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Risk Analysis of Oyster Mushroom Cultivation Success through Artificial Neural Network with Back propagation Algorithm

Fazri Aslam^{1,*)}, Riri Syafitri Lubis²⁾

^{1,2}Universitas Islam Negeri Sumatera Utara, Medan, Indonesia

*)email: fazri0703201037@uinsu.ac.id

Abstract

Consumption mushroom cultivation is still rare in most parts of Indonesia, although the demand for this agricultural product continues to increase. Mushroom business opportunities are actually quite promising. This research aims to analyze the prediction of the risk level of oyster mushroom cultivation success using the artificial neural network method with the Back propagation algorithm. This research combines qualitative and quantitative approaches, with data analysis methods in the form of Back propagation algorithm training implemented through MATLAB *software*. Based on the results of testing or training conducted using the 5-3-1 Artificial Neural Network (JST) architecture and *Epoch* 1, the minimum *error* is 0.6 or 4 kg of yield (IDR 80,000), while the maximum *error* is 0.7 or 5 kg of yield (IDR 100,000). with a training MSE of 0.0964 with This means that artificial neural networks can create patterns to predict the yield of oyster mushroom cultivation.

Keywords: Risk Analysis, Oyster Mushroom Farming, Artificial Neural Network, Back propagation Algorithm

Abstrak

Budi daya jamur konsumsi masih jarang ditemukan di sebagian besar wilayah Indonesia, meskipun permintaan terhadap produk pertanian ini terus meningkat. Peluang bisnis jamur sebenarnya cukup menjanjikan. Penelitian ini bertujuan untuk menganalisis prediksi tingkat risiko keberhasilan budi daya jamur tiram menggunakan metode jaringan saraf tiruan dengan algoritma Backpropagation. Penelitian ini menggabungkan pendekatan kualitatif dan kuantitatif, dengan metode analisis data berupa pelatihan algoritma Backpropagation yang diimplementasikan melalui software MATLAB. Berdasarkan hasil pengujian atau pelatihan yang dilakukan dengan menggunakan arsitektur Jaringan Syaraf Tiruan (JST) 5-3-1 dan Epoch 1 adalah error minimum yaitu 0,6 atau 4 kg hasil panen (Rp 80.000), sedangkan error maksimum yaitu 0,7 atau 5 kg hasil panen (Rp 100.000). dengan MSE pelatihan yaitu 0.0964 dengan Ini berarti bahwa jaringan syaraf tiruan dapat membuat pola untuk memprediksi hasil panen budidaya jamur tiram.

Kata kunci: Analisis Resiko, Budidaya Jamur Tiram, Jaringan Syaraf Tiruan, Algoritma Backpropagation

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*) Corresponding Author

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Introduction

Indonesia is an agricultural country, which means the agricultural sector requires special attention from the government to build a solid and competitive foundation. Therefore, the agricultural sector is one of the main pillars in driving economic growth. As a country with an agriculture-based economy, the role of this sector is vital in the overall national economy. This can be seen from the high number of people or labor that depend on the agricultural sector for their livelihood. Agriculture is the backbone of the Indonesian economy.

The agricultural sector is the main source of livelihood for most Indonesians, as almost half of the country's labor force is involved in the sector. In addition to its role in providing sufficient food, the agricultural sector is also expected to absorb labor, contribute to the country's foreign exchange earnings, and become the main driving force of the national economy. Therefore, agricultural development is considered an effective measure to reduce poverty and improve people's welfare. One of the business opportunities that still has great potential in this field is consumption mushroom cultivation. Although mushroom cultivation is still rare in many parts of Indonesia, the demand for this product continues to increase, making it a promising business opportunity [1].

Oyster mushroom cultivation in the Sumatra Mushroom Garden, precisely on Jl. Medan - Batang Kuis market 9 tembung, Percut Sei Tuan District, Deli Serdang Regency, is a business that was established in 2010, this business was established because at that time there was a deviate in the property sector, therefore then this business was chosen because previously the owner already had an interest and hobby to build this oyster mushroom business [2]. While running this Sumatran Mushroom Garden business, the business owner and his employees experienced many obstacles and risks. This business once resulted in a vacuum for 1 year, namely in 2013 due to lack of attention to risk and the risk became large. In 2014 this business was started again until now because this business began to rise by producing mushroom seeds and not only cultivating mushrooms alone [3].

