

Original Research

Application of The Extreme Learning Machine to Predict the Amount of Duck Egg Sales (Case Study: Barokah Farm)

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Abstract

Barokah Farm is a duck farm that produces two varieties of eggs, salted duck eggs and fresh duck eggs. In the midst of deal preparation, the challenge often arises in maintaining an sufficient stock of eggs, especially since the production of salted eggs has not been able to fulfil customers' demands. The accessibility of duck eggs impacts transactions, as stock levels must adjust with requests to avoid abundance and deficiencies. This considers the Extraordinary Learning Machine (ELM) strategy to predict the transactions of salted and fresh duck eggs. The purpose of this research is to apply the ELM strategy to forecast the amount of duck egg transactions at Barokah Farm and to survey the error rate or percentage of error. Deals forecasts are conducted employing a testing plot to distinguish ideal hyperparameters. From the test parameters that have been tried, it is found that average value is able to reduce the percentage error to less than 10%, where the least MAPE test was gotten from the number of features 4 of 2.050% for salted eggs and 1.796% for fresh eggs. Using multiple neurons of 7 with a MAPE value of 0.329% for salted eggs and 0.466% for fresh eggs. While for the data ratio, the best ratio was found to be 80%:20% with a MAPE value of 0.401% for forecasting salted eggs transaction and 0.550% for fresh eggs. It also applied a biner sigmoid activities function with the least MAPE value of 0.032% for salted eggs and 0.524% for fresh eggs. This shows that the Extraordinary Learning Machine can perform well in forecasting transaction of salted and fresh eggs.

Keywords

Extreme Learning Machine, Percentage Error, Predict, Barokah Farm, egg

1. Introduction

Indonesia has abundant natural resources, including mining, forestry, agriculture, plantations, fisheries and peatlands. People utilize this natural wealth to build businesses in various sectors. One of the rapidly growing businesses is farming, especially farming layers of ducks. Duck egg production in Indonesia increased from 349,356.20 tons in 2022 to 358,220.20 tons in 2023, with a significant contribution from the province of East Java. In East Java, duck egg production also increased, from 45,219.6 tons in 2022 to 46,214.4 tons in 2023 (Badan Pusat Statistika, 2024). Situbondo

Regency contributed to duck egg production which increased from 291,935.00 kg in 2022 to 298,357.57 kg in 2023.

Barokah Farm, located in Mlandingan District, Situbondo Regency, is one of the duck egg farms that has been operating since 2022. This farm produces between 900 and 1,400 duck eggs per day, with two product variations, namely fresh duck eggs and salted eggs. Despite its high production capacity, Barokah Farm often faces problems in stock management, both undersupply and oversupply of eggs. Undersupply can result in loss of

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customers, while oversupply can cause eggs to rot, considering that eggs are a commodity that spoils quickly.

Effective supply management is essential to ensure timely and appropriate product distribution, as well as to reduce costs and meet consumer needs (Widyarto et al. 2012). To overcome this problem, Barokah Farm needs to make more accurate sales predictions based on previous sales data. With the use of sales data from 2022 to 2024, Barokah Farm can estimate market demand and optimize egg inventory so that none are wasted.

One solution that can be applied is to use machine learning, especially the Extreme Learning Machine (ELM) method. ELM is a type of artificial neural network that can be used for regression and classification analysis and has advantages in accuracy and learning speed (Alpaydin, 2010). Previous studies have shown that ELM can provide better results than other methods, such as backpropagation and ARIMA, in various prediction applications.

In this study, researchers will apply the ELM method to predict the amount of duck egg transactions at Barokah Farm. The collected data will be split into training and testing data to obtain optimal results. By using two activation functions, namely biner sigmoid and bipolar, it is hoped that this study can contribute to improving duck egg supply management at Barokah Farm.

2. Research Method

2.1. Duck Egg Sales

Sales include the entire selling process, from pricing to product delivery to consumers (Navarin M, 2007). Duck eggs, which are rich in animal protein and delicious, are marketed in two variations: salted and fresh duck eggs. Salted eggs are preserved to meet consumer demand, while fresh eggs have a shorter shelf life and can be damaged if unsold. Duck egg sales data from November 2022 to October 2024 will be used for analysis. Past sales data patterns can be used as a reference in choosing the right forecasting method, with four types of patterns in time series: trend, seasonal, random, and cyclical (Baroto, 2002, pp. 31-35). Based on the identification, duck egg sales at Barokah Farm are classified as random patterns because consumer demand

can rise and fall suddenly without a clear pattern. This study aims to predict sales of salted and fresh eggs at Barokah Farm, with an emphasis on the importance of the right amount of stock to increase sales.

