



Available online at <http://scik.org>

Commun. Math. Biol. Neurosci. 2022, 2022:10

<https://doi.org/10.28919/cmbn/7082>

ISSN: 2052-2541

## COMPARISON OF BACKPROPAGATION AND ERNN METHODS IN PREDICTING CORN PRODUCTION

SIGIT SUSANTO PUTRO\*, MUHAMMAD ALI SYAKUR, EKA MALA SARI ROCHMAN,

HUSNI, MUSFIROTUMMAMLU'AH, AERI RACHMAD

Department of Informatics Engineering, Faculty of Engineering, University of Trunojoyo Madura, Bangkalan,  
Indonesia

Copyright © 2022 the author(s). This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

**Abstract:** East Java is one of the producers of food crops in Indonesia. Some food crop commodities in East Java Province are corn, soybeans, peanuts, sweet potatoes, and cassava. These food crops have many benefits to make the demand for production increase. The uncertain amount of food crop production will be a problem for the Department of Agriculture and Food Security of East Java Province in determining a policy. To overcome this problem, a system is needed to predict the production of food crops in East Java. This study compares the Backpropagation algorithm and Elman Recurrent Neural Networks (ERNN). The data in this study were obtained from the Department of Agriculture and Food Security of East Java Province starting from 2007-2020 per quarter. The result of this research is that trial scenario 1 produces the best MSE value of 0.00000063 on the Backpropagation algorithm compared to ERNN which only gets an MSE value of 0.00000627. Trial scenario 2 produces the best MSE value, which is 0.00000003 in the Backpropagation algorithm with gradient descent momentum, this is also better when compared to ERNN which gets an MSE value of 0.00000407. It can be concluded that the best algorithm in this study is

---

\*Corresponding author

E-mail address: [sigit.putro@trunojoyo.ac.id](mailto:sigit.putro@trunojoyo.ac.id)

Received December 14, 2021

Backpropagation with gradient descent momentum because it produces MSE values with good prediction results from all algorithms compared.

**Keywords:** corn; backpropagation; ERNN; gradient descent momentum.

**2010 AMS Subject Classification:** 92B20.

## 1. INTRODUCTION

East Java is one of the producers of food crops in Indonesia. Several kinds of food crop commodities in East Java are rice and secondary crops (maize, cassava, sweet potatoes, soybeans, and peanuts) [1]. Palawija crops are usually referred to as seasonal crops which can be used as food crop rotation when the climate and weather are not favorable. The existence of palawija plants is also an effort to create a diversity of types of food in Indonesia. With the diversity of food crops in Indonesia, it can increase food security when the main commodity, namely rice, experiences a decline in prices. In addition, in 2019 the amount of rice production in East Java decreased by 0.62 million tons [1]. This instability in rice production is one proof of why the government must maintain the production of other food crops to stabilize the country's food security.

Corn is the main secondary food commodity in Indonesia [2][3]. Corn is a food plant that contains carbohydrates other than rice and is a food crop commodity with the largest production after rice. Corn seeds can be used as food, animal feed, industrial raw materials and can be processed into various types of food [4][5]. In addition to corn, there are also soybeans, peanuts, cassava, and sweet potatoes which have many benefits, including soybeans as raw material for various processed products such as tempeh, soy sauce, tofu, and soy milk. The benefits of these food crops make the demand for production increase, but the uncertain amount of food crop production will be a problem for the Department of Agriculture and Food Security of East Java Province in determining a policy. Therefore, a system is needed to predict food crop production in the East Java region.

Several methods are often used to make predictions, such as research comparing the Double Exponential Smoothing (DES) and Artificial Neural Network (ANN) methods that have been

carried out for forecasting the development of COVID-19 in Indonesia. Another research comparing the method of Exponential Smoothing and Backpropagation Neural Networks in prediction systems. The results of their research show that Backpropagation Neural Network is superior to Exponential Smoothing [6].

Several Artificial Neural Network methods that can be used for prediction are the Backpropagation algorithm and Elman Recurrent Neural Network (ERNN). Research using Backpropagation Neural Network and Elman Recurrent Neural Network (ERNN) has been carried out for forecasting cement sales at PT Semen Indonesia (Persero) Tbk using monthly sales data from January 2006 to March 2018. The results of this study state that the best model for the system is cement forecasting at PT Semen Indonesia (Persero) Tbk, namely Backpropagation Neural Network [7].

In addition, predictive research that compares 3 methods at once, namely Exponential Smoothing, Backpropagation, and Elman Recurrent Neural Network, has been carried out for the prediction of palawija production using 7 datasets. The results of this study indicate that the Elman Recurrent Neural Network is the best method for predicting palawija production [8].

