

Early Detection of Banking Crises in Indonesia with Adaptive Neuro Fuzzy Inference System

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Banking crises occurring in a country have a devastating impact on the country's economy and financial system. The threat of the coming banking crisis in Indonesia can be detected by looking at the movement of banking performance indicators such as Total Assets, Bad Debt Ratio, Return on Assets and Loan to Deposit Ratio. So far there is no standard or standard benchmark to indicate the condition of the banking system is in a crisis condition. Therefore it is very necessary to establish an early warning system that can detect a banking crisis in Indonesia so that appropriate policies to deal with disruptions can be taken immediately to prevent the occurrence of the crisis. Many methods are developed to develop a model that can provide such an early warning. Neuro-Fuzzy is one of the most commonly used methods of prediction or diagnosis, with fairly good accuracy. Neuro-Fuzzy is a combination of a Backpropagation Neural Network concept with the fuzzy logic concept. In this study, the authors tried to use the Neuro-Fuzzy method to perform early detection of the banking crisis in Indonesia.

Keywords: banking crises, indicators of banking performance, neuro-fuzzy, ANFIS.

I. INTRODUCTION

Banking crises occurring in a country have a devastating impact on the country's economy and financial system. The banking crisis has occurred in Indonesia, the crisis was triggered by the economic crisis that occurred in mid-1997. The economic crisis began with the Asian currency crisis that the fall of the Thai Baht exchange rate by 27.8 percent in the third quarter in 1997 and followed weakening of currency exchange rate Won, Ringgit, and Rupiah. The crisis is also influenced by internal factors that are not hedging private debt, a weak system of supervision and regulation of banking and loss of public confidence in the government. There is no sudden crisis [10], the threat of impending crisis can be detected by looking at the movement of economic indicators such as the balance of payments position, economic growth, exchange rate inflation, interest rate, and money supply.

With the condition of vulnerable national banks, the fluctuation of the rupiah has caused some banks to experience massive banking liquidity. The weakening of the rupiah led to liabilities in foreign exchange rising sharply, which made it difficult for banks' liquidity conditions. This is exacerbated by the condition of debtors who also face difficulties in meeting foreign currency liabilities to banks. The magnitude of liquidity difficulties may eventually lead to a national banking crisis.

Based on these problems it is necessary to build an early warning system that can detect a banking crisis in Indonesia, thus, appropriate policies to deal with disruptions can be taken immediately to prevent such crises.

Many methods are developed to develop a model that can provide such an early warning. Neuro-Fuzzy is one of the most commonly used methods of prediction or diagnosis, with fairly good accuracy [13]. Neuro-Fuzzy is a combination of Backpropagation Neural Network concept

with the fuzzy logic concept. Fuzzy-based systems can be expressed as "if-then" -shaped knowledge that provides the advantage of not requiring mathematical analysis for modeling, otherwise, the fuzzy system can also process human-oriented reasoning and knowledge that is oriented towards qualitative aspects [9]. While artificial neural networks have the advantage of facilitating the classification of an object based on a set of features into the input system, because only by entering a number of features and then do training with the data, able to distinguish one object with another object [13]. The Neuro-Fuzzy method consists of 5 layers in which each layer has a different treatment. In Neuro-Fuzzy, the training process on multiple neural networks with multiple data pairs is useful for updating the fuzzy inference system parameters [3].

This research used the Neuro-Fuzzy method which is a combination of fuzzy and neural network logic to predict banking crisis based on parameters of banking performance indicators in Indonesia.

II. RELATED WORK

A. Banking Crisis

The crisis is a condition where one of the following conditions is met [1]:

- Non-performing assets account for 10% of total banking system assets;
- The cost of saving the banking system is 2% of GDP;
- There has been a massive transfer of ownership of banks to the government; and
- A widespread "bank-run" or government emergency action occurs in the form of freezing of public savings, the closure of bank offices for a considerable length of time, or the implementation of a comprehensive deposit guarantee.

