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Development of a Production Machine Maintenance Predictive Model Using the Elman Recurrent Neural Network Algorithm

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ABSTRACT

PT Simba Indosnack Makmur is a factory that produces snacks. In the production process, the problem that is often faced by the Quality Control section is that it often finds non-standard product weights. This problem is caused by a machine that already requires maintenance. The long maintenance submission process has an impact on reduced production targets. The data used in this study is data on the weight of 12 gram food products from August 2, 2021-April 30, 2022, for 222 days, 504 per day. By implementing a predictive maintenance model that utilizes time series data in the production process and implementing the Elman Recurrent Neural Network (ERNN) it will be able to provide notifications for machine maintenance. The Elman structure was chosen because it can make iterations much faster, thus facilitating the convergence process. The input vector used uses windows size. The results of the study using a target error of 0.001 show the smallest MSE value, namely on windows size 11 with a value of 0.002833. Then by using 13 neurons in the hidden layer, the minimum error value is 0.003725. Using ERNN with windows size 11 and hidden layer 13 neurons gives the best results in prediction.

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1. INTRODUCTION

The maintenance management system is very important for the overall performance of any production system [1]. Productivity depends on the effectiveness of the maintenance system, while effective and efficient production planning depends on the ability of planners to predict adequately some important parameters of the maintenance system [2]. Having adequate knowledge about the maintenance parameters for a particular production system will improve other functions such as scheduling and planning functions thereby increasing the overall system performance. Several methods have been applied in maintenance management, including operations research for various problems related to maintenance [3], markov models in the problem area of equipment maintenance and replacement [4], simulation models for planning preventive maintenance activities [5], mathematical models for studying time characteristics machine downtime associated with various maintenance environments [6].

Unplanned maintenance is a major problem in asset intensive industries such as manufacturing. The impact can be very costly due to extended production downtime. Not only resulting in urgent repairs and investment in new machines and parts [7]. Predictive maintenance uses predictive analytics to determine machine life and probability of failure on a given day. The concept is to use information to schedule maintenance before equipment fails, avoiding unnecessary costs associated with repairs and lost production [8]. It is important to note that predictive maintenance offers obvious advantages over preventive maintenance

[9], which employs a fixed cycle of replacements and repairs, often based on vendor specifications. Preventive maintenance is often inaccurate and results in excessive costs because repairs are scheduled too late. Predictive maintenance, on the other hand, can take into account historical data to more accurately predict the probability of failure [10].

PT. Simba Indosnack Makmur is a factory that produces snacks or snacks whose products are marketed to various countries such as Malaysia, Vietnam, China to Australia. In the production process the machine works very optimally, the problem that is often faced by the quality control department is that it often finds non-standard product weights. This problem is caused by a machine that already requires maintenance. So far, the maintenance process has to get approval from the manager, which sometimes takes quite a long time to be inspected so that the maintenance process is delayed, which results in reduced production targets. PT. Simba Indosnack Makmur, located in Bogor, West Java, produces an average of 500 units of one type of snack a day, with the importance of maintaining quality standards, checking the weight of snacks is very necessary. The reason for the non-standard weight is due to the condition of the machine that requires maintenance. If the machine is not maintained and continues to produce, non-standard can occur repeatedly, even though the machine must continue to operate to meet production targets. Although maintenance is currently carried out regularly, there are still frequent non-standard production weights.

Methods that can be used for predictions in data mining include classification with naive bayes, decision trees, k-nearest neighbors and neural networks. Several parts of the neural network such as backpropagation neural network, multilayer perceptron and recurrent neural network (RNN) are widely used to make financial predictions. Backpropagation is considered to have a strong ability to process financial data, while the multilayer perceptron has the ability to map more complex inputs and outputs [11]. In this study, the Elman recurrent neural network (ERNN) method was applied. One of the prediction methods in data mining was chosen because it is more appropriate to analyze for forecasting [12]. Elman RNN is appropriate for predicting time series data because it has a memory of the results of the previous propagation so that the pattern of the input data can be seen. This process is not found in Artificial Neural Network (ANN) which only processes data as input and does not process past information as additional input, so that ANN does not have past pattern memory. In this study, the prediction of production results from non-standard machines was carried out using ERNN [13]. ERNN is a method that can do learning and forecasting for time series data. The use of ERNN is expected to be able to provide predictive results that have the smallest error, one of which is the hyperpameter tuning process. With ERNN's ability to study past patterns and use of production weight data classified into three classes, namely under standard, standard and over standard, the use of ERNN is expected to be able to provide predictive results that have the smallest error, one of which is hyperpameter tuning.