In some of the prediction studies above that use the Backpropagation algorithm and Elman Recurrent Neural Networks (ERNN), some show Backpropagation is better than Elman Recurrent Neural Networks (ERNN) but there is also the opposite. Therefore, in this study, we will compare the Backpropagation and Elman Recurrent Neural Networks (ERNN) algorithms.

The main contribution of this research is to predict maize production using Backpropagation Algorithm Artificial Neural Networks and Elman Recurrent Neural Networks (ERNN) as well as adding Gradient Descent momentum (GDM) optimization to the training algorithm.

## **2. PRELIMINARIES**

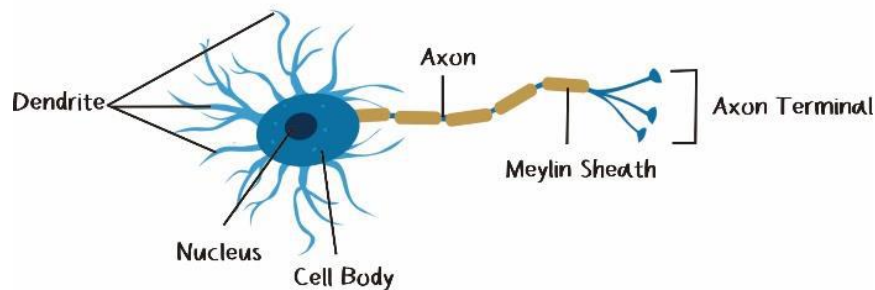
The forecasting process is forecasting an event or something in the future by using the relevant data or variables. The forecasting process uses data in the past which is processed by using an algorithm and based on a theoretical explanation so that it is not only considered as a guess but has

been based on a strong theory [9].

Forecasting or prediction can also be interpreted as an attempt to predict something in the future by using data in the past (historical data) within a certain period and utilizing relevant information [11].

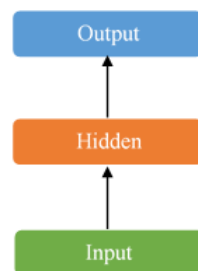
### A. Artificial Neural Network

An artificial Neural Network or commonly called Artificial Neural Network is an algorithm that imitates human neural networks [10]. Like the human brain, the ANN consists of neurons that are interconnected to deliver an impulse. The structure of the human nerve cell consists of the soma (nerve cell body) which is the site of synthesis and integration of nerve impulses. Dendrites have a function to collect all messages to be sent to the nerve cell body (input, processing). The axon (neurite) has the function of carrying the nerve impulse to all other nerve cells (output). This can be seen in Figure 1.



**Figure 1.** Human Neural Network

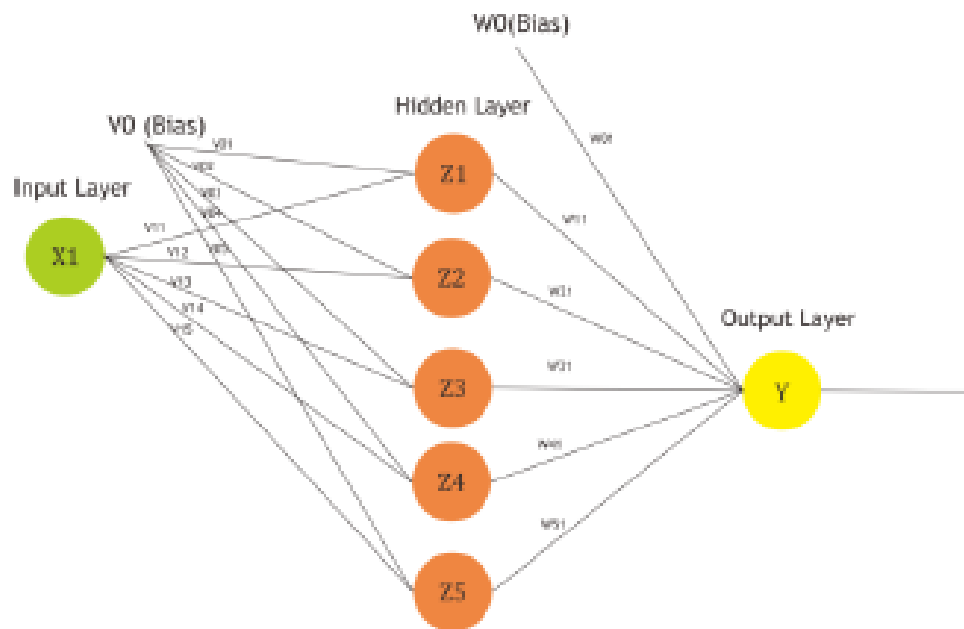
Each simple artificial neural network has 3 sets of layers, namely input, hidden, and output as depicted in Figure 2.



