

Implementation of Backpropagation Artificial Neural Network Algorithm for Turkey Currency Crisis Detection Based on Financial Pressure Index

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ABSTRACT

The currency crises that hit Turkey in 1994, 2001, and 2018 caused the depreciation of the Turkish lira and caused severe adverse effects, especially in the economic sector. In response to these events, this study aims to develop a predictive model capable of identifying future currency crises to help mitigate potential losses. The purpose of this study is to build an early warning model for currency crises in Turkey based on macroeconomic indicators using the Multilayer Perceptron Backpropagation (MLPBP) approach, optimized with the SGD, ADAM, NADAM, and AdaBound algorithms. The independent variables consist of 11 macroeconomic indicators from January 1990 to December 2022, while the response variable is the perfect signal value determined through the Financial Stress Index (FSI). The analysis reveals that the best performing model is the MLPBP optimized with NADAM, achieving an accuracy of 97.29% on the validation data and 93.33% on the test data. The detection results show that no currency crisis is expected to occur in Türkiye from January 2023 to December 2024. This study highlights the

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importance and potential of machine learning approaches, particularly neural network models, in improving early detection and prevention of currency crises.

ملخص

شهدت تركيا أزمات عملة متكررة في أعوام 1994، 2001، و2018، أدت إلى تدهور قيمة الليرة التركية وتسببت في آثار سلبية جسيمة، لا سيما على القطاع الاقتصادي. وفي مواجهة هذه الأحداث، تهدف هذه الدراسة إلى تطوير نموذج تنبؤي قادر على الكشف المبكر عن أزمات العملة المستقبلية للمساعدة في التخفيف من الخسائر المحتملة. تستند الدراسة إلى بناء نموذج إنذار مبكر لأزمات العملة في تركيا باستخدام المؤشرات الاقتصادية الكلية من الفترة بين يناير 1990 وديسمبر 2022، معتمدة على طريقة الشبكة العصبية متعددة الطبقات مع التغذية الراجعة (MLPBP)، ومحسنة باستخدام خوارزميات SGD، وADAM، وNADAM، وAdaBound. شملت المتغيرات المستقلة 11 مؤشرا اقتصاديا كليا، في حين تمثل المتغير التابع قيمة إشارة مثالية مستمدة من مؤشر الضغط المالي (FPI). أظهرت نتائج التحليل أن النموذج المحسن باستخدام خوارزمية NADAM حقق أفضل أداء، حيث بلغت دقته 97.29% على بيانات التحقق و93.33% على بيانات الاختبار. كما أظهرت نتائج الكشف أنه لا يُتوقع حدوث أزمات عملة في تركيا خلال الفترة من يناير 2023 إلى ديسمبر 2024. تؤكد الدراسة على أهمية وفعالية استخدام تقنيات التعلم الآلي، وخصوصا نماذج الشبكات العصبية، في تحسين الكشف المبكر والوقاية من أزمات العملة.

RESUMÉ

Les crises monétaires qui ont frappé la Türkiye en 1994, 2001 et 2018 ont entraîné une dépréciation de la livre turque et ont eu de graves répercussions, en particulier dans le secteur économique. En réponse à ces événements, cette étude vise à développer un modèle prédictif capable d'identifier les crises monétaires futures afin d'aider à atténuer les pertes potentielles. L'objectif de cette étude est de construire un modèle d'alerte précoce des crises monétaires en Türkiye basé sur des indicateurs macroéconomiques à l'aide de l'approche Multilayer Perceptron Backpropagation (MLPBP), optimisée avec les algorithmes SGD, ADAM, NADAM et AdaBound. Les variables indépendantes sont constituées de 11 indicateurs macroéconomiques de janvier 1990 à

décembre 2022, tandis que la variable réponse est la valeur du signal parfait déterminée par l'indice de stress financier (FPI). L'analyse révèle que le modèle le plus performant est le MLPBP optimisé avec NADAM, qui atteint une précision de 97,29 % sur les données de validation et de 93,33 % sur les données de test. Les résultats de la détection montrent qu'aucune crise monétaire n'est prévue en Türkiye entre janvier 2023 et décembre 2024. Cette étude souligne l'importance et le potentiel des approches d'apprentissage automatique, en particulier des modèles de réseaux neuronaux, pour améliorer la détection précoce et la prévention des crises monétaires.

