Pak.j.stat.oper.res. Vol.18 No. 4 2022 pp 1015-1025 DOI: http://dx.doi.org/10.18187/pjsor.v18i4.3927

Pakistan Journal of Statistics and Operation Research

An Intelligent Hybrid Model Using Artificial Neural Networks and Particle Swarm Optimization Technique For Financial Crisis Prediction

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Abstract

Financial crisis prediction is a critical issue in the economic phenomenon. Correct predictions can provide the knowledge for stakeholders to make policies to preserve and increase economic stability. Several approaches for predicting the financial crisis have been developed. However, the classification model's performance and prediction accuracy, and legal data, are insufficient for usage in real applications. So, an efficient prediction model is required for higher performance results. This research proposes a novel two-hybrid intelligent prediction model using an Artificial Neural Network (ANN) for prediction and Particle Swarm Optimization (PSO) for optimization. The model can be used for early detection of currency crises. At first, a PSO technique produces the hyperparameter value for ANN to fit the best architecture. They are weights and thresholds. Then, they are used to predict the performance of the given dataset. In the end, ANN-PSO generates predictions value of crisis conditions. The proposed ANN-PSO model is implemented on time series data of economic conditions in Indonesia. Dataset was obtained from International Monetary Fund and the Indonesian Economic and Financial Statistics. Independent variable data using 13 potential indicators. Meanwhile, the dependent variable uses the perfect signal value based on the Financial Pressure Index. Experimental analysis shows that the proposed model is reliable based on the different evaluation criteria. The case studies show that predictive data results are consistent with the actual situation, which has helped predict a financial crisis.

Key Words: Crisis; Financial; Machine Learning; Optimization; Prediction

Mathematical Subject Classification: 60D05

1. Introduction

The financial crisis is also known as a balance of payments crisis, which occurs when the value of a country's financial assets fluctuates so rapidly while the function of money as an intermediary of exchange and a store of value is not fulfilled. It is defined as a situation in which the state of the economy of a country deteriorates significantly. This decline is usually the result of a financial crisis and can manifest as stagflation, recession, or economic depression. During times of crisis, the value of gross domestic product, liquidity, property prices and stocks all plummeted.

There are two major financial crises occurred, namely the 1997 East Asian Financial Crisis and the 2008 Global Financial Crisis. The financial crisis 1997 was caused by a lack of transparency and government credibility, which resulted in structural and policy distortions (Corsetti et al., 1999), while the 2008 was primarily caused by rapid innovations in financial products such as securitization practices and "credit default swaps." Property speculation and inaccurate credit ratings exacerbate the situation. Due to the contagious effect of a globally integrated financial system and the rapid spread of information, the development of the crisis spread to other continents in both cases and, in a short time, became a global crisis. For example, the financial crisis in 1997 quickly spread to several Asian countries, such as South Korea, Hong Kong, Laos, the Philippines, Malaysia, and Indonesia. Its impact has drastic changes that lead to complicated financial problems. Indonesia is one of the worst affected countries. The cost needed to save the Indonesian economy at that time was the most expensive (Tarmidi, 2003).

According to World Bank data, Indonesia encountered the worst economic growth in 1998, with a minus value of 13.1%. While the global financial crisis in 2008 was caused by the subprime mortgage crisis in the United States, it also affected several Southeast Asian countries, including Indonesia. Indonesia's economic growth has slowed from 6.01% to 4.63%, according to data released by the Indonesian Central Statistics Agency. The impact of the two financial crises in Indonesia shows that the government does not have optimal crisis anticipation. It is because there is no crisis signal to detect an upcoming crisis, so there is a need for a model that can generate a crisis signal. The dynamics of the crisis reveal a significant relationship between the financial and currency crises (Dewi et al., 2018). In this way, financial crisis prediction is possible.