**Figure 2.** layers of Artificial Neural Network

## B. Backpropagation

The typical topology of the Backpropagation algorithm has 3 layers, namely the input layer where the data is entered. The hidden layer is where the data is processed and the output layer is where the results of the input are given [11]. Before getting to know the Backpropagation algorithm. So it would be better if you can know the architecture of the Backpropagation algorithm. Figure 3 shows the Backpropagation Algorithm Architecture.



**Figure 3.** Architecture of the Backpropagation Algorithm

Figure 3 depicts an architecture with the number of neurons in the input layer = 1, the number of neurons in the hidden layer = 5, and neurons in the output layer = 1. The number of weights  $V$  depends on the number of neurons in the input layer and hidden layer, then the number of weights  $V$  that connects the two The layer is  $(1 \times 5 = 5)$ . If there is a bias between the input layer and the hidden layer, the total weight of  $V$  is  $((1+1) \times 5 = 10)$ . This also applies to the weights connecting the hidden layer and the output layer. Based on this, this study uses the architecture shown in table 1.

**Table 1.** Number of Layers and Neurons of Backpropagation Algorithm

Number of layers	3
Input Neuron	1
Hidden Neuron	5
Output Neuron	1

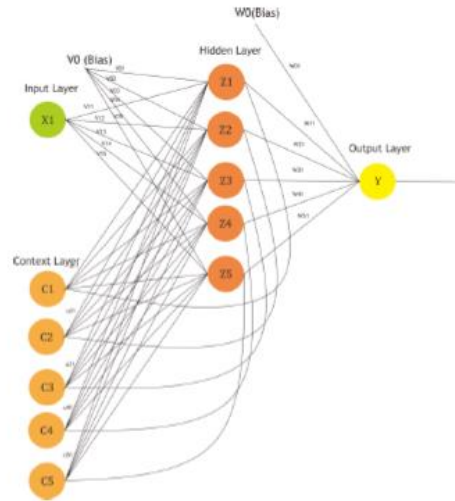
The architecture of the number of layers and the neurons of the Backpropagation algorithm has 3 layers consisting of an input layer, a hidden layer, and an output layer. Each layer has 1 input neuron, 5 hidden neurons, and 1 output neuron.

While the Elman Recurrent Neural Networks (ERNN) algorithm is a development of the Backpropagation ANN algorithm. The thing that distinguishes it from Backpropagation is that there is feedback on the hidden layer of ERNN. The result of this feedback is an additional layer called the context layer [12]. The ERNN architecture can be seen in Figure 4.

Figure 4 explains that the Elman Recurrent Neural Networks (ERNN) algorithm has 4 layers, namely the input layer, hidden layer, output layer, and context layer. There is 1 neuron in the input layer as input, 5 neurons in the hidden layer, 1 neuron in the output layer, and 5 neurons in the context layer. The neurons in the context layer are the output values of the hidden layer ( $t-1$ ) which are used as additional input so that the number of neurons in the context layer is the same as the hidden layer [12].

There is a connection between the hidden layer and the context layer with a weight value of one. The result of backward propagation in the context layer is the previous value of the hidden layer [13].

## COMPARISON OF BACKPROPAGATION AND ERNN METHODS



**Figure 4.** ERNN Algorithm Architecture.

**Table 2.** Number of Layers and Neurons of Backpropagation Algorithm

Number of layers	4
Input Neuron	1
Hidden Neuron	5
context Neuron	5
Output Neuron	1

There are 2 processes in the Backpropagation and ERNN algorithms, namely:

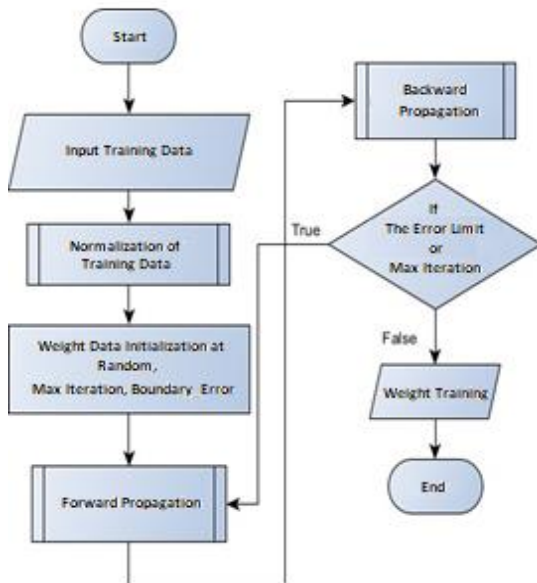
### 1. Training Process

In the Backpropagation algorithm, the training process can be interpreted as an iteration of the forward and backward propagation processes which aims to obtain trained weights and biases. The Elman Recurrent Neural Networks algorithm has a process that is almost the same as the Backpropagation algorithm, the difference is that in the Elman Recurrent Neural Networks algorithm there is feedback on the hidden layer and the result of this feedback is an additional layer called the context layer. The neurons in the context layer will be additional input to the training process.

