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Optimization Analysis Model Determining PNMP Mandiri Loan Status Based on Pearson Correlation

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Abstract

PNPM Mandiri is an organization engaged in financing small and medium enterprises in the community. The problem that always occurs is an error in determining the loan status resulting in bad credit. This study aims to present a classification analysis model for determining loan status at PNPM Mandiri. The classification analysis model was built using the Perceptron algorithm artificial neural network. The analysis model will later be optimized using the Person Correlation (PC) method to measure the accuracy of the variables used. The research dataset is based on historical data from the last 2 years as many as 67 data samples. The analysis variables consist of Business Type (X1), Loan Amount (X2), Collateral (X3), Income (X4), and Expenses (X5). The results of the analysis show that the model built can provide optimal classification results. These results can be seen based on the results of variable measurements using the PC method indicating that variable X2 has no significant relationship. With the results of these measurements, the performance of the artificial neural network presents maximum results in determining loan status. Overall, the results of this study can provide an effective analytical model as well as an alternative solution for determining loan status.

Keywords: Classification Analysis, Loan Status, PNPM Mandiri, Artificial Neural Networks, Person Correlation

1. Introduction

The National Program for Independent Rural Community Empowerment (PNPM Mandiri Rural or PNPM-Rural or Rural PNPM) is one form of community empowerment program [1]. PNPM Mandiri has a working area and targets adopting the mechanisms and procedures of the Kecamatan Development Program (PPK) [2]. PNPM Mandiri consists of 2 forms of programs, namely providing assistance to the poor in the form of loan funds and providing community business capital loans [3]. This PNPM Mandiri work program also has the aim of assisting the community to improve organizations at the community level to improve community welfare [4].

The borrowing process at PNPM Mandiri itself has occurred and is taking place in every rural area spread across all sub-districts and city districts [5]. Based on the facts, it can be seen that this creates a problem in the process of controlling loan funds, where there are many cases of bad credit experienced by PNPM Mandiri [6]. This problem occurs because the loan analysis process is still done manually so this can lead to errors in determining the granting of loan status [7].

The process of determining the status of the loan has become a problem for the providers of funds [8]. In overcoming these problems, an analytical model is needed that can be used as a form of illustration in decision-making [9]. The analytical model is presented in the process of classifying prospective borrowers [10]. By building the analysis model, it is expected to be able to overcome problems in granting loan status [11].

Previous research in the analysis of lending status shows that the analytical model built using the C4.5 algorithm shows good results in the classification of lending status [12]. Furthermore, the same research by applying the Simple Additive Weighting method produces alternative solutions in making decisions regarding the feasibility of providing loans [13]. The analytical model on the decision support system by adopting the Smart method presents results that are quite effective in determining loan status [14].

Based on the results of previous studies, it was explained that the loan status at PNMP Mandiri by applying the nave Bayes method presented an accuracy value of 85.71% and an error value of 14.29% [15]. The same study also presents the TOPSIS (Technique For

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Order Preference By Similarity To Ideal Solution) method which gives results by presenting the best alternative in determining the loan status [16]. Based on this research, the analysis process can be optimized by building an analytical model in determining the credit status of PNPM Mandiri.

The analytical model in overcoming difficulties in dealing with PNMP Mandiri lending status in this study will apply the concept of a neural network (ANN). ANN is an analytical method that can present a fairly good output in solving a problem [17]. ANN can provide optimal results to be used as an alternative solution in decision-making [18]. ANN presents a very good performance in modeling a problem to provide the best solution [19].

The ANN classification analysis model in PNPM Mandiri's credit status assessment will adopt the perceptron algorithm. The algorithm can classify a problem by presenting a fairly good output [20]. The perceptron algorithm works by performing mathematical calculations in a form of neural network cells [21]. The perceptron algorithm is also a simple ANN training method consisting of one neuron with a weight that is set using an activation function [22]. The perceptron algorithm has also provided an optimal level of accuracy in conducting analysis based on the output obtained [23]. Not only that, the perceptron algorithm provides good performance with the results of the level of measurement on the value of Square Error (RMSE) and R2 [24].

