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# Implementation of Neural Network in Early Detection of Financial Crisis in Singapore

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**Abstract.**
The financial crisis that occurred in 1997 and 2008 had a negative impact on several countries, including Singapore. A financial crisis can occur suddenly so it can endanger a country's economy if it is not prepared for it. Therefore, early detection of financial crises is needed as a form of crisis warning so that the government can anticipate and prepare appropriate policies. The independent variables used are monthly data of 11 key macroeconomic and financial indicators of Singapore's economy from January 1990 to June 2021. The Perfect signal is used as the dependent variable in the crisis early detection system. This study aims to build a model of a financial crisis detection system in Singapore using Multilayer Perceptron Backpropagation (MLPBP) as a neural network algorithm by comparing the optimization of Stochastic Gradient Descent (SGD) and Nesterov-accelerated Adaptive Moment Estimation (Nadam). The optimal hyperparameter value in the model was searched using the grid search method based on the accuracy and obtained the best model with 11-11-1 network architecture, best optimization is Nadam, learning rate = 0.1; $\mu$= 0.975; v=0.999; ε=[10]∧(-8) ; batch size = 128, epoch = 100, and sigmoid activation function. Testing the model with data testing obtained an accuracy of 95.89%, a sensitivity of 98.36%, and a specificity of 83.33%. The results of the Perfect Signal prediction show that from January to June 2021 it is predicted that there will be no financial crisis in Singapore.

**Keywords:** neural network, early detection, financial, crisis, Singapore

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## 1. INTRODUCTION

Singapore is known for its dynamic and open economy with a strong macroeconomic foundation. However, due to the openness and complexity of its economic system, Singapore is vulnerable to the "contagious" effects of global and regional crises [1]. The financial crisis is a disturbance in the financial market which results in inefficient distribution of funds to economic actors [2]. According to Goldstein, et al. [3] A currency crisis is defined as an episode in which an attack on a currency leads to currency depreciation, a large decline in foreign exchange reserves, or a combination of both.

In the last three decades, at least two major financial crises occurred, the Asian financial crisis in 1997 and the global financial crisis in 2008. The financial crisis in 1997 in Asia was caused by the devaluation of the Thai bath currency [4]. This has resulted in several Southeast Asian countries experiencing a crisis, one of which is Singapore. Singapore recorded an economic decline of 2.2% at the end of 1998 [5] and the Singapore dollar depreciated by 16% against the US dollar. Meanwhile, the global financial crisis in 2008 was caused by the low-quality housing credit crisis or subprime mortgages in the United States. The crisis had an impact on the depreciation of the exchange rate and a decline in various economic sectors [6].

The impact of the two financial crises experienced by Singapore shows the importance of early detection of financial crises so that the government is able to anticipate crises by implementing optimal policies. The dynamics of the crisis show that there is a significant relationship between the currency crisis and the financial crisis [7]. Therefore, the modeling of financial crisis signals can be approached using currency crisis indicators. Several studies have been conducted to identify and analyze macroeconomic indicators that can be used to predict the financial crisis. Imansyah [8] detects crises using a signaling approach model for prediction and classification through data pattern recognition. The leading indicator approach assumes that prior to the crisis, macroeconomic indicators will have an abnormal pattern [9]. This research will carry out early detection of financial crises using the “leading indicator” approach which was first developed by Kaminsky, Lizondo, and Reinhart [10].

Difficult patterns found in macroeconomic indicator data can be identified using a neural network. One of the neural network algorithms is Multilayer Perceptron Backpropagation (MLPBP). Based on the research of Sevim, et al. [9] MLPBP architectural neural network model is the best model for detecting the Turkish financial crisis compared to the decision tree and logistic regression models. As for the research of Bluwstein, et al. [11] compares several methods, namely, machine learning methods, namely decision tree, random forest, extremely randomized tree, support vector machine, logistic regression, and neural networks to detect financial crises in 17 countries. using 11 macroeconomic indicators from 17 countries during 1870 – 2016 and the results obtained that the neural network method produces greater accuracy