Keywords: Currency Crisis, Macroeconomic Indicators, Multilayer Perceptron Backpropagation (MLPBP), Financial Pressure Index (FPI), Early Crisis Detection.

JEL Classification: C23

1. Introduction

Turkey has access to a large export market because it is at the crossroads of international trade routes and has an open economy. However, Turkey's economic openness makes it vulnerable to financial crises. One part of a financial crisis is a currency crisis. A currency crisis occurs when excessive demand for foreign currency causes a country's currency to weaken (Sitorus et al., 2022). Meanwhile, according to Goldstein, et al. (2000), and Edison (2000,2003) define a currency crisis as an episode in which an attack on a currency causes currency depreciation, a large decrease in foreign exchange reserves, or a combination of both.

Since the 1990s, numerous financial crises have emerged globally, such as the Asian Financial Crisis (1997–1998), the Turkish crisis (2001), and the Global Financial Crisis (2008). Turkey has experienced three major currency crisis episodes: in 1994, 2001, and 2018. The 1994 crisis began due to the government's failure to implement sound macroeconomic policies. The banking and private sectors were heavily burdened by volatile short-term capital flows, leading to a massive devaluation of the Turkish lira. Macroeconomic instability and high budget deficits drove inflation to unprecedented levels. The lira depreciated by 70% against the

U.S. dollar, and overnight interest rates skyrocketed from 70% to 700% (Durgut, 2002; Sakar, 2009).

Although the economy recovered through the 1999 Economic Stabilization Program, it was not sustainable. The 2001 crisis re-emerged due to political tensions between Prime Minister Bulent Ecevit and President Ahmet Nejdet Sezer, which triggered a loss of investor confidence, capital outflows, and further devaluation (Durgut, 2002). The third crisis, in 2018, was largely driven by geopolitical tensions, particularly U.S. sanctions related to Iran and the detention of an American pastor by Turkey. These tensions triggered economic instability and led to a sharp 41% depreciation of the lira (Oyvay, 2018; Zanotti & Thomas, 2017). Although Turkey received financial support from Eastern allies, the impacts of the crisis were significant (Jamilah et al., 2023).

Given the repeated occurrence of currency crises in Turkey and their devastating impacts, the development of an early warning model is crucial for safeguarding economic stability. Several previous studies have addressed this issue. Sugiyanto et al. (2019) used the MRS-ARCH (2,1) model with real interest rate indicators, while Sugiyanto et al. (2018) demonstrated that indicators such as bank deposits, trade rates, and real exchange rates are effective for crisis detection in Indonesia. In the Turkish context, Sevim et al. (2014) used artificial neural networks (ANNs), decision trees, and logistic regression with 32 macroeconomic indicators. Ecer (2013) compared multilayer perceptron (MLP), radial basis function (RBF), and support vector machines (SVM) for bank health classification. Aydin and Cavdar (2015) applied ANN using seven macroeconomic variables for crisis detection. Additionally, Bluwstein et al. (2021) employed a wide array of machine learning models, including decision trees, random forests, and SVMs, using data from 17 countries. Pertiwi et al. (2023) applied ANN with ADAM optimization for financial crisis detection in Indonesia. These studies confirm the potential of ANN-based models for accurate crisis prediction, primarily due to their lower reliance on restrictive assumptions (Sun & Lei, 2020).

Building on these insights, this study develops a multilayer perceptron neural network (MLP-NN) model with backpropagation, enhanced by four different optimization algorithms: SGD, ADAM, NADAM, and AdaBound. Ten macroeconomic indicators, adapted from Kaminsky et al.

(1998), are used as model inputs to detect patterns leading to currency crises in Turkey.

This study contributes to the literature by comparing several training algorithms within the MLP-NN framework, allowing for a more comprehensive understanding of the model's performance. While prior studies in Turkey have employed ANN or traditional machine learning techniques, they often rely on a single optimization method or lack systematic comparison. The novelty of this study lies in its methodological refinement and empirical focus on optimizing neural network training for early warning purposes. The findings indicate that one of the optimization methods outperforms the others in terms of accuracy, sensitivity, and specificity.

