Accuracy Analysis of ANN Back Propagation, Neuro-Fuzzy, and Radial Basis Function: A Case of HDI Forecasting

Syaharuddin, Dewi Pramita, Toto Nusantara, Subanji

Abstract*: One measure of the progress of a region or country is the increase in the Human Development Index (HDI) which includes life expectancy, per capita income, and old school expectations. HDI becomes an essential reference in time-series data, so it needs to be done forecasting process with reliable method. We use HDI data as much as the last nine years in West Nusa Tenggara province, which is one of the regions with the highest HDI acceleration in Indonesia in recent years. We do forecasting by comparing three methods namely Back Propagation (BP), Neuro-Fuzzy (NF), and Radial base Function (RBF), covering forecasting with 3 models of training and testing on the Back Propagation method, 9 training and testing models on A Neuro-Fuzzy method, and 1 training and testing model in the Radial base Function method. While the parameter accuracy (error) used in this forecasting is Mean Square Error (MSE). Based on the results of the simulation obtained NTB province predictions in 2019 using the Back Propagation (BP) method of 67.46 (increased by 0.23%); The RBF method amounted to 67.3 (fixed); and the NF method of 67.18 (decreased by 0.17%). From these results, the conclusion that in this case, the BP method is very good at doing simulation and decision-making results. The results were obtained from simulated data witt type training TRAINGDA, TRAINGDX, and TRAINRP. But simulation using type TRAINRP has the best parameter output with a performance (R) of 0.99194, a validation check of 1000, a gradient of 13.8, and a level of accuracy of 99.39%.

***Keywords*: Forecasting, HDI, Back Propagation, Neuro-Fuzzy, Radial Basis Function**

I. INTRODUCTION

Development is an effort or process to make a better change. The development process involves changes in various aspects, such as social, political, economic, education, health, and culture. Therefore, development is an absolute requirement for the continuity and progress of a country [1]. One measure or indicator that can be used to see the development and improvement of the quality of human resources that can bring about the conditions of successful development, namely the Human Development Index (HDI) [2].

The Human Development Index (HDI) is a composite index that is calculated based on life expectancy, education level, and income of a region from the district to the national level. HDI is made as an indicator to measure the development of an area and is also one single statistical indicator that can be used as a reference for social and economic developments [3].

The human development approach is not merely a goal but is a process. Specifically, the United Nations Development Program (UNDP) defines four main elements in human development, namely equity, productivity, empowerment, and sustainability. From these various interests, the government always forecast HDI data to determine future policies [4].

Time series forecasting is a process that used present or past data to develop models for future prediction or trends [5]. In addition, as for this forecasting benefit because HDI is an important indicator to measure success to build the quality of life of people (society or population). Then, HDI can also determine the ranking or level of development of a region or country. For an area or country, HDI is also a strategic data because, in addition to being a measure of government performance, HDI is also used as one of the allocators for the determination of the General Allocation Fund (GAF) for development in its government area.

Many models or methods can be used for forecasting, but the method is still single, meaning that it is unable to train on compound data [6]. Therefore, in this case, the research team used artificial intelligence techniques using Artificial Neural Networks (ANN). Several types of ANN are widely used in the field of forecasting namely Back Propagation (BP), Neuro-Fuzzy (NF), and Radial Basis Function (RBF).

Forecasting using ANN such as Back Propagation can provide excellent predictive results with MAPE results reaching 96% [7],[8]. While predicting with time series data objects conducted by Muhammad Isa (2013) shows MAPE reaching 96-98%. This indicates that ANN Back Propagation is very suitable for time series data prediction [9]. In addition, many researchers say that Neuro-Fuzzy tends to have small error values and high accuracy because of detailed attention to all variables. Neuro-Fuzzy does not require a lot of data and long periods of time. Meanwhile, the method by involving matrix size into the number of compound data as input for both training data and targets is very suitable to be simulated using the Radial Basis Function method [10],[11]. Therefore, each method has advantages and parameters when used for future data simulation or prediction, the research team intends to predict HDI data by testing the accuracy of these three methods.