2. METHOD

The data used in this study is data on the weight of 12 gram Choco Drink food products from August 2 2021-April 30 2022 at PT Simba Indosnack Makmur. The model training data used is data from 2 August 2021-28 February 2022, while data from 1 March -30 April 2022 is for model test data. The training data is used for learning patterns by the ERNN architecture. After obtaining the best model, then the model is tested on data testing and later it will be seen whether the resulting model has high accuracy or not. The amount of data is 222 which includes the weight of the product produced by the machine as much as 504 per day, sample data can be seen in Table 1.

Table 1. Sample dataset

Date	Production of Choco Drink snack (gram)								
	1	2	3	4	5	6	...	503	504
02/08/2021	12	12	13	12	12,8	12,7	...	12,2	12
03/08/2021	12	12,9	12	12	12,7	12	...	11,9	12,1
04/08/2021	13,6	12	12	12,1	12	11,8	...	12,7	12
05/08/2021	11,8	13,6	11,5	12,1	12	11,9	...	12	12,9
06/08/2021	13,6	12	11,7	12,1	13,1	12	...	12,1	11,8
07/08/2021	13,2	12	12,8	12,7	12	12	...	12,7	12,7
10/08/2021	12,1	12,8	13,1	12	12	11,6	...	12	12,2
...	...	...	...	...	...	...	...	...	...
29/04/2022	12	11,9	12	12,2	12,8	12	...	12	12
30/04/2022	12	12	11,9	11,8	11,8	11,9	...	12	11,8

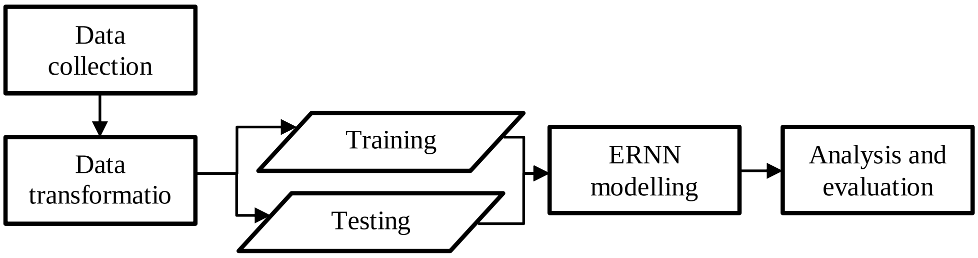

Figure 1. Research stages

At the data collection stage, researchers visited PT. Simba Indosnack Makmur and interviews with production and maintenance managers. In addition to being given access to data on the production of 12 gram food products for 9 months, quality control procedures and machine maintenance processes were also explained. The data will later be plotted into time series data to be processed using Elman RNN. In determining the product standard, namely using a weight reference, if the product weighs less than 11 grams it is called under standard and if it weighs more than 12 grams it is called over standard, it can be seen in Table 2. Production machine maintenance scheduling must obtain approval from the production manager, with the delay in the production data collection report, the maintenance process will be delayed. In determining the maintenance status based on the results of interviews with the manager, refer to Table 3. The higher the status, the higher the number of non-standard products and the need for action for machine maintenance. In the preprocessing carried out several stages. The stages in pre-processing are the creation of new attributes that state the number of products that are over, under, standard, the number of both and maintenance status.

Table 2. Product status by weight

Number	Product weight	Status
1	< 11 gram	Under standard
2	11-12 gram	standard
3	>12 gram	Over standard

Table 3. Maintenance status

Number	The number of products is not standard	Status
1	<100	1
2	100-200	2
3	200-300	3
4	>300	4

