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APPLICATION OF ARTIFICIAL NEURAL NETWORK METHOD IN CURRENCY CRISIS DETECTION IN INDONESIA BASED ON MACROECONOMIC INDICATORS

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ABSTRACT:

The global crises of 1997 and 2008 that affected various countries had significant impacts on the economies of developing countries in the world, including Indonesia. If not addressed, these impacts could have adverse effects on Indonesia. Therefore, it is necessary to have an early warning system for currency crises to anticipate the negative effects of such crises. This study employs the Financial Pressure Index (FPI) crisis threshold approach with perfect signal value as the dependent variable and 13 macroeconomic indicators as independent variables to develop an early warning model for currency crises in Indonesia using Artificial Neural Network method with Multilayer Perceptron Backpropagation algorithm and adding Adaptive Moment Estimation (Adam) optimization in weight modification process. The testing results on validation and test data show that Adam optimization produces high accuracy, sensitivity, and specificity. Based on the best model, it is found that the period from July 2021 to June 2022 has a perfect signal value of 0, meaning that there will be no crisis in Indonesia from July 2022 to June 2023. In conclusion, this study shows that the Artificial Neural Network method with Adam optimization can effectively detect currency crises in Indonesia.

Keyword: Adam Optimizer, Artificial Neural Network, Crisis Detection, FPI, Perfect Signal
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INTRODUCTION

Indonesia is classified as a developing country, which is evident from its dependence on foreign economies. Indonesia can feel the negative impacts of global economic instability, such as experiencing a currency crisis. A currency crisis is a situation in which a country's currency deteriorates dramatically. According to Hidayah, Sugiyanto, & Slamet (2019), Indonesia has experienced two major crises, namely the East Asian Financial Crisis that began in July 1997 and the Global Financial Crisis that began in October 2008, as well as several smaller financial crises, such as in mid-2005. The East Asian financial crisis in 1997 was caused by Thailand's currency crisis and the currency crises of several Southeast Asian countries, including Indonesia. Meanwhile, the global crisis in 2008 was caused by the bankruptcy of property businesses or subprime mortgages in the United States.

The consequences of these crises on the decline of economic activities have highlighted the importance of building early detection systems because the impact of such crises can be severe on Indonesia's economy (Adebun et al., 2019). According to Tölö (2020), crisis prediction models help determine the timing of policies by providing information about the likelihood of a crisis. There are 15 crisis indicators used to indicate the existence of a currency crisis in a country (Kaminsky et al., 1997).

There are several methods that can be used to detect currency crises, one of which is neural networks. Several studies have used neural networks in crisis detection, such as Fioramonti's (2008) research on the detection of country debt crises using Artificial Neural Networks, which found that the model was able to detect country debt crises that occurred in developing countries from 1980 to 2004. Then, Sevim et al. (2014) compared neural network models, logistic regression, and decision trees to detect financial crises in Turkey using a perfect signal approach. The results showed that the neural network model was the best. In addition, Bluwstein et al. (2021) conducted research on the comparison of machine learning methods, such as decision trees, random forests, extremely randomized trees, support vector machines, logistic regression, and neural networks to detect crises. Based on the study, the best model for crisis detection was the neural network model. Wu et al. (2022) conducted research on financial crisis prediction with integrated Z-scores and multilayer perceptron backpropagation artificial neural networks on several companies in China. This analysis concluded that the artificial neural network model was better at predicting financial crises than integrated Z-scores. Several studies have concluded that artificial neural networks excel in crisis detection due to their high accuracy, stability, and less dependence on assumptions (Sun & Lei, 2020).

Based on the previous explanation, the researcher wants to analyze early detection of financial crises in Indonesia using artificial neural network methods with multilayer perceptron back propagation algorithm and adding Adam optimization. The indicators used are 13 major macroeconomic indicators in Indonesia.