Major problems in the banking industry can be sourced from the real sector, the internal banking sector, and drastic changes to certain economic indicators which, among other things, are shown by the drastic decline in real GDP growth, the increase in real interest rates, the decrease in ICOR, the sharp depreciation of the exchange rate, and a sharp increase in inflation, credit expansion, and capital inflow [8]. The banking crisis also tends to arise when macroeconomic conditions worsen [1]. In this case, low GDP growth is closely related to the increased risk in the banking industry. In addition, the increased risks to the banking industry can also be attributed to high inflation rates and stabilization of the inflation rate will lead to a

sharp increase in real interest rates which in turn increases the likelihood of a banking crisis.

In the case of the banking crisis in the Asian region, certain factors that specifically affect the crisis in the Asian region are the appreciation of the exchange rate followed by a very sharp depreciation and a sharp increase in foreign debt banking followed by high event-of-default [8]. Furthermore, the problem that is quite heavy (but not yet in crisis phase) in the banking industry generally comes from domestic factors such as excessive credit expansion in the consumer sector and fluctuations in the real interest rates of public savings. At the same time, the banking problems leading to the crisis are largely due to excessive credit expansion stemming from external debt and sharp fluctuations in the real effective exchange rate.

B. Fuzzy Logic

Crisp Set and Fuzzy Set

The Crisp set is defined by the items in the set. If a member of A, then the value corresponding to a is 1. However, if a is not a member of A, then the value corresponding to a is 0. Notation $A = \{x \mid P(x)\}$ indicates that A contains item x with P(x) is true. If XA is a characteristic function of A and property P, then it can be said that P(x) is true, if and only if $XA(x) = 1$. [12]

The fuzzy set is based on the idea of extending the range of characteristic functions such that the function will include real numbers at intervals [0,1]. The membership value indicates that an item in the universe of speech is not only 0 or 1, but also the value that lies between them. In other words, the truth value of an item is not only true or false. Value 0 indicates wrong, value 1 indicates true and there are still values that lie between true and false. [12].

Fuzzy Inference System: Sugeno Method (TSK)

The fuzzy inference system using the Sugeno method, having the consequent characteristic is not a fuzzy set but is a linear equation with variables corresponding to the input variables. This method was introduced by Takagi Sugeno Kang in 1985. [12]

There are 2 models for the fuzzy inference system using TSK method, ie model TSK orde-0 model and TSK orde-1 model. [12]

a. Fuzzy Sugeno Orde-0 Model

IF $(x_1 \text{ is } A_1) \circ (x_2 \text{ is } A_2) \circ (x_3 \text{ is } A_3) \circ \dots \circ (x_N \text{ is } A_N)$
Then $z = k$

With A_i being the set of i -fuzzy as antecedents, $^{\circ}$ is the fuzzy operator (like AND or OR), and k is a constant (const) as consequent. [12]

b. Fuzzy Sugeno Orde-1 Model

IF (x_1 is A_1) $^{\circ}$... $^{\circ}$ (x_N is A_N) THEN $z = p_1 * x_1 + \dots + p_N * x_N + q$

With A_i being the set of i -fuzzy as antecedents, $^{\circ}$ is a fuzzy operator (like AND or OR), and p_i is a constant (firm) to- i and q is also a constant. [12]

The aggregation and defuzzy process for obtaining firm values as output for M fuzzy rules is also done by using weighted averages, ie [12]:

$$z = \frac{\sum_{k=1}^M \alpha_k z_k}{\sum_{k=1}^M \alpha_k} \quad (1)$$

C. Artificial Neural Network

Artificial Neural Network or Artificial Neural Network is one of the artificial representations of the human brain that always tries to simulate the learning process in the human brain. This neural network is implemented using a computer program capable of completing a number of calculation processes during the learning process. One of the artificial neural network architecture (JST) is a network with multiple layers (multilayer feedforward). Multilayer feedforward consists of: a set of sensor units that are the input layers, one or more layers located between the input layer and the output layer (having one or more hidden layers) is called the hidden layer, and an output layer [12], as shown in Figure 1.

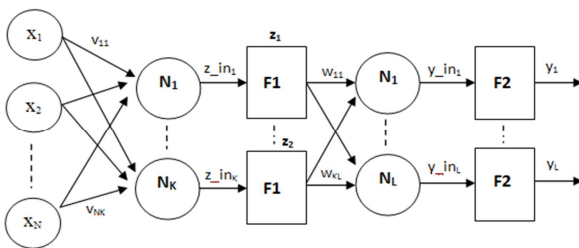


Figure 1. Neural Network Architecture with Multiple Layers

Multilayer network learning process using supervised learning methods (supervised learning), the backpropagation algorithm based on error correction rules.