2.2. Machine Learning

Machine Learning is the study of algorithms that learn to perform certain tasks by humans automatically (Shalev-Shwartz & Ben-David, 2014). In this case, it teaches how to solve an existing problem to make predictions that will obtain new, more accurate conclusions from a previously learnt pattern. Machine learning is a part of artificial intelligence that can influence various other aspects, such as mathematics, statistics, and some theoretical aspects of computer science.

2.3. Extreme Learning Machine

Extreme Learning Machine (ELM) was introduced by Huang in 2004 as a single hidden layer feed-forward neural networks (SLFNs) method (Huang, et al., 2004). ELM is designed to overcome the weaknesses of other algorithms with the aim of accelerating the learning process and producing good predictions. The parameter determination process is carried out randomly, including input weight and hidden bias, to prevent instability of the prediction results. ELM uses a simpler and more effective mathematical model compared to other feed-forward neural networks. The extreme learning machine method has several stages that need to be done in predicting data sets. The following is a description of the flow of stages in the extreme learning machine method.

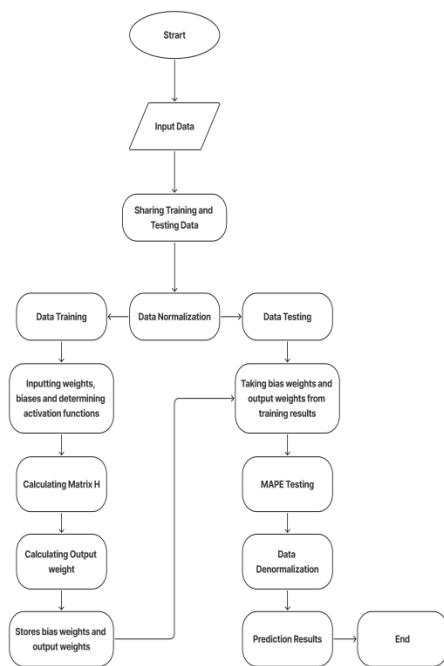


Figure 1 Flowcart Extreme Learning Machine

2.3.1. Normalization Data

Normalization data is aimed to make the range of input values unequal or to reduce high to low values, which have a range of values in the tens to thousands. The input will be processed to a lower value so the sales data must be adjusted so it can be processed to get a low normalised value. This normalization allows data to have the same limits in a certain time span so it can reduce data noise. In this study, normalization is used to make the sales data has the same scale range between training data, testing, and also new data that will be added. According to Jain and Bhandare, the data normalization process can use the Min-Max Normalization method (Jain & Bhandare 2011):

$$y' = \frac{(y - \min)}{(\max - \min)} \quad (1)$$

Description:

y' = value of the data normalization result

y = original data value

$\min$ = minimum value in the feature data set y

$\max$ = maximum value in the feature data set y

2.3.2. Training Model

The training stage must be done before starting the prediction process, with the aim of obtaining the output weight value. According to Huang, Zhu, and Siew

(2006), the training process is carried out through several steps as follows:

- Initializing the input weight and bias. This value is initialized randomly with a range between -1 and 1.
- Performing calculations for all layers in the hidden layer using the activation function, the following equation is use :

$$H_{init\ trn} = x_{trn} \cdot w^T + b \quad (2)$$

- The output of the hidden layer or matrix H is calculated using two activation functions in this study, namely the biner and bipolar sigmoid activation functions.
- Performing calculations of the Moore-Penrose Generalized Inverse/Moore-Penrose Pseudo Inverse Matrix (H^+) from the output results of the hidden layer with the activation function. With the following equation formula :

$$H^+ = (H^T H)^{-1} H^T \dots\dots \quad (3)$$

- Calculating the output weight from the hidden layer to the output layer. Using the following equation :

$$\beta = H^+ t \quad (4)$$

2.3.3. Testing Model

The testing stage is performed to evaluate the ability of the extreme learning machine as a method for making predictions. The phase of testing is based on the input weight, bias, and output weight that are appropriate from the training calculation. The following are the stages of testing:

- Initializing the input weight and bias obtained in the training calculation
- Performing calculations using the activation function to calculate the hidden layer output
- The output weight value that has been obtained in the training process is then used to calculate the output layer, which is the prediction result. The following is the equation for calculating the output layer value:

$$p = H\beta \quad (5)$$

2.3.4. Denormalization Data

Denormalization data stage has a function to generate or return the normalized value to the original value. The following is the equation formula for the data denormalization stage.

$$y = y'(max - min) + min \dots\dots (6)$$

2.3.5. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a measure of prediction accuracy based on absolute value to determine the level of error in a prediction result based on data. In this study, MAPE is used to provide a percentage or error value from the prediction result. Here is the MAPE formula along with the testing scheme that will be carried out:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y' - y}{y} \right| \times 100 \dots\dots\dots (7)$$

2.3.6. Sigmoid Activation

The sigmoid activation function is used to get the smallest error value for the prediction. The activation function will be tested to determine which activation function is the best with the smallest error value. According to Srimuang & Intarasothonchun (2015), extreme learning machines have several types of activation functions. In this study, two types of activation will be used to test its performance; the following are two activation functions that will be used:

a. Biner Sigmoid Activation Function

This activation function is used in this study or calculation because it has a value range of 0 to 1, so it can be used for networks with output values in the interval 0 to 1 and also output values of 0 or 1. The biner sigmoid activation function has the following equation formula:

$$H = \frac{1}{1 + \exp^{-x}} \dots\dots\dots (8)$$

b. Bipolar sigmoid activation function

This activation function is the same as the biner sigmoid activation function but has a different range of values, namely from -1 to 1.

$$H = \frac{1 - \exp^{-x}}{1 + \exp^{-x}} \dots\dots\dots (9)$$

3. Results and Analysis

3.1. Result Collection Data

Data collection from November 2022 to October 2024 that has been identified in the previous stage. All data comes from daily historical data on duck egg sales obtained from Barokah Farm, totaling 731 data. Sales

data as primary data in the form of salted and fresh eggs sales.

3.2. Result Preprocessing Data

This stage involves the initial processing of data collected from Barokah Farm managers, which will be input into an Excel file in CSV format to be imported into the system. The purpose of this process is to change the initial data format to make it easier to understand and analyze. During this process, the data will undergo a transformation to form features that are more suitable for predictive analysis. In this study, the data will be transformed into two feature forms, namely features 4 and 5. Feature 4 will form a pattern where X1 represents the first day's data, X2 for the second day, X3 for the third day, and X4 for the fourth day. After the formation of the feature, there will be target data (Y) and in the second row data X1 will contain the value of X2 in the previous row. Table 1 is an example of transformation data on salted duck egg sales using feature 4.

Table 1 Transformation Data

No	Salted Duck Egg				
	X1	X2	X3	X4	Target/Y
1	403	475	600	565	400
2	475	600	565	400	565
3	600	565	400	565	564
4	565	400	565	564	390
5	400	565	564	390	440
...	...	...	...	...	...
727	533	648	534	503	548

3.3. Result Splitting Data

At this stage, the data that has been prepared for analysis will be divided into two parts, training data and testing data, with four different ratios 60%: 40%, 70%: 30%, 80%: 20%, and 90%: 10%. The selection of this ratio is based on previous research showing that the smallest error value is obtained with a larger amount of training data (Apriliyanti et al., 2023). Training data is used to build a model, while testing data is used to test the results of the model that has been built. In the

Extreme Learning Machine method, modeling is carried out after data division therefore the resulting model can generalize the data to be predicted well.

3.4. Result Training Model

The calculation in the Extreme Learning Machine (ELM) model training process involves determining the input weights and biases randomly, followed by calculating the output weights using the calculations in the training process to produce a model that can predict new data. Table 2, is the result of the initialization of input weights, biases, and output weights from the training process.

Table 2 Input Weight

<i>Input Weight</i>					
W	X1	X2	X3	X4	Tar-get/Y
1	0,466649	0,453535	-0,933149	0,312450	0,372243
2	-0,036867	0,645053	0,332259	-0,94213	0,475903
3	0,543165	0,42990	-0,2482936	0,543310	0,466649
4	-0,35785	0,73255	0,582155	-0,05637	-0,99693
5	-0,30488	0,10101	0,3603544	0,94163	-0,9442

Bias: Matrix Bias = 1, X1 = -0,14480296, X2 = -0,51715478, X3 = -0,02404908, X4 = 0,61491239, Target/Y = 0,30419774

Output weight: -1,48549443, -5,15087478, -8,19870476, 7,90806206, 8,09191607

3.5. Result Testing Model

The testing process in Extreme Learning Machine (ELM) begins after the model is trained. The input weights and biases that have been randomly initialized during the training process are used to process the testing data. Input data from the testing dataset is put into the same activation function as that used during training, resulting in an activation matrix that reflects the output of the neurons in the hidden layer. Next, the output weights that have been calculated during training are applied to the activation matrix to produce the final prediction. The results of this prediction are then compared to the actual target values to evaluate the performance of the model, using the mean absolute percentage error, which provides an idea of how well the model can generalize and predict new data that has never been seen before. The following are the table prediction

results along and the testing process with the model hyperparameters.