The International Monetary Fund (IMF) believes that an early warning system for economic crises is essential. Financial exchange rates can be used as an indicator to represent a country's economic condition (Corsetti et al., 1999). The exchange rate becomes significant because it can be used as an instrument to assess a country's economic condition. A country with a stable currency value indicates that the country's economic conditions are stable. Extremely volatile exchange rates will disrupt economic activity in both the real and monetary sectors. So good exchange rate management is required in order for the exchange rate movement to be stable, so that fluctuations can be predicted and the economy can continue to run smoothly. It is expected to help prevent future economic crises. Thus, as a result, the government can enact policies and regulations that will help to strengthen Indonesia's economic strength. For example, domestic consumption, investment, exports, and government spending (Dewi et al., 2018). The research is expected to provide benefits for academics, policymakers, and investors in the future. Policymakers should pay close attention to suspicious companies in particular. Meanwhile, investors can plan on mitigating the risks that may arise.

Various studies stated that the financial crisis prediction system is still looking for the ideal method in predicting future financial conditions. It can use statistical theory and machine learning implementation. Both methods can generate accurate predictions, and other methods can still optimize them. In this research, optimization techniques are combined with machine learning methods to improve model performance to obtain the best model.

The research proposes a machine learning method with optimization techniques based on previous studies. It has the advantage of utilizing a comprehensive data set to develop predictive models by using 13 potential indicators (Kaminsky et al., 1998). It leads to the development of research on prediction systems that can be carried out. Therefore, it produces a model that can be used for prediction with accurate and factual performance, allowing it to predict a country's economic condition and decide on actions to avoid unwanted risks.

The development of an empirical model has been proposed. Comelli employs two regression models, probit and logit. The signal model approach uses several indicators to provide information about crisis signals. The mathematical model detects financial crises by using machine learning methods to make predictions and classifications based on pattern recognition on financial data (Comelli, 2016). Meanwhile, the statistical model uses a combination of Volatility and Markos Switching by using several potential indicators (Sugiyanto et al., 2018).

Machine learning methods such as Artificial Neural Network (ANN), Support Vector Machine (SVM) (Anggoro & Novitaningrum, 2021), Decision Tree (DT), Naïve Bayes (NB), Bayesian Belief Network (BNN) (Albashrawi & Lowell, 2016), and K- Nearest Neighbor (KNN) (Uthayakumar et al., 2018) were used as a prediction model. This research is used as a reference for other researchers to test the capability of each model. Furthermore, the ANN method is the most accurate predictive model. DT and BBN produce relatively good results, while SVM and NB are the weakest models (Dutta et al., 2017). ANN methods outperform to Logistic Regression and Decision Tree (Sevim et al., 2014). In addition, ANN is also used as a Hybrid method with K-NN (Uthayakumar et al., 2018; Fricke, 2017). ANN is a method that learns about data patterns by optimizing the objective function. Among them are the number of variables, nodes, and hidden layers that influence prediction performance, which is an essential issue in machine learning ((Kılıç et al., 2021); (Erzurum Cicek & Kamisli Ozturk, 2021); (Camero et al., 2020)). The popular optimization techniques used in neural networks are Stochastic Gradient Descent (Sun et al., 2020), Ant Colony Optimization (Uthayakumar et al., 2020), and Particle Swarm Optimization (Aly et al., 2019). PSO outperforms other optimization techniques (Zhou et al., 2020). Furthermore, the research claims that ANN model with PSO technique outperforms other methods, such as Hybrid Neural Fuzzy Inference System, Classification and Regression Tree, Support Vector Machine, Multiple Linear Regression, and Conditional Inference Tree (Zhang et al., 2020).

At present, there are many methods for predicting a economic crisis, but their performance in not obvious. This paper presents an intelligent hybrid model by combining Artificial Neural Network algorithms and Particle Swarm Optimization techniques that able to detect and predict an economic crisis. The final results conducted are consistent with the actual result and have good performance results. The indicators used are potential indicators from Kaminsky's research consist of 13 indicators. The data was obtained from the official websites of the International Monetary Fund and the Indoneines the US dollar interest rate, exchange rate, and foreign exchange reserves are taken from Bank Indonesia data.

