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Application of Backpropagation Artificial Neural Networks for Optimizing Corn Production Prediction in Karo Regency

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ABSTRACT

Corn production in Karo Regency, North Sumatra, plays a crucial role in supporting regional food security and the local economy. However, fluctuations in production caused by unpredictable environmental conditions and limited data-driven forecasting methods have made it difficult for policymakers and farmers to plan effectively. This study aims to address this problem by developing a model to predict corn production using the Backpropagation Neural Network (BPNN) method. The study utilized 302 cleaned datasets, with Planted Area and Harvested Area as input variables, and Production as the output variable. The dataset was divided into 70% for training and 30% for testing. Five BPNN architectures (ranging from 2-4-1 to 2-12-1) were tested using three activation functions (Sigmoid, ReLU, and Tanh), with a maximum of 200 iterations and a learning rate of 0.01. The best results were achieved by the 2-12-1 architecture with the Tanh activation function, obtaining an R-squared value of 94.86% and a Mean Squared Error (MSE) of 0.0039. These findings demonstrate that the Backpropagation Neural Network is effective for forecasting corn production and can serve as a valuable decision-support tool for sustainable agricultural planning in the region.

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1. INTRODUCTION

Agricultural productivity remains a critical factor in ensuring national food security, particularly for staple and strategic commodities such as corn. In Indonesia, corn serves not only as a food source but also as a key raw material in the animal feed and processing industries. However, in several corn-producing regions, including Karo Regency, production levels fluctuate significantly each year due to changes in land use, climatic variability, and limited technological adoption in production planning. These fluctuations hinder the ability of local governments and farmers to forecast output accurately and optimize resource allocation. Therefore, developing an accurate and adaptive forecasting model is essential to support evidence-based agricultural decision-making in Karo Regency.

Corn is a cereal or grain crop that plays a crucial role in the context of agriculture and food security in Indonesia. As one of the main food crops, corn not only serves as a substitute for rice, but also provides a source of carbohydrates, calories, and protein that are important for the community's nutritional balance. Corn is increasingly important along with population growth and the development of the animal feed industry [1]. With two seasons in Indonesia, corn is able to adapt and is considered suitable for the country's climate [2]. One of the suppliers of corn production in North Sumatra is Karo Regency. Karo Regency is divided into 17 sub-districts with an area of 2,127.25 km². More than 75% of the population of Karo Regency earns a living as farmers, making the agricultural sector a major contributor to the regional economy [3].

Maintaining and increasing production, particularly in Karo Regency, is crucial given the increasing demand for corn. This increased demand stems from demand from several sectors, particularly the food and animal feed industries. Given the importance of corn as an agricultural commodity in Karo Regency, forecasting year-to-year production is necessary. This forecast is useful for monitoring the development of the corn farming sector in the region [4].

Prediction, which is often equated with forecasting, is the result of an activity that involves the process of predicting, forecasting, or estimating something in the future through scientific methods or purely subjective [5]. Successful prediction can provide a deep understanding of future conditions, and one of its many benefits is facilitating production planning for the future [6]. The prediction function is used to identify patterns in data by utilizing a number of variables to estimate other variables whose type or value is not yet known [7].

One strategy to overcome the difficulty in predicting corn production in Karo Regency is the backpropagation method. Layered artificial neural networks, which are mathematical models modeled after biological neural network architectures, include backpropagation [7]. Currently, artificial neural networks are used to identify patterns in data or understand complex interactions between inputs and outputs. One popular training technique for ANNs is backpropagation, which directs them to perform a given task. This artificial neural network architecture utilizes backward error correction and forward learning. Due to its high accuracy, this network is often used in pattern identification, forecasting, and prediction [8].

2. METHOD

The method used in this research is the Backpropagation Artificial Neural Network or Neural Network Backpropagation [9]. This stage contains research stages such as data collection, data processing and explanation of the architecture used in the Backpropagation Artificial Neural Network method.

2.1. Data retrieval

The initial stage of this research is dataset collection conducted at the Karo Regency Agriculture Office. The data collected consists of variables used to support the training and testing process, such as: Planted Area, Harvested Area, and Production. The dataset will be saved in CSV format and then uploaded to Google Drive to ensure data can be easily accessed at any time. The dataset used is a time series from 2004 to 2023, which will be divided into training data and testing data, with 70% for training data and 30% for testing data. The total number of data used is 302 after performing the outlier cleaning process.