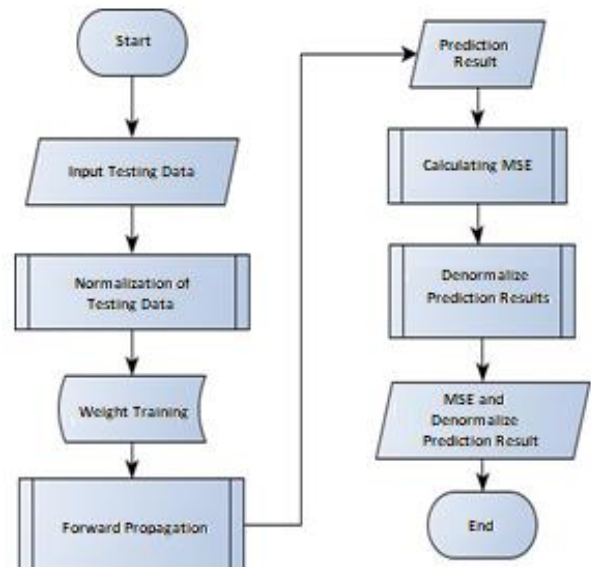
## 2. Testing Process

This process is a process that is carried out on test data, in the Backpropagation and Elman Recurrent Neural Networks testing process only the forward propagation process is carried out. In the test process, the data testing process is carried out using the weights from the training process. The weights generated in the training process are used for the system testing process. The test results are in the form of quarterly food crop predictions whose error value is calculated using Mean Square Error by comparing the target data and the predicted data.

Figures 5 and 6 describe the training and test process of the Backpropagation algorithm as well as Figures 7 and 8 regarding ERNN. There are 3 sub-processes of training, namely the stages of normalization of training data, forward propagation, and backward propagation.



**Figure 5.** Flowchart Training



**Figure 6.** Flowchart Testing

What distinguishes the Backpropagation and ERNN algorithm training processes is the forward propagation sub-process. The Backpropagation and ERNN algorithms have different forward propagation processes when calculating the value of but the process of calculating the value is the same for both algorithms. The flowchart of the Backpropagation algorithm forward propagation process can be seen in Figure 9 dan 10.