D. Adaptive Neuro-Fuzzy Inference System

Neuro-Fuzzy Inference System is a set of rules and an inference method combined in a connected structure and then carried out training and adaptation [12]. One model that is a form of adaptive network that functions just like a fuzzy inference system is the Adaptive Neuro-Fuzzy Inference System (ANFIS). Adaptive Neuro-Fuzzy Inference System (ANFIS) is an adaptive network based on fuzzy inference system [12].

ANFIS parameter is divided into two, namely the premise and consequence parameters that can be adapted with hybrid algorithm. Hybrid algorithm proposed by J.S.R Jang (1997) is a combination of two methods of learning that is least square estimation (LSE) and backpropagation. Hybrid training is done in two steps, namely step forward and back. The ANFIS architecture is functionally the same as Sugeno's fuzzy rule base model.

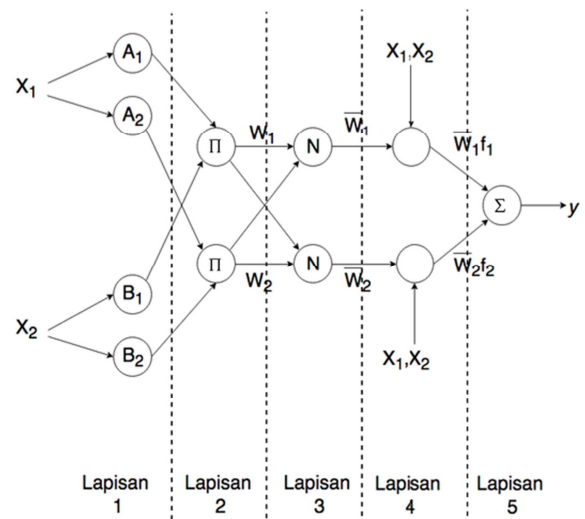


Figure 2. ANFIS Network Architecture

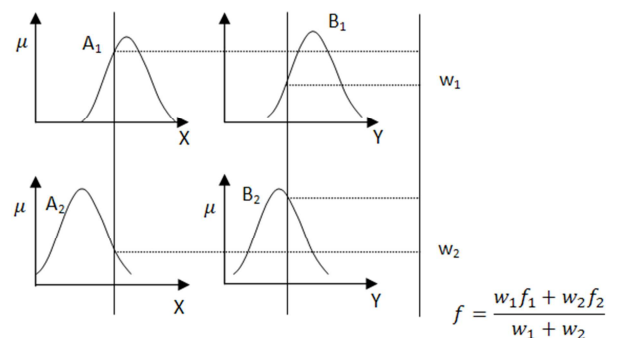


Figure 3. Mechanism of reasoning for the Sugeno model

The Sugeno ANFIS network consists of the following layers [12]:

The Sugeno ANFIS network consists of the following layers (Jang, 1997 in Sri Kusumadewi and Sri Hartati, 2010: 379-380):

- a) Each neuron i in the first layer is adaptive to the parameters of an activation function. The output of each neuron is the degree of membership given by the membership function of the input, ie: $\alpha_{A1}(X_1)$, $\alpha_{B1}(X_2)$, $\alpha_{A2}(X_1)$, or $\alpha_{B2}(X_2)$.

For example, suppose the membership function is given as:

$$\mu(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}} \quad (2)$$

where $\{a, b, c\}$ are the parameters, usually $b = 1$. If the values of these parameters change, then the shape of the curve that occurs will also change. These parameters are known as premise parameters.

- b) Each neuron in the second layer is a fixed neuron whose output is the result of the input. Usually used AND operator. Each node represents the predicate of the i rule.

$$O_{2,i} = w_i = \alpha_{A1}(X_1) \cdot \alpha_{B1}(X_2), \quad i = 1, 2 \quad (3)$$

- c) Each neuron in the third layer is a fixed node which is the result of the ratio calculation of α predicate (w), from the rule i to the sum of the total α predicates.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad \text{with } i = 1, 2. \quad (4)$$

This result is known as normalized firing strength.

