Grid Search-Optimized Artificial Neural Network Model for Rice Yield Prediction Using Weather and Soil Data in Malang City

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ABSTRACT

This research optimizes an Artificial Neural Network (ANN) model using Grid Search (GS) for predicting the rice yields in Indonesia. The purpose of this research was to enhance the performance of the ANN model by systematically tuning its hyperparameters to improve its predictive accuracy. This research uses the Multilayer Perceptron (MLP) method, and a comprehensive GS method was employed to explore various hyperparameter combinations, including the number of hidden layers, activation functions, solvers, regularization parameters, and learning rates. The optimization process involved evaluating each hyperparameter configuration using cross-validation to select the best model based on performance metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), and Mean Squared Error (MSE). The study's results indicate that the optimized ANN model achieved an R^2 of 97.41%, MAE of 766.69, and MSE of 1859857.06, outperforming the model without hyperparameters. This study highlights the effectiveness of the GS optimization in enhancing the ANN model performance, demonstrating that Hyperparameter Tuning (HT) is crucial for achieving improved prediction accuracy. This study concludes that the ANN model can be optimized for practical use in predicting the rice yields, as it shows strong performance.

Keywords-artificial neural network; rice yield prediction; grid search

I. INTRODUCTION

Rice has long been a fundamental food source for millions in Indonesia, forming the core of the country's food security. As one of the world’s leading agrarian nations, Indonesia’s capacity to guarantee a consistent rice production is vital for both the economic stability and national well-being [2]. However, the diverse geographical and climatic conditions across the country pose significant challenges to maximizing the rice yields [3]. The fluctuating weather patterns, including unpredictable rainfall, temperature variations, and episodes of drought or flooding, frequently compromise the agricultural productivity, leading to significant variability in crop yields [4]. These challenges are further worsened by the heterogeneity of the soil conditions across the archipelago, with differences in the pH, moisture levels, and nutrient availability that directly affect the crop growth [5].

The variability in climate and the differences in soil quality make predicting the rice yields a challenging and uncertain task. These environmental factors interact in nonlinear ways, which makes it difficult to develop reliable forecasting models. Erratic rainfall, for example, can cause both droughts and floods, disrupting planting and growing seasons and directly impacting the crop health [6]. Given this complexity, the need for precise and adaptable predictive models has never been greater to help farmers and policymakers make informed decisions to maintain and improve the agricultural productivity.

ANNs have recently emerged as an effective solution for modeling the crop yields in such uncertain and complex environments. ANNs have demonstrated the ability to handle large, noisy, and multivariate datasets, making them well-suited for applications in precision agriculture and smart farming [7]. The primary strength of ANNs is their capacity to discover hidden patterns and relationships in data that may be difficult to identify with traditional statistical techniques. Their ability to adapt to the changing environmental conditions makes them effective in predicting outcomes, such as the rice yield, where factors, like temperature, rainfall, and soil quality, are interconnected. However, despite the promising results of ANN models in predicting rice yields [8], one of the main challenges is optimizing their performance. The performance of an ANN can vary significantly depending on the configuration of its hyperparameters [9]. Poorly tuned hyperparameters can lead to overfitting, underfitting, or suboptimal model performance, making it challenging to obtain accurate predictions [10], particularly when working with complex agricultural datasets that involve numerous variables and high uncertainty.

Several studies have addressed the application of ANN in agricultural yield prediction. ANNs were applied to predict the rice yields by utilizing environmental parameters, like rainfall, temperature, humidity, and soil pH, achieving promising results [11]. The ANN method was used to predict the rice harvest yields based on planting land parameters [12]. In the field of optimization techniques, studies, such as [13], have demonstrated the effectiveness of hyperparameter optimization methods, including GS, in enhancing the performance of machine learning models in agricultural contexts. GS optimization was also employed with an ANN model for the wheat yield prediction, resulting in substantial improvements in the model accuracy compared to the baseline ANN model [14] or in the rice yield prediction, where it led to a significant reduction in the prediction error, underscoring the importance of HT for achieving high-performance models [15]. Furthermore, several researchers have combined weather and soil data to improve the yield prediction. Authors in [16] combined meteorological data with soil quality parameters to forecast the crop yields, emphasizing the importance of multi-dimensional datasets for increasing the prediction accuracy.