2. The Material and Method

A financial crisis can be identified by Financial Pressure Index (FPI) (Corsetti et al., 1999). FPI combines the US dollar interest rate, exchange rate, and foreign exchange reserves are taken from Bank Indonesia data. Formula to calculate FPI in Equation 1.

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

e_t is the US dollar exchange rate in month t. r_t is foreign exchange reserves in month t. i_t is the interest rate from Bank Indonesia in month t. FPI values are compared with a threshold value to determine the month of the crisis. Formula to calculate a threshold value in Equation 2.

$$T = \bar{x} + a\sigma \tag{2}$$

Threshold (T) is the sum of the average value of FPI with the standard deviation multiplied by the value of a. The a value used are a = 1.5, a = 2, a = 2.5 and a = 3. Determination of the crisis conditions is used to find the Perfect Signal (PS) as an independent variable. PS is a series of signals that can provide a crisis warning for 12 months before the time considered FPI. It assigns a value of 1 for 12 months before a crisis occurs and 0 when a crisis occurs. PS value determined on the condition in Equation 3.

$$PS_i = \begin{cases} 1, if\ \exists k=1,2,\ldots,12\ FPI_{i+k} > T, \\ 0, others \end{cases} \tag{3}$$

2.1. Artificial Neural Network

Artificial Neural Network (ANN) is inspired by a complex learning system consisting of interconnected neurons. It can select information such as classifying a pattern. ANN can estimate the range of a mathematical model so that it can increase linearly or nonlinearly (Fausset L., 1994).

ANN has three different models: Multilayer Perceptron, Radial Basis Function, and Kohonen Network. This research uses the Multilayer Perceptron model, a general model for prediction problems (Fricke, 2017). Multilayer Perceptron is a model that describes a set of inputs into a set of outputs using a nonlinear activation function that uses a feedforward neural network, with the information only moving in one direction, from the input node through the hidden node and the output node. Neuron's output can be described using Equation 4.

$$y_i = f\left(\sum X_j W_{ij}\right) + \theta_j \tag{4}$$

The connection weights, W_{ij} connect the input to hidden layer and show the j neuron threshold. The network's transfer function is denoted by f, and the neuron's inputs are denoted by X_j. The primary goal of developing and training a neural network model is to discover, update, and optimize parameters to minimize objective functions and make accurate predictions for new inputs.

2.2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is applied population-based metaheuristic optimization algorithms (Qi et al., 2018). The population consists of many particles that are seeded with a population of random solutions to solve the problem. Each particle can replace the candidate solution and change the position equivalent to the particle speed through the search space using a dynamic speed equivalent to historical behavior to move towards the optimal position. Therefore, the particles go to a better area during the search process (Grosan et al., 2006). Formula to calculate the displacement position and velocity of the particle in Equation 5 and Equation 6.

$$Vi\ (t) = Vi\ (t-1) + c1\ r1\left[\left(Xpbest - Xi\ (t)\right)\right] + c2\ r2\left[\left(Xgbest - Xi\ (t)\right)\right] \quad (5)$$

$$Xi(t) = Xi(t-1) + Vi(t) \quad (6)$$

During training iteration, each particle remembers its own best position $Xpbest$, and the global best value $Xgbest$ is determined from all of these. The particles are attracted by $Xpbest$ and $Xgbest$, as shown in expression (5). The particle velocity vectors V are modified at each iteration according to (5). Factors c1 and c2 are empirically determined and are used to balance exploration and convergence. Expression is used to calculate the new position (6). $r1$ and $r2$ are random numbers uniformly distributed in the interval 0 and 1 . The Uniform distribution's random value aids in improving global search capability and optimizes local search capability at low dimensions caused by finite particles (Dai et al., 2018). $Xpbest$ is the best position of a particle with the best fitness function and $Xgbest$ is the global best position with the best fitness value among all the particles.