The MLPBP method has a weakness in determining the initialization of the initial weight so that it can be trapped in the local minimum and requires a long computation time for complex problems. Therefore, optimization is needed that can overcome these problems. The optimization technique that is well-known and most widely used is Stochastic Gradient Descent (SGD) optimization. SGD optimization is used to find local minimum values generated from parametric functions so as to avoid local minimums and find global minimums. However, for large data, SGD optimization tends to take a long time to run the algorithm [12]. Timothy Dozat [13] introduced the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimization, which is an adaptive learning rate method that uses a different learning rate. in each weight update process so that it has a better performance in finding local minimum values in the MLPBP model compared to the SGD optimization. The Nadam optimization is a combination of the Adam optimization algorithm which is an extension of the SGD algorithm with Nesterov's Accelerated Gradient (NAG). This optimization takes advantage of NAG to improve the convergence speed and quality of the neural network model. This study aims to build a model for the early detection of financial crises using a neural network by comparing the optimization of SGD and Nadam.

## 2. RESEARCH METHOD

This study uses 11 macroeconomic indicators based on research by Kaminsky, et al. [10] in the form of monthly data from January 1990 to June 2021. The 11 indicators are foreign exchange reserves, imports, exports, term of trade, real exchange rates, real interest rates, lending rate/deposit rate, stock prices STI (Straits Times Index), M1, M2 multiplier, and M2/foreign exchange reserves. The research data were obtained from the International Monetary Fund (IMF) and the Monetary Authority of Singapore (MAS). The dependent variable used is the perfect signal based on the Exchange Market Pressure (EMP) using a threshold that is able to describe the crisis conditions in Singapore. The following steps are used in the research:

1. Collecting research data.
2. Determine the perfect signal value based on the Exchange Market Pressure (EMP) value using a threshold value that describes the crisis conditions in Singapore.
3. Conducting descriptive statistical analysis and plotting the data to describe the 11 indicators of the financial crisis in Singapore.
4. Perform data preprocessing.
5. Withholding data on the last 12 months.
6. Checking for missing values and duplication of data on research data.
7. Divide the data into training data and test data with a ratio of 8:2.

8. Standardize data using z-score normalization.
9. Handling unbalanced classes on training data using Synthetic Minority Over-Sampling Technique (SMOTE).
10. Tuning SGD and Nadam optimization hyperparameters using the grid search method.
11. Modeling the MLPBP model with SGD and Nadam optimization
12. Comparing the test results of the MLPBP model with SGD optimization and MLPBP with Nadam optimization on validation data and test data based on accuracy, sensitivity, and specificity.
13. Apply the best model to predict the financial crisis in Singapore.

## 2.1. Financial Crisis Approach

The financial crisis can be identified through the Exchange Market Pressure (EMP) approach. EMP is calculated as in Eq. (1) [14].

$$EMP_t = \Delta e_i - \left(\frac{\sigma_e}{\sigma_r}\right) \Delta r_i EMP_t = \Delta e_i - \left(\frac{\sigma_e}{\sigma_r}\right) \Delta r_i \quad (1)$$

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

where $E_t$ $R_t$, and $\sigma_{e,r}\sigma_{e,r}$ are the dollar exchange rate at moth *t*, the gross foreign exhange reserves of Central Bank at moth *t*, and standar deviation of the dollar exchange rate and the gross foreign exhange reserves.

The Threshold (T) value that describes the crisis condition is determined using the formula Eq. (2).

$$T = \bar{x} + a\sigma T = \bar{x} + a\sigma \quad (2)$$

where the $a$ coefficient is $a = 1.5$ ; $a = 2$ ; $a = 2.5$; and $a = 3$ in the financial crisis literature.

The presence of a crisis has been defined as in Eq. (3).