Table 3 Input Weight

No	Actual Value	Prediction Value
1	552	549,76901235
2	535	531,75654454
3	632	631,15588081
4	630	608,14166032
5	570	557,2163403
...	...	...
146	548	549,33367726

3.5.1. Testing of Features

Feature of testing is used to find with the aim of determining which is the best number of features that can obtain the smallest error value in the prediction results. In addition, the benefit of testing based on feature variations is to obtain an analysis of how the number of features influences the error value that appears. In this test, features 4 and 5 are used in the number of egg sales. The best number of features is expected to get better recognition results for the training and testing process of the model. Testing is run 5 times on each feature using a parameter variation of the number of neurons 5, a data ratio of 80%: 20% and a biner sigmoid activation function.

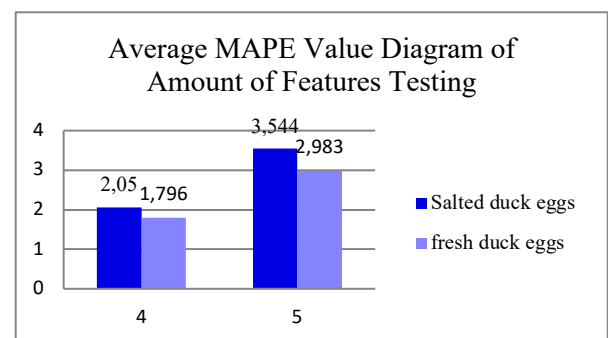


Figure 2 Average MAPE Value Diagram of Amount of Features Testing

Based on the test results shown in Figure 2, it can be concluded that by using four features, the smallest average MAPE is 2.050% for salted eggs and 1.796% for fresh eggs. The MAPE value for four features is smaller

than using five features. This can be caused by the many features used, resulting in less training and testing data. Conversely, the more training and testing data, the better the prediction quality will be.

3.5.2. Testing the Amount of Neurons

Testing the amount of neurons determining the best number of neurons that can produce the smallest error value in the prediction results and analyzing the effect of the number of hidden nodes on the resulting error value. In this test, the number of neurons is 4, 5, 6, and 7 features are used with 5 trials on each neuron. The parameters to be used with a feature variation of 4, a data ratio of 80%: 20%, and a biner sigmoid activation function.

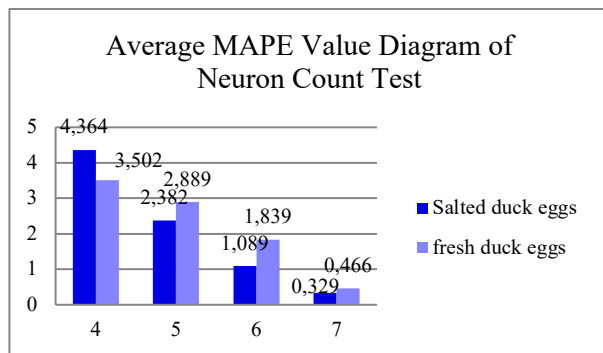


Figure 3 Average MAPE Value Diagram of Neuron Count Test

Based on the test results shown in Figure 3, it can be concluded that by using neuron 7, the smallest average MAPE of 0.329% for salted eggs and 0.466% for fresh eggs was obtained. The MAPE value for the number of neurons is smaller than for neurons 4, 5, and 6. This proves that the addition of neurons makes the MAPE value smaller.

3.5.3. Testing of Data Ratio

Testing of data ratio will get the best amount of training and testing data to get the smallest error value in the prediction results and analyze the flow of data ratio to the error value. The data ratios used in this study are 90%:10%, 80%:20%, 70%:30%, and 60%:40% with variations in feature parameters 4, the number of neurons 7, and the biner sigmoid activation function. Testing will be carried out 5 times on each data ratio.