- d) Each neuron in the fourth layer is an adaptive node to an output.

$$O_{4,i} = \bar{w}_i y_i = \bar{w}_i (c_{i1}x_1 + c_{i2}x_2 + c_{i0}); \quad (5)$$

with $i = 1, 2$.

with $\bar{w}_i$ is normalized firing strength in the third layer and $\{c_{i1}, c_{i2}, c_{i0}\}$ are parameters of the neuron. Parameters in the layer are called consequent parameters.

- e) Each neuron in the fifth layer is a fixed node which is the sum of all inputs.

$$O_{5,i} = y = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

In the field of artificial intelligence, neuro-fuzzy refers to a combination of artificial neural networks and fuzzy logic.

Neuro-fuzzy is proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes both techniques by combining human-like fuzzy reasoning styles with learning and connectionist structures of neural networks. Neuro-fuzzy hybridization is widely referred to as Fuzzy Neural Network (FNN), Neural Fuzzy System (NFS) or Neuro Adaptive Neuro Fuzzy Inference System (ANFIS).

III. PROPOSED METHOD

The process of implementing and comparing the accuracy of predicted results with Neuro-Fuzzy is described as follows:

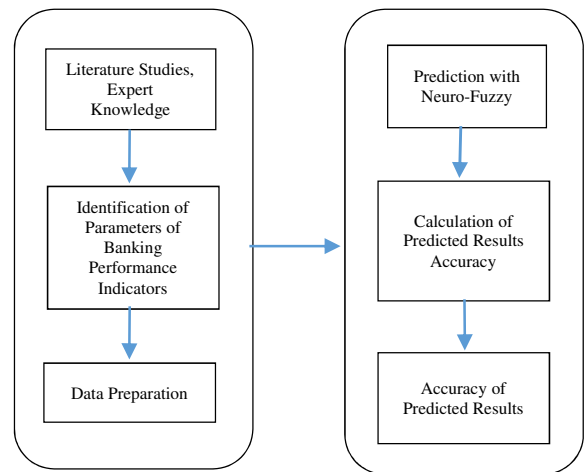


Figure 4. Research Stages

The activity details of this process are described as follows:

1. Preparation and determination of parameters of banking performance indicators to be used in prediction. In this process, literature studies and discussions with experts are conducted. After that done collection and preparation of data.
2. Neuro-Fuzzy Implementation for prediction of banking crisis in Indonesia. This prediction system has several parts, namely the design of data clustering (clustering data) and the design of ANFIS system. The design is made using several steps and steps as follows:
 - a. The first stage is to enter data of banking performance indicators.
 - b. The next stage is to conduct training using ANFIS learning algorithm.
 - c. After the training and obtained optimal network conditions, tested using the value of network parameters from the training results.

- d. Displays the final output of ANFIS calculation in the form of banking crisis prediction.

3. Accuracy Calculation

The existing data is divided into two parts, where the first part is used as training data, while the second part is used as test data. In the test conducted RMSE calculations and accuracy using the equation below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \bar{y}_i)^2}{N}} \quad (7)$$

Where n is the number of data, y_i is the network target and $\bar{y}_i$ is the network output.

$$akurasi = \frac{\sum angkabonar}{\sum angkapengujian} * 100\% \quad (8)$$

4. Comparison of Accuracy

From the test results with attention to several combinations of different amounts of trainer data, the RMSE comparison process and accuracy are made so that ANFIS capability in prediction based on indicator parameters and early detection of the crisis for a certain period of time will be known.

Banking Performance Indicators

Banking Performance is a description of banking condition in a certain period either concerning fundraising aspect and fund distribution, which is usually measured by several indicators: Total Asset, Bad Debt Ratio, Return on Assets, Loan to Deposit Ratio and Macro Economy (Rupiah exchange rate, Real interest rate, Inflation, M2 Ratio). In this study, the indicators to be used are Total Assets, Bad Debt Ratio, Return on Assets and Loan to Deposit Ratio.