COMPARISON OF BACKPROPAGATION AND ERNN METHODS

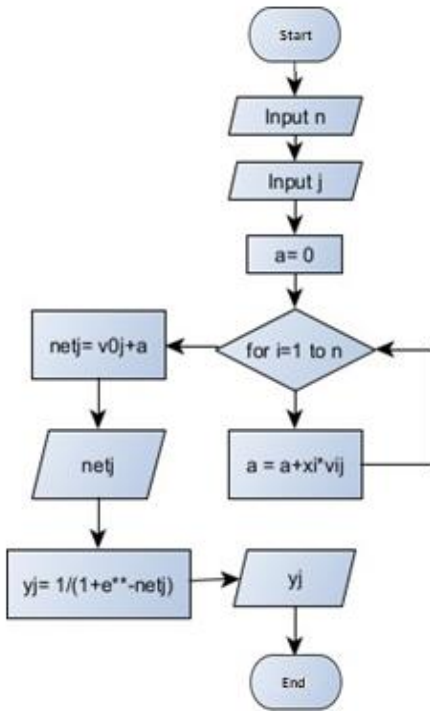


Figure 7. Flowchart  $y_j$  Backpropagation

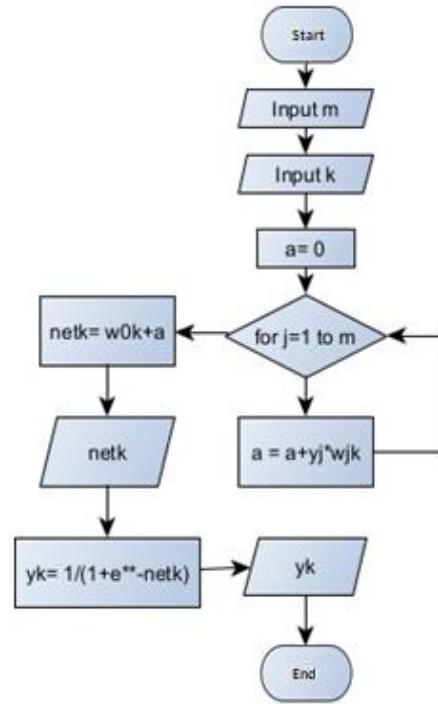


Figure 8. Flowchart  $y_k$  Backpropagation

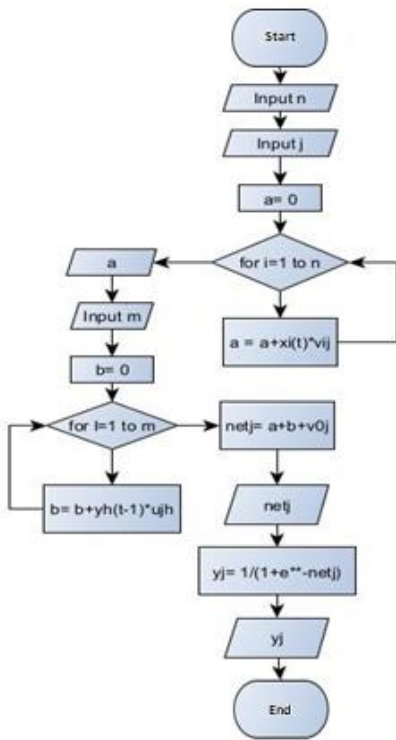


Figure 9. Flowchart  $y_j$  ERNN

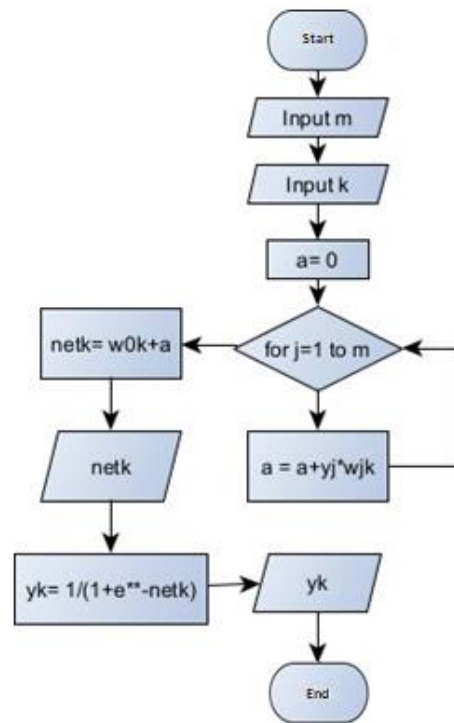


Figure 10. Flowchart  $y_k$  ERNN

### C. Normalization and denormalization

In this study using the min-max normalization method, this method changes the data into a range of zero to one (0-1) [14]. Normalization aims to get data with a smaller size that represents the original data without losing its characteristics. The normalization formula can be seen from the equation below:

$$X_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Description :

$X_n$  = Normalized data value

$X_0$  = Actual data value

$X_{min}$  = smallest data value of all actual data

$X_{max}$  = The largest data value of all actual data

After the training process is complete, the value that comes out in the output layer is still in the form of normalization, so a denormalization process must be carried out to return the normalized value to the actual value. The denormalization formula can be seen from the equation below [15]:

$$x_i = y (x_{max} - x_{min}) + x_{min} \quad (2)$$

Description:

$X_i$  = Normal data value

$y$  = Target value

### D. Means Square Error (MSE)

In this study, Means Square Error (MSE) is used to compare the value that comes out in the output layer with the actual value or the target value [16][17]. MSE is the mean squared forecast error. To calculate MSE, you can use the equation below [18][19][20]:

$$MSE = \sum_{k=1}^n \frac{(t_k - y_k)^2}{n} \times 100\% \quad (3)$$

Where, is the average squared error, the value of is the actual data while is the predicted data and the amount of data is indicated by n.

### 3. MAIN RESULTS

#### A. Data Collection

The data obtained from the Department of Agriculture and Food Security of East Java Province consists of the last 14 years starting from 2007-2020 per quarter. Then choose the parameters that will be used as input data and determine the data that will be used as target data. In this study, there is the amount of production as an input parameter for prediction.