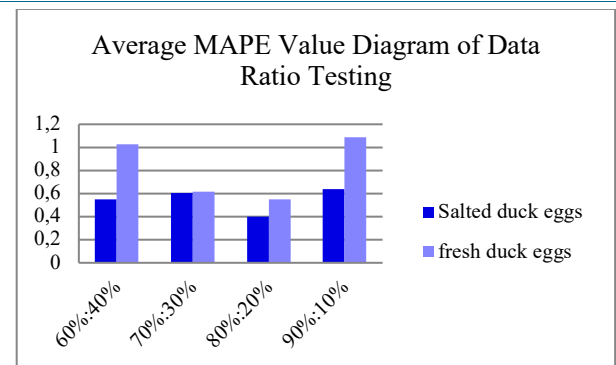


Figure 4 Average MAPE Value Diagram of Data Ratio Testing

Based on the test results seen in Figure 4, it can be concluded that the use of the training and testing data ratio also affects the MAPE value. Where the smallest MAPE value is 0.401% for the prediction of salted egg sales with a data ratio of 80%:20% and 0.550% for fresh eggs with a ratio of 80%:20%. This proves that each use of the data ratio affects the MAPE value; the data pattern greatly affects the data. From the data ratio test, it can be concluded that the limited amount of training data will cause the testing process to be less than optimal due to the lack of variation in data patterns used in the system, thus increasing the error value. In addition, if the testing data is limited, it can increase errors, especially for outliers.

3.5.4. Testing of Activation Function

Testing of the activation function aims to analyze the effect of the activation function used on the error value obtained and also to choose the best activation function. In this test, two activation functions are used, namely biner sigmoid and bipolar. The testing parameters that will be used are feature 4, the number of neurons 7, and the data ratio 80%:20% with 5 testing trials on each activation function.

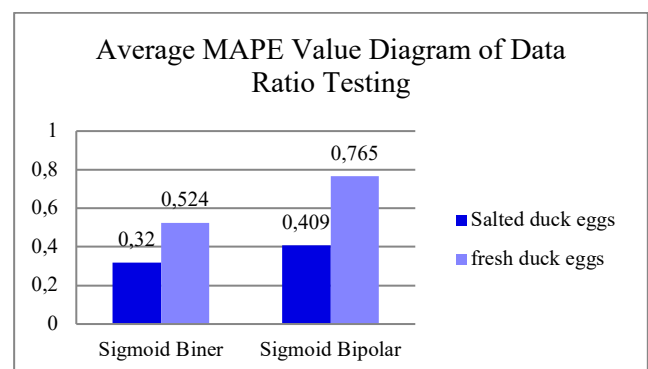


Figure 5 Average MAPE Value Diagram of Data Ratio Testing

Based on the test results, it is proven that the average MAPE value obtained in 5 trials for salted eggs has the smallest value of 0.032% for salted eggs and 0.524% for fresh eggs. This proves that the performance of the biner sigmoid activation function is better than the bipolar sigmoid.

3.6. Results of implementation

The best variation is used in creating a simple system to predict the number of sales of Barokah Farm duck eggs. The system is used to predict the sales of salted and fresh duck eggs, by entering egg sales data. Then after the data is inputted, the prediction of salted and unsalted egg sales will appear.

Figure 6 Display of Barokah Farm Duck Egg Sales Prediction System

4. Conclusion

1. The application of the Extreme Learning Machine method to predict the sales of Barokah Farm duck eggs is applied by using a simple system that is able to predict egg sales with the best variation that has been tested by inputting the sales value and then will be predicted.
2. Barokah Farm duck egg sales prediction using the extreme learning machine method can be applied effectively by performing several stages that are then tested with a testing scheme to obtain better test hyperparameters. In this study, it has been found that the lowest MAPE test results were obtained from the number of features 4 of 2.050% for salted eggs and 1.796% for fresh eggs. With the use of the number of neurons of 7 with a MAPE value of 0.329% for salted eggs and 0.466% for fresh eggs. While for the data ratio, the best ratio was found, namely 80%:20% with a MAPE value of 0.401% for predicting

salted egg sales and 0.550% for fresh eggs. As well as the use of a biner sigmoid activation function with the smallest MAPE value of 0.032% for salted eggs and 0.524% for fresh eggs. From the testing parameters that have been tested, it was found that the average value was able to produce an error percentage of less than 10%. This proves that the Extreme Learning Machine can work well in predicting sales of salted and fresh eggs.

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