Thailand Statistician
October 2026; 24(4): 999-1011
http://statassoc.or.th
Contributed paper

Financial Crisis Detection in Thailand Based on Currency Crisis Index Approach Using Artificial Neural Network

Sugiyanto* [a], Winita Sulandari [a], Etik Zukhronah [a], Riskhia Hapsari [a], and Ihsan Fathoni Amri [b]

[a] Department of Statistics, Faculty of Mathematics and Science, Sebelas Maret University, Central Java, Indonesia.

[b] Department of Data Science, Faculty Science and Agricultural Technology, Muhammadiyah Semarang University, Jawa Tengah, Indonesia.

*Corresponding author; e-mail: sugiyanto61@staff.uns.ac.id

Received: 29 July 2024
Revised: 19 June 2026
Accepted: 19 June 2026

Abstract

The 1997 financial crisis in Thailand had a variety of adverse effects, ranging from the depreciated baht, negative economic growth, increased unemployment, to declining stock prices. Thailand took a long time to recover from these impacts. Therefore, financial crisis detection is needed to prevent or minimize the impact of the crisis. This study aims to build a model that can predict the financial crisis in Thailand using multilayer perceptron (MLP). Four different optimizations were applied to obtain the optimal model, namely SGD, Adam, Nadam, and AdaBound. The model employs eleven macroeconomic indicators as input variables and uses the perfect signal derived from the Currency Crisis Index (CCI) as the target variable. This study used the CCI approach to determine Thailand's crisis conditions from January 1991 to December 2022. Based on the results, the best model for predicting Thailand's financial crisis is the MLP model with Nadam optimization trained using 11-6-1 network architecture, learning rate of 0.2, batch size of 128, and epoch of 100. The model produced an accuracy of 99.44% on validation data and 98.61% on testing data. The model prediction results suggest a low likelihood of a financial crisis in Thailand from January 2023 to December 2024.

Keywords: Financial crisis detection, multilayer perceptron, currency crisis index, Nadam optimization, macroeconomic indicators.

1. Introduction

A financial crisis is a condition that can lead to economic instability in a country. This circumstance can arise when some financial institutions or assets lose the majority of their value, causing the country's economy to experience a very significant decline (Ali 2009). In the past three decades, financial crises have occurred in various countries. One such crisis was the Asian financial crisis of 1997-1998 which began when Thailand declared that it was unable to repay its external debt on July 2, 1997. This was followed by the unsuccessful policy of the Thai government to float the

baht exchange rate (Surapati et al. 2021). Since then, the baht has continued to depreciate, leading to the collapse of Malaysian, South Korean, Philippine, and Indonesian currencies (Leighter 2007).

The financial crisis caused Thailand to experience negative growth of 1.4% and increased unemployment. According to Thailand's Department of Labor Protection and Welfare (1999), about 4,900 companies went bankrupt and had to lay off 408,967 workers. A total of 58 non-bank financial institutions in Thailand were also closed due to bankruptcy (Sen-e 2017). The impacts of this crisis have highlighted the necessity of creating early detection of financial crises in Thailand. With an early crisis detection system in place, the Thai government can prepare anticipatory measures to prevent or minimize the impact of future crises.

Financial crises can be predicted using a variety of methods. One of them is an artificial neural network with a multilayer perceptron algorithm. Several studies related to financial crisis detection using artificial neural networks have been conducted in various countries. Sevim et al. (2014) developed a financial crisis early detection model in Turkey using 32 indicators by comparing artificial neural networks, decision trees, and logistic regression models. The results showed that the artificial neural network model produced better performance than other models. Bluwstein et al. (2023) also conducted research on financial crisis detection models using 11 macroeconomic indicators from 17 countries by comparing several machine learning methods, namely decision tree, random forest, extremely randomized tree, support vector machine, logistic regression, and artificial neural network. Of all these methods, an artificial neural network is the best method with the highest accuracy value. Meanwhile, Pertiwi et al. (2023) modeled financial crisis detection in Indonesia using an artificial neural network and produced excellent accuracy, which was 98.68%. Those studies indicate that financial crisis detection can be effectively modeled by artificial neural networks. Its less dependence on assumptions makes this method even better (Sun and Lei 2021). However, few studies have specifically focused on Thailand's financial setting, particularly those integrating Currency Crisis Index (CCI)-based crisis labeling with a systematic comparison of different optimizers within the Multilayer perceptron (MLP) framework. This gap motivates the present study to explore MLP with multiple optimization techniques for predicting financial crises in Thailand.

