

# Resilient Backpropagation Neural Network on Prediction of Poverty Levels in South Sulawesi

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## ABSTRACT

Poverty is a topic that continues and is always discussed up to this time, as a benchmark indicator of how the level of welfare and prosperity in the lives of people in a country. Several attempts have been made by the central and regional governments to reduce poverty levels, including “Bantuan Langsung Tunai” (BLT) and the “Program Keluarga Harapan” (PKH). However, poverty reduction in Indonesia is still slowing down, including in South Sulawesi. Based on this, this study aims to predict poverty levels in South Sulawesi. Factors thought to influence poverty levels are the Human Development Index (HDI), the Open Unemployment Rate (TPT), and the Gross Regional Domestic Product (GRDP). The data used are data from 2010 to 2014. The method used is a backpropagation neural network with a resilient algorithm or better known as a resilient backpropagation neural network (RBNN). The results of the prediction of poverty levels using predictors of HDI, TPT, and GRDP showed that the analysis of the RBNN reached its optimum using architecture [3- 9 - 1] and reached convergence at the 81<sup>th</sup> iteration with an accuracy rate of 95.34%.

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## 1. INTRODUCTION

Poverty is one indicator that must be considered by the government. This is because poverty is an important aspect in measuring the level of community welfare. Several attempts were made by the central or regional government to reduce poverty, asking for “Bantuan Langsung Tunai” (BLT) and the “Program Keluarga Harapan” (PKH). However, poverty reduction in Indonesia is still slowing down. It is known that the number of poor people in Indonesia in March 2019 reached 25.14 million people. Compared to September 2018, the number of poor people increased by 529.9 thousand people. However, at the end of 2019 it was still 9.41% [1]. The number of poor people in South Sulawesi in the last 5 years is still above 500 thousand people. Compared to previous years, the number of poor people has decreased, but not significant, as in 2017 the poverty rate in South Sulawesi reached 9.38% and the following year 9.06%, meaning that in one year it only fell by 0.32%. The accumulation of poverty levels in South Sulawesi in the last five years only decreased by 0.48% [2], [3].

Poverty in recent years has become one of the important topics in research. As research on the analysis of factors that affect poverty in Indonesia for 5 years. The analysis shows that the HDI and the unemployment rate affect changes in poverty levels in 33 provinces in Indonesia [4]. Then research on how much influence from inflation, education, income, household consumption, and the Human Development Index (HDI) affect poverty levels in Indonesia. The result is that poverty levels in Indonesia are influenced by large household consumption and HDI [5]. Both of these studies use multiple linear regression analysis. Clustering analysis has also been used to analyze poverty data. Such as poverty data research in Yogyakarta. The research uses Fuzzy C-means algorithm and K-means algorithm. The results of the analysis show that by using 15 indicators that affect poverty levels, the K-means algorithm gives better results than Fuzzy C-means [6]. Other studies apply

backpropagation neural networks (BNN) to predict poverty levels. The results of the analysis show that the prediction model with BNN gives better results than other mathematical models [7]. Next is the analysis of poverty levels using generalized regression neural networks (GRNN) [8]. The response of the two studies above is the metric data.

Based on the description above, this study will predict poverty levels with predictors of the human development index (HDI), the level of open unemployment (TPT) [4], and add one new variable, namely gross regional domestic product (GRDP). The method used is based on research conducted by Mulyani [7], namely using BNN. The difference is this research uses responses in the form of nonmetric data (categorical) and the algorithm used is the resilient algorithm.

Neural network (NN) is one of the analytical techniques that can be used in various disciplines [9]. This method is one part of Artificial Intelligence (AI) which is formed based on the human nervous system. Various types of NN are able to show their potential in solving problems [10]. One indicator in NN is the level of accuracy. One method in NN that can produce optimum accuracy is backpropagation [11]. The disadvantage of backpropagation neural networks (BNN) is the achievement of slow convergence. One that can be used to overcome these problems is to use a resilient algorithm [11]. This method is often known as resilient backpropagation neural network (RBNN). This RBNN is able to provide faster convergence than BNN methods in the training data used in simulations. This resilient algorithm is first used in single dimension and two dimensional data. But now it can be developed into multidimensional [12].

The RBNN has been applied in various fields. For example, research on estimating waiting times in queues at a bank [13]. The analysis shows that the RBNN provides a better estimate of waiting time than using time series analysis. The second study is about optimizing accuracy in predicting financial distress in 2017 [14]. Based on this research the optimum accuracy is 90.48%. The results of the accuracy with the RBNN were 23.81% higher than using the logistic regression model. Next is the application of RBNN in anoxic biotrickling filters to remove hydrogensulfide from artificial biogas [15]. The results obtained are NN with a resilient algorithm capable of eliminating H<sub>2</sub>S in biogas quickly without damaging biogas levels. The next RBNN is used in the validation of macroscopic traffic flow models compared to the automatic differentiation software (ADOL-C) method. The research shows that the RBNN provides more accurate and optimum model results in the settlement of traffic flow cases [16]. The results of the RBNN in some of these studies have shown that the resilient algorithm performance at BNN gives better results than other algorithms, both using metric, nonmetric, and data series data.

