Early warning system modeling for rice supply using backpropagation artificial neural network to manage imported rice

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Abstract. Rice is a staple food in Indonesia. Although Indonesia produces a large amount of rice, it cannot meet domestic rice needs. The unpredictable domestic rice supply prompted the government to import rice. Moreover, rice imports are one of the efforts to provide rice stock. On the other hand, importing rice can decrease domestic rice prices because it creates a market competitor. This study uses backpropagation artificial neural networks to develop a prediction system for rice supply crises in Indonesia based on models similar to currency crisis prediction systems. The study identified key variables and indicators for predicting rice supply crises, including rice production, consumption, prices, land area, and population. Data from January 2012 to December 2022 was analyzed. The optimal neural network architecture achieved a Mean Squared Error (MSE) of 0.209192. The analysis revealed that rice consumption, land area, and total population are the most strongly correlated indicators of a rice commodity crisis

1 Introduction

Rice is a staple food in Indonesia, crucial for dietary and economic reasons. Despite substantial domestic production, Indonesia faces challenges in meeting its rice needs, leading to increased reliance on imports. Importing rice helps stabilize supply but can lower domestic prices and deplete foreign exchange reserves. The dual nature of rice imports—stabilizing supply while affecting domestic markets—highlights the need for effective forecasting [1]. The unpredictability of domestic rice supply has led the government to import rice, which can stabilize supply and lower domestic prices due to increased market competition. Previous research findings indicate that Indonesia has been importing rice from 2000 to 2023 for various reasons such as maintaining availability, strengthening rice reserves, preparing for El Nino events, and catering to the increasing population. The impact of rice imports on Indonesia's rice market is highlighted, showing that while imports help maintain stability in rice availability, inappropriate policies can negatively affect domestic farmers [2]. Continuous trade can affect Indonesia's Economy because importing rice also encourages a decrease in foreign exchange reserves. Import is buying an item from abroad, causing an outflow of payments, while outflows can lower national income [3].

Moreover, when too many imports come into a country in relation to its exports—which are products shipped from that country to a foreign destination—it can distort a nation's balance of trade and devalue its currency. The devaluation of a country's currency can have a considerable impact on the everyday life of a country's citizens because the value of a currency is one of the most significant determinants of a nation's economic performance and gross domestic product (GDP). So, maintaining the appropriate balance of imports and exports is crucial for a country. The importing and exporting activity of a country can influence the country's GDP, its exchange rate, and its level of inflation and interest rates. It's not a matter of one being better or worse. In a healthy economy, both imports and exports are experiencing growth. If one grows at a greater rate than the other, this can impact the Economy negatively [4].

In this study, a simulation of the occurrence of a rice commodity crisis in Indonesia was carried out with a neural network backpropagation approach by making predictions of rice commodity crises based on historical data from various sources to support balance trade between import and export and to support the Government policy to decide to trade. Backpropagation is one of the most popularly used training algorithms. The algorithm uses two calculation stages: a forward analysis to calculate the magnitude of the error between the actual output and the target and a countdown that reproduces the error to be then used to correct the synaptic weights on the entire neuron [5]

Improving forecasting accuracy is critically relevant for predicting Indonesia's rice commodities issue. This work's principal purpose is to provide a method for improving the accuracy of predictions. Statistical models are frequently employed in forecasting, and numerous researchers use statistical models for price

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predictions [6]. Nonetheless, although the statistical models are simple and effective, they cannot adequately capture the nonlinear properties of the price time series due to the nonlinearity and instability of the price time series [7]. The neural network model can accurately characterize nonlinearity and has distinct advantages when addressing nonlinearity issues. The neural network model utilized in price predictions has an excellent predicting effect and robust performance [8]. The backpropagation neural network model is the most prevalent and appropriate for predicting various nonlinear situations. It has excellent nonlinear mapping capabilities and performs better forecasts [9, 10]. Traditional statistical models used for rice price predictions often fail to capture the nonlinear dynamics of price time series. Neural network models, particularly those using backpropagation, offer a promising alternative due to their ability to handle nonlinearity and provide accurate forecasts. While previous research has focused on rice price forecasting, there is a gap in analyzing the potential crises in rice commodities related to import policies and external factors.