MATERIALS AND METHODS

2.1. Research Method

This research analyzes 13 macroeconomic indicators consisting of imports, exports, foreign exchange reserves, Composite Stock Price Index (CSPI), loan-deposit interest rate spread, real deposit interest rates, real BI rate-FED rate spread, bank deposits, real exchange rate, trade exchange rate, M1, M2 multiplier, and M2 reserve ratio. The data used consists of monthly data from January 1990 to June 2022, obtained from the International Financial Statistics (IFS) website and Bank Indonesia (BI). The 13 macroeconomic indicators data are used as independent variables, while the dependent variable used is the perfect signal value. The steps used in this research are:

1. Collecting data on the 13 macroeconomic indicators.
2. Determining the descriptive statistics of each macroeconomic indicator.
3. Determining the perfect signal value using the Financial Perfect Index (FPI) value.
4. Performing data preprocessing consisting of cutting the last 12 months of data, checking for missing values and data duplication, dividing the data into training and testing data with an 8:2 ratio, standardizing the data with z-score normalization, and performing SMOTE to address imbalanced data.
5. Performing hyperparameter tuning using grid search.

6. Creating a multilayer perceptron backpropagation model with Adam optimization and the best hyperparameters.
7. Evaluating the model on the testing data.
8. Applying the best model to predict currency crises in Indonesia.

2.2. *Currency Crisis Approach*

According to Sevim et al. (2014) crises can be detected using the financial pressure index (FPI) approach. FPI calculation using Eq. (1)

$$\text{FPIt} = \frac{\left(\frac{e_t - \mu_e}{\sigma_e}\right) - \left(\frac{r_t - \mu_r}{\sigma_r}\right) + \left(\frac{i_t - \mu_i}{\sigma_i}\right)}{3} \quad (1)$$

$$e_t = \left(\frac{E_t - E_{t-1}}{E_{t-1}}\right); r_t = \left(\frac{R_t - R_{t-1}}{R_{t-1}}\right); i_t = \left(\frac{I_t - I_{t-1}}{I_{t-1}}\right)$$

where E_t is the currency exchange rate against the US dollar in the t, R_t is the foreign exchange reserve in the t-month and the I_t is the interest rate in the t-month

dengan E_t adalah nilai tukar mata uang terhadap dollar AS pada bulan ke t, R_t adalah cadangan devisa pada bulan ke t, dan I_t adalah suku bunga pada bulan ke t

Then is to determine the threshold to describe the crisis conditions with Eq. (2)

$$\text{T} = \mu + \alpha\sigma \quad (2)$$

with α = 1,5; 2; 2.5; 3
Crisis determination can be obtained with Eq. (3)

$$\text{crisis} = \begin{cases} 1, if\ FPI > T \\ 0, others \end{cases} \text{, where 1 for crisis and 0 for uncrisis} \quad (3)$$

After obtaining crisis conditions, the next step is to make a crisis signal 12 months before a crisis occurs with Eq. (4)

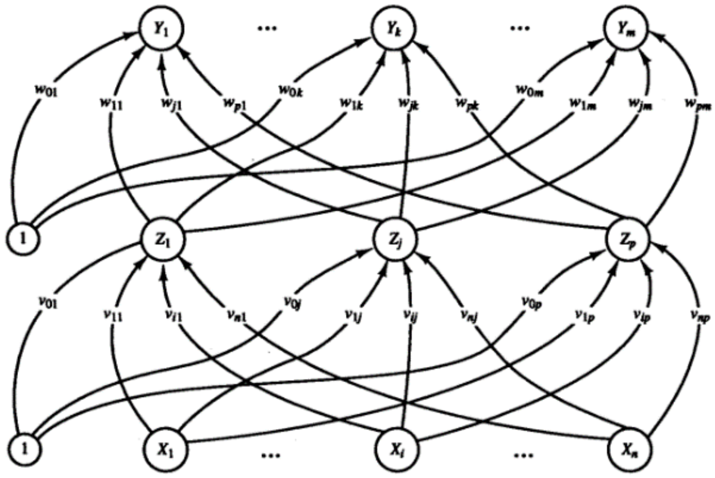
$$PS_i = \begin{cases} 1, jika\ \exists\ k = 1, 2, .., 12\ \ FPI_{i+k} > T \\ 0, lainnya \end{cases} \quad (4)$$

