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Optimization of Blood Clam Supply Control Using the Artificial Neural Network (ANN) Method

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A B S T R A C T

Mr. Badul MSME faces problems in managing blood clam inventory, namely excess and shortage of stock. To overcome this, research was conducted to design an inventory prediction system using the Artificial Neural Network (ANN) method with the Backpropagation algorithm. The ANN model used has an architecture with 10 input neurons, 10 hidden neurons, and 1 output neuron. The inventory data is normalized before the training process, then the results are denormalized to get the actual prediction. The developed model shows good performance with a very low Mean Squared Error (MSE) value of 2.7359e-06, as well as a correlation coefficient of 0.91478, which shows a strong relationship between predictions and actual data. The prediction results cover the period from January 2023 to December 2024. In January 2023, the inventory was predicted to be 96,050 kg, declining in February to 89,205 kg, and dropping sharply to 68,670 kg in March and April. Inventory increases again in May to August with fluctuations from 75,515 kg to 89,205 kg. A similar pattern occurs in 2024, starting with 96,050 kg in January, decreasing in March and April, then increasing again in the middle of the year, and decreasing again towards the end of the year, with the lowest inventory of 65,933 kg in November and December.

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1. INTRODUCTION

In companies and businesses, the main goal is to make a profit or profit. Every business must also pay attention and manage inventory in meeting consumer demand and reduce cost of inventory and the risk of loss as a result of excess or shortage of inventory. In getting profit, there are things that must be considered, namely how we control the optimal food supply. One of the businesses that is concerned about its inventory is the blood clam collecting business. If there is a shortage of inventory, the business experiences a loss of sales and cannot get the maximum profit for sales. Meanwhile, if there is excess inventory, the business incurs more costs due to the large number of blood clams stored. Therefore, the business optimizes inventory control. Optimization is the process of finding the best solution to a problem, by maximizing or minimizing a certain value under existing conditions or constraints. The main goal of optimization is to get the optimal or most efficient result of a system, process, or function. (Devita and Wibawa 2020). Optimization has a critical role to play in solving challenges in complex areas such as engineering, healthcare, and machine learning (Chauhan et al. 2025). Optimum efficiency can only be achieved if combustion parameters are precisely controlled (Iqbal et al. 2025). Inventory control is an effort so that the stored inventory is not too much but also not too little (Hartono and Andaresta 2021). Inventory control is largely concentrated on a deterministic approach, which may not be able to regulate the complexity of the actual environment (Nand 2025).

Inventory is a material or product that is stored and will be used to meet a need (Ramadhan and Saifuddin 2024). Inventory is one of the factors that determine the smooth production of production, so inventory must be managed appropriately (Larasati, Yateno, and Japlani 2022). The need for optimal inventory is to prepare the raw materials needed at the production stage to ensure a smooth process and prevent stock outages at the lowest possible cost (Purba, Rohmatin, and Karim 2024). Inventory management aims to minimize all the different cost sets, which is beneficial for the overall management of business entities (Stoilov and Stoilova 2025). Successful Inventory management is the key to success for any retail business (Ping, Wong, and Han 2025). Shellfish is an Indonesian fishery commodity with Among the different types of shellfish, the blood shellfish is one of the most demanded by the public (Purnamasari, Nafisyah, and Sari 2024). Mussels are a food source that comes from the seabed which is often consumed because it contains high protein, one of which is a type of blood mussels (Handayani, Kurniawan, and Adibrata 2020). Shellfish are the main organisms used in co-culture systems to absorb suspended organic waste in the water (Kabangnga, Heriansah, and Nursida 2024).

MSME XYZ is one of the businesses located on the banks of the Rokan river, Rokan Hilir Regency, precisely in Bagansiapiapi which is engaged in trading. This MSME is located in West Bagan Village, Bangko District with operating hours depending on the tide. Before becoming a port for unloading blood shells, this place used to be a fishery warehouse where the port was moored for Rokan Hilir water surveillance ships. XYZ MSME sell blood shells in various regions such as Dumai, Pekanbaru, Medan and Batam and Malaysia. This research phenomenon shows that the amount of supply and demand is often inconsistent or inaccurate, and frequently changes. If there is a shortage of supply, the company will experience lost sales and will not be able to maximize profits from sales. Meanwhile, if there is an excess of supply, the company will incur additional costs due to the large amount of blood clams stored.