**Table 3.** Sample data on corn production in Bangkalan Regency

Quarterly area and year	production (tons)
Bangkalan 1st quarter 2007	11981,55
Bangkalan 2nd quarter 2007	11882,31
Bangkalan 3rd quarter 2007	11792,15
Bangkalan 1st quarter 2008	11711,06
Bangkalan 2nd quarter 2008	11639,06
Bangkalan 3rd quarter 2008	11576,13
Bangkalan 1st quarter 2009	11522,28
Bangkalan 2nd quarter 2009	11477,52
Bangkalan 3rd quarter 2009	11441,83
Bangkalan 1st quarter 2010	11415,21
Bangkalan 2nd quarter 2010	11397,68
Bangkalan 3rd quarter 2010	11389,23
Bangkalan 1st quarter 2011	11389,85
Bangkalan 2nd quarter 2011	11399,56
Bangkalan 3rd quarter 2011	11418,34
Bangkalan 1st quarter 2012	11446,2
Bangkalan 2nd quarter 2012	11483,14
Bangkalan 3rd quarter 2012	11529,16

#### B. Testing of Backpropagation and ERNN methods

The trials in this study were carried out by dividing the training data from 70% to 90%, maximum iterations, and changes in the learning rate value. Therefore, the test scenario carried out is as shown in the table below. The number of layers used in the Backpropagation algorithm is 3 layers with 1 input neuron, 5 hidden neurons, and 1 output neuron. While the number of layers for the ERNN algorithm is 4 layers with 1 input neuron, 1 hidden neuron, 5 context neurons, and 1 output neuron. Table 5 will show the MSE value of the test changes carried out with different amounts of train and testing data and LR.

**Table 4** Trial Scenario 1

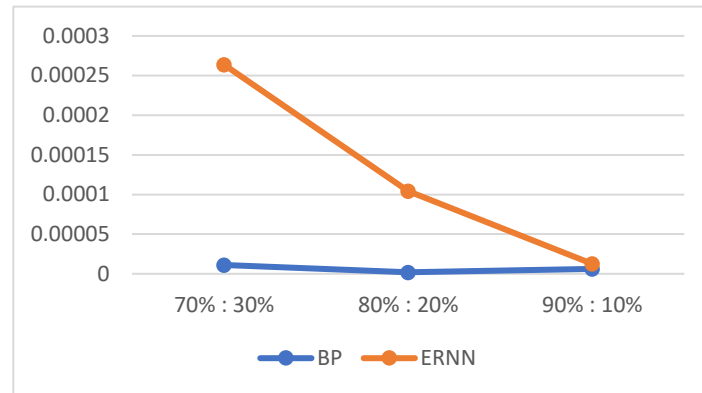
No	Scenario	Trial
1	Distribution of training data and test data	70 : 30, 80 : 20, 90 : 10
2	Maximum iteration	2000
3	Learning rate (LR)	0.1-0.9
4	Minimum error	0.00001
5	Activation Functions	Binary Sigmoid

**Table 5.** Result MSE BP and ERNN

Train : Test	LR	BP	ERNN
70% : 30%	0.1	0,00012364	0,00172311
	0.2	0,0001041	0,00008217
	0.3	0,00008172	0,00007988
	0.4	0,00003158	0,0000982
	0.5	0,00004002	0,00007562
	0.6	0,00002443	0,00014784
	0.7	0,00004178	0,00018677
	0.8	0,0000066	0,00022646
	0.9	0,00001111	0,00025265
80% : 20%	0.1	0,00009303	0,00013851
	0.2	0,0000679	0,00005633
	0.3	0,00005244	0,00002843
	0.4	0,00004956	0,00005461
	0.5	0,00001974	0,00000427
	0.6	0,00000206	0,0000017
	0.7	0,00000461	0,00006485
	0.8	0,00000214	0,00008157
	0.9	0,00000192	0,00010253
90% : 10%	0.1	0,00009303	0,00916573
	0.2	0,00004973	0,00001765
	0.3	0,00002279	0,00000876
	0.4	0,00002063	0,00000563
	0.5	0,00001174	0,00000648
	0.6	0,00000978	0,00000935
	0.7	0,00000799	0,00000652
	0.8	0,00000091	0,0000067
	0.9	0,00000063	0,00000627

## COMPARISON OF BACKPROPAGATION AND ERNN METHODS

From the several trials shown in table 5, the best MSE results were obtained in a comparison of training and testing of 90% and 10% with a learning rate of 0.00000063 for Backpropagation and 0.00000627 for ERNN. This proves that Backpropagation's performance is still superior to ERNN for corn production prediction data in the district. Bangkalan. Figure 10 shows the comparison of the MSE value between backpropagation and ERNN from the test results with a learning rate of 0.9