In this study will use nonmetric data from poverty level data. Where the poverty level data will be categorized into 2, namely the first category is the low poverty rate (< average of South Sulawesi) and the second category is the high poverty rate (≥ average of South Sulawesi).

## 2. RESEARCH METHOD

The data used in this study are secondary data obtained from the South Sulawesi BPS which consists of poverty level data as a response, and HDI, TPT, GRDP as predictors recorded in 2010 to 2014. The data are 120, consisting of 24 districts / city recorded for 5 years. The response used is nonmetric data, so the poverty level is converted into 2 categories. the first category with index 0, which is a low poverty rate (< South Sulawesi average). the second category is index 1, which is a high poverty rate (≥ South Sulawesi average). RBNN is an efficient machine learning method in producing a prediction. The RBNN architecture in figure 1.

The difference in the use of resilient algorithms in BNN with other algorithms is the update of new values on each weight to determine new weights, as shown in Figure 1. Changes in the adaptive value take place during the algorithm process in the training data run in accordance with the learning rule as equation (1).

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^+ \times \Delta_{ij}^{(t-1)}, & \text{jika } \frac{\partial F^{(t-1)}}{\partial w_{ij}} \times \frac{\partial F^{(t)}}{\partial w_{ij}} > 0 \\ \eta^- \times \Delta_{ij}^{(t-1)}, & \text{jika } \frac{\partial F^{(t-1)}}{\partial w_{ij}} \times \frac{\partial F^{(t)}}{\partial w_{ij}} < 0 \\ \Delta_{ij}^{(t-1)} & \text{untuk yang lain} \end{cases} \quad (1)$$

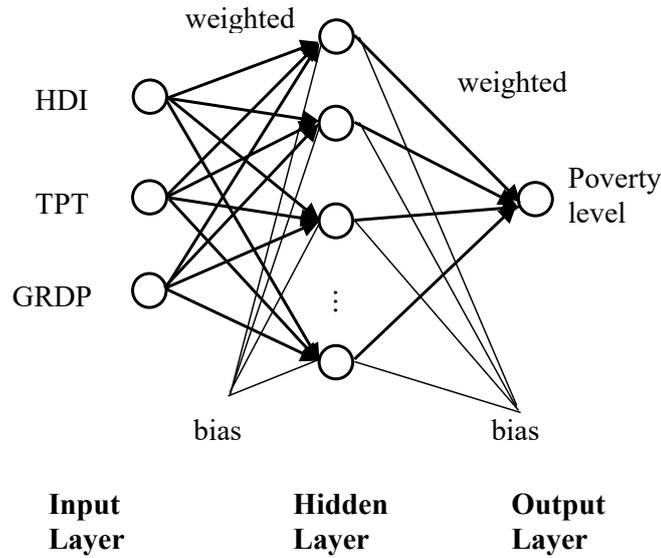


Figure 1. RBNN Architecture on Research

Where  $0 < \eta^- < 1 < \eta^+$  [11].

In other words, this adaptive function functions as follows: 1) if  $\partial F$  against  $w_{ij}$  changes the sign, then  $\Delta_{ij}$  is reduced by the  $\eta^-$ ; 2) if the partial derivative does not change the sign, then  $\Delta_{ij}$  increases. After  $\Delta_{ij}$  for each weight is adjusted, weight updates also follow very simple rules, as shown in the equation (2).

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, & \text{jika } \frac{\partial F^{(t)}}{\partial w_{ij}} > 0 \\ +\Delta_{ij}^{(t-1)}, & \text{jika } \frac{\partial F^{(t)}}{\partial w_{ij}} < 0 \\ \Delta_{ij}^{(t-1)} & \text{untuk yang lain} \end{cases} \quad (2)$$

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}$$

However, if the partial derivative results change marks, for example the results in the previous stage are too large, then the weight change is:

$$\Delta w_{ij}^{(t)} = -\Delta w_{ij}^{(t-1)}, \text{ jika } \frac{\partial F^{(t-1)}}{\partial w_{ij}} \times \frac{\partial F^{(t)}}{\partial w_{ij}} < 0 \quad (3)$$

The algorithm in the RBNN is as follows:

For all weights and biases in the hidden layer used [11].



parts, namely training and testing data, the next step is to analyze the training data to form a model. Then validate the results obtained from the training data using testing data. After the results are formed, then determine the level of accuracy.