The cost incurred to store blood shells is in the form of ice and duct tape. The cost of ice incurred by the company every month is Rp. 1,530,000, while the cost of duct tape is Rp. 150,000. Please note that when the supply of blood mussels is overstocked, the mussels must be stored first in fiber ice and let for 2 to 3 days if more than that blood mussels expire, and can decrease in price. Therefore blood mussels can also die and suffer from decay. The period of starting order for blood mussels according to the tides of the seawater of Bagansiapiapi, for example when the tide the fishermen immediately depart for the sea at 06:00 am, returning home at 06:00 pm, meaning the leadtime of the blood mussels is an average of 12 hours.

All of these problems are caused because XYZ MSME have not had the right way to determine the supply of blood shells. With the right inventory calculation, the company can minimize the total cost in the change in inventory levels. The research was conducted on XYZ MSME because the control at this company still uses an uncertain estimation system, causing management difficulties in determining the supply of blood shells.

Artificial Neural Network (ANN) yang digunakan dalam studi ini bermanfaat untuk forecasting demand, optimization of inventory, logistics planning, and making more accurate predictions about future inventory needs. ANN membantu bisnis mengoptimalkan inventory levels, production schedules, and procurement activities to increase parts production productivity.

The Artificial Neural Network (ANN) method is not commonly used in calculating material stock requirements because it originates from an artificial intelligence approach. However, Artificial Neural Networks (ANN) have several advantages over conventional methods such as Economic Order Quantity (EOQ) and Material Requirement Planning (MRP). The EOQ method has the advantage of simplicity in calculation, but it has limitations because it assumes that demand is constant and stable. In real business conditions, which often experience fluctuations in demand, this assumption becomes less relevant, while MRP is highly dependent on product structure data (Bill of Material) and a fixed production schedule. If there is a sudden change in demand, the MRP method requires relatively complex manual adjustments.

2. LITERATURE REVIEW

Inventory is one of the factors that determine the smooth production of production, so inventory must be managed appropriately. In this case, the to maintain continuity of production and generate profits, companies must be able to determine the ideal amount of inventory. This is because a lack of inventory will be just as bad as an excess of inventory, because both conditions have the same consequences (Larasati, Yateno, and Japlani 2022). There are several types of inventory, where each type has special characteristics and different management methods, namely (Fenny Hidha Rahmawati and Esthi Adityarini 2021): (1) Factory suppliers are goods that can have the function of smoothing the production process, such as engine oil, engine cleaning materials. (2) Goods in process are goods that are being worked on. (3) Production is complete, i.e. goods that have been completed in the production process and are waiting for their sale.

Inventory control is one of the activities that are closely related to each other in the overall production operations of a company (Hidayat and Sitania 2024). Inventory control is an effort so that the stored inventory is not too much but also not too little (Hartono and Andaresta 2021). Inventory control is a set of control policies to determine the level of inventory that must be maintained, when orders to increase inventory should be placed and how large orders should be held (Karamoy, Jan, and Karuntu 2022). Inventory control aims to find out the optimal quantity in each purchase of raw materials, the point that indicates the time to place a reorder, the maximum inventory, and the total cost of raw material inventory to avoid the risk of running out and also excess raw materials so as to minimize the company's raw material costs(Larasati, Yateno, and Japlani 2022).