Determining the lending status by using an artificial neural network method that can provide effective results in decision-making [25]. The perceptron algorithm in artificial networks can be used as the best solution in dealing with the problem of bad credit risk [26]. The perceptron artificial neural network model has also been able and used in evaluating credit problems [27].

Analysis of the classification of optimization models on artificial neural networks can present the maximum model to present precise and accurate output [28]. One of the methods used can be seen from the performance of the Person Correlation (PC) method. This method is the basis used to measure the relationship between variables (X) and variable (Y) [29]. This method is also able to present the level of relationships that occur in a neural network analysis model [30]. The PC method works by performing mathematical calculations to measure the strength of the correlation between data in a pattern analysis [31]. With the PC method, ANN performance is able to present optimal output so that the analysis model built is more effective and efficient [32]. The use of the PC method itself has worked optimally to maximize the artificial neural network model formed [33]. PC method is used in developing analytical models in machine learning to present a fairly good performance in the analysis [34]. With this, the classification analysis model optimized by the PC method presents the appropriate indicator variables in determining the status of PNMP Mandiri loans. It is based on the PC method that can be deployed to test each variable used in the analysis [35].

Based on the previous explanation, this research will build a pattern to analyze credit status in PNPM Mandiri using the perceptron algorithm artificial neural network method. The analysis of the model will be optimized using the PC method to test each variable used. The novelty of this research simply presents an analytical model that can test the strength between variables to present maximum analysis results. With this novelty, the classification model optimally provides certainty in determining the status of the loan. In general, this research is also able to make a major contribution to PNPM Mandiri in making decisions to determine loans to be made in the next period.

2. Research Methods

The credit status classification analysis model can be described in a research framework. The description of this research framework can present the stages of the process carried out to obtain optimal analysis results in determining the status of the loan. The step-by-step process is presented starting with analyzing the dataset that can be obtained from the PNPM Mandiri, then continuing with the variables in building the analysis pattern. After the pattern of analysis is formed based on the specified variables, the next process is to transform the dataset. After the transformation process, the data set was analyzed using a perceptron artificial neural network.

The analysis process is presented in the form of training and network testing. This process aims to see the consistency of the previously formed analysis pattern in producing output. After the perceptron artificial neural network analysis process is carried out, the final process is to examine the relationship between the results of the neural network analysis and the data using the PC method. this method can measure the level of correlation of each variable with the output. The stages of the process can be presented in the research framework depicted in Figure 1.

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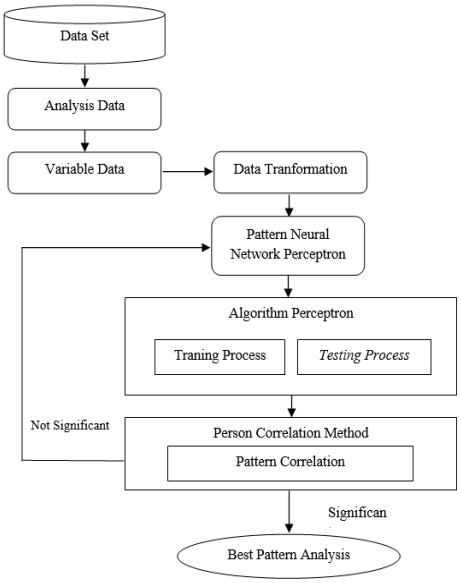

Figure 1. Research Framework

Figure 1 presents the stages of the classification analysis pattern model in determining loan status at PNPM Mandiri. The analysis process uses the artificial neural network method perceptron algorithm and person correlation in measuring the performance of the analysis model. The analysis process with the perceptron algorithm will later be carried out in the training and testing stages. The training process will involve as much as 55 data and testing as much as 12 data. The process of measuring the correlation with the PC was carried out on all 67 datasets to measure the accuracy between the variables used. Further stages of the process can be described, among others:

a. Data Analysis Process

The data analysis process aims to view and examine the data that will be used in building analysis patterns. The dataset used in the analysis process comes from PNPM Mandri Kec. Difficult Water, Kab. Solok, West Sumatra Province as many as 67 data samples. The sample research dataset can be presented in Table 1.

b. Determining Variable Analysis.