MLP is an artificial neural network architecture that can be developed to model crisis conditions. This model can identify complicated patterns or nonlinear patterns in macroeconomic indicators data, which makes MLP suitable for financial crisis prediction (Sevim et al. 2014). During MLP modeling, selecting the appropriate optimization is important since the effectiveness of each method can vary significantly across different datasets. Thus, it's essential to experiment with various optimization techniques and choose the one that works best for a particular dataset. Several optimizations that can be used are stochastic gradient descent (SGD), adaptive moment estimation (Adam), Nesterov-accelerated adaptive moment estimation (Nadam), and adaptive gradient methods with a dynamic bound of learning rate (AdaBound).

According to Kaminsky et al. (1998), crises can be predicted using macroeconomic indicators. The aim of this research is to build a model that can explain past crises and can be used to predict the Thai financial crisis using a multilayer perceptron algorithm based on eleven Thai macroeconomic indicators. During the training process, several optimizations are used to improve the process of finding optimal weights, including SGD, Adam, Nadam, and AdaBound.

2. Related Theories

2.1. Currency Crises Index (CCI)

According to Abdurrahman and Wiranatakusuma (2017), financial crises can be identified through the CCI approach which is obtained from (1).

$$\mathrm{CCI}_t = \Delta e_t + \left(\frac{\sigma_{\Delta e}}{\sigma_{\Delta r}}\right)\Delta r_t, \quad \Delta e_t = \left(\frac{e_t - e_{t-1}}{e_{t-1}}\right), \Delta r_t = \left(\frac{r_t - r_{t-1}}{r_{t-1}}\right), \tag{1}$$

where e_t and r_t is monthly exchange rate against US dollar and monthly foreign exchange reserves at month t, respectively.

This study assumed that a financial crisis occurs when a threshold of CCI is exceeded. The threshold value that indicates a crisis is determined using (2).

$$T = \mu_{\mathrm{CCI}} + \alpha\sigma_{\mathrm{CCI}}, \tag{2}$$

where the coefficient α ranges from 1.5 to 3. It is a heuristic value intended to increase signal performance (Sevim et al. 2014). A crisis signal is fired when abnormal changes are detected in the pattern of indicators compared to specified threshold value. The determination of crisis conditions is defined through (3).

$$\mathrm{Crisis} = \begin{cases} 1, & \text{if } \mathrm{CCI}_t > T \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Subsequently, the perfect signal value is determined based on crisis conditions. Perfect signal is a series of signals that can provide warning for 24 months before a crisis occurs. The determination of perfect signal can be written mathematically as in (4).

$$\mathrm{PS}_t = \begin{cases} 1, \text{ if } \exists m = 1, 2, \ldots, 24 \text{ subject to } \mathrm{CCI}_{t+m} > T \\ 0, \qquad\qquad \text{otherwise.} \end{cases} \tag{4}$$

Perfect signal takes the value of 1 for 24 months preceding the crisis and 0 right when the crisis happens and when there is no crisis in the following 24 months (Sevim et al. 2014).