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In conducting data simulation, the research team used Matlab software, because this software is very good for data simulation especially for developing Graphical User Interfaces (GUI) that are able to process data in multilayer form [12],[13]. The results of the simulation of each method will illustrate the accuracy with different error levels. A good method is the method with the lowest error or the highest level of accuracy, and also note that the HDI predictive output is reasonable. This means that it follows the model rules described from the data that are trained or learned.

II. RESEARCH METHODS

This research is quantitative descriptive research because the type of data used is quantitative data (in the form of numbers). The Human Development Index (HDI) data used is data from 10 regencies/cities in West Nusa Tenggara province for the last 10 years taken from the Central Statistics Agency. Furthermore, the data is divided into two namely for training and testing. Data training is taken from the first 9 years, while the last 1 year data is used as a testing to see the level of accuracy at the construction stage of this network.

Then we developed the MATLAB Graphical User Interface (GUI) for training, prediction, and checking the accuracy of the Back Propagation, Neuro-Fuzzy, and Radial Basis Function methods. Then simulate each method and check the error level (Mean Square Error-MSE) in each method's training model. After that, interpret and conclude the best method with the highest level of accuracy or the lowest error rate.

$$MSE = \frac{\sum_{t=1}^{n} (X_t - F_t)^2}{n} \qquad (1)$$

Where X_t is the actual data in period-t, F_t is the forecasting value in period-t, n is the amount of data, and t is the time series used [14], [15].

A method with the highest level of accuracy or the lowest error level will serve as a network for predictor.

III. RESULT AND DISCUSSION

A. Back Propagation Prediction Results

At this stage the research team first constructs an algorithm / prediction flow chart using Back Propagation so that the flowchart is shown in Figure 1 below.

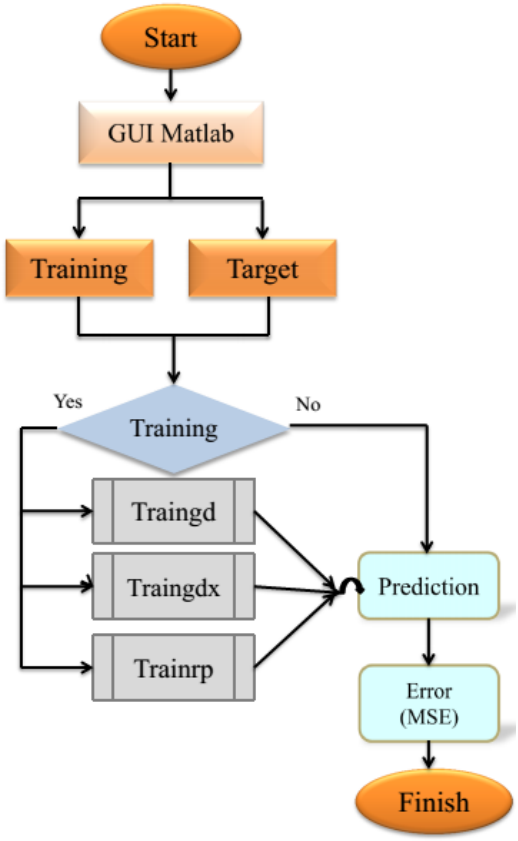

Fig. 1: Flowchart of Back Propagation

Data input used in this study was nine years from 10 regencies/cities and NTB province data, which amounted to 11, so the total input data was 99 input. The input data is divided into two, namely 9 x 10 matrix as training data, namely 2010-2017 data and 10 x 1 matrix as target data, namely 2018 data. Forecasting using three types of Back Propagation network training consisting of Traingd, Traingdx, and Trainrp. This is done to see the accuracy of each training method. The simulation results can be seen in Figure 2, Figure 3, and Figure 4 below.