The PSO method is based on acceleration, and each particle goes to its $Xpbest$ and $Xgbest$ locations at each iteration. Each particle in the search space for k-dimension and m-size can be represented as: $Xi = (x_{i1}, x_{i2}, \dots, x_{in},)(t)$; $Vi = (v_{i1}, v_{i2}, \dots, v_{in},)(t)$ which can be updated using Equation 5 and 6. $Xpbest$ denotes the best location reached with particle i at time t, whereas $Xgbest$ denotes the best position connected with the entire swarm.

2.3. ANN training optimization-based PSO

PSO methodology employs particle collection to inquire into solutions in the state space. Each particle records ANN parameters that need to be tweaked during the last training session: thresholds and weights (Gudise & Venayagamoorthy, 2003).

The ANN-PSO hybrid algorithm's fundamental steps are shown in Figure 1:

1. Import data set for experimental.
2. Define the ANN structure and determine a parameter of weights and thresholds.
3. Compute the parameter's value used in the network by summing the total number of neurons in the ANN's input, hidden and output layers.
4. Set PSO parameters for each solution to position and velocity.
5. Calculate the error of each particle and determine $Xpbest$ and $Xgbest$.
6. Determine the position and velocity of each particle by using Equation 5 and Equation 6.
7. Define the best fitness value of $Xpbest$, and the best position of the particles, $Xi(t)$. If the best fitness value, $Xpbest$ is more than the current fitness value, $f(Xi(t))$, update $Xpbest$ and the solution's location, $Xi(t)$ by using the current fitness value.
8. If the best value for the current population for each solution is more than the population fitness value $Xgbest$, then use the solution of the current fitness value to adjust the best population fitness value.
9. Weights and thresholds are displayed as results of the ANN parameters.

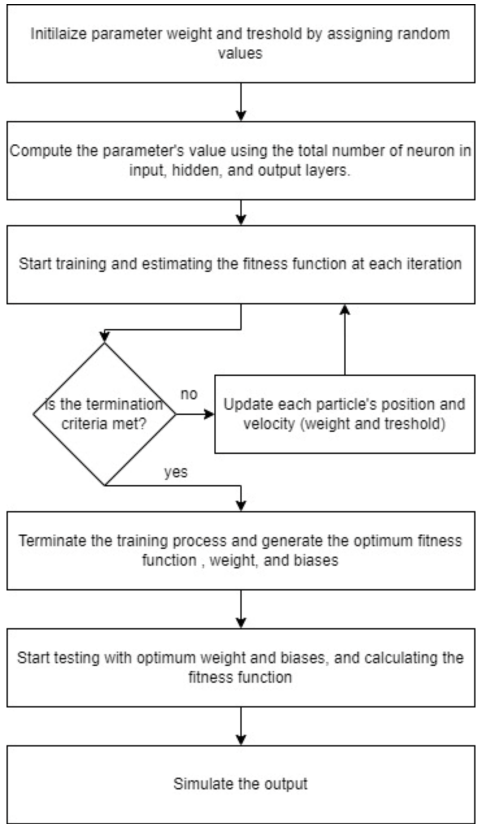

Figure 1. ANN-PSO hybrid algorithm's fundamental steps

2.4. Evaluation Criteria

The performance for evaluation criteria is accuracy, specificity, and sensitivity. Accuracy is the probability of the data set were correctly classified. Specificity is a measurement of the number of instances correctly classified in the negative class. Sensitivity is a measurement of the number of instances correctly classified in the positive class. The formula for calculating each performance is determined by Equation 7, Equation 8, and Equation 9.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

$$Specificity = \frac{TN}{TP + TN} \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

The number of positive instances that are correctly classified is referred to as True Positive (TP). The number of positive instances that were incorrectly classified is referred to as False Negative (FN). False Positives (FP) is the number of negative instances that were incorrectly classified. True Negative (TN) is the number of correctly classified negative instances.