Table 1. Performance Indicators of Commercial Banks (Billion Rupiah) [15]

Indicator	2003	2004	2005	2006	2007	2008	2009
Total Assets	1.112,2	1.272,3	1.469,8	1.693,8	1.735,7	1.396,8	1.521,3
Third-party funds	888,6	963,1	1.127,9	1.287,0	1.310,2	1.025,6	1.238,9
Loan	477,19	595,1	730,2	832,9	862,4	935,1	842,7
Loan to Deposit Ratio	53,7	61,8	64,7	64,7	65,8	91,2	68
Return On Assets	2,5	3,5	2,6	2,6	3,3	2,5	3,1

IV. EXPERIMENTAL RESULTS

The neuro fuzzy model used to predict the banking crisis in Indonesia can be seen in Figure 5. Factors affecting the

banking crisis, namely Total Assets, Bad Debt Ratio, Return on Assets, and Loan to Deposit Ratio is a fuzzy variable.

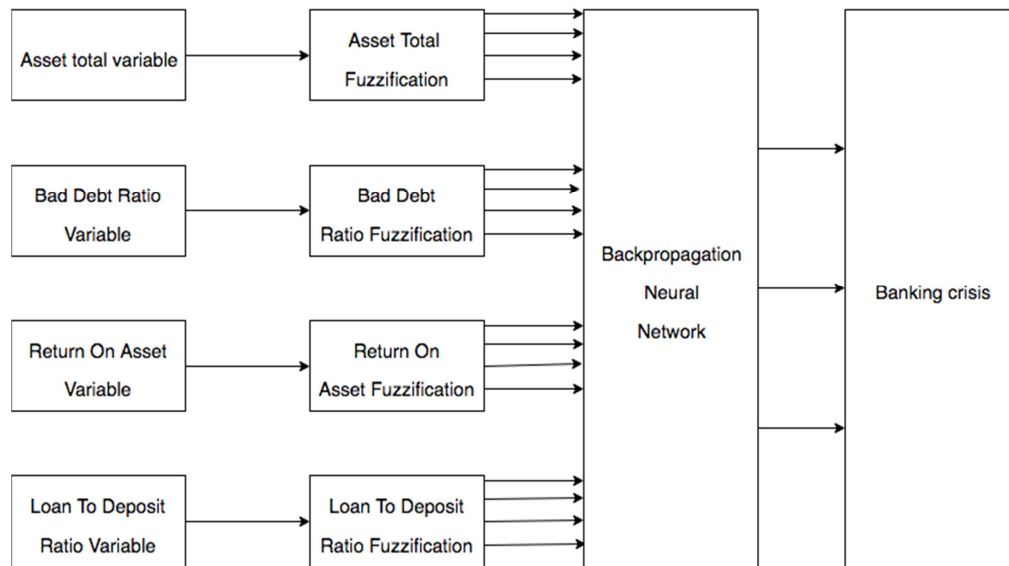


Figure 5. Neuro fuzzy system model for early detection of banking crisis

ANFIS modeling steps are as follows:

- Step 1: Gives pairs of input and output data for training.
- Step 2: ANFIS trains FIS with FIS initialization, ie setting the initial price parameter of membership function in FIS. FIS Inisialisasi include: selection of numbers membership function (membership function), selection of membership function types (triangle or gaussian), selection of the number of training iterations (epoch).
- Step 3: ANFIS trains FIS by modifying the membership function parameters until the minimum difference between FIS output and training data is obtained output.
- Step 4: Validation model is the FIS testing process that has been trained by anfis, however using data input / output that has not been trained to FIS.

The built application consists of training and testing forms. Testing is done after training on the system with various combinations between the training data and test data. Testing aims to calculate the RMSE value and system accuracy level (comparison of actual targets with network output results).

Performance in the ANFIS model training process is measured by RMSE. The number of epoch selected is 100 times, the type of Gaussian membership function. Performance of data training process and data testing with backpropagation algorithm generated RMSE 0.000020 for

training data model 1 and RMSE 0.000021 for training data model 2.