2.2. Multilayer perceptron

The MLP is a widely used type of artificial neural network, which is an information processing system that has characteristics of neural networks found in the human body (Fausett 1994). The MLPs have at least one hidden layer between the input and output layers, allowing them to overcome the limitations of single-layer neural networks in pattern recognition. Each layer is completely connected to the next. This method employs a backpropagation algorithm that adjusts the weights of an artificial neural network architecture in the backward direction (backward propagation) to attain a minimum error value between predicted results and the actual target (Andrijasa and Mistianingsih 2010). The training process of MLP has three stages, including feedforward, backpropagation, and weight update (Géron 2017). Figure 1 is an MLP architecture with one hidden layer.

2.3. Optimization

Optimization can be utilized in MLP models to increase performance in determining the optimum weights. This section provides an overview of several optimization methods used in artificial neural network.

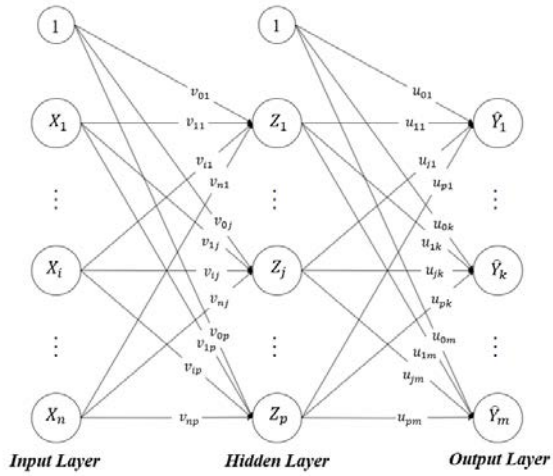


Figure 1 The MLP architecture with one hidden layer

2.3.1 Stochastic Gradient Descent (SGD)

SGD is a variation of gradient descent optimization. The SGD algorithm begins by taking random data, then the loss generated from the data is minimized using the gradient rule (Umar et al. 2020). This optimization updates the weights with a constant learning rate and aims to find the weight parameters that can minimize the loss value. The weight update process with SGD optimization begins with calculating the gradient value (g) by deriving the loss function (L) using (5).

$$g = \nabla_w L\big(f(x,w), y\big), \tag{5}$$

where w is the weight, x is the input variable, $f(x,w)$ is the prediction result, and y is the actual target. The gradient is used to calculate the weighted gradient with the following equation:

$$\overline{g}_h = \gamma \overline{g}_{h-1} + \eta g_h,$$

where $\overline{g}_h$ is the weighted average for h^{th} iteration, γ is the momentum, and η is the learning rate. The momentum parameter in SGD optimization determines the impact of the weight change from previous iteration on the update at current iteration. Then, the new weight can be calculated as follows:

$$w_h = w_{h-1} - \overline{g}_h.$$

2.3.2 Adaptive moment estimation (Adam)

Adam was developed for the first time by Kingma and Ba (2015). This optimization is a combination of the Adaptive Gradient Algorithm (Adagrad) and Root Mean Squared Propagation (RMSprop). It calculates an adaptive learning rate for each weight by estimating the first and second gradient moments to update the weights (Amin et al. 2019).

The first moment $\left(m_h^{(1)}\right)$ and second moment $\left(m_h^{(2)}\right)$ estimates are calculated using (6) and (7), respectively.

$$m_h^{(1)} = \beta_1 m_{h-1}^{(1)} + (1-\beta_1) g_h, \tag{6}$$

$$m_h^{(2)} = \beta_2 m_{h-1}^{(2)} + (1-\beta_2) g_h^2, \tag{7}$$

where β_1 is exponential decay rate for the first moment and β_2 is exponential decay rate for the second moment. The first and second moment estimates were then corrected using (8) and (9), respectively

$$\hat{m}_t^{(1)} = \frac{m_t^{(1)}}{1-\beta_1^t}, \tag{8}$$

$$\hat{m}_t^{(2)} = \frac{m_t^{(2)}}{1-\beta_2^t}. \tag{9}$$

Subsequently, the weight update is calculated based on following equation with ε being a small number added to avoid errors due to division by 0.

$$w_t = w_{t-1} - \frac{\eta}{\sqrt{\hat{m}_t^{(2)}} + \varepsilon} \hat{m}_t^{(1)}.$$