Artificial Neural Network (ANN) are distributed parallel information processing architectures, consisting of interconnected processing units, each with its own memory and inspired by the human brain (Kapucu and Akpolat 2024). Artificial Neural Network (ANN) is a stimulus received from neurons is referred to as the input layer and is then processed through one or more hidden layers, while in the hidden layer there is an activation function (Wayan and Ayuni 2025). Artificial Neural Network (ANN) can play an important It has an important role in the development of supply chain management by improving various aspects such as demand forecasting, inventory management, logistics optimization, and risk analysis. The Artificial Neural Network (ANN) is one of the computational models inspired by biological neural networks in the human brain (Soori, Arezoo, and Dastres 2023). Artificial Neural Network (ANN) inspired by biological systems neurons but simplifies its functions to make it computationally efficient (Islam, Bouzerdoum, and Belhaouari 2024). Improving the practical efficiency of neural networks is a worthwhile endeavor, as they are able to identify complex patterns in consumption and help in determining optimal levels of supply (Cholodowicz and Oriowski 2024).

Backpropagation is a gradient-based method that applies an automatic mode of reverse differentiation to calculate the gradient required for parameter updates in a neural network (Dalm et al. 2024). Layered Perceptrons sering menggunakan backpropagation, a supervised learning algorithm, to modify neuron weights in hidden layer networks. Because hidden layer networks have many layers, the output layer part comes from the hidden layer part because the input pattern is used as a training pattern (Rahmiyanti, Defit, and Yunus 2021).

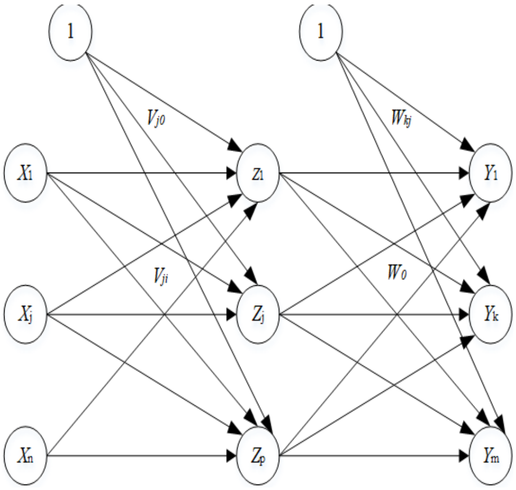

Figure 1. Backpropagation architecture
(Source: pocessed data)

Figure 1 shows a backpropagation architecture with n inputs consisting of input layers numbering n neurons, each receiving one feature of input data (unit X), m output (unit Y), and one layer of hidden neurons (unit Z). The weight w_ij is the weight from the input unit to the hidden unit (v_j0 is the bias on the Z_j hidden unit), while W_kj is the weight from the hidden unit to the output unit, with W_k0 as the bias on the Y_k output unit. Data normalization is carried out by neural networks in the process of only recognizing data binaries with the formula below (Lasarudin and Maku 2022):

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

Where:

X' is the standard data, X is the initial data, a is the maximum value of the initial data and b is the minimum value of the initial data.

Data denormalization is a neural network process that will be converted to initial data with the formula below (Lasarudin and Maku 2022):

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

Where:

x = Original data/ initial data
a = Maximum value of original data
b = Minimum value of original data
x’ = Data from normalization results