The potential of an optimized ANN model has not been extensively explored. In response to this gap, this study introduces a GS-Optimized ANN model designed to enhance the accuracy and robustness of rice yield predictions by systematically identifying the best set of hyperparameters. GS is a well-established technique in machine learning for conducting an exhaustive search over a specified range of parameter values to find the optimal combination [17, 18]. This study aims to improve the performance of the ANN model by integrating it with GS and systematically tuning its hyperparameters to increase the predictive accuracy in the rice yield prediction.

Several earlier studies, such as [19, 20], where the role of weather and soil factors in predicting the rice yield was examined, remain limited. However, these studies had limitations because they did not utilize hyperparameters to optimize the method's parameters for improved performance. This study addresses the specific gap by examining weather and soil factors. It uses HT combined with GS to identify the optimal parameters for the ANN method, improving the accuracy and rice yield predictions. This research aims to develop a more interpretable, efficient, and scalable model that offers actionable insights for farmers, agricultural policymakers, and technology developers in the region. The findings of this study are expected to serve as a valuable tool for improving the agricultural decision-making, supporting sustainable farming practices, and enhancing Indonesia’s food security. Given the increasing challenges of climate change and environmental degradation, accurate yield predictions enable stakeholders to make more informed decisions, optimize resource use, and enhance the agricultural resilience.

II. RESEARCH METHODS

This study proposes the use of ANNs, specifically the MLP architecture, to forecast the rice yields based on meteorological and soil condition data. The methodology is further elucidated through the flow chart presented in Figure 1, which visually delineates the steps involved, from the data collection and preprocessing to the model development, training, and evaluation.

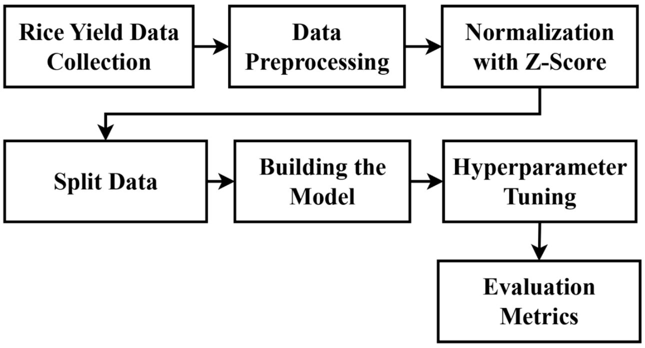

Fig. 1. Research flow diagram.

A. Data Collection

The data required to create a reliable predictive model for the rice yield in Malang City can be divided into two main categories: meteorological data and agricultural data. These datasets are crucial because they supply the input features needed to train a machine learning model capable of accurately predicting the rice yields based on environmental conditions and agricultural parameters. Meteorological data are essential for understanding the environmental conditions that directly affect the rice production. These data usually include measurements, such as rainfall, air temperature, and humidity, all of which significantly influence the growth and development of the rice crops. Rainfall, for example, is a crucial factor in the rice cultivation because the rice plants require a consistent water supply at various stages of their growth. Variations in the rainfall patterns can cause droughts or floods, both of which can significantly impact the rice yields. Likewise, the air temperature affects the rate of growth and development in rice plants, with extreme temperatures disrupting the crop growth. Humidity, on the other hand, impacts the rates of evaporation and transpiration, which can alter the crop's water needs.

The Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG) provides the weather data necessary to monitor these variables, offering detailed records of the climate patterns and seasonal changes. These records, spanning multiple years, are essential for modeling how the climate conditions affect the rice yields. Using weather data enables the model to account for the annual variability and unpredictable nature of the climate, which is particularly important for areas like Malang that experience significant seasonal shifts in weather. Along with the weather data, agricultural data offer key insights into the rice production, harvest areas, and other important factors that influence the agricultural output. The Central Statistics Agency (BPS) is the main source of this information, which includes historical data on the rice production and harvest areas in the Malang region from 2009 to 2024, totaling 528 data points available on the Kaggle website [21].