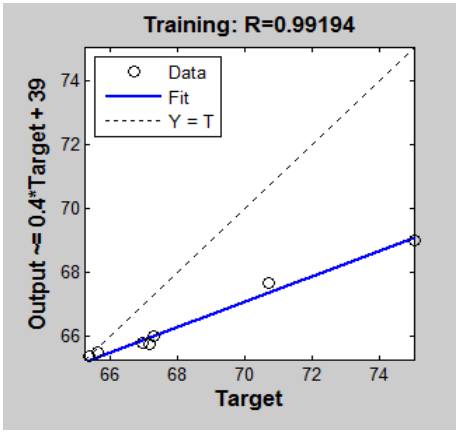

Fig. 2: Level of Accuracy Using Traingd

Based on Figure 2 above, it can be seen that the value of R (performance) is 0.99194, or the level of accuracy shows a value of 99.39%. This happens when training in MATLAB with an epoch of 1000 iterations, a performance of 0.423, a gradient of 13.8, and a validation check of 1000. The prediction results are in Table 1 below.

Table 1: Forecast Results of Traingd

Regency / City	Forecast
West Lombok	65.7343
Central Lombok	65.3673
East Lombok	65.3561
Sumbawa	65.6633
Dompu	65.771
Bima	65.4769
West Sumbawa	67.6504
North Lombok	65.2666
Mataram City	69.235
Bima City	69.0214
NTB Province	65.9816

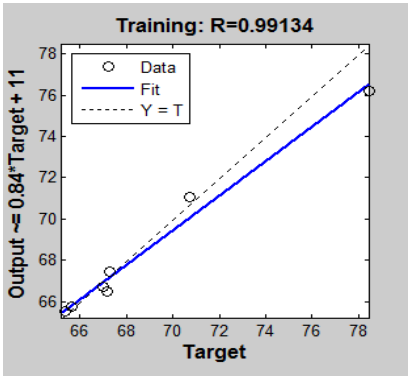

Fig. 3: Level of Accuracy Using Traingdx

Based on Figure 3 above, the value of R (performance) is obtained at 0.99134, or the level of accuracy shows a value of 98.28%. This happens when training in MATLAB with an epoch of 1000, a performance of 0.456, a gradient of 0.244, and a validation check of 963. The results of predictions are according to Table 2 below.

Table 2: Forecast Results of Traingdx

Regency / City	Forecast
West Lombok	66.4889
Central Lombok	65.5567
East Lombok	65.5478
Sumbawa	66.2991
Dompu	66.6914
Bima	65.7585
West Sumbawa	71.0394
North Lombok	65.2173
Mataram City	76.2140
Bima City	74.8438
NTB Province	67.4664

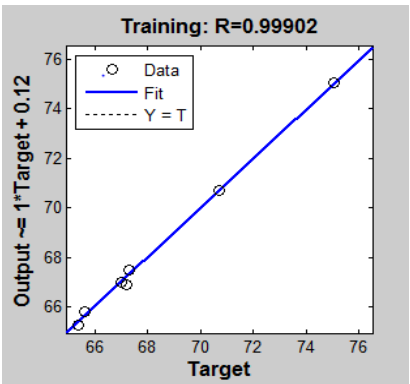

Fig. 4: Level of Accuracy Using Trainrp

Based on Figure 4 above, the R value (performance) is obtained at 0.99902, or the accuracy level shows a value of 99.80%. This happens when training in MATLAB with epochs of 123 iterations, performance of 0.00969, gradient of 0.263, and validation checks of 41. The prediction results are in accordance with Table 3 below.

Table 3: Forecast Results of Trainrp

Regency / City	Forecast
West Lombok	66.9042
Central Lombok	65.2772
East Lombok	65.332
Sumbawa	66.3211
Dompu	66.9807
Bima	65.79
West Sumbawa	70.7144
North Lombok	64.9467
Mataram City	76.4941
Bima City	75.0312
NTB Province	67.4636

Based on the simulation results in Table 1, Table 2, and Table 3 above, the prediction results for NTB Province are obtained according to Table 4 below.