3. RESEARCH METHOD

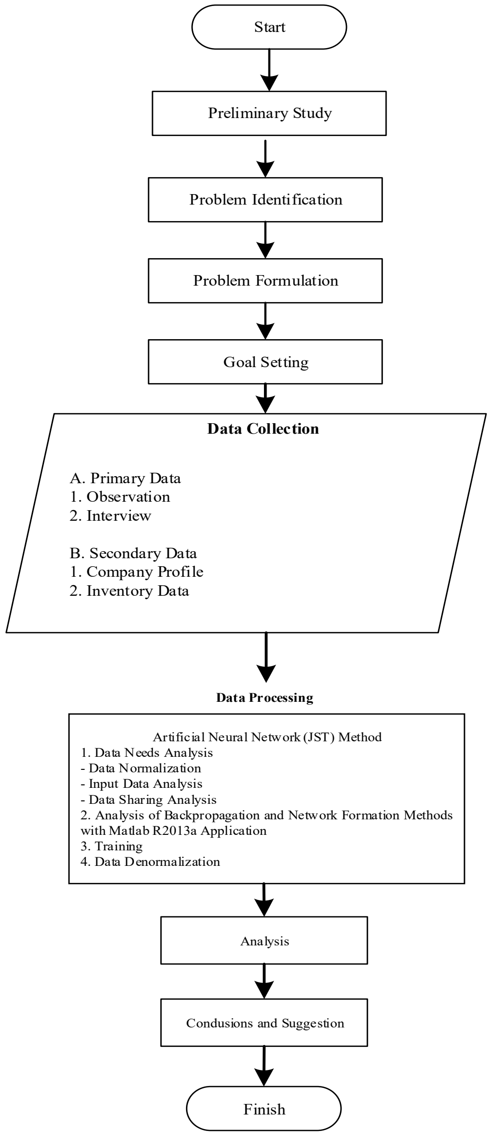

Figure 2. Research methodology flowchart
(Source: pocessed data)

The research methodology is the stage that will be passed in carrying out the research that outlines the stages used from the beginning to the end of the research. The steps to be taken are shown via the flowchart in Figure 2.

4. RESULT AND DISCUSSION

The limitations of this study are as follows:
1. Data collected by researchers in 2023-2024
2. Data collection was conducted during visits to the homes of the owners of MSME XYZ

Data Needs Analysis

Data needs analysis is a data processing process carried out in analyzing data that will be used in completing the calculation of the backpropagation algorithm to optimize the supply of blood shells in 2023 to 2024. In this process, the researcher must determine the inputs and targets, determine the amount of data needed, normalize the data and divide the data for training and testing. To do all of this, there are the stages that must be done as follows.

Table 1. Data on the supply of blood shells for 2023-2024 XYZ MSME

Period	Clove	Potai	SKP	SK	Average
Jan 23	35200	67200	81000	164500	86975
Feb 23	45000	68000	82200	161000	89050
March 23	47400	68400	83400	153600	88200
Apr 23	43400	61400	82000	155000	85450
May 23	40400	65400	78000	158000	85450
June 23	40900	62900	72800	157000	83400
July 23	40900	68900	75000	158000	85700
Augus 23	34600	66600	76300	157000	83625
Sep 23	35200	69200	70400	160000	83700
Octo 23	36000	60000	74500	156000	81625
Nov 23	35000	60000	74300	148500	79450
Dec 23	32500	64500	80800	161100	84725
Jan 24	40000	62000	68300	158800	82275
Feb 24	31700	64700	78700	151900	81750
March 24	33000	65000	79600	151400	82250
Apr 24	38000	63000	76500	157600	83775
May 24	38000	67000	79100	155800	84975
June 24	34900	68900	71500	155360	82665
July 24	33900	60900	79600	160360	83690
Augus 24	27600	60600	72500	160460	80290
Sep 24	36500	62500	72000	162410	83352,5
Octo24	33700	66700	79000	163610	85752,5
Nov 24	29800	67800	73800	160610	83002,5
Dec 24	35700	68700	73900	161000	84825

(Source: processed data)

Data Normalization

Data normalization is carried out to adjust the values for the training data and test data. So that the data value after normalization is in the range of 0-1 to avoid the dominance of large-value variables over small-value variables in the calculation of Backpropagation Artificial Neural Networks. In the normalization of the data, the formula X' = (0.8 (X-b)) / ((a-b)) + 0.1
Max Value = 164.500
Min Value = 27.600

$$\text{Januari 23} = \frac{35.200+67.200+81.000+164.000}{4} = 86.975$$
$$= \left(\frac{(0,8)\text{x}(86.975\text{-}27.600)}{4}\right) + 0,1$$
$$= \left(\frac{(0,8)\text{x}(59.375)}{136.900}\right) + 0,1$$
$$= \frac{47.500}{136.900} + 0,1 = 0,446$$

Table 2. Data recapitulation after normalization

Period	Normalized Data
January 2023	0.446
February 2023	0.459
March 2023	0.332
Apr 2023	0.499
May 2023	0.499
June 2023	0.424
July 2023	0.439
August 2023	0.427
September 2023	0.427
October 2023	0.415
November 2023	0.402
December 2023	0.433
January 2024	0.419
February 2024	0.416
March 2024	0.419
Apr 2024	0.428
May 2024	0.435
Juny 2024	0.421
July2024	0.427
August 2024	0.407
September 2024	0.425
October 2024	0.439
November 2024	0.423
December 2024	0.434

(Source: processed data)

Input Data Analysis

Input data analysis is a part of determining input data that will later be used as input neurons in the Backpropogation Network Architecture.