Oyster mushroom production risks can be caused by several obstacles that arise during the oyster mushroom cultivation process. These constraints in cultivation can be caused by environmental factors, temperature or humidity and weather. Improper handling can also be a major factor resulting in substandard quality oyster mushrooms. This condition can result in losses for oyster mushroom cultivators if it occurs continuously. In oyster mushroom cultivation, obstacles must be investigated to find out the causes and how to handle them so as not to cause great risk [4]. Risk is an important aspect that must be considered, because poor risk management can cause large losses. Risks can arise at any time, so careful analysis is needed in managing risks in oyster mushroom cultivation. Risk analysis starts from risk identification, risk level measurement, risk priority mapping to strategy formulation in the oyster mushroom cultivation business. This is done to facilitate the decision-making process in oyster mushroom cultivation activities so as to reduce the level of risk and reduce the level of loss due to risk [5]. The author analyzes the risk of oyster mushroom cultivation through artificial neural networks with the Back propagation Algorithm.

Artificial Neural Network is an information processing paradigm inspired by the way biological nervous systems, such as the brain, process information. The main element of this paradigm is the innovative structure of the information processing system. This structure consists of many interconnected processing elements (neurons) that work together to solve various problems. Artificial neural networks have the ability to recognize patterns or activities based on past data [6]. Artificial neural networks learn data from the past so that they can make decisions on data that they have never known. This method has a main characteristic, which is to minimize the error in the resulting output. The term "artificial" is used because this neural network is implemented through a computer program

that is capable of carrying out various calculation processes during the learning stage. The back propagation method itself is included in supervised learning algorithms that use error correction rules as the basis for learning [7].

Artificial neural networks are information processing systems designed to mimic the way the human brain works in solving problems through a learning process. One algorithm that is often used in artificial neural networks is back propagation, which is known to have a high level of accuracy, especially in making predictions [8]. Back propagation is an algorithm used for supervised learning in artificial neural networks (ANN). This algorithm aims to determine the weight (weight) on each neuron so that it can minimize the error value by utilizing the training data provided [9]. One of the advantages of an artificial neural network (JST) is its ability to continue learning (adaptive) and fault tolerance. This allows JST to form a robust system and continue to work consistently even in the face of interference or damage [10].

Methods

This research was conducted at the Sumatra Mushroom Farm, which is located on JI Medan - Batang Kuis Pasar 9 Tembung, Percut Sei Tuan District, Deli Serdang Regency, North Sumatra 20372. The data used is primary data obtained directly from the research location, with Sumatra Mushroom Farm as the sample. Data collection was conducted through interviews based on a questionnaire specifically designed for the purpose of the study. This primary data includes the identification of risks in oyster mushroom cultivation, such as unsterile equipment, employee hygiene, errors in the selection of sawdust, spraying that is too strong, as well as the risk of flooding at the site. This research uses a qualitative and quantitative approach, with data analysis through the Back propagation training algorithm using MATLAB software. The input data used comes from risk factor variables in oyster mushroom cultivation, including independent variables (independent/X) and dependent variables (dependent/Y): Input: X_1 = Equipment is not sterile, X_2 = Employee hygiene, X_3 = Mistakes in mushroom bag-logs or seedlings, X_4 = Water spraying is too strong, X_5 = Flooding occurs at the location. Output: Y = Predicted risk of oyster mushroom cultivation success.

Back propagation Artificial Neural Networks

Artificial neural networks are a forecasting method that has a low data error rate and is effective in the generalization process, because it is supported by adequate training data and a learning process that adjusts the weights. This allows the model to forecast time series data for several periods to come. One of the algorithms used in artificial neural networks for forecasting is the back propagation algorithm [11]. Back propagation Artificial Neural Network consists of three layers, namely input layer, hidden layer, and output layer [12][13][14].

Back propagation training consists of three phases. The first phase is the forward phase, where the input pattern computed forward from the input screen to the output screen using a predefined activation function. The second phase is the backward phase, where the difference between the network output and the desired target is calculated as the error. This error is then propagated backwards, starting from the line directly connected to the units in the output screen. The third phase involves modifying the weights to reduce the error.