Table 1. Research Dataset

Year	District Name	Planted Area	Harvested Area	Producti on
2004	Barusjahe	85	59	2.710
2004	Berastagi	55	35	1.262
2004	Dolat Rayat	134	75	3.296
2004	Maple	3.905	3.434	16.792
2004	Kabanjahe	663	519	2.386
2004	I need	6.201	6.152	28.190
2004	LauBaleng	8.415	8.085	39.953
2004	Mardingding	10.120	10.019	45.969

2.2. Data Preprocessing and Normalization

The data collected in the study will then be preprocessed. In this study, the researchers carried out several preprocessing stages, namely detecting outliers and data correlation, where the purpose of this stage is to identify deviant data and understand the relationship between variables to improve the accuracy and validity of the analysis. After preprocessing, the next stage is data normalization. The purpose of normalization is to make the data easier to interpret and process by machine learning algorithms. By using a uniform value range such as [0, 1], the formula for the normalization stage is as follows [10].

$$N\ data = \frac{x - min}{max - min} \times (d - c) + c \quad (1)$$

2.3. Artificial Neural Network Architecture*Backpropagation*

The basic workings of an artificial neuron in an Artificial Neural Network, including how inputs are processed through weights, summed, passed through an activation function, and produce outputs that are then used by other neurons [11]. This approach allows machines to learn from data and make predictions or judgments based on that learning by simulating the activity of biological neurons in the human brain [12]. The figure below shows the Backpropagation ANN Architecture used in this study.

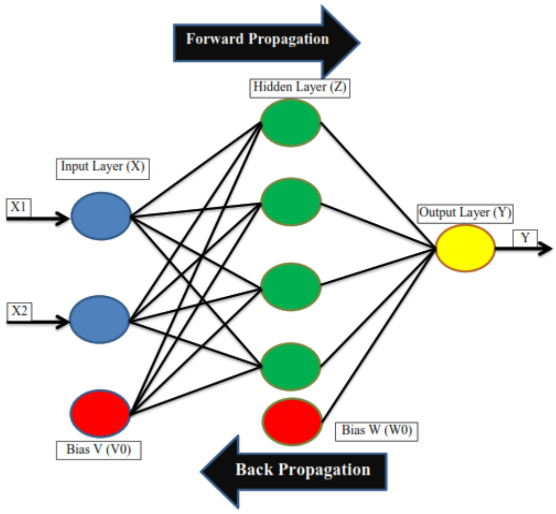

Figure 1. Backpropagation ANN Architecture

The architecture of the Backpropagation Artificial Neural Network (BPNN) used in this study is illustrated in Figure 1. The network consists of three main layers, namely the input layer (X), the hidden layer (Z), and the output layer (Y). Each neuron in the input layer is connected to every neuron in the hidden layer through weighted connections, while the output layer produces the final prediction value. The forward propagation process occurs from the input layer to the output layer, while the backpropagation process adjusts the weights and biases (V and W) to minimize prediction errors [13][14]:

2.3.1 Input Layer (*Input Layer*)

The neurons in this layer serve as inputs in the Backpropagation ANN. Depending on the amount of data or parameters being processed, the number of neurons in this layer can be changed. The neurons in this layer are referred to as input layer neurons. In the Backpropagation ANN architecture, the input layer neurons are denoted as Xi (X1, X2, X3,…..Xn).

2.3.2 Hidden Layer (*Hidden Layer*)

Located in the middle, this layer serves as a bridge connecting the input and output layers. This layer, known as the hidden layer, is composed of neurons. In the Backpropagation ANN architecture, the hidden layer neurons are denoted as Zi (Z1, Z2, Z3,….Zj).

2.3.3 Output Layer (*Output Layer*)

This layer contains neurons that function as the output values of the Backpropagation ANN. In the Backpropagation ANN architecture, the output layer neurons are denoted as Yi (Y1, Y2, Y3,….Yk).