Previous research that examined rice commodities only examined the forecasting of rice prices—examining the price sale forecasting in rice milling units compared to 2 (two) forecasting methods, linear regression, and backpropagation artificial neural network. The results showed the value of MSE on a linear regression method of 0.214, while an artificial neural network obtained an MSE value of 0.00099713. Based on the value of the MSE, the smallest MSE was forecasted by the backpropagation neural network method [11]. The rice price in the Republic of the Union of Myanmar was used as a case study that resulted in four main factors affecting rice prices and production. The model with four input factors demonstrated an accuracy of over 80% [12]. By identifying previous research, this research used an artificial neural network rather than a statistics method because it can enhance the accuracy. The crisis can occur by examining several variables that were never examined in the other research. This research aims to overcome problems regarding rice import policies and the rice commodity crisis in Indonesia by predicting the rice commodity crisis caused by foreign trading. The emergence of international trade is because no single nation in the world can produce all goods and services to meet the needs of its entire population.

2 Research method

The variables used in this study were secondary data related to rice commodities in Indonesia, derived from the Central Bureau of Statistics, such as the amount of rice production [13], rice consumption [14], land area [15], total population [16], and retail price of rice [17]. The data were historical data from January 2012 to December 2022. The total data obtained was 132 data. The 120 and the 12 data were used for training and validation, respectively. The k-fold cross-validation method was used for validating.

This study used the index of commodity market pressure (CMPI) value to determine crisis variables in the constituent variables of neural networks. These constituent variables use historical data. The CMPI equation:

$$CMPI_t = \delta pd_t = \frac{pd_t - pd_{t-1}}{pd_{t-1}} \tag{1}$$

Whereas:

$CMPI_t$: the value of the index of commodity market pressure in the period t

δpd_t : percentage changes in domestic commodity prices in period t

pd_t : domestic commodity prices at the time of t

Commodity prices are used as variables that represent the occurrence of commodity scarcity, where the interaction between demand and supply causes price formation. In the case of rice commodities, domestic rice demand is assumed to be constant, so if there is a surge in domestic prices, domestic supply will decrease. Determining crisis conditions (Cr) based on the CMPI:

$$Cr_t = \begin{cases} 1, & if\ CMPI_t > \mu_{CMPI} + m\sigma_{CMPI} \\ 0, & otherwise \end{cases} \tag{2}$$

Critical conditions are expressed in binary numbers that are 0 and 1. A value of 1 means a crisis occurred, while a value of 0 means no crisis. Determining the value of the binary variable Rt describing the occurrence of a crisis in the signaling window period with a specific horizon is expressed:

$$R_t = \begin{cases} 1, & \exists Cr_p = 1; p = t, \dots, t+h \\ 0, & otherwise \end{cases} \tag{3}$$

Whereas:

R_t : realization of the crisis in the period t

Cr_t : crisis at the time of t

p : crisis period

The neural network architecture was designed by dividing data into 3 [18]. There are training, validation, and forecasting data [19]. The initiated epoch (a stopping criteria parameter) in this research was 1000 after normalizing the data, then determined a learning rate of 0.05 and a goal of 0.00001. The replication of network training was done ten times to get the best network architecture [20, 21]. Furthermore, network validation will be performed to determine the level of network accuracy using the k-fold cross-validation method, and the lowest error rate will be calculated using the mean squared error (MSE) measurement.

K-fold cross-validation is an approach used to determine the accuracy of a system if the training data and test data are randomly changed [22]. It works by dividing sample data into k parts randomly and equally significantly. This method is repeated as frequently as required k times with each experiment using fold-to-k data to test data and the rest as training data [23]. It is necessary to calculate the accuracy of each fold using the confusion matrix to find out the evaluation results. The final step was to analyze the parameter's sensitivity of the indicators to find out the influence of each indicator on the probability of a crisis occurring.

The definition of a Confusion matrix is a tool that analyses whether the classifier is good at recognizing tuples from different classes [24]. Before data analysis, it is essential to classify crisis signals in the confusion matrix. The crisis signals are classified into four types: good signal, noise, missing signal, and good silent. The confusion matrix can be represented in Table 1.