2.3.3 Nesterov-accelerated adaptive moment estimation (Nadam)

Nadam is an optimization algorithm that combines the Adam with Nesterov accelerated gradient (NAG). This optimizer improves the convergence performance of neural network training by incorporating Nesterov momentum into the Adam framework (Dozat 2016). In Nadam, the first and second moment estimates of the gradients are computed similarly to Adam (Kingma and Ba 2015). The first moment estimate m_t and the second moment estimate v_t are calculated as follows:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t, \quad v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2,$$

where g_t represents the gradient at iteration t, while β_1 and β_2 are exponential decay rates for the first and second moment estimates. These moment estimates are then corrected for bias using

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t}.$$

The parameter update rule in Nadam incorporates the Nesterov momentum term and is defined as

$$w_{t+1} = w_t - \eta \frac{\beta_1 \hat{m}_t + \frac{(1-\beta_1)}{1-\beta_1^t} g_t}{\sqrt{\hat{v}_t} + \varepsilon},$$

where w_t denotes the weight parameter at iteration t, η is the learning rate, and ε is a small constant added to avoid division by zero. By integrating Nesterov momentum with adaptive learning rate estimation, Nadam is able to provide faster convergence and improved stability during neural network training (Dozat 2016).

2.3.4 Adaptive gradient methods with dynamic bound of learning rate (AdaBound)

AdaBound is a variation of Adam optimization designed to be more resilient to extreme learning rates. This optimization combines Adam and SGD methods together with the adaptive method applied at the beginning of training and gradually transforming into SGD as time increases (Luo et al. 2019).

Similar to Adam and Nadam, AdaBound also offers first moment and second moment estimations. These moments are not corrected. Instead, there is a truncation in the learning rate that exceeds the limit, as follows:

$$\hat{\eta}_h = \text{Clip}\left(\frac{\eta}{\sqrt{m_h^{(2)}}}, \eta_l(h), \eta_u(h)\right),$$

where $\eta_l(h)$ is the lower bound and $\eta_u(h)$ is the upper bound at t^{th} iteration obtained from (10) and (11), respectively

$$\eta_l(h) = \left(1 - \frac{1}{(1-\beta_2)h+1}\right)\eta^*, \tag{10}$$

$$\eta_u(h) = \left(1 + \frac{1}{(1-\beta_2)h}\right)\eta^*. \tag{11}$$

The clip function produce the same value as $\frac{\eta}{\sqrt{m_h^{(2)}}}$ if the value is in the interval $\left[\eta_l(h), \eta_u(h)\right]$, but converts values smaller than $\eta_l(h)$ to $\eta_l(h)$ and values larger than $\eta_u(h)$ to $\eta_u(h)$. Subsequently, the learning rate at h^{th} iteration is obtained from (12) and the new weights are calculated using (13).

$$\eta_h = \frac{\hat{\eta}_h}{\sqrt{h}}, \tag{12}$$

$$w_h = w_{h-1} - \eta_h m_h^{(1)}. \tag{13}$$

2.4 Model evaluation

Model evaluation is needed to measure the performance of a model that has been established. In classification tasks, model evaluation can be done using a confusion matrix as shown in Table 1 (Han et al. 2012).

Table 1 Confusion matrix

Classification		Predicted	
		Positive	Negative
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Based on data in the confusion matrix, several performance criteria can be calculated as follows.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%, \tag{14}$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\%, \tag{15}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%, \tag{16}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\%, \tag{17}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}. \tag{18}$$

Accuracy, shown in (14), measures the proportion of correctly classified observations. Precision, obtained from (15), represents the proportion of predicted positive cases that are truly positive. Sensitivity, shown in (16), measures the proportion of actual positive cases correctly identified, while specificity, shown in (17), measures the proportion of actual negative cases correctly identified. The F1-score, shown in (18), is the harmonic mean of precision and sensitivity and is particularly useful for imbalanced data.