2.3. *Artificial Neural Network*

According to Fausett (1994), an artificial neural network (ANN) is an information processing system that has characteristics similar to the neural networks in the human body. There are three types of layers in ANN: the input layer, which is the layer that receives input values in the form of binary or continuous numbers; the hidden layer, which is the layer between the input and output layers; and the output layer, which is the layer that produces the output of the artificial neural network. There are three main components of artificial neural networks: architecture, algorithm, and activation function. There are several types of neural network architectures, such as single layer networks, multilayer networks, and recurrent networks. Meanwhile, commonly used activation functions include sigmoid, softmax, identity, and others. Artificial neural networks have hyperparameters such as the number of layers, the number of neurons in each layer, learning rate, and number of epochs.

2.4. *Multilayer Perceptron Backpropagation*

Multilayer Perceptron Backpropagation (MLPBP) is a training process that adjusts the weights of a neural network architecture using backpropagation to achieve minimum error between predicted and actual output values (Andrijasa & Mistianingsih, 2010). MLPBP consists of *three stages: forward propagation, backward propagation, and weight modification. Optimization can be applied to improve MLPBP performance. MLPBP has three layers: input, hidden, and output layers, and is suitable for predictive analysis (Gou, 2020; Li & Cao, 2020; Du et al., 2021). An example architecture of a multilayer neural network model is illustrated in Figure 1.*



Gambar 1. Arsitektur *Multilayer Neural Network* (Fausett,1994)

2.5. Optimasi *Adaptive Moment Estimation* (Adam)

Adaptive Moment Estimation (Adam) is a combined optimization of AdaGrad and RMSprop used to update weights on neural networks (Kingma & Ba, 2015). Adam's optimization calculates the adaptive learning rate for each weight by estimating the first gradient moment and the second gradient moment to perform weight updates. Adam's algorithm has two additional hyperparameters, namely exponential decay rate for the first moment (β_1) and exponential decay rate for the second moment (β_2). Adam's optimization algorithm according to Kingma and Ba (2015) is:

Look up gradient values or derivatives of a loss function by using Eq. (5)..

$$g_t = \nabla_{w_{t-1}} f_t(w_{t-1}) \tag{5}$$

Then look for the estimation of the first moment (m_t) and the estimate of the second moment (v_t) using Eq. (6) and Eq. (7).

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \tag{6}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) {g_t}^2 \tag{7}$$

The next stage is to find the estimated first and second moments corrected using Eq. (8) and Eq. (9).

$$\widehat{m}_t = \frac{m_\mathrm{t}}{1-{\beta_1}^t} \tag{8}$$

$$\hat{v}_t = \frac{v_t}{1-{\beta_2}^t} \tag{9}$$

Then is to search for the latest weights using Eq. (10).

$$w_t = w_{t-1} - \frac{\eta \widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{10}$$

2.6. Model Evaluation

According to Wonohadidjojo (2021) to measure the performance of the netowrk neural model in classifying can use a confusion matrix, where the prediction value is compared with the actual value.

Tabel 1. *Confusion matrix*

Klasifikasi		Prediksi	
		Positif	**Negatif**
Aktual	**Positif**	True Positif (TP)	False Negatif (FN)
	Negatif	False Positif (FP)	True Negatif (TN)

Based on the data from Table 1 can be used to calculate accuracy, sensitivity, and specificity. Accuracy formulated with Eq. (11) demonstrate the correct accuracy of classification and in accordance with the target. Sensitivity formulated with Eq. (12) show the accuracy of predictions against data that are considered correct. The specificity value shown by Eq. (13) show the accuracy of predictions against data that is considered wrong.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{11}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \tag{12}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \tag{13}$$

RESULT AND DISCUSSION

3.1. Descriptive Statistics

A description of the data that is the minimum, maximum, and average values for each indicator is shown in Table 2..