ERNN is a variation of the Multi Layer Perceptron. However, in ERNN there are several nodes whose positions are close to the input layer which is related to the hidden layer. The nodes contain the contents of one of the previously trained layers. In principle, input is propagated in a feed forward manner which is then given a learning rule. This type of network can maintain a state sequence and allow it to do several jobs at once, for example, such as sequence prediction which is beyond the capabilities of the Multi Layer Perceptron. The input is not only the value from outside the network, but is added to the output value from the hidden neurons from the previous propagation. After the input is determined, then the amount of training and testing data is also determined. The distribution of data used for training is 90% and data testing is 10%. The distribution of data for training and testing must be done correctly in order to obtain a good model. Formation of the model on ERNN includes determining the number of hidden networks and the number of epochs. Determining the number of hidden networks and the number of epochs is done by trial and error to get the best model [14]. The training process on ERNN is carried out using the Elman backpropagation algorithm. In general, Elman backpropagation is the same as regular backpropagation, it's just that in the Elman backpropagation algorithm the output value hidden at the previous time will be an additional input that is entered in the context layer [15]. An overview of the ERNN process can be seen in Figure 2.

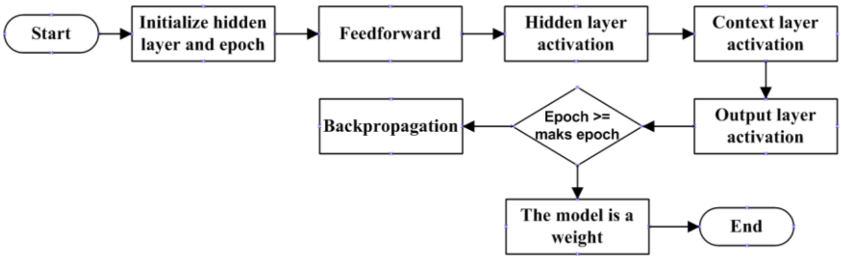

Figure 2. Elman Recurrent Neural Network Process

The evaluation stage includes the stages and analysis on testing the test data that is applied to the model obtained. In the test will be obtained accuracy and prediction error. accuracy and error values obtained from MSE. The best model is determined by the smallest MSE value of the several parameters tested.

3. RESULT AND DISCUSSION

3.1. Data transformation

After checking the dataset there is no missing value and then the data transformation is carried out with the results in Table 4. The resulting data is supervised data with the status attribute as a class attribute.

Table 4. Transformed data

Date	Amount of standard	Amount of over standard	Amount of over standard	Amount of non-standard	Status
02/08/2021	405	98	1	99	1
03/08/2021	318	184	2	186	2
04/08/2021	328	176	0	176	2
05/08/2021	277	227	0	227	3
06/08/2021	312	192	0	192	2
07/08/2021	291	213	0	213	3
10/08/2021	324	180	0	180	2
...	...	...	...	...	...
29/04/2022	211	293	0	293	3
30/04/2022	283	219	2	221	3

The results of the calculation of under and over standard can be seen in Figure 3, it can be seen that the number of over standard is very much compared to the under standard. The combination of over and under standards is called non-standard. From the graph in Figure 4, it appears that the standard amount is more than the non-standard amount. However, there are conditions where the non-standard amount exceeds the standard amount, namely on 24/08/2021, 25/08/2021, 06/09/2021, 27/09/2021, 28/09/2021, 09/10/ 2021, 24/11/2021, 04/12/2021, 09/12/2021, and 29/04/2022.

Figure 3. Plot of over standard and under standard data

Figure 4. Plot of over standard and non-standard data

The number of data with status 3 is 56, Status 2 is 164 and status 1 is 2 data. Data with status 3 has an average of 229,5, data with status 2 has an average of 161 and data with status 1 has an average of 99. The graph depicting the distribution of non-standard data can be seen in Figure 6 and the graph depicting the distribution of status can be seen in Figure 5.

Figure 5. Plot of status data

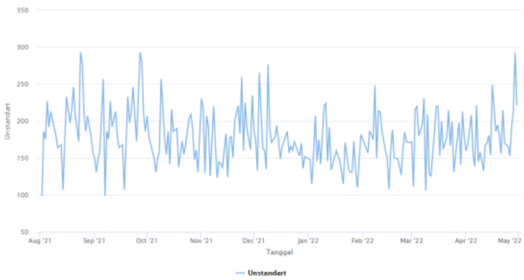

Figure 6. Plot of non-standart data

Data preprocessing aims to select data used as research data, but previously the data was normalized first. Where the results of the data normalization are then represented in sliding windows with a window size of five. The sliding windows process resulted in reduced research data because the initial data determination process changed. Research data with sliding windows 5 are then grouped into two groups, namely training data as much as 90% of the total data and testing data as much as 10% of the research data.