The training of the backpropagation algorithm is as follows:

Step 0: Initialize all weights with small random numbers

Step 1: If the termination condition has not been met, perform steps 2-9

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Step 2: For each pair of training data, perform steps 3-8

Phase 1: Forward propogation

Step 3: Each input unit receives the signal and forwards it to the hidden unit above it.

Step 4: Calculate all outputs in the hidden unit z_j (j=1,2,...,p)

$$z_{net_{j}} = v_{jo} + \sum_{i=1}^{n} x_{i} v_{ji}$$
 (1)

$$z_j = f(z_net_j) = \frac{1}{1 + e^{-z_net_j}}$$
 (2)

Step 5: Calculate all network outputs at unit y_k (k = 1,2,...,m)

$$y_{net_k} = w_{ko} + \sum_{j=1}^{p} z_j w_{kj}$$
 (3)

$$y_k = f(y_net_k) = \frac{1}{1 + e^{-y_net_k}}$$
 (4)

Phase II: backward propagation

Step 6: Calculate the Factor δ of output units based on the error in each output unit $y_k(1,2,...,m)$

$$\delta_k = (t_k - y_k)f'(y_n et_k) = (t_k - y_k)y_k(1 - y_k)$$
(5)

 δ_k is the unit error used in changing the weight of the screen below (step 7).

Calculate the weight change rate w_{kj} (which will be used later to change the weight $w_{(kj)}$) with an acceleration rate of α

$$\Delta w_{kj} = \alpha \delta_k z_j$$
; k = 1,2,...,m; j = 0,1,...,p (6)

Step 7: Calculate the factor δ of hidden units based on the error in each hidden unit z_j (j=1,2,...,p)

$$\delta_{-} \operatorname{net}_{j} = \sum_{k=1}^{m} \delta_{k} w_{kj}$$
 (7)

Factorδ hidden units:

$$\delta_{j} = \delta_{-} \operatorname{net}_{j} \ f'(z_{-} \operatorname{net}_{j}) = \delta_{-} \operatorname{net}_{j} \ z_{j} (1 - z_{j})$$
 (8)

Calculate the weight change rate v_{ij} (which will be used later to change the weight $v_{(ij)}$)

$$\Delta v_{ij} = \alpha \delta_i x_i \; ; j = 1,2,...,p \; ; i = 0,1,...,n$$
 (9)

Phase III: Weight change

Step 8: Calculate all weight changes

Change in the weights of the lines leading to the output units:

$$w_{(kj)}(new) = w_{kj}(old) + \Delta w_{kj} \quad (k = 1,2,...m; j = 1,2,...,p)$$
 (10)

Change in line weights leading to the hidden unit:

$$v_{ii}$$
 (new) = $v_{(ii)}$ (old) + Δv_{ii} (j = 1,2,...p; i = 1,2,...,n) (11)

Step 9: Optimality test: Has the stopping condition been met?

Once the training is complete, the network can be used for pattern recognition. At this stage, only forward propagation (steps 4 and 5) is applied to determine the network output. If the activation function used is not a binary sigmoid, then steps 4 and 5 need to be adjusted. Likewise, the derivatives in steps 6 and 7 [15]. For further explanation of the research procedure, see Figure 1 below:

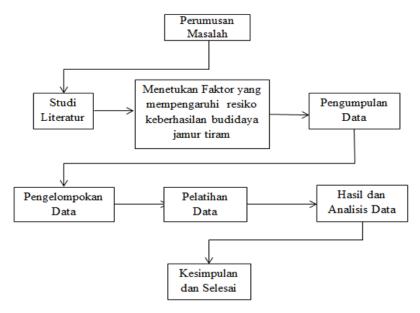


Figure 1 . Research Procedure

Results and Discussion

Data Grouping

This research was conducted by grouping the data first. Table 1 and Table 2 presents the data on the risks of successful oyster mushroom cultivation are obtained and grouped. After conducting observations and research for one month, data that has been grouped according to its criteria and data to support during data training is obtained, the supporting data used is temporary output data of crop yields for one month.