**Figure 10.** Graph of MSE comparison between Backpropagation and ERNN

### C. Backpropagation and ERNN trials with Gradient Descent optimization

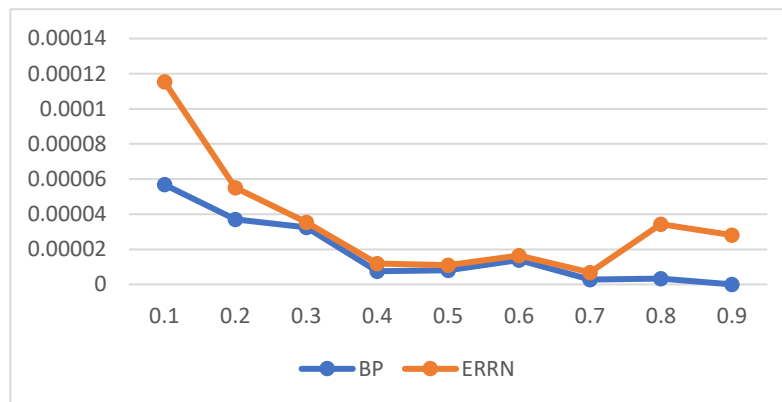
The trial scenario at this stage is used to compare the Backpropagation gradient descent algorithm with momentum and ERNN gradient descent with momentum. The addition of this momentum value aims to reduce the significant weight changes. In the trial, the best backpropagation and ERNN were at a learning rate of 0.9, so in this trial, it will be reused without recombining other parameters. The second trial scenario can be seen in table 6.

**Table 6** Trial Scenario 2

No	Scenario	Trial
1	Distribution of training data and test data	90 : 10
2	Maximum iteration	2000
3	Learning rate (LR)	0.9
4	Minimum error	0.00001
5	Activation Functions	<i>Sigmoid biner</i>
6	Weight optimization	0.1-0.9

**Table 7.** MSE BP and ERNN results with gradient descent optimization

GDM	BP	ERNN
0.1	0,00005683	0,00005859
0.2	0,00003712	0,00001792
0.3	0,00003249	0,00000291
0.4	0,00000751	0,00000431
0.5	0,00000803	0,00000297
0.6	0,00001386	0,00000253
0.7	0,00000279	0,00000407
0.8	0,00000339	0,00003101
0.9	0,00000003	0,00002801

**Figure 11.** Graph of MSE comparison between Backpropagation and ERNN with GDM

From test scenario 2 shown in table 7, the best MSE results are obtained at a momentum value of 0.9 with an MSE value of 0.000000003 for Backpropagation and 0.00000407 for ERNN at a momentum value of 0.7. This proves that Backpropagation's performance is still superior to ERNN for corn production prediction data in the district. Bangkalan. Figure 11 shows the comparison of the MSE value between backpropagation and ERNN with Gradient Descent optimization from the test results with a learning rate of 0.9.

## CONCLUSION

Based on the system testing that has been carried out and the results of several research trial scenarios that have been carried out, it can be concluded that:

## COMPARISON OF BACKPROPAGATION AND ERNN METHODS

1. Based on the results of the analysis in test scenario 1 which compares the Backpropagation algorithm and Elman Recurrent Neural Networks by using data sharing of 90% for training data and 100% for test data, the minimum error is 0.00001, the learning rate is 0.9, the maximum number of iterations is 2000 and the function binary sigmoid activation, the MSE obtained is 0.00000063 from the Backpropagation algorithm in the Bangkalan corn dataset, which is smaller than the ERNN which only gets an MSE value of 0.00000627.
2. The results of the analysis of trial scenario 2 which compares the Backpropagation algorithm with gradient descent momentum of 0.9, the smallest MSE is 0.00000033 and MSE is 0.00000407 for ERNN with Gradient Descent momentum optimization of 0.7 Bangkalan.
3. Giving weight optimization to the Backpropagation and ERNN algorithms makes the prediction results and MSE test values smaller than without using weight optimization. This is because the optimization function can optimize the weight value for use in the testing process.

**ACKNOWLEDGMENT**

The authors would like to thank University of Trunojoyo Madura, for the opportunity to make research with contract number 3074/UN46.4.1/PT.01.03./2021. And the author also thanks to the Department of Agriculture and Horticulture in the East Java provincial agriculture office for their assistance in providing data in this research.

**CONFLICT OF INTERESTS**

The author(s) declare that there is no conflict of interest.

**REFERENCES**

- [1] BPS Jawa Timur, Agricultural Indicators for East Java Province 2019. Badan Pusat Statistik Provinsi Jawa Timur, 2019.
- [2] A. Wanto, Prediction of corn productivity in Indonesia as an effort to anticipate imports using backpropagation artificial neural networks, SINTECH (Science Inf. Technol. J.) 1 (2019), 53–62.