$KC = \{1\ ,\ if\ EMP > T\ 0\ ,\ if\ EMP < T$ , dengan 1 is a crisis and 0 is not crisis. (3)

The next step is to calculate the perfect signal defined Eq. (4). The perfect signal is an series of signals that gives a warning of a crisis during the 12-month period before the time at.

$$Perfect\ Signal_i = \begin{cases} 1\ ,\ \text{if}\ \exists k = 1,2,\ldots,12 & \text{subject to}\ EMP_{i+k} > T \\ 0\ ,\ \text{otherwise} \end{cases}$$

$$Perfect\ Signal_i = \begin{cases} 1, \text{ if } \exists k = 1,2,\dots,12 \quad \text{subject to } EMP_{i+k} > T \\ 0, \text{ otherwise} \end{cases} \tag{4}$$

## 2.2. Neural Network

A Neural network is a computational information processing system that has characteristics similar to human biological neural networks [15]. In a neural network, there are three main points; the neural network architecture, training algorithms, and activation functions. Architecture is a form of a pattern of relationships between neurons arranged in layers. The architectures that are often used are single-layer networks, multilayer networks, and recurrent networks. Neural network algorithms that can be used are the Hebb, adaline, perceptron, backpropagation, and others. While the activation function is a determinant of the output value of a neuron. Examples are sigmoid, threshold, identity, softmax, and others. The Neural network is a parametric model that adjusts the data by modifying the network parameter values. These parameters are commonly referred to as hyperparameters [16]. Some of the hyperparameters used in the neural network are the number of hidden layers, the number of neurons in the hidden layer, batch size, learning rate, and epochs.

## 2.3. Multilayer Perceptron Backpropagation

The Multilayer perceptron is the result of the generalization of the perceptron architecture with one layer, so it has at least one hidden layer which is located between the input layer and the output layer [17]. Learning this algorithm is done using backpropagation. Multilayer perceptron with backpropagation learning algorithm (MLPBP) is used due to its superiority over other neural network algorithms such as radial basis function (RBF) and recurrent neural network (ANN) [9]. The backpropagation algorithm performs forward propagation to obtain the error value that is used to change the weight values in the backward direction (backward propagation) with 3 stages; the feedforward of the input training pattern, the backpropagation of the associated error, and the adjustment of weights and biases [18]. The following multilayer perceptron backpropagation architecture with one hidden layer is shown in Figure 1.

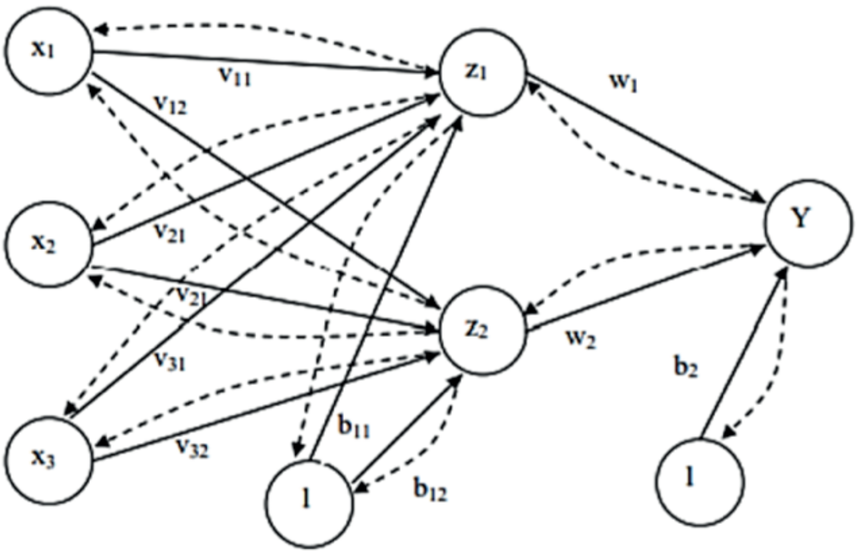



**Figure** 1: Architecture of MLPBP [17].

### 2.4. Criteria for Model Evaluation

The model that has been formed needs to be evaluated, one of which uses a confusion matrix [19]. The confusion matrix with two classes is shown in Table 1.