Table 2. Descriptive Statistics

Variable	Minimum	Average	Maximum
Import	1067.60	8040.76	21962.00
Export	1750.00	9114.57	27322.00
Foreign Exchange Reserves	5259.70	61169.18	146869.99
JCI	226.68	2452.20	7228.91
Interest ratio on deposits and loans	0.65	1.55	2.85
Real deposit interest rates	0.68	11.40	54.94
The difference between real BI rate and real FED rate	1.25	8.13	59.88
Bank deposits	25867.00	1776243.80	6343214.79
Real exchange rate	373.27	8321.63	21266.10
Trade exchange rates	0.85	1.22	1.86
M1	18856.00	553486.34	2339449.79
The ratio of M2 to foreign exchange reserves	0.000954899	0.003595780	0.007050362
M2 multiplier	1.66	6.44	86.97

Based on the data from Table 2 it is known that macroeconomic indicators have different ranges of values. The indicator with the largest range of values is the bank deposit indicator, while the indicator with the smallest range of values is the indicator of the ratio of M2 to foreign exchange reserves.

3.2. Crisis Conditions in Indonesia

The condition of the currency crisis in Indonesia can be identified using the Financial Pressure Index (FPI) approach. FPI values in the range of January 1990 to June 2020 were calculated and compared using thresholds with coefficient values α of 1.5, 2, 2.5, and 3. The results of the comparison of FPI and threshold values can be seen in Figure 2..

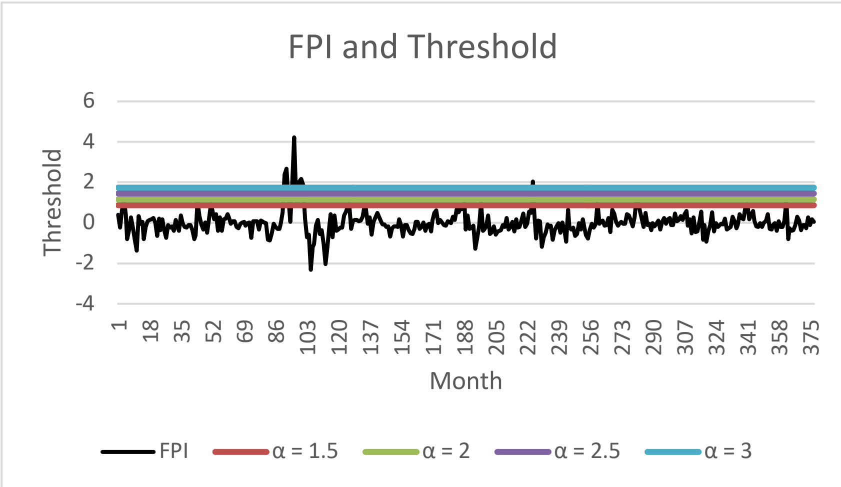


Figure 2. FPI and Threshold Values

The condition of the Indonesian currency crisis from January 1990 to June 2021 on the four coefficients of the FPI calculation can be seen in Table 3.

Table 3. Crisis Month Based on FPI and Threshold Comparison

Coefficient (α)	Crisis Month
1,5	Mei 1991, September 1993, April 1994, Agustus 1997, September 1997, Oktober 1997, Desember 1997, Januari 1998, Februari 1998, April 1998, Mei 1998, Juni 1998, Juli 2000, September 2005, Juni 2006, Oktober 2008, September 2011, Juni 2013, Juli 2013, Juni 2018 , Maret 2020
2	Mei 1991, Agustus 1997, September 1997, Oktober 1997, Desember 1997, January 1998, Februari 1998, April 1998, Mei 1998, Juni 1998, Oktober 2008
2.5	Agustus 1997, September 1997, Desember 1997, Januari 1998, April 1998, Mei 1998, Juni 1998, Oktober 2008
3	Agustus 1997, September 1997, Desember 1997, Januari 1998, April 1998, Mei 1998, Juni 1998, Oktober 2008

Based on the results in Table 3, it is known that the threshold with coefficients of 1.5 and 2 is sensitive in determining crises in Indonesia, as it can detect crises outside of the real conditions. The threshold with coefficients of 2.5 and 3 is capable of detecting currency crises according to the real conditions in Indonesia. Both thresholds detect crises in the same month, so one of the thresholds is chosen. This study uses a threshold with a coefficient of 2.5 to classify crisis conditions.