3.2. Processing with Elman RNN

a. Training with window size value

The first experiment is to get the right window size value which is the test parameter in order to get results that have a high degree of accuracy. There were several experiments conducted, and the results used as an initial reference were the maximum number of epochs, namely 100,000 and 1,000,000. Training will stop if it has received MSE < target error or has reached the specified maximum epoch. The training parameters for testing windows size values can be seen in Table 5.

Table 5. Parameter training for windows size with an epoch of 100.000

Parameter	Value	Information
Target error (MSE)	0.001	The target process stops
Learning rate	0.1	System learning speed
Hidden number	3	The number of hidden layers

Maximum epoch	100.000	Number of iterations
Transfer Function	Sigmoid	
Weight	Random (0 and 1)	

The training result of this experiment is the value of the window size which is used to find the smallest MSE value with a predetermined process epoch. The smallest MSE value obtained is 0,003277 with a total of 100,000 epochs, this result is obtained at the input/windows size value of eight.

b. Training with the number of neurons in the hidden layer
The number of neurons greatly affects the accuracy of the prediction results for the data used in the Elman Recurrent Neural Network. The number of neurons in the hidden layer that are suitable for bandwidth prediction is obtained through an experimental process by conducting several training times. As an initial reference the learning rates used are 0,01 and 0,02. The target error is 0,001 with a maximum epoch of 1,000,000 where the process will stop if the value of the performance function is less than or equal to the predetermined target error or has reached the maximum epoch value.

Table 6. Parameters for testing the number of neurons with a target error of 0,001

Parameter	Value	Information
Target error (MSE)	0,001	The target process stops
Learning rate	0,1	System learning speed
Hidden number	3,5,7,10,15,20, 25, 30	The number of hidden layers
Maximum epoch	100,000	Number of iterations
Transfer Function	Sigmoid	
Weight	Random (0 and 1)	

The experimental results obtained using different numbers of neurons in the hidden layer, the results obtained show that with a total of thirteen units of neurons, the smallest error value (MSE) of all experiments is 0,003725. The next process is to test the training results using a different number of neurons in each experiment.

c. Analysis of training results with windows size
The training process carried out using the windows zise parameter shows that the number of input nodes is 8 which produces the smallest MSE value, namely 0,003277. During training with a target of 0,001, the maximum epoch value set is 100,000, the MSE value increases when the number of input neurons is 12, which is 0,054172.

d. Analysis of training results with the number of hidden layers
Testing using the parameter number of hidden layers with the parameters shown in Table 5. During training with a learning rate of 0,01, the best configuration was obtained with the smallest MSE value, namely the number of hidden layer 13 neurons, which was 0,003725.

e. Analysis of Testing Results
In this study the testing data used was 10% of the total data used. The data used for testing is new data that is not included in the training process. The level of accuracy of the results of the testing process is strongly influenced by the weight of the training results, which shows the network's ability to recognize the patterns being trained. Based on the results of the experiments carried out, with an error tolerance target of 0.001 with the value of each parameter equal to the value contained in the training process for the number of hidden layer neurons. The test results produced different MSE values as shown in Table 7. Based on the testing results, the smallest MSE value was obtained, namely the number of hidden layer 13 neurons, which was 0,002422.

Table 7. Test results with a target error of 0,001

Neuron Hidden	MSE
3 (three)	0,002513
5 (five)	0,002510
7 (seven)	0,002526
9 (nine)	0,002625
13 (thirteen)	0,002422
15 (fifteen)	0,002813

4. CONCLUSION

Based on the results of the research and discussion that has been carried out, the developed system is capable of recognizing patterns and can predict the number of non-standard products using the ERNN method. So that with the predicted results of patterns that appear non-standard, the production department can apply for machine maintenance immediately. The results of training using Windows Zise 8 at a maximum of 100,000 epochs obtained the smallest MSE value of 0,003277. The results of training using Windows size 11 at a maximum epoch of 1,000,000 obtained the smallest MSE value of 0,002833. Then the training results for the number of neurons in the hidden layer obtained the smallest MSE value, namely the number of neurons 13 of 0,003725. The results of testing using parameters in the experiment on the number of hidden layer 13 neurons obtained the smallest MSE value of 0,002422.

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