Overall, this model can serve as a valuable tool for policymakers in developing data-driven early warning systems, thereby supporting macroeconomic policy planning and financial risk management. Furthermore, the approach developed in this study has the potential to be replicated in other countries with similar economic structures.

2. Literature Review

2.1. Currency Crisis Identification

Sevim et al. (2014) conducted a financial crisis approach through the financial pressure index (FPI) which uses the US dollar exchange rate, foreign exchange reserves, and Bank Indonesia interest rates. The FPI calculation formula is as follows

$$FPI_t = \frac{\left(\frac{e_t - \bar{x}_e}{\sigma_e}\right) - \left(\frac{r_t - \bar{x}_r}{\sigma_r}\right) + \left(\frac{i_t - \bar{x}_i}{\sigma_i}\right)}{3} \quad (1)$$

$$e_t = \left(\frac{e_t - e_{t-1}}{e_{t-1}}\right), r_t = \left(\frac{r_t - r_{t-1}}{r_{t-1}}\right), i_t = \left(\frac{i_t - i_{t-1}}{i_{t-1}}\right) \quad (2)$$

Where e_t is the currency exchange rate against the U.S. dollar in month t , r_t is the foreign exchange reserves in month t , and i_t is the interest rate of the Central Bank of the Republic of Turkey in month t .

The threshold determination uses the following formula.

$$Threshold = \mu_{FPI} + a\sigma_{FPI} \quad (3)$$

with the coefficient a used being 1.5, 2, 2.5, and 3.

The following equation can be used to determine the crisis condition.

$$\text{Crisis} = \begin{cases} 1, & \text{if } \text{FPI}_t > \text{Threshold} \\ 0, & \text{if } \text{FPI}_t < \text{Threshold} \end{cases} \quad (4)$$

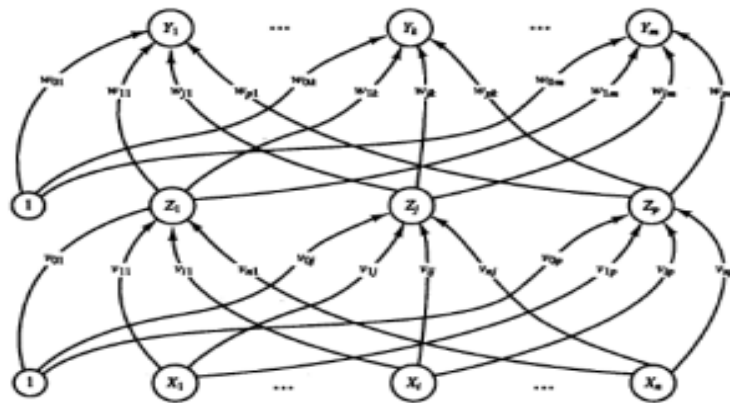
Furthermore, in this study, the perfect signal value provides a warning 24 months before the crisis occurs. The signal is defined in the following equation.

$$\text{PS}_t = \begin{cases} 1, & \text{if } \exists i = 1, 2, \dots, 24 \text{ FPI}_{t+i} > \mu_{\text{FPI}} + a\sigma_{\text{FPI}} \\ 0, & \text{others} \end{cases} \quad (5)$$

2.2. Multilayer Perceptron Backpropagation

Multilayer perceptron (MLP) is the most commonly used type of artificial neural network. These systems mimic the characteristics of neural networks in the human body (Fausett, 1994). MLPs have at least one hidden layer between the input and output layers, which allows them to overcome the limitations of single-layer neural networks in terms of pattern recognition. Each layer in an MLP is fully connected with the next layer. The method uses a backpropagation algorithm, which adjusts the weights on the neural network architecture backward to minimize the error between the predicted result and the actual target. The MLP training process consists of three stages, namely feedforward, backpropagation, and weight update. Figure 1 shows an MLP architecture with one hidden layer.