Table 1 . Research Data						
Time	X_1	X_2	X_3	X_4	X_5	
Day 1	4	4	4	3	4	
Day 2	4	4	4	4	4	
Day 3	4	4	4	3	4	
•••	•••	•••	•••	•••	•••	
Day 30	4	4	3	4	4	

Price (Rp) **Time** Weight (Kg) Day 1 20000 1 Kg 40000 Day 2 2 kg 20000 Day 3 1 Kg Day 30 6 Kg 120000 2040000 Total 102 Kg

Table 2 . Harvest Data

After the data is obtained. The data is then normalized to produce data that ranges from 0.1 to 0.9.

 $X = 0.8 x \frac{(X-b)}{(a-b)} + 0.1$ (12)

Description: b = minimum value, a = maximum value

 X_1 the maximum value is 4 and the minimum value is 2.

X₂ the maximum value is 4 and the minimum value is 2.

X₃ the maximum value is 4 and the minimum value is 3.

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 X_4 the maximum value is 4 and the minimum value is 3.

 X_5 the maximum value is 4 and the minimum value is 3.

Y the maximum value is 120,000 and the minimum value is 20,000.

Normalized value
$$X_1 = 0.8 \times \frac{(X_1 - b)}{(a - b)} + 0.1 = 0.8 \times \frac{(4 - 2)}{(4 - 2)} + 0.1 = 0.8 \times 1 + 0.1 = 0.9$$

Normalization
$$X_2 = 0.8 x \frac{(X_2 - b)}{(a - b)} + 0.1 = 0.8 x \frac{(4 - 2)}{(4 - 2)} + 0.1 = 0.8 x 1 + 0.1 = 0.9$$

Normalization
$$X_3 = 0.8 x \frac{(X_3 - b)}{(a - b)} + 0.1 = 0.8 x \frac{(4 - 3)}{(4 - 3)} + 0.1 = 0.8 x 1 + 0.1 = 0.9$$

Normalization X₄= 0.8
$$x \frac{(X_4-b)}{(a-b)} + 0.1 = 0.8 x \frac{(3-3)}{(4-3)} + 0.1 = 0.8 x 0 + 0.1 = 0.1$$

Normalization
$$X_5 = 0.8 \times \frac{(X_5 - b)}{(a - b)} + 0.1 = 0.8 \times \frac{(4 - 3)}{(4 - 3)} + 0.1 = 0.8 \times 1 + 0.1 = 0.5$$

Normalization
$$X_5 = 0.8 \times \frac{(X_5 - b)}{(a - b)} + 0,1 = 0.8 \times \frac{(4 - 3)}{(4 - 3)} + 0,1 = 0.8 \times 1 + 0,1 = 0.9$$

Normalization $Y = 0.8 \times \frac{(Y - b)}{(a - b)} + 0,1 = 0.8 \times \frac{(20.000 - 20.000)}{(120.000 - 20.000)} + 0,1 = 0.8 \times 0 + 0,1 = 0.1$

The calculation above is an example of normalization calculation for day 1.

Table 3 . Normalized Research Data

Time	X_1	X_2	X_3	X_4	X ₅
Day 1	0.9	0.9	0.9	0.1	0.9
Day 2	0.9	0.9	0.9	0.9	0.9
Day 3	0.9	0.9	0.9	0.1	0.9
•••					
Day 30	0.9	0.9	0.1	0.9	0.9

Table 4 . Normalized Harvest Data

Time	Weight (Kg)	Normalization
Day 1	1 Kg	0.1
Day 2	2 kg	0.3
Day 3	1 Kg	0.1
•••	•••	•••
Day 30	6 Kg	0.9

Table 3 and Table 4 presents the normalization results from day 1 to day 30 and the results of normalization calculations for harvest data from day 1 to day 30.

Data Training and Data Results

Table 5 . Training Data

	10010011101111000						
No.	X_1	X_2	X ₃	X_4	X_5	Υ	
1	0.9	0.9	0.9	0.1	0.9	0.1	
2	0.9	0.9	0.9	0.9	0.9	0.3	
3	0.9	0.9	0.9	0.1	0.9	0.1	
30	0.9	0.9	0.1	0.9	0.9	0.9	

Table 5 presents 30 data points. Training starts by calculating data from day 1 to day 30. The calculation uses input 5, Hidden Layer 3 and Output 1.

Data Training

Step 0: Initialize all weights. Table 6 presents the i77igurenitialize the weights randomly with a small random number.