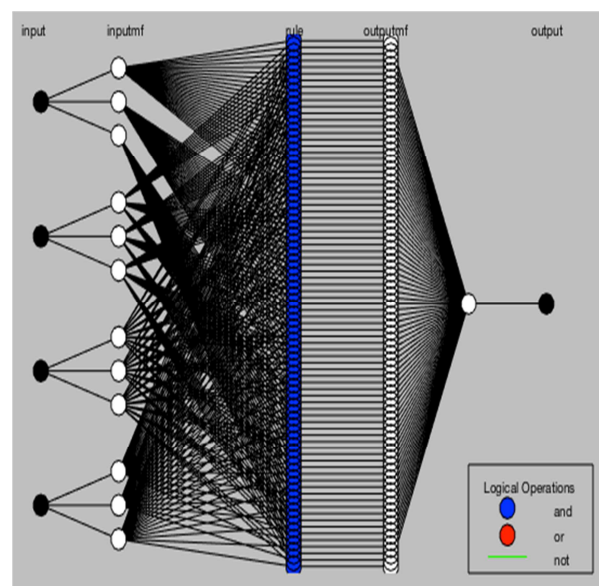


Figure 6. ANFIS Model Structure

In Figure 6. can be seen ANFIS model from training data by using four input variables which is data of banking performance indicator that is Total Asset, Bad Debt Ratio, Return on Assets, and Loan to Deposit Ratio.

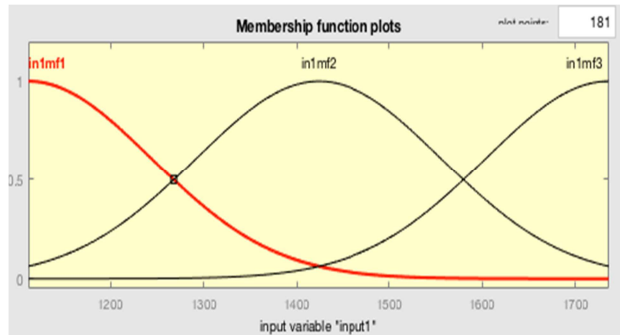


Figure 7. Graph of Gauss Membership Function from Data Training

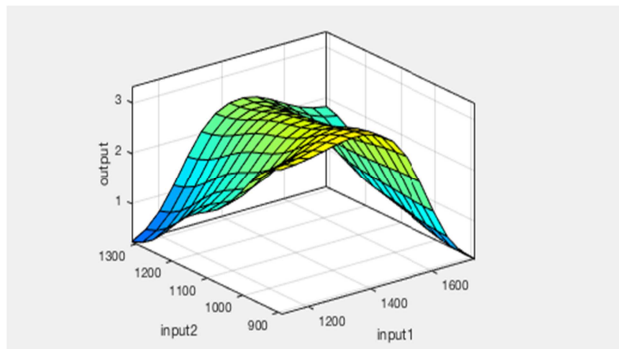


Figure 8. Surface Viewer Data Training

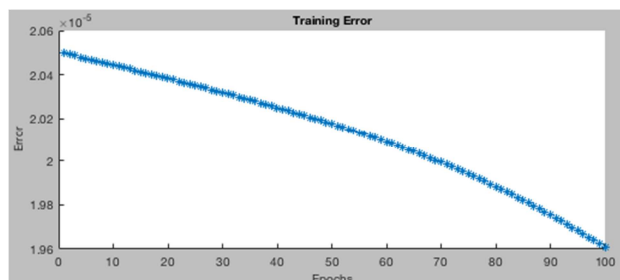


Figure 9. Graph of Data Training Error

In Figure 9. Can be seen the results of testing by using training data has a very small training error value so that the prediction value close to the actual value.

V. CONCLUSION

Based on the discussion of the neuro-fuzzy model, the ANFIS model (adaptive neuro-fuzzy inference system) applied to the prediction of banking crisis with indicator of Total Asset, Bad Debt Ratio, Return on Assets, and Loan to Deposit Ratio, from 2003 - 2009, the following conclusions are made: the best model for the banking crisis prediction data according to the smallest RMSE on data training and data testing is the first model with input model based on

Total Assets (1 input - 1 output), Gauss membership function. In the process of training prediction banking crisis using ANFIS model has an RMSE value of 0.000020. The result is still better than inflation prediction using a conventional method. Judging from the results of RMSE on testing of very small value, it can be concluded that the prediction of banking crisis can use the ANFIS model.