2.3.4 V Weight + Bias

Weights and biases are used to connect each neuron in the input layer and the hidden layer. The weight V is crucial for the learning process, as it connects neurons in the input layer to the hidden layer. Meanwhile, biases are optional and serve to speed up the network training process [10].

2.3.5 W Weight + Bias

Weights and biases are used to connect each neuron in the output and hidden layers. The weight W is the weight that connects these two layers and is very important for the ANN learning procedure. Meanwhile, bias is optional and can help speed up the training process [15].

3. RESULTS AND DISCUSSION

This section will explain the results and discussion of the research on corn production prediction using Backpropagation Artificial Neural Networks as follows;

3.1 Construction of Backpropagation Artificial Neural Network Model

In developing the Backpropagation JST model, researchers determined several parameters used in the training process, as follows:

1. Layer : 2-4-1
2. Learning Rate : Adam (0,01)
3. Epoch/Iteration : 200
4. Calbacks : EarlyStopping, ModelCheckpoint
5. Losses : MSE

The following output shows the performance of the built Backpropagation ANN model. The model training process involves using the sigmoid activation function, which plays a crucial role in determining the output of the neuron. Furthermore, the Adam optimizer with a learning rate of 0.01 is used to update the weights during the training process. The loss function applied is the Mean Squared Error (MSE), which is a measure of the error between the model's prediction and the actual value. To improve training efficiency, an EarlyStopping callback with a patience of 20 is implemented to stop training if there is no significant improvement in the value loss over several epochs.

```
Epoch: 200, Learning Rate: 0.01
Epoch 200/200
 1/25 ──────────────────── 0s 35ms/step - loss: 7.6858e-04
Epoch 200 selesai

Layer: dense_19
Bobot (Weights):
[[-1.2825096   0.14873534 -0.9511793  -8.624604  ]
 [-2.9485009  -2.9729803   3.3371522  -9.949642  ]]
Bias (Biases):
[ 0.5581569  1.9252087 -1.404924   0.9745859]

Layer: dense_20
Bobot (Weights):
[[-1.9549525]
 [-1.7171153]
 [ 2.360147 ]
 [-2.5542135]]
Bias (Biases):
[0.10494161]


Epoch 200: val_loss improved from 0.00110 to 0.00109, saving model to model_checkpoints/best_model.keras
25/25 ──────────────────── 0s 6ms/step - loss: 0.0010 - val_loss: 0.0011 - learning_rate: 0.0100
```

Figure 2. Iteration Process

After conducting iterations, it was found that the lowest validation loss was achieved at the 200th iteration, with a value of 0.00109. At the 199th iteration, it can be seen that the validation loss is still at 0.0011 and continues to carry out further iterations up to a maximum of 200 iterations. During iterations, it is not uncommon to find the best weights and biases before the 200th iteration because researchers utilize EarlyStopping to automatically stop the iteration if during the next 20 iterations there is no decrease in validation loss. Thus, the 200th iteration will be used in the model that will be built to predict corn production in Karo Regency.

3.2 Model Evaluation

After the training process, it is crucial to conduct a thorough evaluation of the developed model. This evaluation aims to measure the model's ability to make accurate predictions. This process involves comparing the original data with the predicted data generated by the developed model, as follows.

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
    Luas Tanam  Luas Panen    Actual      Predicted
0     0.037845    0.038965    6294.0    4884.465820
1     0.047566    0.054033    8792.0    5929.318359
2     0.976837    1.000000  163366.0  128006.570312
3     0.088251    0.079103   12929.0    9258.592773
4     0.060727    0.062361   10163.0    6887.003906
..         ...         ...       ...            ...
86    0.003760    0.003223     559.0    2996.789307
87    0.064768    0.064412   11284.0    7174.173828
88    0.090611    0.088603   15068.0   10172.310547
89    0.305317    0.274139   46367.0   38847.867188
90    0.076929    0.077680   13045.0    8634.302734