B. Data Preprocessing

Proper preprocessing of data is a key step to ensure that they are suitable for training an ANN model. The quality of the input data directly impacts the accuracy and performance of the predictive model. Data preprocessing involves several steps that prepare the dataset for effective model training, helping to eliminate the inconsistencies and biases. The present study outlines the main steps involved in data preprocessing, followed by a diagram to visualize the flow of these steps.

The first step in data preprocessing is data cleaning, which involves identifying and correcting issues, such as missing values, duplicates, and outliers. Missing values can occur when some data points are not recorded or are incomplete. These gaps can lead to biased results; therefore, it is essential to address them properly. Imputation techniques, such as filling the missing values with the mean, median, or using more advanced methods, like regression or nearest-neighbor imputation, are often employed. Additionally, duplicate data can occur during data collection, causing redundancy and distorting the results. These duplicates must be identified and removed to preserve the dataset's integrity. Outliers, or extreme values that significantly differ from the rest of the data, can distort the model's learning process and compromise its predictions. Statistical methods or domain-specific rules can be used to identify and remove or adjust the outliers. Some of the data in the original datasets may be irrelevant for predicting the rice yields. For example, while weather variables, such as rainfall, temperature, and humidity, are crucial for prediction, other less important features might add redundancy and reduce the model's effectiveness. Data extraction ensures that only the most relevant features are included, thereby reducing the noise in the model, enhancing its ability to generalize, and accelerating the training process.

Following data extraction, the subsequent stage in the preprocessing procedure is data transformation, which ensures that the data are in a suitable format for training the ANN model. This includes several essential steps, such as transforming the categorical variables into numerical forms using methods, like one-hot encoding or label encoding. Additionally, the units of measurement across various features are standardized, such as aligning rainfall in mm and temperature in degrees Celsius/°C, to ensure consistency throughout the dataset. This step is essential because the ANN model requires numerical input, and using consistent units helps ascertain that no feature has an outsized impact on the model. Furthermore, normalization or standardization of numerical features is performed to bring all variables onto a comparable scale, which helps the ANN converge more efficiently during training. After data transformation, feature selection is performed to identify and keep the most relevant variables for predicting the rice yields. This step involves analyzing the dataset to determine which features, such as rainfall, temperature, humidity, and soil conditions (e.g., pH, moisture content, and nutrient levels), have the most influence on the yield predictions. By employing techniques, such as correlation analysis and Recursive Feature Elimination (RFE), redundant or irrelevant features that do not significantly contribute to the model's performance can be eliminated. Feature selection not only enhances the model's accuracy by emphasizing the most important data, but also decreases the computational complexity, making it more efficient. This simplified dataset, containing only the most impactful features, is then ready for training the ANN model, ensuring that the model learns from the most critical variables while avoiding overfitting.

C. Normalization (Z-score)

Normalization is a crucial step in data preprocessing, especially when employing algorithms like ANNs. Since ANN models are sensitive to the scale of input features, it is essential to ensure that all features contribute equally to the model's learning process. If one feature has a much larger scale, it can dominate the learning process, causing the model to give disproportionate importance to that feature. To avoid this, normalization adjusts the scales of the features so that each has a similar range and influence on the model's learning. A common method for this is Z-score normalization, also known as standardization. The Z-score normalization method transforms the data by scaling each feature to have a mean of 0 and a standard deviation of 1. This standardization technique is especially effective for datasets where features have different units or vastly different scales. In the case of ANN models, applying Z-score normalization improves the model's convergence speed during training, as the network can process features more uniformly. It also helps prevent the model from becoming biased toward features with larger magnitudes. The formula for Z-score normalization is provided using:

$$Z = \frac{x-\mu}{\sigma} \qquad (1)$$

where Z is the normalized value (the Z-score), x is the original value of the feature, μ is the mean of the feature, and σ is the standard deviation of the feature.