Table 1: Confussion matrix.

| | Prediction | | |
|---|---|---|---|
| | **Class** | **Positive** | **Negative** |
| **Actual** | Positive | *True Positive* (TP) | *False Negative* (FN) |
| | Negative | *False Positive* (FP) | *True Negative* (TN) |

From Table 1 we can find the values of accuracy, sensitivity, and specificity. Accuracy is a value that indicates a measure of the right classification ability according to the target. Sensitivity is a measure of the system's ability to make predictions on data that is considered correct. Meanwhile, specificity is defined as the ability of the system to predict data that is considered wrong. The formula for calculating accuracy, sensitivity, and specificity is written in Eq. (6).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \, \text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (6)$$

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

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

## 3. RESULTS AND DISCUSSION

### 3.1. Financial Crisis Conditions in Singapore

The condition of the financial crisis in Singapore can be identified using the EMP (Exchange Market Pressure) approach from January 1990 to June 2021. The EMP is calculated every month using the formula (1). The EMP results are compared with the threshold at a sigma coefficient of 1.5; 2; 2.5; and 3. The condition of the month is classified a crisis if the EMP is greater than the threshold. The graph of the calculation results of the EMP and the threshold for each sigma is shown in Figure 2.

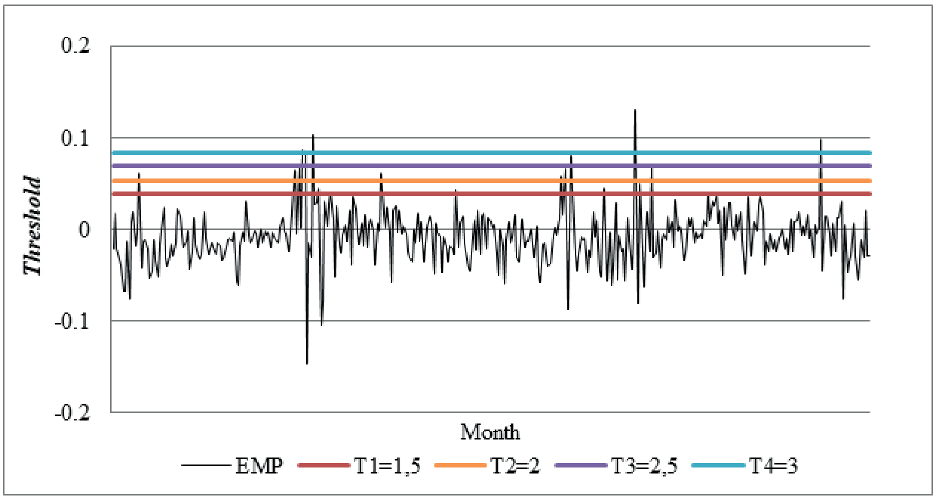



**Figure** 2: Calculation results of emp and threshold.

The results of the financial crisis conditions in Indonesia from January 1990 to June 2021 based on the EMP with four sigma coefficients ($a$) can be seen in Table 2.

Table 2: Months of crisis based on comparison of emp with threshold.

| Sigma Coefficient | Crisis Month |
|---|---|
| 1.5-sigma | March 1991, August 1997, July 1997, October 1997, December 1997, January 1998, May 1998, August 1998, February 1999, March 2001, April 2004, August 2008, September 2008, January 2009, May 2010, September 2011, May 2012, September 2014, January 2015, May 2019 |
| 2-sigma | March 1991, August 1997, October 1997, December 1997, January 1998, May 1998, March 2001. August 2008, October 2008, January 2009, September 2011, May 2012, May 2019 |
| 2,5-sigma | December 1997, January 1998, May 1998, January 2009, September 2011, May 2019 |
| 3-sigma | December 1997, January 1998, May 1998, September 2011, May 2019 |

Based on Table 2, it is known that the 2.5-sigma is the most appropriate sigma coefficient because the month of crisis detection results is in accordance with the real situation in Singapore. The next step is to form the perfect signal value as the dependent variable in this study. The Perfect signal is worth 1 for 12 months before a crisis occurs and is worth 0 when a crisis occurs or otherwise. Perfect signal labeling is only from January 1990 to June 2020. Meanwhile, from July 2020 to June 2021 as prediction data are not labeled because in the next 12 months after that month the crisis conditions are not yet known. The results of labeling the perfect signal value from 365 observations obtained 314 months labeled 0 and 51 months labeled 1.