After determining the threshold, the next step is to determine the perfect signal that will be used as the dependent variable. The perfect signal value for the 12 months before the crisis will be 1, while it will be 0 if there is a crisis or so on. The labeled data is from January 1990 to June 2021.

3.3. Preprocessing Data

Data preprocessing is carried out with the aim of preparing data for further analysis. The initial step is to cut the last 12 months of data and use it for prediction data. Then there is a stage of checking for missing values and data duplication. The checking stage resulted in no missing values and duplicate data. After that, the data is divided into training and testing data with an 8:2 ratio, resulting in 301 training data and 76 testing data. Next, the training and testing data are transformed using z-score normalization to equalize the interval of the 13 indicator data.

The proportion of classes with perfect signal 1 and classes with perfect signal 0 in the training data has a ratio of 24:277. This indicates that the data is imbalanced, so it requires handling techniques such as the SMOTE technique. The SMOTE technique increases data in the minority class. The result of the SMOTE technique is that the data has a ratio of 277:277.

3.4. Formation Model

The formation of the model was done using one of the artificial neural network architectures, namely Multilayer Perceptron Backpropagation (MLPBP) with Adam optimization. The dependent variable or neurons in the input layer used were 13 macroeconomic indicators, while the independent variable or neurons in the output layer used was the perfect signal in binary class form. The activation function used in the hidden layer and output layer was sigmoid. The loss function used was binary crossentropy with a training process conducted on a batch size of 128 and the number of epochs of 100. Based on the research by Kingma and Ba (2015), the exponential decay rate value for the estimation of the first moment was 0.9, the exponential decay rate for the estimation of the second moment was 0.999, and epsilon was 10^{-8}. The number of neurons in the hidden layer was determined using grid search in the range of 1 to 13. The optimal learning rate was determined through the grid search technique with an interval of 0.001 to 1.

In this study, there was hyperparameter tuning using grid search to determine the number of neurons in the hidden layer and the optimal learning rate that made the model optimal. The results of the grid search are shown in Figure 3.

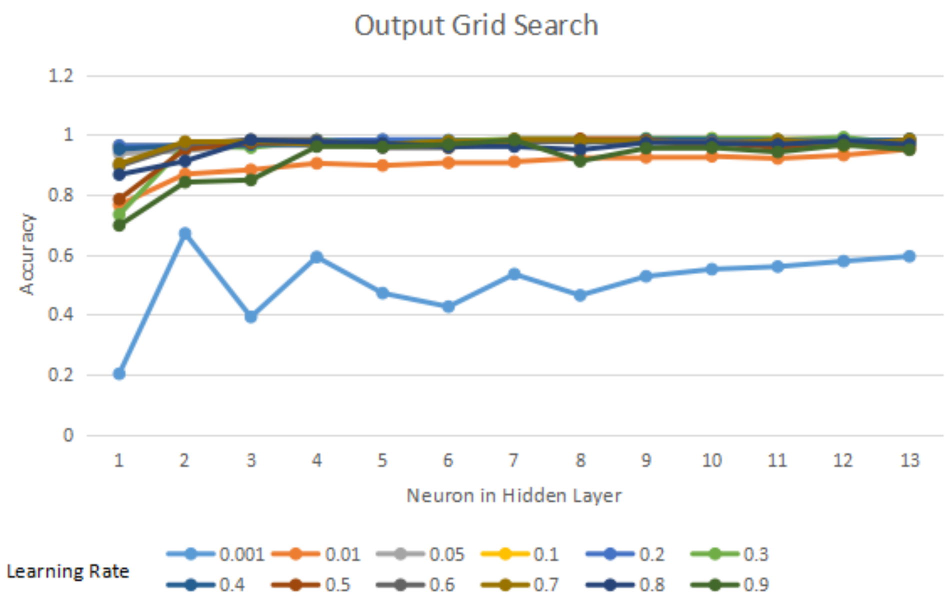


Figure 3. Grid Search Accuracy Results

The best hyperparameter results in MLPBP with Adam optimization are 12 neurons in a hidden layer, the best learning rate is 0.3. This model has an average accuracy of 98.73% on 5-fold cross validation data. The best model structure is shown in Figure 4 where X shows the input layer neuron, B shows bias, Z shows the hidden layer neuron, and Y shows the layer output neuron.