Ta	Table 6 . Day 1 Weight Initialization							
	Input to Hidden Layer							
Weight	Z ₁	\mathbf{Z}_2	Z ₃	Z_4	Z ₅			
V_1	0.1	0.3	0.1	0.1	0.4			
V_2	0.4	0.3	0.6	0.8	0.5			
V_3	0.3	0.9	0.7	0.3	0.1			
	Hidden La	ayer to Ou	ıtput Lay	er				
Weight	w_1	W ₂	W ₃					
Υ	0.3	0.1	0.5	V	/ _{kj}			
	Input Bias to Hidden layer							
Bias	1	2	3					
V_{j0}	0.9	0.8	0.7					
	Hidden To Output Bias							
Bias	1							
Wko	0.1							

Step 3: Each input unit receives the signal and forwards it to the hidden unit.

Step 4: Calculate all outputs in the hidden units

$$z_{net_{j}} = v_{jo} + \sum_{i=1}^{n} x_{i} \ v_{ji}$$
 (1)

 $z_{net_1} = 0.9 + (0.9 \times 0.1) + (0.9 \times 0.3) + (0.9 \times 0.1) + (0.1 \times 0.1) + (0.9 \times 0.4) = 1.72$

 $z_net_2 = 0.8 + (0.9 \times 0.4) + (0.9 \times 0.3) + (0.9 \times 0.6) + (0.1 \times 0.8) + (0.9 \times 0.5) = 2.5$

 $z_{net_3} = 0.7 + (0.9 \times 0.3) + (0.9 \times 0.9) + (0.9 \times 0.7) + (0.1 \times 0.3) + (0.9 \times 0.1) = 2.53$

$$z_j = f(z_net_j) = \frac{1}{1 + e^{-z_net_j}}$$
 (2)

$$Z_1 = \frac{1}{1 + e^{-1.72}} = 0.8481$$

$$Z_2 = \frac{1}{1 + e^{-2.5}} = 0.9241$$

$$Z_3 = \frac{1}{1 + e^{-2,53}} = 0,9262$$

Step 5: Calculate all Network outputs in the unit

$$y_{net_k} = w_{ko} + \sum_{j=1}^{p} z_j w_{kj}$$
 (3)

$$y_k = f(y_net_k) = \frac{1}{1 + e^{-y_net_k}}$$
 (4)

 $y_net_k = 0.1 + (0.8481 \times 0.3) + (0.9241 \times 0.1) + (0.9262 \times 0.5) = 0.9099$

$$Y_k = \frac{1}{1 + e^{-0.9099}} = 0.713$$

Step 6: Calculate the unit output factor based on the Error in each unit.

$$\delta_k = (t_k - y_k)f'(y_n e t_k) = (t_k - y_k)y_k(1 - y_k)$$
(5)

Error = Target - Y_k = 0.1 - 0.713 = -0.613

Square of error = $(-0.613)^2 = 0.3758$

$$\delta_k = (0,613)(0,713)(1-0,713) = -0,1254$$

Weight Change to change the weight with the value α = 0.1

$$\Delta w_{kj} = \alpha \delta_k z_j$$
; k = 1,2,...,m; j = 0,1,...,p (6)

 $\Delta W_0 = 0.1 \times (-0.1254) = -0.0125$

 $\Delta W_1 = 0.1 \text{ x (-0.1254) x 0.8481} = -0.0106$

 $\Delta W_2 = 0.1 \text{ x (-0.1254) x 0.9241} = -0.01158$

 $\Delta W_3 = 0.1 \text{ x (-0.1254) x 0.9262} = -0.01061$

Step 7: Calculate the hidden unit based on the error

$$\delta_{-} \operatorname{net}_{j} = \sum_{k=1}^{m} \delta_{k} w_{kj}$$
 (7)

 δ net₁ = -0.1254 x 0.3 = -0.0376

 $\delta_{\text{net}_2} = -0.1254 \times 0.1 = -0.0125$

 $\delta_{net_3} = -0.1254 \times 0.5 = -0.0627$

$$\delta_{i} = \delta_{net_{i}} f'(z_{net_{i}}) = \delta_{net_{i}} z_{i}(1 - z_{i})$$
(8)