Data Sharing Analysis

In the Backpropogation learning stage, data sharing is carried out to divide between training data and test data from normalized blood clam data. In terms of the percentage of training data and test data of 70%:30 for medium datasets, 80%:20% for larger datasets and 90%:10% for large datasets. After being seen from the provisions of the percentage of training data and test data, the researcher conducted a division of training data using the data of the 80% training and 20% test sections because in general it provides larger training data. This process is carried out in order to produce the best training accuracy value. In the available data, there are 12 monthly data samples from January to December, each containing 12 input variables (X1 to X12) and one target value. At the 80%:20% split stage produces 10 training data and 2 test data, this gives the model more training data, but reduces the amount of test data that can impact under-representation testing.

80%
Division: 20% Training Data = 80% x 12 = 9.6 rounded up to 10
Test Data data = 12 – 10 = 2 data

Analysis of Backpropagation Methods

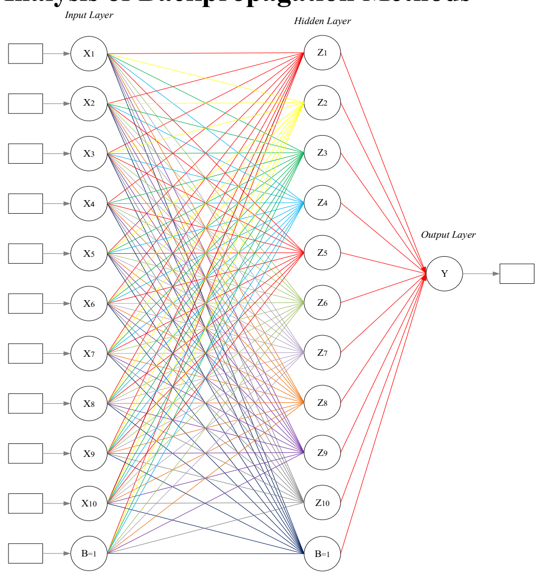

Figure 3. Architecture of backpropagation artificial neural network
(Source: pocessed data)

Image Caption:

1. The Input Layer, is input data from the XYZ MSME blood shells data that has been normalized and ready to be transferred to the hidden layer. The number of inputs is initialized with X1, X2, X3, X4, ... X10.
2. The Hidden Layer is the layer that receives data from the input layer. There are 10 neurons on the hidden layer that are enclosed with the letter Z.
3. Output layer, is a layer that receives data from a hidden layer. The neurons in the output layer are denoted by the letter Y.

Training

The next stage is to conduct training using matlab software (Figure 4).

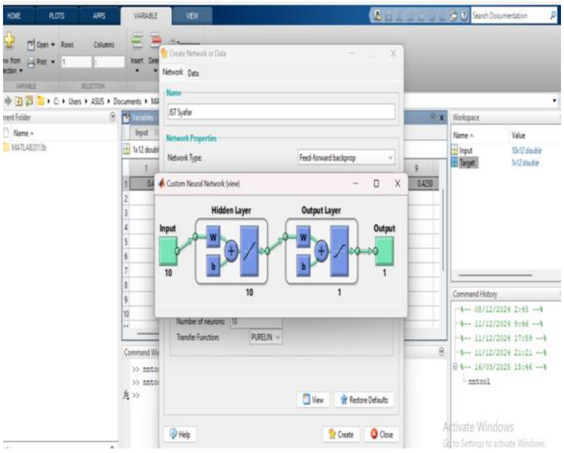

Figure 4. Network data training
(Source: pocessed data

Based on figure 4, this network consists of 10 inputs, 10 a hidden layer, and one output layer. A large amount of hidden layers indicates that this model is quite complex. With 10 inputs, this model has the potential to capture a wide range of features from the input data.