Based on the dataset obtained from PNPM Mandiri, determining the analysis variables will be the initial stage of the process. Based on the previous analysis process, the analysis variables consist of Business Type (X1), Loan Amount (X2), Collateral (X3), Income (X4), and Expenditure (X5) [36]. After the variables are obtained, it is continued to carry out the data transformation process.

Table 1. Research Dataset Samples

No. Contract	Business Type	Loan Amount	Collateral	Income	Expenditure	Status
KT-0001	Trade	Rp.15.000.000	SK	Rp.4,000.000	Rp.2.500.000	Accept
KT-0002	Trade	Rp.50.000.000	sertifikat	Rp.1.500.000	Rp. 1.000.000	Reject
KT-0003	Plantation	Rp.25.000.000	Sertifikat	Rp.1.500.000	Rp.1.200.000	Reject
KT-0004	Fish Pond	Rp.15.000.000	BPKB	Rp.2.500.000	Rp.1.000.000	Accept
KT-0005	Trade	Rp.35.000.000	SK	Rp4.500.000	Rp. 3.000.000	Accept
KT-0006	Trade	Rp.40.000.000	SK	Rp.3.500.000	Rp.2.000.000	Accept
KT-0007	Service	Rp.40.000.000	BPKB	Rp.1.700.000	Rp.1.500.000	Reject
KT-0008	Trade	Rp10.000.000	Sertifikat	Rp.6.000.000	Rp.4.000.000	Accept
KT-0009	Trade	Rp.10.000.000	BPKB	Rp.5.000.000	Rp.2.000.000	Accept
KT-0010	Pond	Rp.40.000.000	SK	Rp.4.000.000	Rp.2.000.000	Accept
KT-0011	Trade	Rp.15.000.000	BPKB	Rp.5.500.000	Rp.3.000.000	Accept
KT-0012	Trade	Rp.7.000.000	Sertifikat	Rp.3.500.000	Rp.1.500.000	Accept

c. Data Transformation Process

The data transformation stage aims to transform the data into data that can be processed using artificial neural networks. The data transformation process produces data in the form of bipolar data consisting of values -1, 0, and 1. The results of data transformation can be seen in Table 2.

Table 2. Data Transformation Results

X1	X2	X3	X4	X5	Y
1	0	1	0	1	1
1	1	1	-1	1	0
1	1	1	-1	1	0
1	0	1	0	1	1
1	1	1	0	0	1
1	1	1	0	1	1
1	1	1	-1	1	0
1	-1	1	1	0	1
1	-1	1	1	0	1
1	1	1	0	1	1
1	0	1	0	0	1
1	-1	1	0	1	1

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Table 2 is the result of the transformation carried out based on the rules and regulations of the PNPM Mandiri itself. The transformation process carried out will adopt the rules of the independent PNPM in determining the status of loans that have occurred. The rules can be seen in Table 3.

Table 3. Transformation Rules

Data Transformation Rules
if the prospective buyer has a business then the transformation value is 1 and vice versa is 0
if the candidate applies for a loan of 0 to 10 million the value is -1, if the loan is 10 million - 14.99 million the value is 0 and for loans above 15 million the value is 1
if the loan candidate has collateral such as certificates, BPKP and SK then the value is 1 and vice versa the value is 0
if a prospective candidate has an income of 1.5 million to 3 million then it is worth 0, if income is above 5 million then it is worth 1 and vice versa if there is no income it is worth 0
if the candidate is willing to spend 1.5 million to 3 million then it is worth 1, if income is above 5 million then it is worth 0

Table 3 presents the rules in the data transformation process in the analysis model to be performed. This rule adopts the regulations for providing loan funds in PNPM Mandiri [36]. Based on the results of the transformation in Table 1, these rules can be adopted properly to change data so that it can be processed using an artificial neural network.

d. Neural Network Pattern (Network Architecture)

This stage is the stage used to build a model of the classification analysis pattern of artificial neural networks. The pattern has an input layer consisting of 5 variables and 1 output variable. The network architecture description can be depicted in Figure 2.