Figure 1: The Single Hidden Layer MLPBP Network



Source: Fausett, L.1994: Fundamentals of Neural Networks: Architectures, Algorithms, and Application

2.3. Stochastic Gradient Descent Optimization

Stochastic Gradient Descent is one of the optimization algorithms based on gradients. This optimization takes random data and calculates the data loss to calculate the gradient and update weight with a constant learning rate. SGD optimization with momentum has a momentum parameter (γ) to determine the influence of the weight change in the previous iteration. The weight shift is forced to continue moving by momentum in order to avoid becoming trapped at a local minimum (Umar et al., 2020). The SGD optimization algorithm is as follows:

Derive the loss function by finding the gradient value using the following formula:

$$g_h = \nabla_w L(f(x_t, w), y_t) \quad (6)$$

Where $L(f(x_t, w), y_t)$ is the loss function used in backpropagation and y_t is the target value.

Calculating weight average.

$$\bar{v}_h = \gamma \bar{v}_{h-1} + \eta g_h \quad (7)$$

Updating weights.

$$g_h = \nabla_w L(f(x_t, w), y_t)$$

2.4. Adaptive Moment Estimation Optimization

Adaptive Moment Estimation (ADAM) is a combined optimization of momentum and Root Mean Squared Propagation (RMSprop) used to update weights in neural networks. ADAM optimization, introduced by Kingma and Ba (2015) utilize an adaptive learning rate for individual weights by calculating both the first and second gradient moments to adjust the weights. The first moment is used to accelerate convergence towards the global minimum, while the second moment is used to calculate the learning rate adaptively at each iteration (Amin et al., 2019). This optimization has two additional hyperparameters, namely the first moment's exponential decay rate (β_1) and the second moment's exponential decay rate (β_2). The ADAM algorithm is as follows:

Derive the loss function by finding the gradient value using the following formula:

$$g_h = \nabla_w L(f(x_t, w), y_t)$$

Calculating first and second-moment estimates.

$$m_h = \beta_1 m_{h-1} + (1 - \beta_1) g_h \quad (8)$$

$$v_h = \beta_2 v_{h-1} + (1 - \beta_2) g_h^2 \quad (9)$$

Calculating the corrected moment estimate.

$$\hat{m}_h = \left(\frac{\beta_1 m_h}{1 - \beta_1^{h+1}} + \frac{(1 - \beta_1) g_h}{1 - \beta_1^h} \right) \quad (10)$$

$$\hat{v}_h = \frac{v_h}{1 - \beta_2^h} \quad (11)$$

Update weights.

$$w_h = w_{h-1} - \frac{\eta}{\sqrt{\hat{v}_h} + \delta} \hat{m}_h \quad (12)$$

2.5. Nesterov-accelerated Adaptive Moment Estimation Optimization

Nesterov-accelerated Adaptive Moment Estimation is a combination of ADAM optimization with Nesterov's Accelerated Gradient (NAG) momentum. This is done to increase the network model's quality and convergence speed by correcting the first moment in ADAM using NAG momentum (Dozat, 2016). The NADAM algorithm is as follows:

Derive the loss function by finding the gradient value using the following formula:

$$g_h = \nabla_w L(f(x_t, w), y_t)$$

Calculating first and second-moment estimates.

$$m_h = \beta_1 m_{h-1} + (1 - \beta_1) g_h$$

$$v_h = \beta_2 v_{h-1} + (1 - \beta_2) g_h^2$$

Calculating the corrected moment estimate.

$$\hat{m}_h = \left(\frac{\beta_1 m_h}{1 - \beta_1^{h+1}} + \frac{(1 - \beta_1) g_h}{1 - \beta_1^h} \right)$$

$$\hat{v}_h = \frac{v_h}{1 - \beta_2^h}$$

Update weights.

$$w_h = w_{h-1} - \frac{\eta}{\sqrt{\hat{v}_h} + \delta} \hat{m}_h$$

2.6. Adaptive Gradient Methods with Dynamic Bound of Learning Rate Optimization

According to Luo et al. (2019), AdaBound is an optimization that combines ADAM and SGD methods together, the adaptive method is

applied at the beginning of training and the SGD is applied at the end of training. The adaptive learning rate method can produce extreme learning rate values that cause unstable training. This optimization applies a learning rate cut in ADAM at the beginning of training inspired by gradient clipping. In addition, AdaBound also utilizes dynamic bounds on the learning rate to ensure that the learning rate stays within its lower and upper bounds, which are initially initialized as zero and infinite. The AdaBound algorithm is as follows:

Derive the loss function by finding the gradient value using the following formula:

$$g_h = \nabla_w L(f(x_t, w), y_t)$$

Calculating first and second-moment estimates.

$$\begin{aligned} m_h &= \beta_1 m_{h-1} + (1 - \beta_1) g_h \\ v_h &= \beta_2 v_{h-1} + (1 - \beta_2) g_h^2 \end{aligned}$$

Truncate the learning rate that exceeds the threshold.

$$\eta_l(h) = \left(1 - \frac{1}{(1-\beta_2)^{h+1}}\right) \eta^* \quad (13)$$

$$\eta_u(h) = \left(1 + \frac{1}{(1-\beta_2)^h}\right) \eta^* \quad (14)$$

$$\begin{aligned} \hat{\eta}_h &= \text{Clip}\left(\frac{\eta}{\sqrt{v_h}}, \eta_l(h), \eta_u(h)\right) \\ \eta_h &= \frac{\hat{\eta}_h}{\sqrt{h}} \end{aligned} \quad (15)$$

Updating weights.

$$w_h = w_{h-1} - \eta_h m_h \quad (16)$$

2.7. Model Evaluation

The confusion matrix is viewed during model evaluation in order to gauge the model's effectiveness. An actual value and the model's projected values are compared in a table called the confusion matrix (Han et al., 2012).

Table 1: Confution Matrix

Actual	Class	Prediction	
		Positif	Negatif
	Positif	True Positive (TP)	False Negative (FN)
	Negatif	False Positive (FP)	True Negative (TN)

The model goodness criteria, which include accuracy, precision, and recall values, can be determined by analyzing the confusion matrix.

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

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

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

3. Data and Methodology

This study uses monthly data from January 1990 to December 2022 obtained from the official websites of the International Monetary Fund (IMF) and the Central Bank of the Republic of Turkey (CBRT). The quality and reliability of this data is very high, given the credibility of these sources, which employ rigorous data collection and validation processes. The comprehensive coverage of relevant economic indicators as well as this indicator data that has been used in the studies of Kaminsky et al. (1998) and Sevim et al. (2014) which proved to be useful as currency crisis detection indicators.

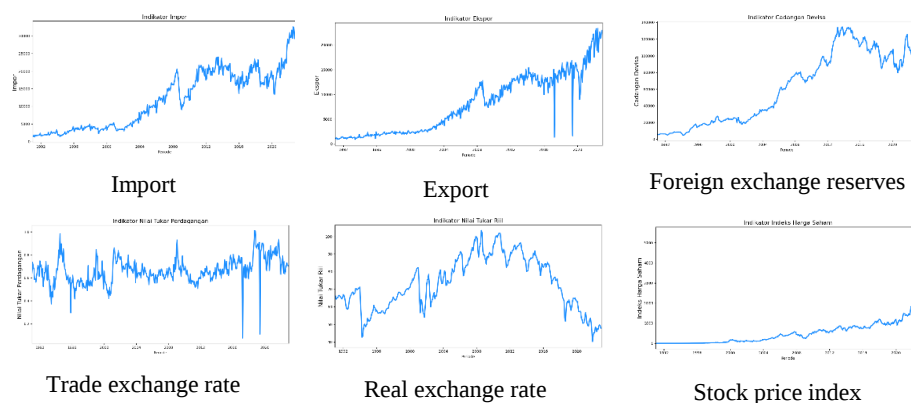
The data consists of eleven macroeconomic indicators: exports, imports, trade exchange rate, the ratio of M2 to foreign exchange reserves, foreign exchange reserves, M1, M2 multiplier, real exchange rate, the difference between Turkey's real interest rate and the Federal Reserve's real interest rate, stock price index, and real deposit interest rate. These indicators are used as independent variables, and the value of perfect signals is used as a dependent variable. The steps involved in the research are as follows:

- a) Collect and prepare the data that will be used in this research.
- b) Determine the perfect signal value based on the Financial Pressure Index (FPI).
- c) Perform data preprocessing, which consists of cutting the last 24 months of data for crisis prediction, checking missing values, dividing the data into training and testing data, normalizing the data using z-score normalization, and handling data imbalance by applying the Synthetic Minority Oversampling Technique (SMOTE).
- d) Construct a multilayer perceptron model with optimization using SGD, Adam, Nadam, and AdaBound methods on the training dataset, following hyperparameter tuning with five-fold cross-validation.
- e) Evaluate the model based on accuracy, precision, and recall. After that, determine the best model.
- f) Predict a currency crisis in Turkey from January 2023 to December 2024.