3. Research Methodology

This study is based on the CCI approach to identify a crisis. Before the crisis assumed by CCI occurs, a perfect signal will give a warning over a 24-month period. In this study, currency crises identified by the CCI are used as a proxy for financial crisis conditions. Therefore, the crisis labels generated from the CCI serve as the target variable for developing the financial crisis detection model. In order to predict future financial crises, multilayer perceptron models are established with macroeconomic indicators as predictor variables and perfect signal value as the target variable. This study used eleven macroeconomic indicators, including imports, exports, foreign exchange reserves, stock price index, lending rate/deposit rate, real interest rate, real exchange rate, terms of trade, M1, M2/foreign exchange reserves, and M2 multiplier. These indicators were selected due to their close linkage to capital flows and systemic risk, as trade, monetary, interest rate, and market indicators collectively capture a country's external vulnerability, liquidity conditions, and financial stability (Kaminsky et al. 1998).

The dataset was obtained from the International Monetary Fund (IMF) and the Bank of Thailand (BOT) websites with monthly periods from January 1991 to December 2022. Upon collection, the dataset was verified to contain no missing values. The steps used in this study are as follows.

a. Prepared the data for this study.

b. Determined the perfect signal value based on the CCI.

c. Performed data preprocessing, including cutting the last 24 months of data as the basis for crisis prediction, divided data into training and testing data sets, normalized data with z-score normalization, and handled data imbalance with Synthetic Minority Oversampling Technique (SMOTE).

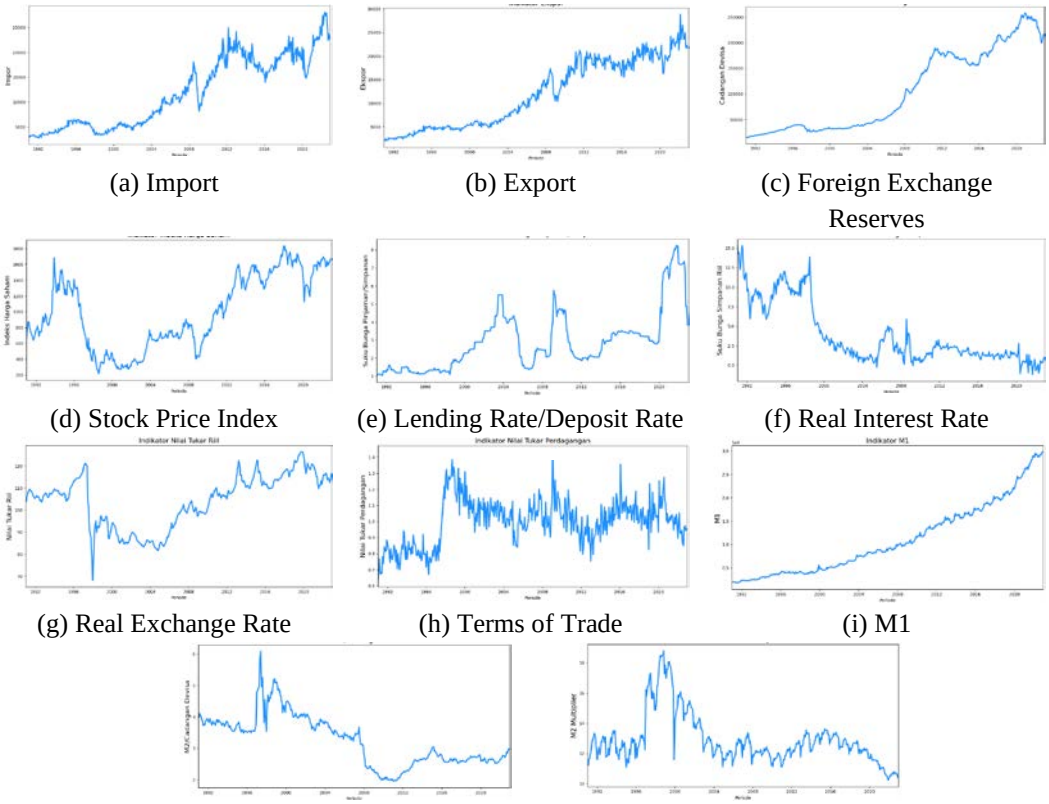
d. Built multilayer perceptron models with SGD, Adam, Nadam, and AdaBound optimizations using the training data set after performing hyperparameter tuning with 5-fold cross validation.