3. Results and Analysis

3.1. Data Acquisition

The independent variables in Kaminsky et al., (1998) are used in this research. They are imports, exports, trade exchange rates, foreign exchange reserves, the composite stock price index (IHSG), real exchange rates, real deposit

 DOI: http://dx.doi.org/10.18187/pjsor.v18i4.3927

rates, bank deposits, loan and deposit interest rates, the difference between the real BI rate and the real FED rate, the M1, M2 multiplier, and the ratio of M2 to foreign exchange reserves. Meanwhile, the dependent variable is determined by the FPI value. It is used to calculate the period of the financial crisis from January 1990 to December 2021. The determination of whether or not a crisis exist using a threshold value with sigma coefficients of 1.5, 2, 2.5, and 3. Table 1 displays the results of the calculation of crisis conditions in Indonesia during that month.

Table 1: Crisis period in Indonesia based on sigma coefficient.

1.5-sigma	2-sigma	2.5-sigma	3-sigma
May 1990	May 1990	August 1997	August 1997
September 1993	August 1997	September 1997	September 1997
April 1994	September 1997	December 1997	December 1997
August 1997	October 1997	January 1998	January 1998
September 1997	December 1997	April 1998	April 1998
October 1997	January 1998	May 1998	May 1998
December 1997	February 1998	June 1998	June 1997
January 1998	April 1998	October 2008	October 2008
February 1998	May 1998		
April 1998	June 1998		
May 1998	October 2008		
June 1998			
July 2000			
September 2005			
June 2006			
October 2008			
September 2011			
June 2013			
July 2013			
June 2018			
March 2020			

Based on the data in Table 1, the study results show that the FPI value using a 2-sigma threshold conveys the crisis conditions. In addition, the 1.5-sigma threshold value is vulnerable to crisis conditions, whereas the 2.5-sigma and 3-sigma threshold values are less vulnerable to crisis conditions. The FPI and threshold value display in Figure 2.

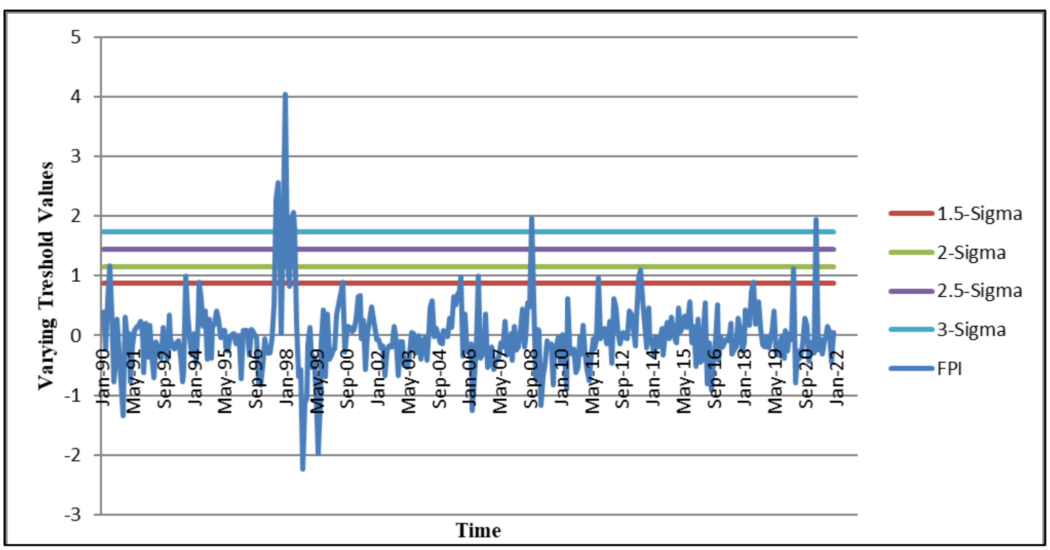

Figure 2 : FPI and threshold value.