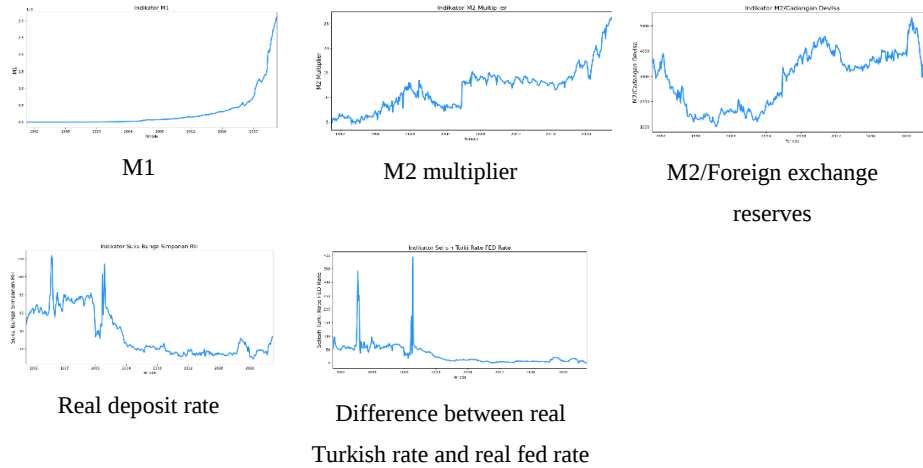
4. Empirical Results

Time series plots of each indicator to determine the characteristics of the indicators during the crisis in 1994, 2001, and 2018 are presented in Figure 2. Figure 2 shows that each indicator fluctuates during a crisis.

Figure 2: Macroeconomic Indicator Time Series Plots



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This study uses the Financial Pressure Index (FPI) to detect crisis conditions in Turkey. This choice is based on the suitability of the FPI approach, which aligns more accurately with the actual crisis conditions in Turkey compared to the Exchange Market Pressure (EMP) index and the Composite Coincident Indicator (CCI). The FPI provides a more comprehensive and precise measure of financial stress, capturing the nuances of Turkey's economic environment. The Financial Pressure Index (FPI) value, which is compared with the threshold and has a coefficient value of 1.5, 2, 2.5, and 3, can be used to determine the crisis conditions in Turkey. The plot of the comparison of the FPI and threshold values is shown in Figure 3.

Figure 3: Financial Pressure Index and Threshold Values

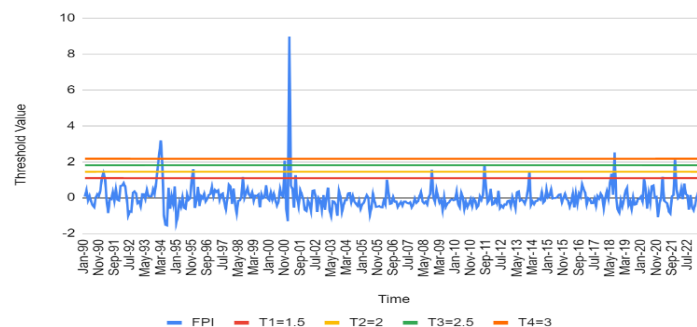


Figure 2 shows a crisis occurs when the FPI value exceeds the threshold. Details of the crisis conditions according to the plot above as shown in Table 2.

Table 2: Turkey's Crisis Condition

Coefficient	Month of Crisis
$\alpha = 1.5$	January 1991, February 1991, January 1994, February 1994, March 1994, April 1994, December 1995, August 1998, November 2000, February 2001, June 2001, October 2008, August 2011, January 2014, June 2018, August 2018, March 2021, November 2021
$\alpha = 2$	January 1994, February 1994, March 1994, April 1994, December 1995, November 2000, February 2001, October 2008, August 2011, August 2018, November 2021
$\alpha = 2.5$	February 1994, March 1994, April 1994, November 2000, February 2001, August 2011, August 2018, November 2021
$\alpha = 3$	February 1994, March 1994, February 2001, August 2018

Based on Table 2, the threshold value with a coefficient of 3 can describe the actual crisis conditions. Next, determine the perfect signal value as the response variable. A perfect signal has a value of 1 for 24 months before the crisis and 0 for the others.