e. Evaluated the models using the testing data set based on accuracy, precision, sensitivity, specificity, and F1-score then determined the best model.

f. Predicted the financial crisis condition in Thailand in January 2023 to December 2024 using the best model that has been established.

4. Results and Discussion

This study used eleven predictor variables, which are macroeconomic indicators that can identify financial crises in Thailand. The patterns of all indicators are shown in Figure 2. In general, each indicator had different behaviors over the study period. During the crisis in 1997-1998, indicators of imports, exports, foreign exchange reserves, stock price index, lending rate/deposit rate, and real exchange rates typically fell. In contrast, the actual interest rate, terms of trade, M2/foreign exchange reserves, and M2 multiplier increased significantly when the crisis occurred, while M1 shows fluctuating behavior.



(a) Import (b) Export (c) Foreign Exchange Reserves

(d) Stock Price Index (e) Lending Rate/Deposit Rate (f) Real Interest Rate

(g) Real Exchange Rate (h) Terms of Trade (i) M1

(j) M2/Foreign Exchange Reserves (k) M2 Multiplier

Figure 2 Time series plot of each macroeconomic indicators

Before modeling the eleven indicators to predict financial crises, the crisis conditions in Thailand from January 1991 to December 2022 were determined using the Currency Crises Index (CCI) approach. The coefficient α values used to specify the threshold are 1.5, 2, 2.5, and 3. A month is considered to experience a crisis if the CCI value exceeds the threshold. The comparison of CCI and threshold values with each coefficient α is depicted in Figure 3, while the list of months identified as experiencing a financial crisis is shown in Table 2.

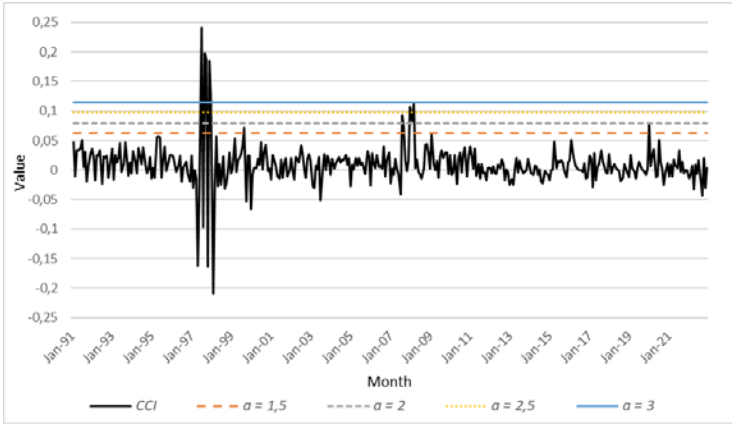


Figure 3 CCI comparison with all thresholds

Table 2 Crisis condition based on each threshold

Coefficient α	Crisis Month
1.5	July 1997, September 1997, October 1997, December 1997, January 1998, September 1999, August 2007, September 2007, January 2008, February 2008, March 2008, January 2020
2	July 1997, September 1997, October 1997, December 1997, January 1998, August 2007, January 2008, February 2008, March 2008
2.5	July 1997, September 1997, October 1997, December 1997, January 1998, January 2008, March 2008
3	July 1997, September 1997, October 1997, December 1997, January 1998

Table 2 indicates that the thresholds with coefficients α of 1.5, 2, and 2.5 are relatively sensitive, as they generated additional crisis signals beyond the periods associated with Thailand's documented financial crises. In contrast, the threshold with $\alpha = 3$ identified only the crisis months associated with the 1997–1998 Thai financial crisis, while lower thresholds produced signals that were not supported by historical crisis records. Therefore, $\alpha = 3$ was selected as the most appropriate threshold for distinguishing crisis and non-crisis conditions and was subsequently used to construct the crisis labels in this study.