Table 1. Confusion matrix.

In signaling windows	The generated signal (crisis)	Not generated signal (not crisis)
Crisis	A (good signal)	C (missing signal)
Not crisis	B (noise)	D (good silent)

The equations of classification of these signals can be expressed:

1. Accuracy is the percentage of classifier accuracy in classifying test sets correctly

$$Accuracy = \frac{A + D}{A + B + C + D} \tag{4}$$

2. Error rate is the percentage of classifier error classifying test sets

$$Error\ Rate = \frac{B + C}{A + B + C + D} \tag{5}$$

3. Precision is a measure of accuracy that determines whether a tuple is labeled positive or genuinely positive.

$$Precision = \frac{A}{A + B} \tag{6}$$

4. Recall is a portion of an adequately classified positive tuple

$$Recall = \frac{A}{A + C} \tag{7}$$

3 Result and discussion

The reason for choosing commodity prices as variables that reflect the occurrence of commodity scarcity is that prices are formed due to the interaction between demand and supply. In the case of primary commodities such as rice, domestic rice demand is assumed to be constant, so there is a surge in domestic prices due to a decrease in domestic supply.

CMPI (Commodity Market Pressure Index) value was used as a crisis variable [25]. Critical conditions are expressed in binary numbers that are 0 and 1. A value of 1 means a crisis occurred, while a value of 0 means no crisis. A crisis occurs when the $CMPI_t$ value exceeds the CMPI mean plus the constant m multiplied by the standard deviation of the CMPI. The CMPI value is obtained from the processing of domestic rice retail price data using the formula:

$$CMPI_t = \delta pd_t = \frac{pd_t - pd_{t-1}}{pd_{t-1}} \tag{8}$$

Among them, $\mathrm{CMPI_t}$ denotes the value of the commodity market pressure index in the t period; $\mathrm{\delta pd_t}$ denotes the percentage of changes in domestic commodity prices in the t period; $\mathrm{pd_t}$ represent domestic commodity prices at t. The calculated value *of m* = 1.5 provides an accuracy rate of 78.33% and a level of precision of 22.22%. This result was still in line with the actual conditions of the crisis. Since the value of *m*=1.5 is relatively good, it can be applied to the model. The crisis period is determined based on the threshold value of CMPI. A crisis is declared if the CMPI value in that period exceeds the threshold. Nine months were declared a crisis, such as January 2014, July 2014, August 2014, November 2014, December 2014, January 2016, January 2018, December 2018, and January 2021, with a CMPI threshold value of 0.026064602.

The total of neurons in the hidden layer is determined by changing the number of hidden neurons in the backpropagation network layer from 5 to 55. The simulation was carried out using program code written in Matlab. Based on the calculation, the 45 neurons gave the lowest MSE value compared to the others. Using a 0.5 probability cutoff to generate alerts, the crisis prediction system using the neural network backpropagation approach for training had an accuracy, error rate, precision, and recall of 58.61%, 41.39%, 39.05%, and 84.09%, respectively. As for validation, accuracy, error rate, precision, and recall were 44.93%, 55.07%, 31.70%, and 80%, respectively.

The data used for training and validation were from February 2012 to December 2021, and the data from January to December 2022 were used to forecast the crisis. Forecasting was carried out using a network. From the derived forecasting, it was found that until December 2022, there was a reasonably high probability of a crisis.

The difference in m value affects the performance of the prediction system with the backpropagation approach. The accuracy, error rate, precision, and recall calculated by m value = 1 were 67.27%, 32.73%, 57.24%, and 86.05%, respectively. So, it can be concluded that with m value = 1, the system could define the crisis period quite well. Determining the signaling window helps policymakers make policies to prevent future rice crises [26]. Therefore, the time used was 12 months. Changes in the length of the signaling window used in the system provide different performances [27]. By changing the length of the signaling window by 6, 12, 18, and 24 months, it was obtained that the best accuracy, error rate, precision, and recall are given when using the 24 months of signaling window length.