Figure 2 presents an analysis model of the artificial neural network classification pattern of the perceptron algorithm in determining loan status at PNPM Mandiri. In the network analysis pattern model, the network weights and bias values are presented in the process of training and testing the network. The final result of this analysis pattern will display the output (y) as the result obtained to determine the loan status.

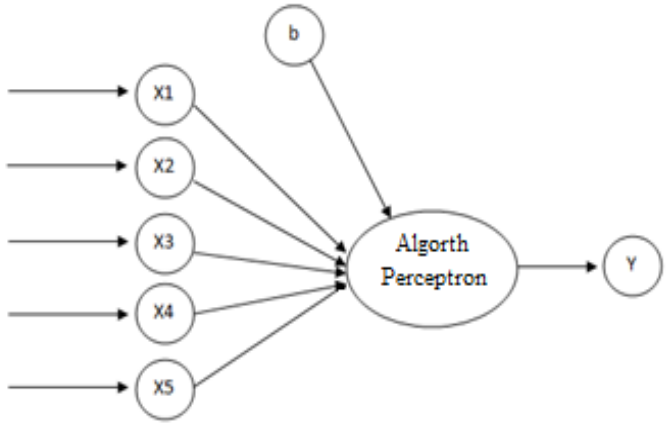

Figure 2. Perceptron Network Pattern Architecture Determines PNPM Mandiri Loans

e. Perceptron Algorithm

The perceptron algorithm is one of the algorithms found in artificial neural networks [37]. This algorithm can provide a model that can perform better training and testing [38]. This algorithm presents a simple model in doing learning [39]. In building a classification analysis pattern model, the role of neurons needs to be considered so that learning performance gives maximum results [40]. The perceptron algorithm has one neuron and a weight value for each input layer [41]. The perceptron learning algorithm can be explained in Formula 1-6 [42].

$$Y\_in = b + \sum xi.wi \quad (1)$$

$$y = \begin{cases} 1 \text{ if } y\_in > \Theta \\ 0 \text{ if } -\Theta \le y\_in \le \Theta \\ 1 \text{ if } y\_in < -\Theta \end{cases} \quad (2)$$

$$wi(new) = wi(long) + \Delta w(i=1,...,n) \quad (3)$$

$$\Delta w = \alpha t x i \quad (4)$$

$$b(new) = b(long) + \Delta b \quad (5)$$

$$\Delta b = \alpha t \quad (6)$$

Formula 1 describes the mathematical calculations in finding the network output value. The output results will be entered into the activation function presented in Formula 2 by looking at the rules that have been presented. If the network output value is not the same as the target value, the process will continue to change the weight and bias values presented in Formula 3-6 [43].

f. Person Correlation (PC) Method

Pearson Correlation (PC) is one of the statistical concepts used to measure the correlation relationship in each data [44]. The PC method is used to maximize the perceptron analysis process that will be carried out in determining loan status. This method can collaborate

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with several other methods to measure the performance of an analytical process [45]. This PC method can also be optimized in reviewing output from the analysis model [46]. The PC calculation can be presented in Formula 7&8 [47].

$$P_{X,Y}=\left(\frac{\text{cov}(X,Y)}{\sigma X.\sigma Y}\right)=\left(\frac{E((\text{cov}(X-\mu X)(Y-\mu Y))}{\sigma X.\sigma Y}\right) \quad (7)$$

$$=\frac{E(XY)-E(X)E(Y)}{\sqrt{E(X.X)-E.E(X)}\sqrt{B(Y.Y)-E.E(Y)}} \quad (8)$$

The formula explains that the value of cov (X, Y) is a covariance value between X and Y. The value of X, Y is also able to measure the standard deviation of. At the value of E (X,Y) it can be said that an expected value of X,Y [47].

3. Results and Discussions

The discussion of this research begins by carrying out the analysis process using the perceptron algorithm. The data set used refers to the results of the transformation that has been carried out previously. The results of the perceptron algorithm artificial neural network analysis process can be seen in Figure 3.