Furthermore, the perfect signal is determined based on the crisis conditions. Perfect signal takes the value of 1 for 24 months preceding the crisis and 0 right when the crisis happens and when there is no crisis in the following 24 months. Perfect signal labeling was conducted from February 1991 to December 2020. Out of 359 observations, 333 were labeled as 0 and 26 as 1.

The last 24 months' data, from January 2021 to December 2022, was trimmed to be used as the basis for crisis prediction. The data in this period only consists of predictor variables as inputs that are used to predict the perfect signal value. With this perfect signal, Thailand's crisis condition in the next 24 months can be predicted. Then, the data that has been trimmed is divided into training and testing data sets with a proportion of 80:20. All predictor variables were normalized using z-score normalization. The normalization parameters (mean and standard deviation) were estimated from the training data and subsequently applied to the testing data to prevent information leakage. In this study, the training data set has a proportion of 269:18 for labels 0 and 1. This shows that there is a class imbalance that needs to be handled using the SMOTE method. The SMOTE method increased the

data in the minority class so that the proportion in the training data set became 269:269 which indicates that the class is balanced.

The preprocessed training data is then used to build the MLP model with SGD, Adam, Nadam, and AdaBound optimization. This study used network architecture with three layers, consisting of one input layer, one hidden layer, and one output layer. In the hidden and output layer, the sigmoid activation function is used, while some hyperparameters are determined based on the results of hyperparameter tuning with the grid search method to obtain the optimal model. The values used in hyperparameter tuning are shown in Table 3, and the results are presented in Table 4.

Table 3 Hyperparameter tuning in this study

Hyperparameter	The Value Used for Tuning
Number of neurons in hidden layer	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Learning rate	0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
Momentum (only for SGD)	0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
Final learning rate (only for AdaBound)	0.1, 0.5, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10

Table 4 Hyperparameter tuning results

Hyperparameter	SGD	Adam	Nadam	AdaBound
Number of neurons in hidden layer	4	5	6	11
Learning rate	0.7	0.2	0.2	0.5
Momentum	0.9	-	-	-
Final learning rate	-	-	-	10

Model evaluation during the hyperparameter tuning stage employed 5-fold cross-validation with binary cross-entropy as the loss function. Although 5-fold cross-validation was used for hyperparameter tuning, the final model evaluation was conducted on a temporally separated testing set to preserve chronological ordering and reduce the risk of look-ahead bias. The best hyperparameter combination, determined by the highest average validation accuracy, was then used to build the MLP models with each optimization method. The training process was performed using a batch size of 128 and 100 epochs. The evaluation results on both validation and testing datasets are presented in Table 5. To identify the most effective model for financial crisis detection in Thailand, the performance of all models was subsequently compared.

Based on Table 5, the MLP model with Nadam optimization produces the best performance among all evaluated optimization methods on both the validation and testing datasets. Therefore, the MLP model with Nadam optimization was selected as the most effective model for predicting financial crises in Thailand. The optimal architecture for this model was determined to be 11–6–1, where the hidden layer consists of six neurons. A single hidden layer was adopted because the dataset size was relatively limited, and previous studies have shown that shallow MLP architectures are generally sufficient for binary financial crisis classification while reducing the risk of overfitting. This architecture was selected through the hyperparameter tuning process, as it provided the best balance between model complexity and generalization capability. The model achieved high accuracy, precision, sensitivity, specificity, and F1-score values, suggesting strong predictive capability for financial crisis detection in Thailand. However, these results should be interpreted with caution due to the limited number of crisis observations and the use of SMOTE for class balancing.