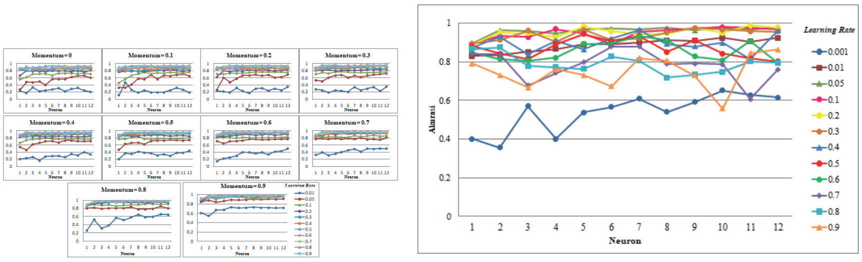
### 3.2. Data Preprocessing

Before further analysis, data preprocessing is needed so that the data can be processed according to the format of the next analysis. There is no missing value or duplication in the data. After that, the data was split into data training and data testing with a ratio of 8:2. The training data is used to build the model, while the testing data is used to evaluate the model. The training data and testing data were transformed using z-score normalization because the 11 independent variables had different ranges. Standardization of z-score using the mean and standard deviation of the training data.

The proportion of classes in the data training between the crisis signal class and the non-crisis signal class is 39:253. This shows that the number of each class in the data is not balanced (balance data) so to handle it, the SMOTE (Synthetic Minority Over-Sampling Technique) method will be used. By using the number of nearest neighbors as $k$ = 5, the number of minority classes or crisis signal classes is 253 observations. Thus, the proportion of crisis and non-crisis signal classes is 253:253 with the total number of training data being 506 observations.

### 3.3. Model Building

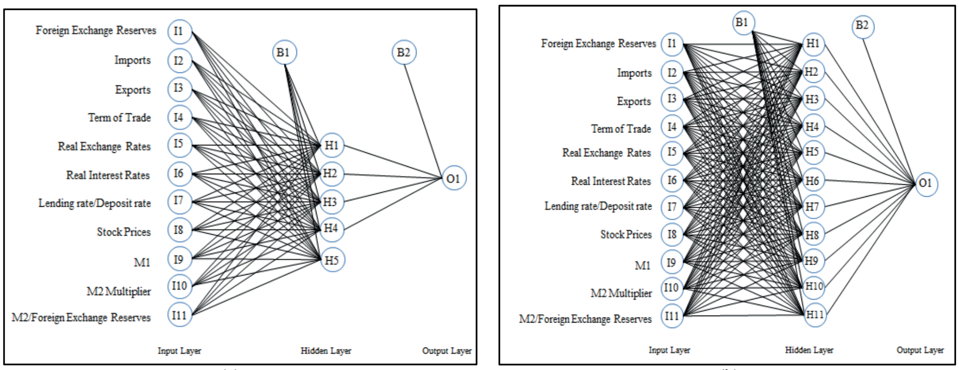
Modeling using multilayer perceptron backpropagation (MLPBP) as one of the neural network algorithms. In this study, a comparison test will be conducted on the optimization of Stochastic Gradient Descent (SGD) and Nadam. Determination of the optimal parameters for each optimization based on the results of hyperparameter tuning using a grid search technique. In MLPBP modeling there is one input layer, one hidden layer, and one output layer. The input layer has 11 neurons which is the number of indicators used as input variables. The number of neurons in the hidden layer is tuning at intervals of 1 to 12. Because the output variable is a binary class then the number of neurons in the output layer is 1 neuron. The value of the learning rate for the optimization of SGD and Nadam is tuned at intervals of 0.001-1. In SGD optimization, the momentum value is tuned at intervals of 0 -1. The activation function in the hidden layer fan output layer uses a binary sigmoid. The model uses a loss function binary cross-entropy, the type of metrics is accuracy, the batch size is 128 and the epochs are 100. The results of the grid search for the number of neurons in the hidden layer, learning rate, and momentum are shown in Figure 3.