- [3] S.D.B. Mau, F. Tedy, P. Batarius, E. Ngaga, Implementation of a decision support system to predict corn crop production results using Bayes' theorem, *Joutica*, 5 (2020), 321–325.
- [4] A. Krisnawati, Soybean as source of functional food, *Iptek Tanam. Pangan*. 12 (2017), 57– 65.
- [5] A. M. K. Umar Dani, Miftah Dieni Sukmasari, Safrullah Salman, Interaction of Liquid Organic Fertilizer and Biofertilizer on Peanut Growth and Yield (*Arachis Hypogaea L*), *J. Ilmu Pertan. dan Peternak*. 8 (2020), 32–38.
- [6] N. Fitriana, R. G. Hindami, T. Salsabila, K. Kariyam, Comparison of the double exponential smoothing method and artificial neural network to predict the development of COVID-19 in Indonesia, *Senatik*. 5 (2020), 312–318.
- [7] A.F. Achmalia, Walid, Sugiman, Forecasting cement sales using backpropagation neural network and recurrent neural network, *UNNES J. Math*. 8 (2019), 92–106.
- [8] W. Aprianti, J. Permadi, H. Rhomadhona, Comparison of Elman Recurrent Neural Networks, Backpropagation Neural Networks, and Exponential Smoothing in Forecasting Palawija Production, *J. Math. Educ. Sci. Technol*. 5 (2020), 206–220.
- [9] A.S. Rachman, I. Cholissodin, M.A. Fauzi, Forecasting sugar production using backpropagation neural network method at Candi Baru Siodarjo PG, *J. Pengemb. Teknol. Inf. dan Ilmu Komput*. 2 (2018), 1683-1689.
- [10] A. Rachmad, E.M.S Rochman, D. Kuswanto, I. Santosa, R.K. Hapsari, T. Indriyani, E. Purwanti. Comparison of the traveling salesman problem analysis using neural network method. In: *International Conference on Science and Technology*. Atlantis Press. 2018, pp. 1057-1061.
- [11] S.P. Siregar, A. Wanto, Analysis of artificial neural network accuracy using backpropagation algorithm in predicting process (forecasting), *Int. J. Inform. Syst. Technol*. 1 (2017), 34-42.
- [12] B. Kusumoputro, H. Suprijono, M.A. Heryanto, B.Y. Suprpto, Development of an attitude control system of a heavy-lift hexacopter using Elman recurrent neural networks, in: *2016 22nd International Conference on Automation and Computing (ICAC)*, IEEE, Colchester, United Kingdom, 2016: pp. 27–31.
- [13] O. Claveria, E. Monte, S. Torra, Multiple-input multiple-output vs. single-input single-output neural network forecasting, *Res. Inst. Appl. Econ.* (2015), [https://www.ub.edu/irea/working\\_papers/2015/201502.pdf](https://www.ub.edu/irea/working_papers/2015/201502.pdf).
- [14] N.P. Sakinah, I. Cholissodin, A.W. Widodo, Prediction of number of newspaper requests using backpropagation neural network method, *J. Pengemb. Teknol. Inf. dan Ilmu Komput*. 2 (2018), 2612–2618.
- [15] A.T.W. Utami, B.S.S. Ulama, Application of backpropagation to improve time effectiveness and accuracy on



## COMPARISON OF BACKPROPAGATION AND ERNN METHODS

- wall-following robot navigation data, *J. Sains Dan Seni ITS*, 4 (2015), 279–284.
- [16] E.M.S. Rochman, W. Agustiono, N. Suryani, A. Rachmad. Comparison between the backpropagation and single exponential smoothing method in sugar production forecasting case, *Commun. Math. Biol. Neurosci.*, 2021 (2021), Article ID 70.
- [17] A. Rachmad, D.R. Anamisa, Forecasting the number of patients diseases using backpropagation, *MATEC Web of Conferences*. 58 (2016) 03005.
- [18] E.M. Sari Rochman, A. Rachmad, M.A. Syakur, I.O. Suzanti, Method extreme learning machine for forecasting number of patients' visits in dental poli (A case study: Community Health Centers Kamal Madura Indonesia), *J. Phys.: Conf. Ser.* 953 (2018), 012133.
- [19] E.M.S. Rohman, A. Rachmad, Predicting medicine-stocks by using multilayer perceptron backpropagation. *Int. J. Sci. Eng. Appl* 5 (2016), 188-191.
- [20] E.M.S. Rohman, A. Rachmad, Forecasting application for simpati telkomsel card using backpropagation (Case study in Bangkalan Madura-Indonesia), *Adv. Sci. Lett.* 23 (2017), 12340-12343.