Pre-processing data will be carried out before further analysis. The first step is to check for redundant data and missing values. The results of checking that no values were missing or duplication of data were then cut into the last 24 months as predictive data. Next, split the data in an 80:20 ratio between the training and testing sets. Training and testing data are z-score normalized so that the value range is the same. The number of label classes 1 and 0 in the training data is different. Therefore, it is necessary to do SMOTE to overcome the imbalance in the class.

Multilayer Perceptron Backpropagation (MLPBP) using SGD, ADAM, NADAM, and AdaBound optimization is one of the artificial neural network designs that was used to create the model. The perfect signal in binary class form was the independent variable, while the dependent variable used was 11 macroeconomic indicators. The output layer and hidden layer both employed the sigmoid activation function.

4.1. Turkey Crisis Detection in 2018-2019

Prior to the establishment of a model for crisis detection in 2023 to 2024, a multilayer perceptron backpropagation model was established with monthly data from 1990 to 2017 to detect the 2018 to 2019 Turkish crisis that had occurred. This was done to check the validity of the artificial neural network in detecting the Turkish currency crisis. The four models that have been formed have the parameters presented in Table 3.

Table 3: Parameters in The Backpropagation Multilayer Perceptron Model

Model	Learning Rate Value	Number of Neurons in Hidden Layer
SGD	0.7	8
ADAM	0.2	9
NADAM	0.3	10
AdaBound	0.3	10

Table 3 shows the optimal values for each model in crisis detection. After determining these values, the models were tested with training and testing data, and the optimal model was selected by comparing the evaluation results. The k-fold cross-validation method with k set to 5 was used for testing the training data. The purpose of k-fold cross-validation is to evaluate the model more accurately and reliably by maximizing the use of available data. The model evaluation results are presented in Table 4.

Table 4: Evaluation Results of The Backpropagation Multilayer Perceptron Model for Crisis Detection in 2018-2019

		Model evaluation		
		Accuracy	Precision	Recall
Validation data	MLPBP-SGD	96.92%	94.37%	100%
	MLPBP-ADAM	96.67%	94.66%	99.05%
	MLPBP-NADAM	97.86%	96.41%	99.52%
	MLPBP-AdaBound	96.87%	95.88%	98.08%
Testing data	MLPBP-SGD	90.48%	90%	90%
	MLPBP-ADAM	92.06%	92%	92%
	MLPBP-NADAM	93.65%	94%	94%
	MLPBP-AdaBound	92.06%	92%	92%

Table 4 suggests that the MLPBP model with NADAM optimization outperforms other optimization methods in terms of accuracy, precision, and recall values. Therefore, Turkish currency crisis detection in 2018 and 2019 using NADAM optimization. The perfect signal value prediction results from January 2016 to December 2017 are used to predict the Turkish currency crisis from January 2018 to December 2019 because a perfect signal of value 1 can provide a crisis warning signal, and a value of 0 can provide a non-crisis warning signal for the next 24 months. The perfect signal value prediction results can be seen in Table 5.

Table 5: The Perfect Signal Value Prediction Results in Januari 2016 to December 2017

Period	Perfect Signal	Period	Perfect Signal
January 2016	1	January 2017	1
February 2016	1	February 2017	1
March 2016	1	March 2017	1
April 2016	1	April 2017	1
May 2016	1	May 2017	1
June 2016	1	June 2017	1
July 2016	1	July 2017	1
August 2016	1	August 2017	1
September 2016	1	September 2017	1
October 2016	1	October 2017	1
November 2016	1	November 2017	1
December 2016	1	December 2017	1

Table 5 shows that the perfect signal from January 2016 to December 2017 is 1, which means that the crisis warning signal for the next 24 months, so it can be concluded that from January 2018 to December 2019 there will be a Turkish currency crisis. This is evidenced by the Turkish crisis in 2018.