After determining the month of the crisis, the perfect signal value must be calculated. PS is a series of signals that can provide a crisis warning for 12 months by giving a value of 1 before the crisis occurs and a value of 0 when the crisis occurs. Label class 1 shows a crisis signal, and label class 0 shows no crisis signal. PS will identify as a dependent variable. The data labeled as PS from January 1990 – December 2020 is used to build and evaluate the classification model. Meanwhile, data from January 2021 to December 2021 is used to predict the financial crisis.

3.2. Pre-processing Data

Pre-processing is carried out to improve the data into a suitable format for further analysis. The following are steps for pre-processing data :

1. Data normalization
   The normalization process uses Z-score normalization to uniform the data range and make prediction calculations easier.
2. Check for imbalance class
   The dependent data has two classes. There are 29 observations in class label 1 (crisis signal). Meanwhile, there are 330 observations of classes labeled 0 (not a crisis signal). The ratio of class 1 to class 0 is 29:330. The model is built on imbalanced class classification, so it is unable to predict a good result for the minority class. Synthetic Minority Over-Sampling Technique (SMOTE) can be used to balance data by creating artificial data based on k - neighbors. The number of neighbors used is five. After the SMOTE process, the class results are 330:330.
3. Partition data
   The data is divided into three categories : training data, validation data, and testing data. First, the data is divided by 80% for training and testing data then 20% for validation data. The training data is used to construct the classification model, while the testing data is used to evaluate the best model, and the validation data is used to evaluate the results of model hyperparameter tuning.

3.3. Build a model using ANN and PSO techniques

There are 13 indicators as input variables, and time indicator used as id and label of crisis signal as output variable. ANN uses one hidden layer with the number of neurons, which is tuned using grid search techniques at intervals of 1 – 13, as much as the independent variable used. In the output layer, there is only one neuron. Binary sigmoid used as activation function and output layer. Meanwhile, PSO techniques were used to determine the best optimal parameter of ANN model with acceleration constant $c1$ and $c2$ of 2 and 1.75 sequentially, inertia weight equal to 0.45, and the maximum number of iterations chosen to implement in the proposed model was equivalent to 500.

The best hyperparameter is determined based on the accuracy value for validation data. Figure 3 shows the results of using the grid search technique to adjust the number of neurons in the hidden layer and the learning rate.