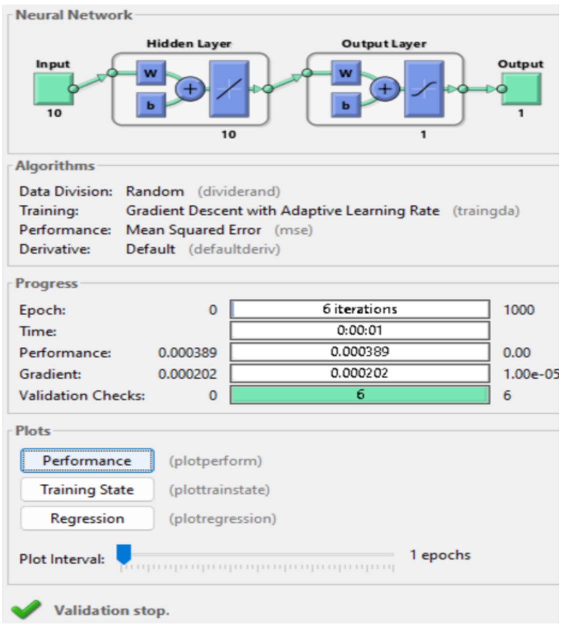

Figure 5. Network data training
(Source: pocessed data)

Based on Figure 5 the epoch value is 6 epoches with a total of 1000 iterations. This shows that training is done in a single stage (epoch).

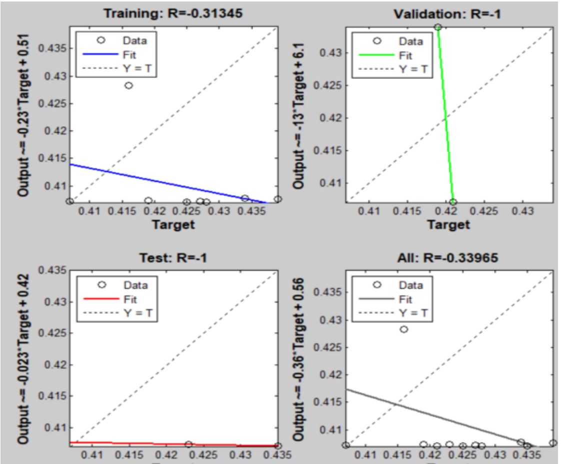

Figure 6. Correlation coherence R test data
(Source: pocessed data)

From the drawing, it can be seen that the training must be carried out several times until the result of the dotted line must be close to the colored line, therefore the training must be carried out repeatedly as in Figure 7.

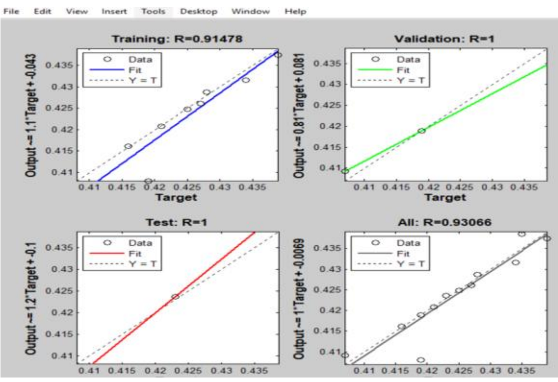

Figure 7. Correlation coherence R test data
(Source: pocessed data)

From Figure 7, it can be seen that the repetition was carried out as many as 120 iterations and the maximum error was 2600 errors. This shows that the training is conducted in multiple epochs, where the model updates its weights repeatedly across the entire dataset. The performance value of the model achieved is 2.52 e-06 This performance value may be the metric chosen to evaluate the model's performance. Lower values indicate that the model is performing better, although without further context it is difficult to assess whether or not this performance is considered good.