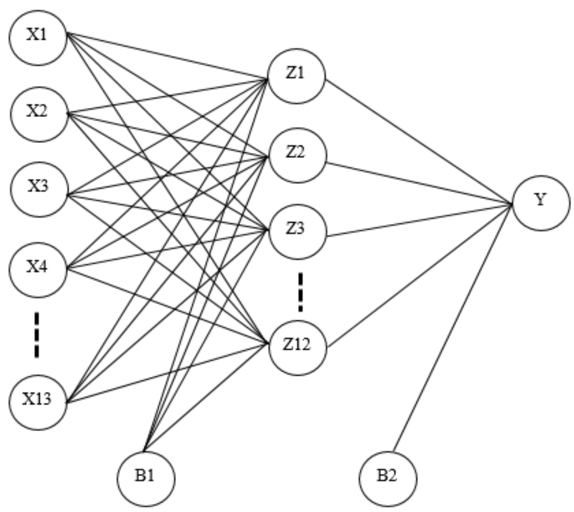


Figure 4. Best Artificial Neural Network Architecture

3.5. Evaluation Model

The next stage is the evaluation of the model on the test data, obtained by the confusion matrix on the test data, namely

Table 4. *Confussion Matrix Test* Data

Classification	Positive Predictions	Negative Predictions
Actual Positive	71	1
Actual Negative	0	4

Data from *confussion matrix* is used for counting evaluation model such as:

Accuracy $= \frac{71+4}{71+4+1+0} \text{ x } 100\% = 98.68\%$

Sensitivity $= \frac{71}{71+1} \text{x } 100\% = 98.61\%$

Specificity $= \frac{4}{4+0} \text{x } 100\% = 100\%$

The results of the evaluation of artificial neural network models on validation data and test data with Adam optimization are shown in Table 5.

Table 5. Evaluation Model Result

Evaluation Model	Validation Data	Data test
Accuracy	98.73%	98.68%
Sensitivity	100%	98.61%
Specificity	100%	100%

Based on the evaluation results in Table 5, it can be seen that the model obtained has a good ability to detect crises. This is because the value of model evaluation in validation data and test data has a high value.

3.6. Currency Crisis Prediction

The model obtained is used to predict the currency crisis in Indonesia in the next few months, namely July 2022 to June 2023. The data used to predict the perfect signal is data from July 2021 to June 2022. Before predicting perfect signals in the prediction data, standardization is carried out using averages and standard deviations in the training data. The results of the predictions can be seen in Table 6.

Table 6. Perfect Signal Prediction Results

Month	Perfect Signal
Juli 2021	0
Agustus 2021	0
September 2021	0
Oktober 2021	0
November 2021	0
Desember 2021	0
Januari 2022	0
Februari 2022	0
Maret 2022	0
April 2022	0
Mei 2022	0
Juni 2022	0

Based on the results in Table 6, it shows that data from July 2021-June 2022 did not signal a crisis for 12 consecutive months. This shows that in July 2022-June 2023 there will be no currency crisis in Indonesia.

CONCLUSSION

Early warning system for currency crisis in Indonesia can be implemented using artificial neural network with Adam optimization. The evaluation results show that the artificial neural network model with Adam optimization has high accuracy, sensitivity, and specificity. The method of artificial neural network with multilayer perceptron backpropagation architecture and Adam optimization has an architecture of 13-12-1, learning rate = 0.3, exponential decay rate for the first moment β_1)= 0.9, exponential decay rate for the second moment β_2= 0.999, batch size = 128, epoch = 100, loss function using binary crossentropy, and sigmoid activation function with initialized weights and initial bias using glorot uniform. Based on the analysis, it is known that the model with the addition of Adam optimization on multilayer perceptron backpropagation is able to detect financial crisis in Indonesia well, with high evaluation values, namely accuracy of 98.68%, sensitivity of 98.61%, and specificity of 100%. Based on the perfect signal prediction, there will be no financial crisis in Indonesia from July 2022 to June 2023.

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