The cutoff probability value used in determining a crisis probability, whether crisis or not, also affects the performance of the prediction system with a backpropagation approach. A threshold value of 0.6 provided the result as the best accuracy, error rate, precision, and recall were 78.69%, 21.31%, 49.49%, and 43.17%, respectively. The backpropagation network model used in the previous training used several parameters: the m parameter, the length of the time horizon (signaling window), and the cutoff probability value. Therefore, it is necessary to analyze the sensitivity of these parameters to obtain the best backpropagation network model [28].

The sensitivity analysis showed that the backpropagation network's performance could be increased if it changed the value of m to 1, the width of the signaling window to 24 months, or a cutoff probability of 0.6. Suppose a backpropagation network is used that changes the value of m to 1 and the signaling window to 24 months for crisis forecasting from January 2022 to December 2022. An alert was raised if the crisis probability exceeded the probability cutoff value of 0.6. Based on these warnings, the probability of a commodity crisis was very low. The probability of a crisis had not undergone significant changes even if rice production was increased by 30% and decreased by 30%. It can be settled that the change in the amount of rice production in this study is not very sensitive to the rice commodity crisis (Table 2).

Table 2. The Scenarios of changes in rice production.

Scenario	Rice production	Critical probability
Increased by 30%	2196.454	0.824182
Increased by 20%	2027.496	0.824452
Increased by 10%	1858.538	0.824721
Constant	1689.58	0.82499
Decreased by 10%	1520.622	0.825258
Decreased by 20%	1351.664	0.825526
Decreased by 30%	1182.706	0.825794

As rice consumption rose, the crisis probability tended to rise despite exceeding the *cutoff probability* limit. It is possible to assume that this study's rise in rice consumption was sensitive to the rice commodity crisis (Table 3).

Table 3. The Scenarios of changes in rice consumption.

Scenario	Rice consumption	Critical probability
Increased by 30%	2108.418	0.945764
Increased by 20%	1946.232	0.922277
Increased by 10%	1784.046	0.889808
Constant	1621.86	0.846036
Decreased by 10%	1459.674	0.788999
Decreased by 20%	1297.488	0.717883
Decreased by 30%	1135.302	0.633913

As the land area decreased, the probability of a crisis tended to rise and be above the *cutoff probability*. It can be concluded that the decline in land area in this study was very sensitive to the rice commodity crisis (Table IV).

Table 4. The Scenarios of land area changes.

Scenario	Land area	Critical probability
Increased by 30%	10496.837	0.001621
Increased by 20%	9689.388	0.013897
Increased by 10%	8881.939	0.108984
Constant	8074.49	0.514934
Decreased by 10%	7267.041	0.90209
Decreased by 20%	6459.592	0.987649
Decreased by 30%	5652.143	0.998561

The probability of the crisis did not change significantly, although the rice price increased by 30% and was lowered by 30%. It can be determined that the modification in the price value of rice in this study was not very sensitive to the rice commodity crisis (Table V).

Table 5. The scenario of the retail price of rice change.

Scenario	Retail price of rice	Critical probability
Increased by 30%	14825.2	0.98143
Increased by 20%	13684.8	0.984444
Increased by 10%	12544.4	0.986975
Constant	11404	0.989099
Decreased by 10%	10263.6	0.990879
Decreased by 20%	9123.2	0.992371
Decreased by30%	7982.8	0.993621

As the number of inhabitants increased, the probability of a crisis rose significantly. It is possible to assume that the rise in population in this study was susceptible to the rice commodity crisis (Table VI).

Table 6. The Scenarios of total population changes.

Scenario	Total population	Critical probability
Increased by 30%	340.067	0.856628
Increased by 20%	313.908	0.770587
Increased by 10%	287.749	0.653778
Constant	261.59	0.514934
Decreased by 10%	235.431	0.373745
Decreased by 20%	209.272	0.251219
Decreased by 30%	183.113	0.158684

From the analysis of the effect of changes in each of these indicators, the indicators susceptible to the rice commodity crisis were rice consumption, land area, and total population. Based on this study, rice production and retail price were not among the indicators sensitive to commodity crises. Based on the result, policies to prevent commodity crises can be carried out by paying attention to indicators sensitive to the rice commodity crisis.