[91 rows x 4 columns]
```

Figure 3. Testing data prediction results

The results of the model testing are presented in Figure 3, which displays a comparison between the actual corn production values and the predicted values generated by the Backpropagation Neural Network. The columns represent normalized input variables (Luas Tanam and Luas Panen), the actual production values, and the predicted output of the model. The close proximity between the Actual and Predicted values indicates that the model performed well in estimating corn production levels, demonstrating high predictive accuracy and consistency.

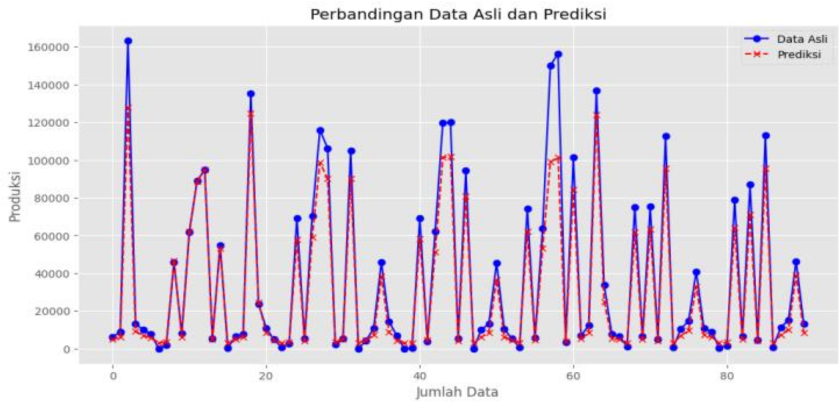

Figure 4. Comparison of Original Data and Prediction Results

The comparison between the actual and predicted corn production values is shown in Figure 4. The blue line represents the actual production data, while the red dashed line represents the predicted values generated by the Backpropagation Neural Network model. The close alignment between the two curves indicates that the model can accurately follow the actual production trend. This visual correlation further supports the quantitative evaluation results, demonstrating that the Backpropagation Neural Network achieved a high prediction accuracy with minimal error variation.

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
Mean Squared Error (MSE): 0.004917234214906
Root Mean Squared Error (RMSE): 0.07012299348221103
R-squared (R²): 0.9357074496566566
```

Figure 5. Prediction Accuracy using MSE, RMSE, and R-Squared

The performance evaluation of the developed Backpropagation Neural Network model is presented in **Figure 5**. The obtained Mean Squared Error (MSE) value was 0.0049, the Root Mean Squared Error (RMSE) value was 0.0701, and the coefficient of determination (R^2) reached 0.9357. These results indicate that the model was able to explain approximately 93.57% of the variance in the data, showing high accuracy and reliability in predicting corn production.

3.3 Comparison of Models with Activation Functions

Activation functions play a crucial role in Backpropagation ANNs, as they determine how neurons interact with inputs and generate outputs. There are various types of activation functions used in machine learning models, such as sigmoid, ReLU, and tanh functions. Each function has distinct characteristics that can affect model performance. The following is a comparison of models with different activation functions:

Table 2. Results of Model Comparison with Activation Function

No	**Model Architecture**	**Iteration (*Epochs*)**	***Learning Rate***	**MSE**			***R-squared* (%)**		
				Sigmoid	**resume**	**Fishy**	***Sigmoid***	**resume**	**Fishy**
1.	2-4-1	Max 200	0,01	0,0049	0,0045	0,0041	93,57	94,07	94,62
2.	2-5-1	Max 200	0,01	0,0040	0,0046	0,0040	94,71	93,88	94,73
3.	2-6-1	Max 200	0,01	0,0042	0,0043	0,0042	94,39	94,27	94,43
4.	2-9-1	Max 200	0,01	0,0039	0,0045	0,0041	94,82	94,03	94,61
5.	2-12-1	Max 200	0,01	0,0043	0,0046	0,0039	94,25	93,90	94,86

Among all the models tested, the best-performing architecture was the 2-12-1 configuration model, which uses the Tanh activation function in its layers. This model showed a very low Mean Squared Error (MSE) of 0.0039 and achieved the highest accuracy of 94.86%. These results indicate that the Tanh activation function significantly improves model performance compared to other activation functions such as Sigmoid and Relu.

3.4 Implementation of Backpropagation ANN Model

Models tested with various Backpropagation ANN architectures are stored in the drive, making them easier to access and use in the future. Storing models in these different architectures also provides flexibility in comparing performance for predicting new data. By having multiple models stored, we can choose the most appropriate model and provide the best results based on the type of input data encountered. Below are the program codes and displays of several models that have been stored in the drive for future prediction needs.