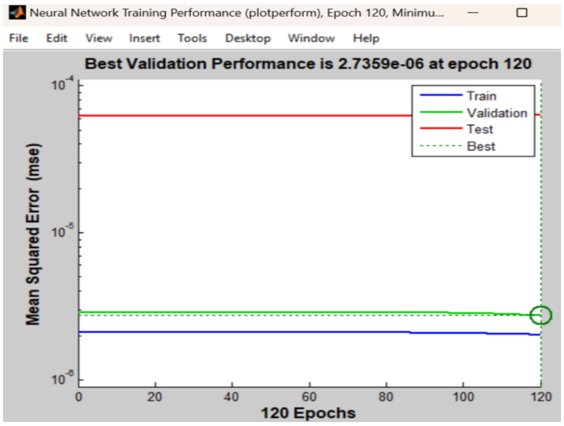

Figure 8. Error goal (MSE) training data
(Source: pocessed data)

Based on the Figure 8, the error goal (MSE) of 2,735e-06 was achieved in the 120th epoch. This model shows that it has reached the desired low error rate. The smaller the value of the MSE, the better the model is at making predictions on the data. It can be concluded that the training has successfully achieved its objectives by achieving the desired level of error.

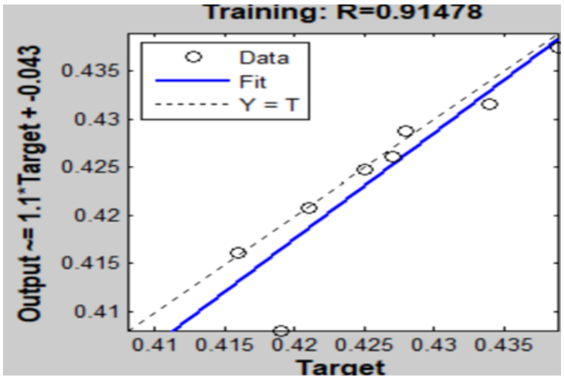

Figure 9. Correlation coefficient of R data training
(Source: pocessed data)

Based on figure 9 of the correlation coefficient value and the based on the Mean Square Error value obtained during the training process, it can be concluded that the Artificial Nerve Network can optimize the supply of blood shells well.

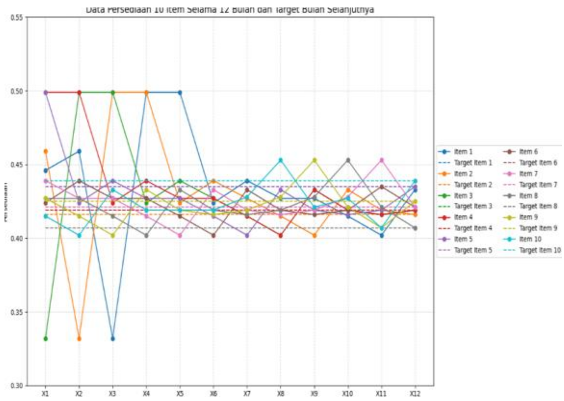

Figure 10. ANN output graph with target training data
(Source: pocessed data)

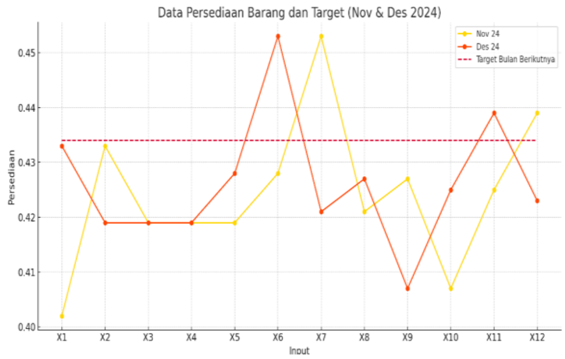

Figure 11. ANN output graph with test data target
(Source: pocessed data)

Table 3. Recapitulation of output results by Artificial Neural Network (ANN) method

Output	2023	2024
Y1	0.50	0.50
Y2	0.46	0.46
Y3	0.34	0.34
Y4	0.34	0.34
Y5	0.38	0.42
Y7	0.42	0.42
Y8	0.46	0.42
Y9	0.42	0.42
Y10	0.42	0.41
Y11	0.38	0.38
Y12	0.38	0.38

(Source: pocessed data)

Data Denormalization

In Artificial Neural Networks, denormalization means changing the output of a previously normalized network back to its original scale.