 δ_1 = (-0,0376)(0,8481)(1 - 0,8481) = -0,0048

 δ_2 = (-0,0125)(0,9241)(1 - 0,9241) = -0,0009

 δ_3 = (-0,0627)(0,9262)(1 - 0,9262) = -0,0043

Step 8: Calculate all weight changes

$$\Delta v_{jo} = \alpha \, \delta_j \tag{13}$$

 $\alpha = 0,1$

Table 7. Weight Change Δv_{io}

	ΔV_0
1	-0.0005
2	-0.0001
3	-0.0004

Weight change to change the weight of V_{ji}

$$\Delta v_{ji} = \alpha \delta_j x_i \; ; j = 1,2,...,p \; ; i = 0,1,...,n$$
 (9)

Table 8 . Weight Change to Change V_{ji}

		0 - 1 - 1	U - Ji
	ΔV_1	ΔV_2	ΔV_3
1	-0.00044	-0.00008	-0.00039
2	-0.00044	-0.00008	-0.00039
3	-0.00044	-0.00008	-0.00039
4	-0.00005	-0.00001	-0.00004
5	-0.00044	-0.00008	-0.00039

The same steps are carried out continuously until we get the weight initialization results from day 1 to day 30. The 30th day initialization results are as follows:

Table 9. Day 30 Weight Initialization

Input to Hidden Layer						
Weight	Z_1	\mathbf{Z}_2	Z ₃	Z_4	Z ₅	
V_1	0.09717	0.29753	0.09777	0.09774	0.39762	
V_2	0.39966	0.29966	0.59971	0.79982	0.49970	
V_3	0.29706	0.89706	0.69798	0.29711	0.09752	
	Hic	dden Layer	to Output L	.ayer		
Weight	W_1	W_2	W_3			
Υ	0.2143	0.0046	0.4069			
	li li	nput Bias to	Hidden lay	yer		
Bias	1	2	3			
Vj	0.8961	0.7996	0.6957			
Hidden To Output Bias						
Bias	1					
W_j	-0.004					

Data Result (Output)

Table 10 presents the output unit factor value results based on the error in each unit (error and squared error), output value and MSE value.

$$\label{eq:MSE} \begin{split} \text{MSE} = & \frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2 \\ \text{Output} = & \text{Target - Error} \end{split} \tag{14}$$

Table 10. Output

Time	Target	Error	Error Squared	Output	MSE
Day 1	0.1	-0.613	0.3758	0.713	0.0964
Day 2	0.3	-0.4468	0.1412	0.7068	
Day 3	0.1	-0.5973	0.3568	0.6973	
		•••		•••	
Day 30	0.9	0.2664	0.071	0.6336	

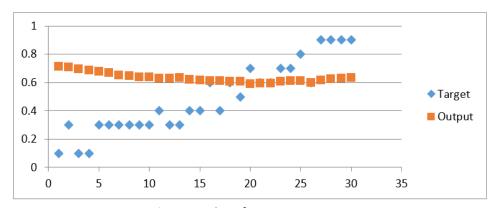


Figure 2. Plot of Target vs Output

Figure 2 present the results of the explanation above obtained the results of the analysis, namely the most influential risk factor, namely errors in mushroom baglogs or seeds, baglog errors increase every day which results in a decrease in yield in the following month.

The results of the above data training (output) show that the minimum error if rounded is 0.6 or 4 kg of harvest (Rp 80,000), while the maximum error if rounded is 0.7 or 5 kg of harvest (Rp 100,000). with a training MSE of 0.0964 with Epoch 1.

Conclusion

In this study, variables were obtained to support the risk factors for the success of oyster mushroom cultivation, namely non-sterile equipment, employee personal hygiene is not maintained, errors in mushroom baglogs or seedlings, spraying water that is too strong, and flooding in the business location. Based on the results of testing or training conducted using the 5-3-1 Artificial Neural Network (JST) architecture and Epoch 1, the minimum error is 0.6 or 4 kg of yield (IDR 80,000), while the maximum error is 0.7 or 5 kg of yield (IDR 100,000). with a training MSE of 0.0964 with This means that artificial neural networks can create patterns to predict the yield of oyster mushroom cultivation. To avoid too much risk this pattern will later be made a decision-making model used by oyster mushroom cultivation farmers as a tool to measure the risks experienced.

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