4.2. Turkey Crisis Detection in 2023-2024

Modeling was also conducted to detect the Turkish currency crisis of 2023 to 2024. The four models that have been formed have the parameters showcased in the Table 6.

Table 6: Parameters in The Backpropagation Multilayer Perceptron Model to Detect The Turkish Currency Crisis of 2023 to 2024

Model	Learning rate value	Number of neurons in hidden layer
SGD	0.9	7
ADAM	0.2	11
NADAM	0.4	10
AdaBound	0.2	10

Table 6 shows the optimal values of each model for crisis detection. Once the values are known, the models are tested with training and testing data and then the results of the model evaluation are compared to determine the best model. Testing on this training data also uses the k-fold cross-validation method. The outcomes of model evaluation are depicted in Table 7.

Table 7: Evaluation Results of The Backpropagation Multilayer Perceptron Model for Crisis Detection in 2023-2024

		Model evaluation		
		Accuracy	Precision	Recall
Validation data	MLPBP-SGD	96.25%	94.46%	98.33%
	MLPBP-ADAM	96.67%	95.30%	98.33%
	MLPBP-NADAM	97.29%	96.44%	98.33%
	MLPBP-AdaBound	96.88%	95.96%	97.92%
Testing data	MLPBP-SGD	90.67%	93.33%	94.41%
	MLPBP-ADAM	92%	93.44%	96.61%
	MLPBP-NADAM	93.33%	95%	96.61%
	MLPBP-AdaBound	92%	93.44%	96.61%

Table 7 shows that the accuracy, precision, and recall values of the MLPBP model assessment using NADAM optimization on validation and test data are greater than those of other optimizations. Consequently, the most effective model for identifying the Turkish currency crisis is the MLPBP model with NADAM optimization.

Prediction of the Turkish currency crisis from January 2023 to December 2024 is carried out using the MLPBP model with NADAM optimization. The perfect signal value prediction results from January 2021 to

December 2022 are used to predict the Turkish currency crisis from January 2023 to December 2024 because a perfect signal of value 1 can provide a crisis warning signal, and a value of 0 can provide a non-crisis warning signal for the next 24 months. The perfect signal value prediction results can be seen in Table 8.

Table 8 shows that the perfect signal for January 2021 to December 2022 is 0, which means that the warning signal is not a crisis for the next 24 months so it can be concluded that in January 2023 to December 2024 there is no Turkish currency crisis.

Table 8: The Perfect Signal Value Prediction Results in January 2021 to December 2022

Period	Perfect Signal	Period	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

Based on the analysis, macroeconomic indicators such as imports, exports, foreign exchange reserves, exchange rates, stock price index, and other monetary indicators showed significant fluctuations during the crisis periods in Turkey, namely in 1994, 2001, and 2018. These fluctuations reflect the economic instability that occurred during those times. To more accurately detect crisis conditions, this study employed the Financial Pressure Index (FPI), which proved to be more aligned with actual conditions compared to other approaches such as the Exchange Market Pressure (EMP) and the Composite Coincident Indicator (CCI).

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The FPI captures financial stress more comprehensively, and a coefficient value of 3 was found to most accurately represent the actual timing of the crises.

Prior to model development, data preprocessing was carried out, including normalization and class balancing using the SMOTE technique to address the imbalance between crisis and non-crisis data. The crisis detection model was then built using a Multilayer Perceptron Backpropagation (MLPBP) approach with four optimization methods: SGD, ADAM, NADAM, and AdaBound. Evaluation results showed that the model optimized with NADAM performed the best in terms of accuracy, precision, and recall on both validation and testing datasets.

The application of the model to detect the 2018–2019 Turkish crisis showed that the perfect signal values from January 2016 to December 2017 were all equal to 1, indicating a crisis warning signal for the next 24 months. This result is consistent with the fact that a crisis did occur in 2018, demonstrating the model's validity in accurately detecting crises. Furthermore, the same model was applied to the 2023–2024 period based on the predicted signal values from January 2021 to December 2022, which were all equal to 0. This indicates the absence of a crisis warning signal for the following 24 months, leading to the conclusion that no currency crisis occurred in Turkey between January 2023 and December 2024. These findings demonstrate that the MLPBP model with NADAM optimization is a reliable and effective tool for detecting and predicting currency crises based on macroeconomic indicators.

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