The concern is widespread regarding population expansion and the agricultural productivity required to sustain it without degrading the environment [29]. The increasing scarcity of land and water resources, environmental degradation, and biodiversity loss have begun to restrict the increase of food production in both wealthy and developing nations. As population and incomes rise, so does the need for food, and addressing the food needs of a growing population for global food security poses a formidable task [30]. Increasing prosperity is accompanied by diets that demand more natural resources per person. This reality and rising populations may cause the worldwide need for food crops to double to quadruple within the next two generations. Food insecurity is under intensifying demand- and supply-side challenges. Demand from consumers in fast-expanding economies will increase as per capita income rises, and population growth will continue to pressure the food system immensely. On the supply side, the rising scarcity of natural resources in some locations, diminishing yield growth rates for some commodities, and the effects of climate change pose concerns. The policies that can be taken care of are diversifying staple foods, increasing the area of productive land, limiting the number of offspring, and many more [31].

4 Conclusion

The neural network backpropagation approach was accurate enough to predict the rice commodity crisis in Indonesia by using 5-fold cross-validation. The parameters used in this study were the constant m = 1.5, the signaling horizon window of 12 months, and the cutoff probability of 0.5. Moreover, the indicators used were rice production, rice consumption, retail price, land area, and total population.

The best architecture obtained was 45 hidden layer neurons, with an MSE of 0.209192. The system predicted the probability of a considerable crisis occurring until December 2020. The sensitivity analysis that had been carried out obtained the best parameters at m=1, the signaling horizon window of 24, and the cutoff probability of 0.6. The indicators sensitive to the increase in the likelihood of a rice commodity crisis were rice consumption, land area, and total population.

References

1. H. Siebert, *The world economy*, Routledge, (2018)
2. R. Badi'ah, D. Wiratama, M. F. Yusuf, D. A. Sari, and D. Ulya, *Dynamics of Rice Imports in Indonesia: Analysis of Development, Causative Factors, Impacts and Solutions*
3. M. Radetzki and L. Wårell, *A handbook of primary commodities in the global Economy*. Cambridge University Press, (2020)
4. L. Kramer. *(2023, September 27) How Importing and Exporting Impacts the Economy*. [Economy]
5. A. I. Suyanto, *Searching, Reasoning, Planning, dan Learning (Revisi Kedua)*, Bandung: Informatika Bandung, (2014)
6. X. Zhao, M. Han, L. Ding, and W. Kang, *Usefulness of economic and energy data at different frequencies for carbon price forecasting in the EU ETS*, Applied Energy, **216**, 132-141, (2018)
7. J. Zhu, P. Wu, H. Chen, J. Liu, and L. Zhou, *Carbon price forecasting with variational mode decomposition and optimal combined model*, Physica A: Statistical Mechanics and Its Applications, **519**, 140-158, (2019)
8. W. Sun and C. Zhang, *Analysis and forecasting of the carbon price using multi—resolution singular value decomposition and extreme learning machine optimized by adaptive whale optimization algorithm*," Applied energy, **231**, 1354-1371, (2018)
9. H. Liu, X. Mi, and Y. Li, *An experimental investigation of three new hybrid wind speed forecasting models using multi-decomposing strategy and ELM algorithm*, Renewable energy, **123**, 694-705, 2018.
10. S. Akkoyun, N. Yildiz, and H. Kaya, *Neural Network Estimation for Attenuation Coefficients for Gamma-Ray Angular Distribution*, Physics of Particles and Nuclei Letters, **16**, 4, 397-401, (2019)
11. M. Aritonang and D. J. C. Sihombing, *An application of backpropagation neural network for sales forecasting rice miling unit*, in 2019 International Conference of Computer Science and Information Technology (ICoSNIKOM), IEEE, 1-4, (2019)
12. T. Zaw, K. M. M. Tun, and A. N. Oo, *Price forecasting by back propagation neural network model*, in 2019 International Conference on Advanced Information Technologies (ICAIT), IEEE, 84-89 (2019)
13. B. S. Chauhan, K. Jabran, and G. Mahajan, *Rice production worldwide*. Springer, (2017)
14. C. Panpakdee and B. Limnirankul, *Indicators for assessing social-ecological resilience: A case study of organic rice production in northern Thailand*, Kasetsart Journal of Social Sciences, **39**, 3, 414-421, (2018)
15. J. Xu and Y. Ding, *Research on early warning of food security using a system dynamics model: evidence from Jiangsu province in China*, Journal of food science, **80**, 1, R1-R9, (2015)
16. H. Pathak, A. K. Nayak, M. Jena, O. Singh, P. Samal, and S. Sharma, *Rice research for enhancing productivity, profitability and climate resilience*, ed: Not Available, (2018)
17. G. G. Marten and N. Atalan-Helicke, *Introduction to the symposium on American food resilience*, Journal of Environmental Studies and Sciences, **5**, 3, 308-320, (2015)
18. M. R. Haque, M. M. Islam, H. Iqbal, M. S. Reza, and M. K. Hasan, *Performance evaluation of random forests and artificial neural networks for the classification of liver disorder*, in 2018 international conference on computer, communication, chemical, material and electronic engineering (IC4ME2), IEEE, 1-5, (2018)
19. [19] M. Shaban, *Deep convolutional neural network for Parkinson's disease based handwriting screening*, in 2020 IEEE 17th International