Table 4: Prediction Result of HDI in NTB Province Using BP

Training	Prediction	Accuracy	MSE
Traingd	65.9816	99.194%	0.1584
Traingdx	67.4764	99.134%	0.0026
Trainrp	67.4636	99.902%	0.0023

Based on Table IV above, information is obtained that the results of predictions with trainees are the best training models with the lowest error rate of 0.0023.

B. Neuro-Fuzzy Prediction Result

At this stage, the research team simulated HDI data according to flowchart such as Figure 5 below.

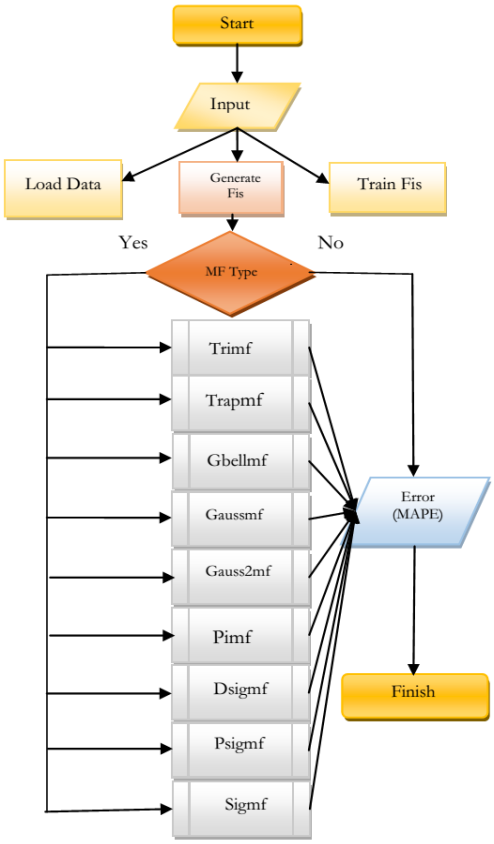

Fig. 5: Flowchart of NF

Based on the simulation results obtained prediction and error results according to Table 5 below.

Table 5: Prediction Results of HDI Using NF Every Function

Regency / City	Forecasting Function							
	Trimf	Trapmf	Gbellmf	Gaussmf	Gauss2mf	Dsigmf	Psigmf	Primf
West Lombok	67.3	67.0	67.2	67.2	67.2	67.0	67.0	67.0
Central Lombok	65.3	65.1	65.2	65.1	65.4	65.1	65.2	65.1
East Lombok	65.3	65.1	65.3	65.3	65.3	65.1	65.1	65.1
Sumbawa	66.8	66.5	66.6	66.5	66.8	66.7	66.5	66.5
Dompu	67.2	66.8	66.8	67.1	67.0	66.9	66.8	66.8
Bima	65.7	65.5	65.5	65.5	65.7	65.5	65.5	65.5
West Sumbawa	70.8	70.5	70.8	70.8	70.7	70.6	70.6	70.5
North Lombok	63.9	63.6	63.8	63.9	63.8	63.6	63.6	63.6
Mataram City	78.5	78.3	78.4	78.5	78.4	78.3	78.3	78.3
Bima City	75.1	74.9	74.9	74.9	75.1	74.9	74.9	74.9
NTB Province	67.3	67.1	67.3	67.3	67.1	67.1	67.1	67.1

Based on Table 5 above, the results of forecasting each type are shown using Neuro-Fuzzy. FIS Train at forecasting uses an Error Tolerance of 0.01, epochs of 100, and MF Type of Linear. In addition, the results of errors based on the results of forecasting have been obtained according to Table 6 below.