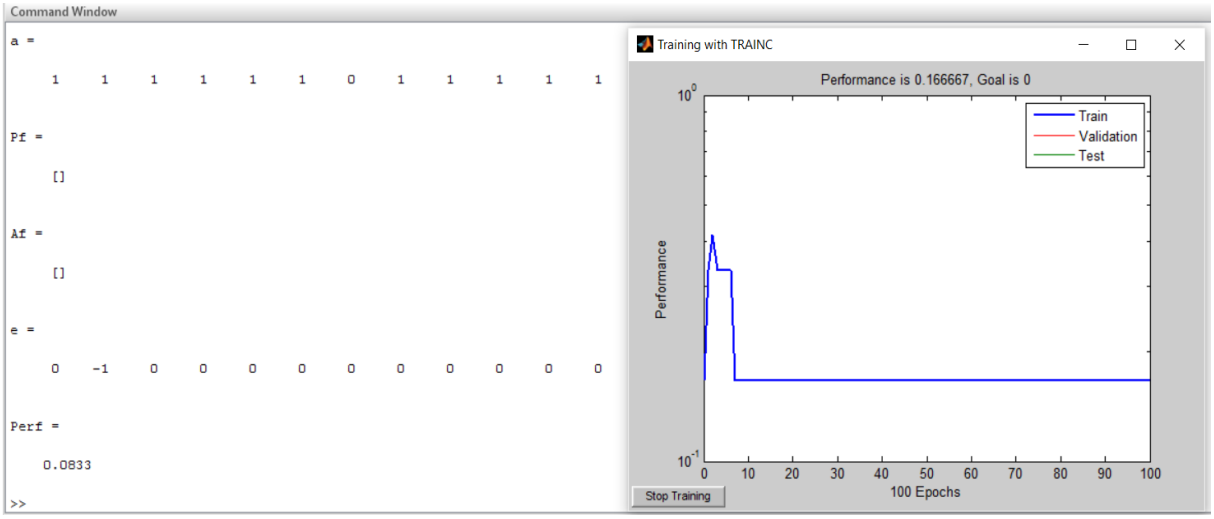

Figure 3. Results of the Perceptron Neural Network Analysis Process

Figure 3 presents the output of the neural network in carrying out a classification analysis of borrowing status. The output results show that the perceptron algorithm is capable of providing output with an error rate of 0.0833 or 8.33% based on the network learning process. The output results can be seen based on the presentation in Table 4.

Table 4. Network Output Results

X1	X2	X3	X4	X5	T	Y	Error
1	0	1	0	1	1	1	0
1	1	1	-1	1	0	1	-1
1	1	1	-1	1	0	0	0
1	0	1	0	1	1	1	0
1	1	1	0	0	1	1	0
1	1	1	0	1	1	1	0
1	1	1	-1	1	0	0	0
1	-1	1	1	0	1	1	0
1	-1	1	1	0	1	1	0
1	1	1	0	1	1	1	0
1	0	1	0	0	1	1	0
1	-1	1	0	1	1	1	0

Table 4 confirms that the output of the analysis has a fairly minimal error rate. The error value is obtained by comparing the network output value (Y) with the target (T). Based on the results obtained, there is 1 data in row 2 which has an error value of -1. This indicates that the analysis model still does not have optimal results, so it is necessary to measure the variables previously used using the person correlation (PC) method. The performance of the PC method will be able to see the relationship that occurs between variables. The correlation test analysis process can be seen in Table 5.

Table 5 presents the output of the correlation test from the analysis pattern in determining loan status. The test results using the PC method found that the relationship between X1 and Y was 0.212, X2 and Y were 0.002, X3 and Y were 0.403, and X4 and Y were 0.044. Variable X5 with Y of 0.059. Based on the results of measuring

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the level of correlation with the PC method, it can be concluded that the variable loan amount (X2) does not affect the determination of loan status.