Symposium on Biomedical Imaging Workshops (ISBI Workshops), IEEE, 1-4, (2020)

20. W. Yan *et al*., *Discriminating schizophrenia from normal controls using resting state functional network connectivity: A deep neural network and layer-wise relevance propagation method*, in 2017 IEEE 27th international workshop on machine learning for signal processing (MLSP), IEEE, 1-6, (2017)
21. N. I. Nwulu, *An artificial neural network model for predicting building heating and cooling loads*, in 2017 International Artificial Intelligence and Data Processing Symposium (IDAP), IEEE, pp. 1-5, (2017)
22. P. Prasetyawan, I. Ahmad, R. I. Borman, Y. A. Pahlevi, and D. E. Kurniawan, *Classification of the Period Undergraduate Study Using Backpropagation Neural Network*, in 2018 International Conference on Applied Engineering (ICAE), IEEE, 1-5, (2018)
23. S. W. Sidehabi, A. Suyuti, I. S. Areni, and I. Nurtanio, *Classification on passion fruit's ripeness using K-means clustering and artificial neural network*, in 2018 International Conference on Information and Communications Technology (ICOIACT), IEEE, pp. 304-309, (2018)
24. D. Maulana and J. Jondri, *Deteksi Gangguan Jantung Premature Ventricular Contractions Menggunakan Sinyal Elektrokardiogram Dengan Algoritma Backpropagation Dan Algoritma Firefly*, eProceedings of Engineering, **6**, 2, (2019)
25. Y. Tao, *Research on the impact of trade uncertainty on national grain supply and risk cost control*, Acta Agriculturae Scandinavica, Section B—Soil & Plant Science, **72**, 1, 92-104, (2022)
26. P. D. Purnamasari, A. A. P. Ratna, and B. Kusumoputro, *EEG based patient emotion monitoring using relative wavelet energy feature and Back Propagation Neural Network*, in 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2820-2823, (2015)
27. N. Alsharif, K. Aldubaikhy, and X. S. Shen, *Link duration estimation using neural networks based mobility prediction in vehicular networks*," in 2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), IEEE, 1-4, (2016)
28. L. Li, Y. Chen, T. Xu, R. Liu, K. Shi, and C. Huang, *Super-resolution mapping of wetland inundation from remote sensing imagery based on integration of backpropagation neural network and genetic algorithm*, Remote Sensing of Environment, **164**, 142-154, 2015.
29. N. Mancosu, R. L. Snyder, G. Kyriakakis, and D. Spano, *Water scarcity and future challenges for food production*, Water, **7**, 3, 975-992, (2015)
30. T. K. Rudel *et al*., *LivestockPlus: Forages, sustainable intensification, and food security in the tropics*, Ambio, **44**, 7, pp. 685-693, (2015)
31. N. Bandumula, *Rice production in Asia: Key to global food security*, Proceedings of the National Academy of Sciences, India Section B: Biological Sciences, **88**, 4, 1323-1328, (2018)