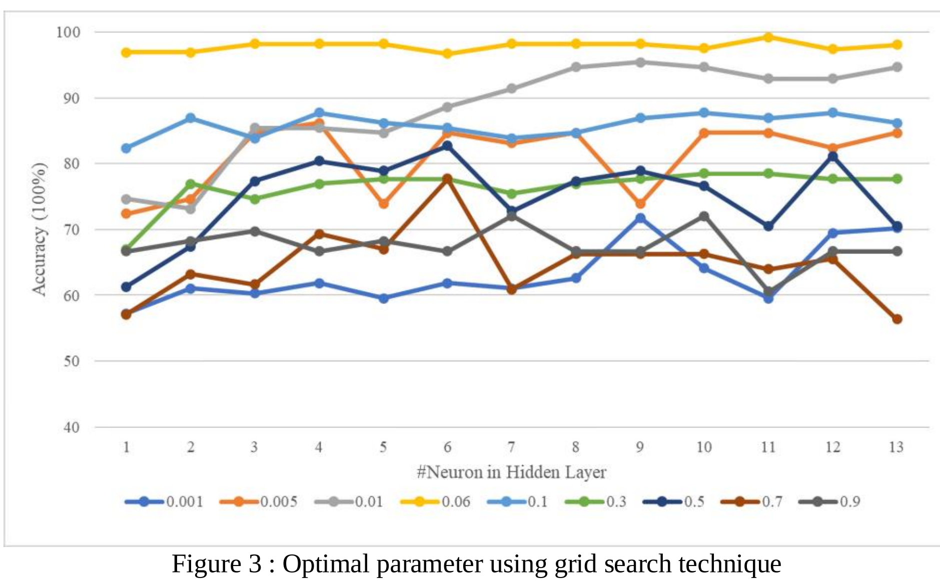

Figure 3 : Optimal parameter using grid search technique

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A model generates the best hyperparameter of 11 neurons hidden layer and a learning rate of 0.06 with a 99.26% accuracy by 5-fold cross-validation. Thus, hyperparameter tuning produces the best model with a network architecture of 13 inputs – 1 hidden layer with 11 neurons – 2 outputs. Figure 4 shows the best architectural model obtained.

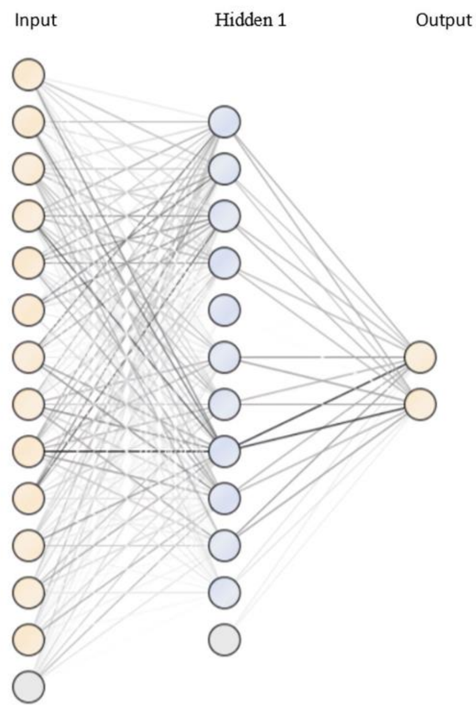
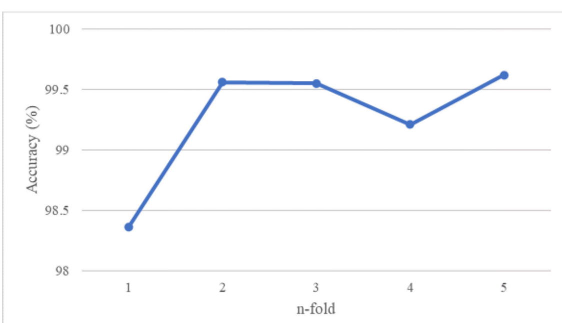
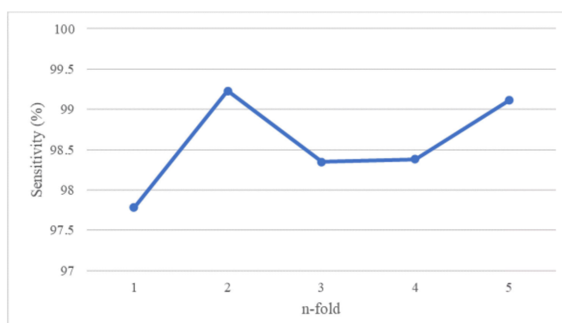


Figure 4 : ANN network architecture by hyperparameter tuning

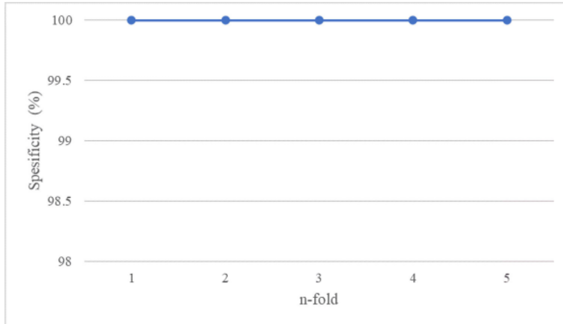
The evaluation results on data validation are accuracy, sensitivity, and specificity. Figure 5.a shows that the accuracy value of 1-fold is 98.36%, 2-fold is 99.56%, 3-fold is 99.55%, 4-fold is 99.21%, and 5-fold 99.62%. Then, it was calculated based on average value and obtained an accuracy of 99.26%.



a: Accuracy of the best model on data validation.



b: Sensitivity of the best model on data validation.



c: Specificity of the best model on data validation.