Based on the results of the correlation test, the classification analysis process will be carried out again without using the loan amount variable (X2). The results of this analysis will later be compared to the performance level of the neural network in conducting the analysis. The test results can be presented in Table 6

Table 5. Results of the Pearson Correlation Test Process

Correlations							
Control Variables			X1	X2	X3	X4	X5	Y
-none-[a]	X1	Correlation	1,000	0,069	-0,134	0,088	0,260	-0,286
		Significance (1-tailed)		0,425	0,356	0,405	0,234	0,212
		df	0	8	8	8	8	8
	X2	Correlation	0,069	1,000	0,343	-0,638	-0,571	-0,565
		Significance (1-tailed)	0,425		0,166	0,024	0,042	0,044
		df	8	0	8	8	8	8
	X3	Correlation	-0,134	0,343	1,000	-0,080	0,085	-0,089
		Significance (1-tailed)	0,356	0,166		0,413	0,408	0,403
		df	8	8	0	8	8	8
	X4	Correlation	0,088	-0,638	-0,080	1,000	0,877	0,805
		Significance (1-tailed)	0,405	0,024	0,413		0,000	0,002
		df	8	8	8	0	8	8
	X5	Correlation	0,260	-0,571	0,085	0,877	1,000	0,527
		Significance (1-tailed)	0,234	0,042	0,408	0,000		0,059
		df	8	8	8	8	0	8
	Y	Correlation	-0,286	-0,565	-0,089	0,805	0,527	1,000
		Significance (1-tailed)	0,212	0,002	0,403	0,044	0,059	
		df	8	8	8	8	8	0

a. Cells contain zero-order (Pearson) correlations.

Table 6. Results of Comparison of Analysis Patterns

Analysis Results Before Correlation Testing								Analysis Results After Correlation Testing						
X1	**X2**	**X3**	**X4**	**X5**	**T**	**Y**	**Error**	**X1**	**X3**	**X4**	**X5**	**T**	**Y**	**Error**
1	0	1	0	1	1	1	0	1	1	0	1	1	1	0
1	1	1	-1	1	0	1	-1	1	1	-1	1	0	0	0
1	1	1	-1	1	0	0	0	1	1	-1	1	0	0	0
1	0	1	0	1	1	1	0	1	1	0	1	1	1	0
1	1	1	0	0	1	1	0	1	1	0	0	1	1	0
1	1	1	0	1	1	1	0	1	1	0	1	1	1	0
1	1	1	-1	1	0	0	0	1	1	-1	1	0	0	0
1	-1	1	1	0	1	1	0	1	1	1	0	1	1	0
1	-1	1	1	0	1	1	0	1	1	1	0	1	1	0
1	1	1	0	1	1	1	0	1	1	0	1	1	1	0
1	0	1	0	0	1	1	0	1	1	0	0	1	1	0
1	-1	1	0	1	1	1	0	1	1	0	1	1	1	0
Performance 91,67%								**Performance 100 %**						

Table 6 presents the test results as well as a comparison of the performance of the pattern model that has measured the correlation relationship. The results of the analysis before taking measurements with a PC present a performance of 91.76% and the results of the analysis after taking measurements with a PC present maximum performance results. The results of this comparison can be seen in that the level of network performance will be optimal after measuring the correlation of each variable used. Based on these results, the update of this study presents the process of measuring the significant level of the pattern of analysis that is built to determine the status of a loan. The results of this study also show that an analytical model built requires measurement of each variable to be used so that the analysis process that occurs will provide optimal results.

4. Conclusion

The process of determining loan status using artificial neural networks optimized with the person correlation (PC) method provides precise and accurate output

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results. As for the results of correlation measurements carried out, the variables that influence the determination of loan status include Business Type (X1), Collateral (X3), Income (X4), and Expenses (X5). With this, the PC method can show variable relationships that can be used as a measuring tool in building models of analytical patterns in artificial neural networks. Based on the performance of the PC method, the neural network classification analysis pattern model in determining loan status presents results with maximum performance values. This will be a major contribution for PNPM Mandiri to adopt the resulting analytical model in determining loan status. Overall, research can be used as a solution in making decisions to determine loan status.

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