Value Max = 164.500

Value Min = 27.600

$$\text{Output Y1} = \frac{(0.50\text{-}0.1)\text{x}(164.500\text{-}27.600)}{4} + 27.600$$

$$= \left(\frac{(0.4)\text{x}(136.900)}{0.8}\right) + 27.600$$

$$= \left(\frac{(154.760)}{0.8}\right) + 27.600$$

$$= 68.450. + 27.600 = 96.050$$

Table 4. Recapitulation of tiraun nerve network results with denormalization results

Period	Result ANN	Result Denormalization (Kg)
Jan 2023	0.50	96.050
Feb 2023	0.46	89.205
March 2023	0.34	68.670
Apr 2023	0.34	68.670
May 2023	0.38	75.515
June 2023	0.38	75.515
July 2023	0.42	82.360
August 2023	0.46	82.360
Sept 2023	0.42	82.360
Octo 2023	0.42	82.360
Nov 2023	0.41	75.515
Dec 2023	0.44	75.515
Jan 2024	0.50	96.050
Feb 2024	0.46	89.205
March 2024	0.34	68.670
Apr 2024	0.34	68.670
May 2024	0.42	82.360
June 2024	0.42	82.360
July 2024	0.42	96.050
August 2024	0.42	96.050
Sept 2024	0.42	82.360
Octo 2024	0.41	82.360
Nov 2024	0.38	65.933
Dec 2024	0.38	65.933

(Source: pocessed data)

The results of Artificial Neural Network (ANN) implementation show that predictions of blood clam inventory requirements are closer to actual conditions than conventional methods. This can be seen from the decrease in excess stock and stock shortages. Thus, blood clam inventory allocation after using Articial Neural Network (ANN) can be said to have gone according to business expectations, as it is able to support smooth operations and storage cost efficiency.

5. CONCLUSION

Based on the results of data processing, the supply of blood shells can be predicted by building and training a prediction model using the Artificial Neural Network (ANN) method with a backpropagation algorithm. Developed model ANN model consists of 10 neuron inputs, 10 hidden neurons, and 1 neuron output. Inventory data from 2023-2024 has been normalized to facilitate the training process, then the results are denormalized again to obtain prediction results in kilograms. The results of the training showed high accuracy, with a very low MSE value (2.7359e-06 and a correlation coefficient (R) of 0.91478, indicating a strong relationship between the prediction results and the realization. Based on the calculations that have been made, it can be concluded that the amount of shellfish inventory in XYZ MSME for the period January 2023 to December 2024 is in kilograms. At the beginning of 2023, inventories are predicted to be 96,050 kg in January and decrease to 89,205 kg in February. Furthermore, there was a sharp decline in March and April, each amounting to 68,670 kg. Inventories increased again in May and June with a value of 75,515 kg, then continued to rise to 82,360 kg in July and 89,205 kg in August. This trend decreased slightly back to 82,360 kg in September and October. In November and December 2023, the total inventory remained at 75,515 kg. Entering 2024, a similar pattern occurs with a prediction of 96,050 kg in January and 89,205 kg in February. March and April again experienced a significant decrease to 68,670 kg, followed by an increase in May and June to 82,360 kg. This study developed a prediction model using an Artificial Neural Network (ANN) with a backpropagation algorithm to project blood clam supply. The model was trained using normalized inventory data from 2023-2024, and the results showed a high level of accuracy (MSE = 2.7359e-06, R = 0.91478). In the study by Choyodowicz and Oryowski (2024), the results of their research indicate that the proposed approach can achieve significant waste reduction compared to the POUT method, while maintaining low stock levels, high replenishment rates, and lower sensitivity to parameter changes. For further research, it is necessary to gain a better understanding of software and information technology in order to facilitate research on topics such as artificial neural network methods.

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