Figure 5: Performance measure of the proposed model on data validation.

The result of the sensitivity value can be seen in Figure 5.b. The sensitivity value for 1-fold is 97.78%, 2-fold is 99.23%, 3-fold is 98.35%, 4-fold is 98.38%, and 5-fold is 99.11%. The total sensitivity value was calculated based on the average value of the five folds and obtained a value of 98.57%.

The specificity value's result shows in Figure 5.c. Each fold yields a perfect result. The total specificity value was calculated based on the average of the five folds and obtained a value of 100%..

The performance of PSO in determining the best hyperparameters on the validation data is shown in Table 2. The accuracy value of a model that correctly predicts the signal for a crisis and not a crisis is 99.26%. The sensitivity value is a model that correctly predicts the signal for a crisis is 98.57%. Meanwhile, the specificity value is a model that can correctly predict the signal for not a crisis is 100 %.

Table 2 : Performance model on data validation.

Accuracy	Sensitivity	Spesificity
99,26%	98,57%	100%

3.4. Evaluation model

The best model was evaluated by 5-fold cross-validation using data testing. Thus, it generates the performance shown in Table 3. On the testing data, the accuracy that correctly predicts the signal for a crisis and not a crisis is 96.8%. The sensitivity value was 97.6% for correctly predicting a crisis signal. Meanwhile, the specificity value for predicting the signal for not being in a crisis was 96.5%. The evaluation results show that the proposed model can provide predictive results in the form of a crisis signal with reliable performance.

Table 3 : Performance evaluation on data testing.

Accuracy	Sensitivity	Specificity
96.8%	97.6%	96.5%

3.5. Predictions of Financial Crisis in Indonesia

The best model is used to predict the condition of the financial crisis in Indonesia. The data used is from January 2021 to December 2021 to predict the condition of the crisis signal next year, namely January 2021 to December 2021. The table shows the results of the prediction of the financial crisis signal in Indonesia.

Table 4 shows that there was no crisis signal from January 2022 to December 2022. As a result, it can be concluded that there will be no financial crisis in Indonesia for the next 12 months following December 2021, that are January 2022 to December 2022.

Table 4 : Result of the crisis signal prediction.

Month	Crisis Signal
January 2022	0

February 2022	0
March 2022	0
April 2022	0
May 2022	0
June 2022	0
July 2022	0
August 2022	0
September 2022	0
October 2022	0
November 2022	0
December 2022	0

4. Conclusion

The hybrid model with ANN and PSO technique can provide reliable performance to detect signals of the financial crisis in Indonesia. The best network architecture model is 13-11-1. The best hyperparameter values using learning rate with value of 0.06, the parameter of PSO using acceleration constant $c1$ and $c2$ of 2 and 1.75 sequentially, the value of inertia 0.45, and the maximum number of iterations chosen was 500. The activation function of the hidden layer and output layer is a binary sigmoid with the initial value used as randomization from the uniform distribution and the initial constant set to 0. The results of ANN and PSO models in the test data have an accuracy value of 96.8%, a sensitivity value of 97.6%, and a specificity value of 96.5%. According to the predictive data, there was no financial crisis from January 2022 to December 2022.

Furthermore, the model can use as a reference for researching early prediction systems in collaboration with related agencies. Thus, the proposed model is expected to be used as a prediction model that can provide accurate and factual results in order to predict a country's economic condition and decide on actions to avoid unwanted risks. This research can be developed by tuning all hyperparameters in order to produce a better model.

Acknowledgment

Authors would like to express gratitude to Universitas Muhammadiyah Surakarta for the research grant Hibah Integrasi Tridharma (HIT) under the grand number 005/A.3-III/FKI/I/2021

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