Table 6: MSE Results of HDI Using NF Every Function

Regency / City	**Forecasting Function**							
	Trimf	***Trapmf***	***Gbellmf***	***Gaussmf***	***Gauss2mf***	***Dsigmf***	***Psigmf***	***Primf***
West Lombok	0.076316	0.37664	0.15235	0.1467	0.10693	0.36135	0.36034	0.37664
Central Lombok	0.095904	0.34512	0.14031	0.14178	0.096406	0.33783	0.26412	0.34511
East Lombok	0.064983	0.352	0.15461	0.17203	0.10872	0.34067	0.34067	0.35301
Sumbawa	0.024585	0.3222	0.11656	0.12319	0.095551	0.17846	0.30567	0.3222
Dompu	0.02192	0.2764	0.057628	0.97642	0.068012	0.13938	0.14424	0.27563
Bima	0.10433	0.26526	0.15617	0.11569	0.087839	0.25089	0.24761	0.26527
West Sumbawa	0.077728	0.30526	0.14278	0.13544	0.12075	0.28768	0.16473	0.30526
North Lombok	0.053899	0.3932	0.10416	0.74395	0.041127	0.25954	0.36721	0.39318
Mataram City	0.077647	0.29347	0.12161	0.11619	0.072963	0.27754	0.27849	0.129347
Bima City	0.028814	0.25263	0.080906	0.08686	0.036494	0.23989	0.23549	0.25277
NTB Province	0.065367	0.33017	0.14114	0.13386	0.31389	0.31577	0.31806	0.32946

Based on the results of the error in Table 6 above, it can be seen that the results of predictions using Trimf type are the best and most accurate training models in each district/city in NTB which is equal to 0.0628. So that the results of the prediction can be restated using Trimf type according to Table 7 below.

Table 7: Forecast Results and Trimf Error

Regency / City	**Forecast**	**MSE**
West Lombok	67.3	0.0763
Central Lombok	65.3	0.0959
East Lombok	65.3	0.0649
Sumbawa	66.8	0.0246
Dompu	67.2	0.0219
Bima	65.7	0.1043
West Sumbawa	70.8	0.0777
North Lombok	63.9	0.0538
Mataram City	78.5	0.0776
Bima City	75.1	0.0288
NTB Province	67.3	0.0653

The following is a rule base graph of the most accurate results in forecasting, namely using the Trimf type in NTB Province.

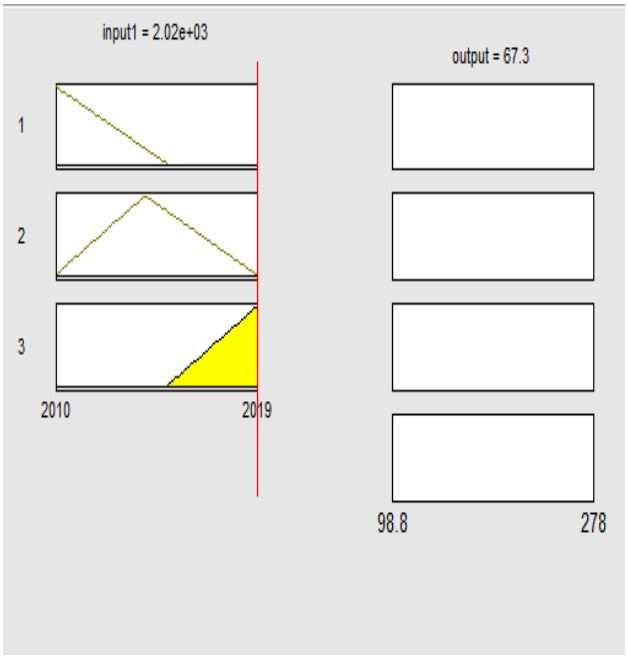

Fig. 6: Forecasting Results of Trimf

C. Radial Basis Function Prediction Result

At this stage, we first construct a prediction flowchart so that the flowchart, according to Figure 7 below.