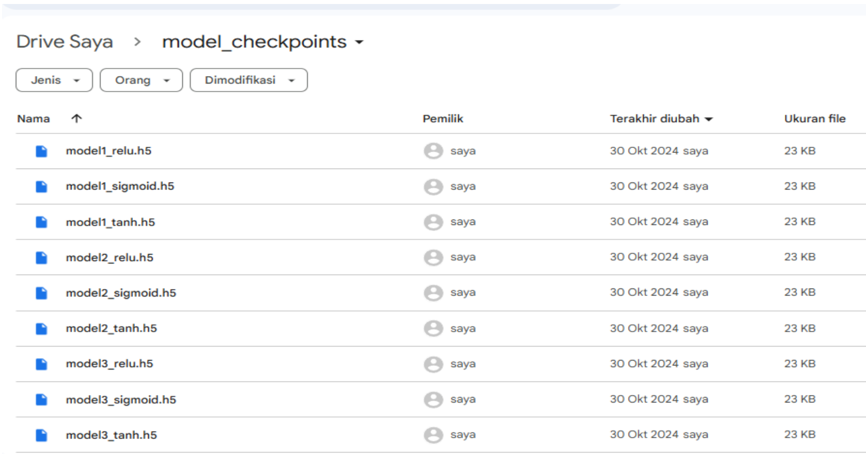

Figure 6. Model storage folder in Drive

To ensure reproducibility and facilitate future use, all trained Backpropagation Neural Network models were stored in Google Drive, as shown in Figure 6. Each file corresponds to a different model architecture and activation function, including ReLU, Sigmoid, and Tanh variations. This systematic storage approach allows researchers to easily retrieve, compare, and apply the most optimal model for further prediction tasks.

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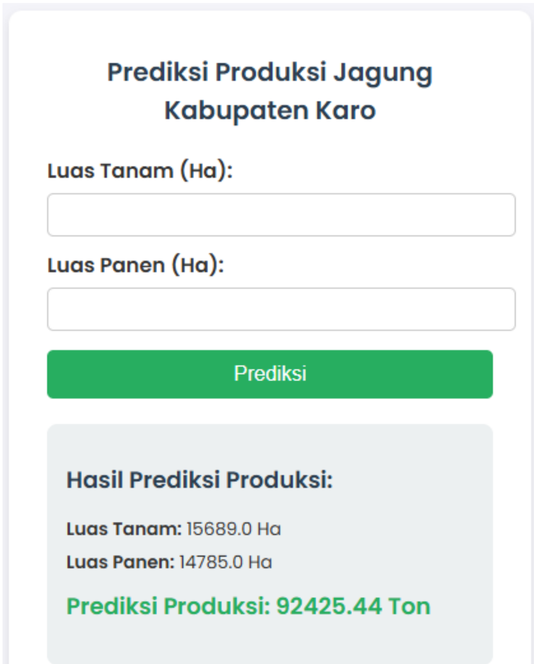

Figure 7. *User interface*Corn Production Prediction in Karo Regency

With this website, it is hoped that users can easily enter input data and get corn production prediction output quickly and efficiently. With this website, it is hoped that users can easily enter input data and get corn production prediction output quickly and efficiently.

4. CONCLUSION

This study successfully developed and implemented an Artificial Neural Network (ANN) model using the Backpropagation method to predict corn production in Karo Regency. The model demonstrated effective performance with a high level of accuracy, as indicated by evaluation metrics such as MSE, RMSE, and R-squared. Among the five tested architectures (2-4-1, 2-5-1, 2-6-1, 2-9-1, and 2-12-1) combined with three activation functions (Sigmoid, ReLU, and Tanh), the 2-12-1 architecture with the Tanh activation function achieved the best performance. This model obtained the lowest Mean Squared Error (0.0039) and the highest R-squared value (94.86%), proving that it can reliably forecast corn production outcomes. The results indicate that the Backpropagation Neural Network can serve as a dependable decision-support tool for agricultural planning and production forecasting in Karo Regency. Future studies are recommended to utilize larger datasets and include additional variables such as rainfall, temperature, and soil conditions to enhance the model's predictive capability and generalization performance.

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