Interestingly, although AdaBound selected 11 hidden neurons during the hyperparameter tuning process, its testing performance remained inferior to that of the Nadam-based model. This finding suggests that increasing the number of hidden neurons does not necessarily improve model generalization. Instead, an appropriate optimization strategy appears to play a more important role in achieving robust predictive performance for financial crisis detection.

Table 5 Comparison of each model's evaluation results

Data	Optimization	Model Evaluation (in Percent)				
		Accuracy	Precision	Sensitivity	Specificity	F1-Score
Validation	SGD	99.07	**99.64**	98.51	98.56	99.07
	Adam	99.26	**99.64**	98.88	98.92	99.26
	Nadam	**99.44**	99.29	**99.62**	**99.64**	**99.45**
	AdaBound	99.26	**99.64**	98.88	99.63	99.26
Testing	SGD	94.44	98.39	95.31	87.50	96.83
	Adam	95.83	98.41	96.88	87.50	97.64
	Nadam	**98.61**	**100.00**	**98.44**	**100.00**	**99.21**
	AdaBound	97.22	98.44	**98.44**	87.50	98.44

Note: Bold values represent the highest value of each column in validation and testing data.

Subsequently, the best model is used to predict the perfect signal in January 2021 to December 2022 through macroeconomic indicators data set in that period. The predicted perfect signal value can provide a sign if there will be a crisis in the next 24 months, from January 2023 to December 2024. A perfect signal of 1 indicates that there is a crisis warning signal, while a perfect signal of 0 indicates that there is no crisis signal for the next 24 months. The perfect signal prediction results are shown in Table 6.

Based on Table 6, the perfect signal is 0 from January 2021 to December 2022 which identifies that there is no crisis signal for the next 24 months. Thus, Thailand is unlikely to experience a financial crisis from January 2023 to December 2024.

Table 6 Perfect Signal Prediction Results for January 2021 to December 2022

Month	Perfect Signal	Month	Perfect Signal
January 2021	0	January 2022	0
February 2021	0	February 2022	0
March 2021	0	March 2022	0
April 2021	0	April 2022	0
May 2021	0	May 2022	0
June 2021	0	June 2022	0
July 2021	0	July 2022	0
August 2021	0	August 2022	0
September 2021	0	September 2022	0
October 2021	0	October 2022	0
November 2021	0	November 2022	0
December 2021	0	December 2022	0

5. Conclusion

This study demonstrates the feasibility of combining CCI-based crisis labeling with multilayer perceptron (MLP) models and modern optimization techniques as an early warning framework for financial crisis detection in Thailand. Using eleven macroeconomic indicators as predictor variables and the perfect signal derived from the Currency Crisis Index (CCI) as the target variable, four optimization methods—SGD, Adam, Nadam, and AdaBound—were evaluated. The results show that the MLP model with Nadam optimization achieved the best predictive performance among the evaluated models, obtaining an accuracy of 99.44% and an F1-score of 99.45% on the validation data, as well as an accuracy of 98.61% and an F1-score of 99.21% on the testing data. These results indicate that the proposed model is capable of effectively identifying financial crisis signals in Thailand. Based on the model predictions, no crisis warning signals were detected during January 2021–December 2022, suggesting a low likelihood of a financial crisis occurring in Thailand during the subsequent period of January 2023–December 2024.

Nevertheless, several limitations should be considered when interpreting the findings. The model was developed solely using Thailand's macroeconomic indicators, which may limit its applicability to countries with different economic structures. In addition, the crisis labels were generated using the CCI framework, which may not fully capture all dimensions of financial distress. The current study also did not incorporate dropout or weight regularization techniques, nor did it evaluate training and validation learning curves to assess potential overfitting. Future research may address these limitations by incorporating regularization methods, learning-curve analysis, additional macroeconomic and financial indicators, alternative crisis identification approaches, and applications to other emerging economies.

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