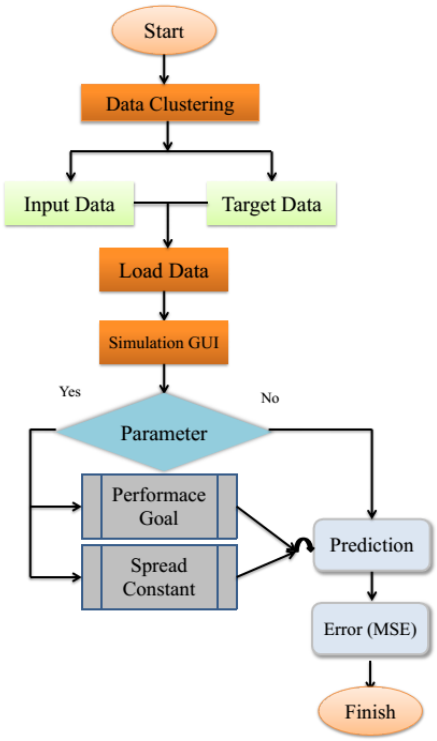

Fig. 7: Flowchart Metode RBF

In predictions using the RBF method, we performed a simulation with 6 steps according to the number of neurons namely 0, 2, 3, 4, 5, 6, 7. Based on the simulation, the results obtained in accordance with Table 8 below.

Table 8: Forecast Results of RBF

Regency / City	Forecast
West Lombok	67.09
Central Lombok	65.50
East Lombok	65.23
Sumbawa	66.81
Dompu	67.14
Bima	65.62
West Sumbawa	70.71
North Lombok	63.83
Mataram City	78.43
Bima City	75.04
NTB Province	67.18

Table 9: MSE Result of RBF

Neurons		MSE
Newrb	0	18.5984
	2	12.8208
	3	6.58387
	4	2.25307
	5	0.297786
	6	0.0530849
	7	0.00786764

Based on Table 9 above, it can be seen that the prediction results with the lowest error rate are using the number of neurons as much as 7 with an error of 0.0079.

D. Comparison of Prediction Results

Based on the simulations carried out on the three methods above, information is obtained that the prediction results of the NTB Province Human Development Index (HDI) are by the following Table 10.

Table 10. Results of Prediction According to the Best Method

Method	Prediction	MSE	Category
BP	67,46	0,0023	Increase
RBF	67.30	0.0653	Stable
NF	67.18	0,0078	Decrease

Based on Table 10 above, we can know that the Back Propagation method with the trainrp training model is very good as a reference in making decisions related to the HDI prediction results in NTB in 2019 which is 67.46 which means an increase of 0.238% from 2018. While the results of predictions in each district/city namely West Lombok amounted to 66.90 (decreased 0.41%), Central Lombok amounted to 65.28 (decreased 0.13%), East Lombok amounted to 65.33 (decreased 0.03%), Sumbawa amounted to 66.32 (decreased 0.67%), Dompu amounted 66.98 (increased 0.02%), Bima amounted to 65.79 (increased 0.006%), West Sumbawa was 70.71 (stable), North Lombok was 64.95 (increased 1.75%), Mataram City was 76.49 (decreased 2.47%), Bima City was 75.03 (decreased 0.01%).

From the results of this prediction, it is expected that the government will remain vigilant and take strategic steps to improve services and development in the fields of education, health, and government expenditure so that some regions declared to be declining based on the results of these predictions can be addressed early.

IV. CONCLUSION

Forecasting is important for determining policy in the future. However, the best method needed to be used in forecasting is to see the lowest error value or the highest level of accuracy. Trials by comparing various methods involving multiple data (multilayer) are needed so that good and reliable results can be obtained. Prediction methods such as Back Propagation, Neuro-Fuzzy, and Radial Basis Function are very good methods. However, in the prediction of the Human Development Index (HDI) data, information is obtained that the Back Propagation method is the best method with a prediction of 67.46 with MSE of 0.0023. From these results the conclusion that in this case, the BP method is very good at doing simulation and decision making results. The results were obtained from simulated data with a performance (R) of 0.99194, a validation check of 1000, a gradient of 13.8, and a level of accuracy of 99.39%.

Furthermore, it needs to be further examined that these three methods, in the case of declining data, such as poverty completion data, are valid as well as this HDI data which is always increasing.

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