The analysis in the RBNN in this study uses the log-sigmoid activation function, because the expected output is in the form of categories 0 and 1. The hidden layer used only consists of 1 layer and the hidden layer is simulated with several different nodes, including 1, 3, 5, 7, and 9. The results of the RBNN analysis for the prediction of poverty levels are in table 1.

Table 1. Predicted Results with RBNN

Training Data			
Predictors	The RBNN Arsitecture	Iteration	Accuracy
HDI, TPT, GRDP	[3 - 1 - 1]	133	45,21%
	[3 - 3 - 1]	117	48,12%
	[3 - 5 - 1]	127	52,11%
	[3 - 7 - 1]	114	59,27%
	[3 - 9 - 1]	106	60,30%
Testing Data			
HDI, TPT, GRDP	[3 - 1 - 1]	112	68,97%
	[3 - 3 - 1]	103	74,88%
	[3 - 5 - 1]	111	82,91%
	[3 - 7 - 1]	97	91,11%
	[3 - 9 - 1]	81	95,34%

The results in table 1 above show that the prediction of poverty levels with 3 factors (HDI, TPT, GRDP) is optimum in architecture [3-9-1] both in training and testing data. The architecture is in a hidden layer using 9 nodes and converges to the 106th iteration for training data and the 81st iteration for testing data. Determination of the optimum prediction results is based on the level of accuracy obtained. Based on table 1 it is known that the highest accuracy of the training data is 60.30%. The analysis using training data aims to determine the prediction model for poverty levels using the RBNN. Furthermore, the model formed is validated using testing data.

The results of the analysis in table 1 show that there is a consistency of results between training data and testing data. The results of the prediction of poverty levels using the RBNN show that the more nodes used in the hidden layer, the faster the convergence and accuracy will increase. This can be seen in the results of the iteration obtained. Prediction of testing data by using 9 nodes produces the highest accuracy value and achieves faster convergence. The resulting accuracy is 95.34% and reaches convergence with an iteration of 81 times.

This study obtained results in line with previous studies, getting optimum results with a faster convergent process. As research on the prediction of financial distress companies. The results obtained are optimum predictions with an accuracy level of 90.48% and reach convergence at 4,536 iterations. The iteration in other RBNN architectures is > 5,000 times [14]. This study obtained results that are in line with this RBNN research which is also more effective than other NN methods, such as research on heat transfer. The analysis shows that the RBNN is more effective and efficient in predicting the results of heat transfer [10]. Other research also shows the same thing, namely that the RBNN is faster at achieving convergence and optimum results in high-dimensional data analysis [17].

In contrast to previous research, conducted by Mulyani [7], in this study using nonmetric data. So the output produced is also different. In the previous research, it was in the form of metric data, namely the percentage of poverty level, whereas in this study it was in the form of nonmetric data with categories 0 and 1. The iteration of the prediction of poverty level in this study was also better. The optimum results for prediction using training data in this study occurred in the 106<sup>th</sup> iteration, while the research conducted by Mulyani [7] optimum at 5,000 iterations.

The application of the RBNN for the prediction of poverty levels gets better results when compared to the prediction of financial distress companies [14]. In terms of accuracy, the application of the RBNN for predicting poverty rates results in higher accuracy than the prediction of financial distress companies, which is 95.34% for predictions of poverty levels and the prediction of financial distress for companies is only 90.48%. In terms of convergence, poverty rate predictions are also faster when compared to financial distress predictions. It was noted that the prediction of poverty level reached optimum and convergent in the 81st iteration, while the prediction of financial distress was 4,536 [14]. This difference is caused because the number of data samples used and the number of inputs used are different. In the prediction of financial distress, the number of sample data and inputs used is doubled.

Based on the description above, it can be said that the RBNN is one of the NN methods that can produce predictions with efficient and better results than other NN methods. The RBNN is faster at converging in predictions and can produce high accuracy as well. In addition, the RBNN can be used in research with high-dimensional data. This RBNN is not only used for metric data or data series, but can also be used for nonmetric (categorical).

#### 4. CONCLUSION

From the results of the analysis show that the prediction of poverty levels using HDI, TPT, and PDRB predictors converges at the 81st iteration and an accuracy rate of 95.34%. The use of architecture [3 - 9 -1] has given the most optimum results than the use of other architectures. The results above still need further research by comparing the use of different architectures, namely only 1 input (1 predictor) and 2 inputs (2 predictors). So that later can be compared with the results using 3 inputs (3 predictors). This RBNN can be used in various disciplines. So that in the future it can be turned into other fields, such as education and health.

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