(a) (b)

**Figure** 3: Grid search results for neural network parameters (a) SGD optimatization (b) Nadam optimization.

The best hyperparameter tuning results in the MLPBP model with SGD optimization are 5 neurons in the hidden layer; The learning rate is 0.8 and the momentum is 0.9 with accuracy is 96.64% on 5-fold cross-validation data. While the best hyperparameters in the MLPBP model with Nadam optimization are 8 neurons in the hidden layer; learning rate 0.1; $\mu\mu$ = 0.975; $\upsilon$ = 0.999; and $\epsilon = 10^{-8}\epsilon = 10^{-8}$ with the highest accuracy is 98.22%. The final and the best MLPBP with SGD optimization and MLPBP with Nadam optimization structure are pictorially represented as in Figure 4.




(a) (b)

**Figure** 4: The best architecture neural network (a) SGD optimatization (b) Nadam optimization.

## 3.4. Model Comparison

The next stage is testing the best model for each optimization using 5-fold cross-validation and data testing. The evaluation results of the neural network model with

SGD optimization are compared with the evaluation results of the neural network model with Nadam optimization. The comparison results are shown in Table 3.

TABLE 3: Comparison of SGD and nadam optimization evaluations.

| Model Evaluation | Data Validation | | Data Testing | |
|---|---|---|---|---|
| | NN- SGD | NN-Nadam | NN-SGD | NN Nadam |
| Accuracy | 95.65%. | 98.22%. | 91.78% | 95.89% |
| Sensitivity | 97.25%. | 99.21%. | 95.08% | 98.36% |
| Specificity | 97.41%. | 99.21%. | 75% | 83.33% |

Table 3 shows that the evaluation of the neural network model with Nadam optimization on validation data and data testing has higher accuracy, sensitivity, and specificity than the neural network model with SGD optimization. It can be concluded that the neural network model with the Nadam optimization is better at modeling the early detection of the financial crisis in Singapore.

### 3.5. Prediction of Financial Crisis in Singapore

The best model, which is an MLPBP with Nadam optimization, will then be used to forecast the financial crisis in Singapore for the next few months, from June 2021 to July 2022. The data used to predict the crisis signal is data from July 2020 to June 2021. Before predicting the crisis signal on the prediction data, standardization of the data is done first using the mean and standard deviation of the training data. The results of the crisis prediction show that from July 2020 to June 2021, there will be no-crisis signals consecutively for 12 months, so it can be concluded that from July 2021 to June 2022 there will be no financial crisis in Singapore.

## 4. CONCLUSION

The condition of the financial crisis in Singapore can be identified using the EMP with the best threshold at 2.5-sigma. An early detection system for the financial crisis in Singapore can be done using MLPBP by comparing the optimization of SGD and Nadam. The evaluation results show that the MLPBP model with Nadam optimization has a higher evaluation result than the MLPBP with SGD optimization so the MLPBP model with Nadam optimization is better at detecting the financial crisis in Singapore. The MLPBP model with Nadam optimization has an 11-5-1 architecture, learning rate = 0.1, the decay factor for the first moment $(\mu)(\mu)$ = = 0.975, decay factor for the second moment $(\upsilon)$ = 0.999, and $\epsilon = 10^{-8}\epsilon = 10^{-8}$, batch size = 128, epoch = 100, Loss function uses binary cross-entropy and the type of metrics is accuracy, sigmoid activation function with initialized weights and initial bias using glorot uniform. Based on the results of the perfect signal prediction, from July 2021 to June 2022 there will be no financial crisis in Singapore.

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