In this study, the writer predicted a banking crisis using 4 variable indicator that is Total Asset, Bad Debt Ratio, Return on Assets, and Loan to Deposit Ratio from the period of the year 2003 until 2009. For more accurate prediction result it is suggested to add another variable such as Macro Economy, which is also an indicator of banking performance in Indonesia. In the next study, it is advisable to pre-process to improve the accuracy of the neuro-fuzzy model. A neural network system has 2 methods of learning that is a supervised learning method and unattended learning method. In this research using a supervised learning method that is backpropagation. In subsequent research, can try to use unattended learning methods.

REFERENCES

- [1] Dermiguc – Kunt, Asli, and Enrica Detragiache, (1998), "The Determinants of Banking Crises in Developing and Developed Countries", IMF Staff Papers Vol. 45 No. 1 (March), International Monetary Fund, Washington.
- [2] Dewi, Candra, Dany Primanita, Yusi Tyroni Mursityo. (2014). "Prediksi Cuaca Pada Data Time Series Menggunakan Adaptive Neuro Fuzzy Inference System (ANFIS)", Jurnal Teknologi Informasi dan Ilmu Komputer (JTIK), Vol.1, No.1, April 2014, hlm, 18-24.
- [3] Fariza, A. (2007). Performansi Neuro Fuzzy untuk Peramalan Data Time Series. Seminar Nasional Aplikasi Teknologi Informasi (SNATI). Yogyakarta.
- [4] Fitriah, Aidatul, Agus Maman Abadi. (2011). "Aplikasi Metode Neuro-Fuzzy Untuk Prediksi Tingkat Inflasi di Indonesia", Prosiding Seminar Nasional Matematika dan Pendidikan Matematika – Universitas Negeri Yogyakarta, Desember 2011, hlm 8-20.
- [5] Florencia Sukma Christi S. (2011). "Sistem Deteksi Dini Krisis Perbankan Indonesia Dengan Indikator CAR, BDR, ROA, LDR, dan Makro Ekonomi (Studi Kasus Pada Bank Umum) Periode Tahun 2003-2009", Universitas Diponegoro, Semarang.

- [6] Hadad, Muliaman D., Wimboh Santoso, Bambang Arianto. (2003). "Indikator Awal Krisis Perbankan", JEL Classification : E44, G21, www.bi.go.id.
- [7] Hagen von Jurgan and Ho Tai-kuang. (2003). "Money Market Pressure and the Determinants of Banking Crises", Center for European Integration Studies Journal April 2003, University of Bonn.
- [8] Hardy, Daniel C. & Ceyla Pazarbasioglu, (1999), "Determinants and Leading Indicators of Banking Crises: Further Evidence", IMF Staff Papers Vol. 46 No. 3 September/December 1999, International Monetary Fund, Washington.
- [9] Jang, J. S. R., Sun, C. T. E., Mizutani. (1997). Neuro-Fuzzy and Soft Computing. Prentice Hall. London.
- [10] Kaminsky, Graciela, Saul Lizondo, and Carmen M. Reinhart, (1998), "Leading Indicators of Currency Crises", IMF Staff Papers Vol.45 No. 1 (March), International Monetary Fund, Washington. from past mistakes", The Independent Review, v.II, n.1., p.55.
- [11] Kaufman, George F. (1997). "Preventing Banking Crises in the future: Lesson from past Mistakes", The Independent Review, vII, n.1. Summer 1997.
- [12] Kusumadewi, Sri dan Sri Hartati. (2010). "Neuro-Fuzzy Integrasi Sistem Fuzzy & Jaringan Syaraf". Edisi 2. Graha Ilmu Yogyakarta.
- [13] Singla, P., Rai, H. M. dan Singla, S. (2011). "Local Monsoonal Precipitation Forecasting using ANFIS Model: a Case Study for Hisar". Internasional Journal of Research and Reviews in Computer Science, Vol.2 No.3.
- [14] Oktavilia, Shanty. (2008). "Deteksi Dini Krisis Perbankan Indonesia: Identifikasi Variabel Makro Dengan Model Logit". JEJAK Volume 1, Nomor 1, September.
- [15] www.bi.go.id. "Data Perbankan Indonesia" Tahun 1997:1998, 2003-2009. Tanggal akses terakhir 18 Juli 2018.