. Jumantio, "Analisis Faktor Risiko Kejadian Stunting Pada Balita Usia 2–5 Tahun Di Wilayah Kerja Puskesmas Sanoba Kabupaten Nabire," *An-Nadaa J. Kesehat. Masy.*, vol. 9, no. 1, pp. 1–7, 2022.
[27] X.-J. Tang, X. Liu, P.-F. Yan, B.-X. Li, H.-Y. Qi, and F. Huang, "An MLP network based on residual learning for Rice hyperspectral data classification," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022.
[28] C.-F. Tsai and Y.-H. Hu, "Empirical comparison of supervised learning techniques for missing value imputation," *Knowl. Inf. Syst.*, vol. 64, no. 4, pp. 1047–1075, 2022.
[29] J. KUSUMA, B. H. HAYADI, W. WANAYUMINI, and R. ROSNELLY, "Komparasi Metode Multi Layer Perceptron (MLP) dan Support Vector Machine (SVM) untuk Klasifikasi Kanker Payudara," *MIND (Multimedia Artif. Intell. Netw. Database) J.*, vol. 7, no. 1, pp. 51–60, 2022.
[30] J. F. Azzahra, H. Sumarti, and H. H. Kusuma, "Klasifikasi Kasus COVID-19 dan SARS Berbasis Ciri Tekstur Menggunakan Metode Multi-Layer Perceptron," *J. Fis.*, vol. 12, no. 1, pp. 16–27, 2022.
[31] S. S. S., J. Surendiran, N. Yuvaraj, M. Ramkumar, C. N. Ravi, and R. G. Vidhya, "Classification of Diabetes using Multilayer Perceptron," in *2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 2022, pp. 1–5, doi: 10.1109/ICDCECE53908.2022.9793085.
[32] D. Dam Nguyen *et al.*, "Bagging and Multilayer Perceptron Hybrid Intelligence Models Predicting the Swelling Potential of Soil," *Transp. Geotech.*, vol. 36, p. 100797, 2022, doi: https://doi.org/10.1016/j.trgeo.2022.100797.
[33] M. M. Islam *et al.*, "Application of machine learning based algorithm for prediction of malnutrition among women in Bangladesh," *Int. J. Cogn. Comput. Eng.*, vol. 3, pp. 46–57, 2022, doi: https://doi.org/10.1016/j.ijcce.2022.02.002.
[34] Z. Šverko, M. Vrankić, S. Vlahinić, and P. Rogelj, "Complex Pearson correlation coefficient for EEG connectivity analysis," *Sensors*, vol. 22, no. 4, p. 1477, 2022.
[35] X. Du, D. Niu, Y. Chen, X. Wang, and Z. Bi, "City classification for municipal solid waste prediction in mainland China based on K-means clustering," *Waste Manag.*, vol. 144, pp. 445–453, 2022.
[36] T. A. Putra, P. A. Widya, R. Afira, and Y. Elva, "Optimization Analysis Model Determining PNMP Mandiri Loan Status Based on Pearson Correlation," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 6, no. 6, pp. 966–973, 2022.
[37] P. Biswas and T. Samanta, "A method for fault detection in wireless sensor network based on pearson's correlation coefficient and support vector machine classification," *Wirel. Pers. Commun.*, vol. 123, no. 3, pp. 2649–2664, 2022.
[38] F. Beiranvand, V. Mehrdad, and M. B. Dowlatshahi, "Unsupervised feature selection for image classification: A bipartite matching-based principal component analysis approach," *Knowledge-Based Syst.*, vol. 250, p. 109085, 2022.
[39] Y.-J. Mao, H.-J. Lim, M. Ni, W.-H. Yan, D. W.-C. Wong, and

J. C.-W. Cheung, “Breast tumour classification using ultrasound elastography with machine learning: A systematic scoping review,” *Cancers (Basel).*, vol. 14, no. 2, p. 367, 2022.

[40] J. J. Tanimu, M. Hamada, M. Hassan, H. Kakudi, and J. O. Abiodun, “A machine learning method for classification of cervical cancer,” *Electronics*, vol. 11, no. 3, p. 463, 2022.

[41] R. Okunev, “Pearson correlation and using the excel linear trend equation and excel regression output,” in *Analytics for Retail: A Step-by-Step Guide to the Statistics Behind a Successful Retail Business*, Springer, 2022, pp. 83–106.

[42] C. Pancotti *et al.*, “Predicting protein stability changes upon single-point mutation: a thorough comparison of the available tools on a new dataset,” *Brief. Bioinform.*, vol. 23, no. 2, p. bbab555, 2022.

[43] J. Sawatzki, T. Schlippe, and M. Benner-Wickner, “Deep learning techniques for automatic short answer grading: Predicting scores for English and German answers,” in *Artificial Intelligence in Education: Emerging Technologies, Models and Applications: Proceedings of 2021 2nd International Conference on Artificial Intelligence in Education Technology*, 2022, pp. 65–75.

[44] C. Zhang *et al.*, “A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification,” *ISPRS J. Photogramm. Remote Sens.*, vol. 140, pp. 133–144, 2018.

[45] I. N. Anwar, K. Daud, A. A. Abd Samat, Z. H. C. Soh, A. M. S. Omar, and F. Ahmad, “Implementation of Levenberg-Marquardt Based Multilayer Perceptron (MLP) for Detection and Classification of Power Quality Disturbances,” in *2022 IEEE 12th International Conference on Control System, Computing and Engineering (ICCSCE)*, 2022, pp. 63–68.

[46] U. Riyanto, “PENERAPAN ALGORITMA MULTILAYER PERCEPTRON (MLP) DALAM MENENTUKAN KELAYAKAN KENAIKAN JABATAN: STUDI KASUS PT. ABC-JAKARTA,” *JIKA (Jurnal Inform.*, vol. 2, no. 1, 2018.

[47] W. I. Sabilla, C. B. Vista, and D. S. Hormansyah, “Implementasi Multilayer Perceptron Untuk Memprediksi Harapan Hidup Pada Pasien Penyakit Kardiovaskular,” *J-SAKTI (Jurnal Sains Komput. dan Inform.*, vol. 6, no. 1, pp. 57–68, 2022.

DOI: https://doi.org/10.29207/resti.v7i6.5278