By applying this formula, each feature in the dataset is transformed so that its values have a mean of 0 and a standard deviation of 1. Specifically, for each data point, the mean of the feature is subtracted and then divided by the standard deviation. This results in a distribution where most values are between -3 and 3, with 68% of the data points being within 1 standard deviation from the mean, 95% within 2 standard deviations, and 99.7% within 3 standard deviations. Z-score normalization is especially helpful when the features have different units or scales, such as temperature in degrees Celsius/°C, rainfall in mm, and humidity as a percentage. Without normalization, the ANN model may give too much importance to the feature with the largest numerical scale, which could lead to inaccurate predictions. By standardizing the features, Z-score normalization makes sure that all features are treated equally, leading to a more balanced and accurate model.

D. Splitting Data (Train and Test)

Splitting the dataset into two subsets (training and testing) is a crucial step in machine learning. Typically, 70-80% of the data is used to train the model, while the remaining 20-30% is reserved for testing. This split ensures that the model has enough data to learn from while keeping a separate set for evaluating its performance. The purpose is to train the model on the training data, allowing it to learn the patterns, and then test it on unseen data to assess its generalization. This method helps mimic real-world situations where the model needs to make predictions based on new information.

E. Method Implementation

For this study, the MLP architecture of ANN will be employed. The MLP is well-suited for regression tasks, such as predicting continuous values like crop yields. The steps involved in ANN development are shown in Figure 2.

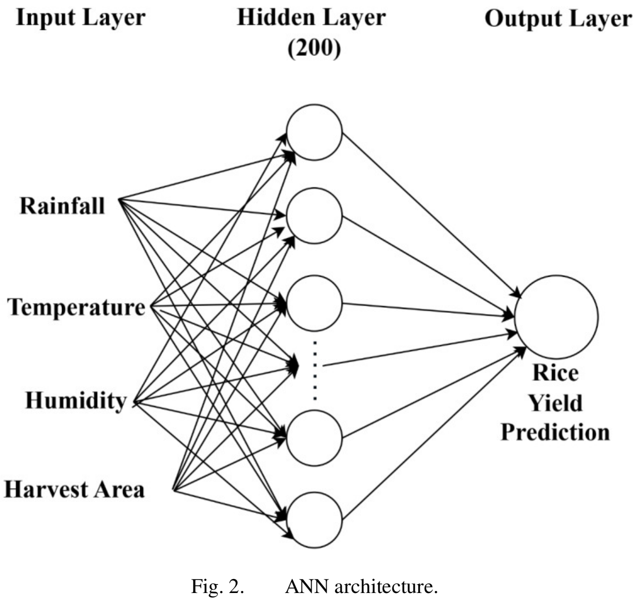

Fig. 2. ANN architecture.

1) Input Layer

The input layer is the initial stage in the ANN, playing a vital role in receiving data for processing across the network. This model contains five essential features that represent significant environmental and agricultural factors influencing the rice yield. These features are:

1. Rainfall: The amount of precipitation that occurs over a specific period. Rainfall is a crucial factor affecting the rice growth and yield.
2. Temperature: Temperature affects various biological processes in rice plants, including photosynthesis, respiration, and growth rates.
3. Humidity: Humidity impacts the rate of transpiration in the rice plants and can also affect the spread of disease.
4. Rice Yield: Historical data on the amount of rice harvested in past seasons offers valuable insights into the expected yields.
5. Harvest Area: The total land area used for rice cultivation. Larger areas usually lead to higher yields, depending on other conditions.

These five features provide the necessary input data that the model uses to learn the patterns between the environmental conditions and rice yields. The data from this layer are fed into the network for further processing through the hidden layers.

2) Hidden Layers

The hidden layers are the core of the ANN and are responsible for learning the complex relationships between the input features and the output (rice yield). These layers perform various computations on the input data and transform them into higher-level representations. The network used in this study has one hidden layer with a predetermined number of neurons. The hidden layer contains 200 neurons that learn the initial abstract features from the input data, focusing on the primary relationship between the environmental variables and rice production outcomes. Each neuron in the hidden layers applies an activation function, typically the Rectified Linear Unit (ReLU), to introduce non-linearity to the model. This non-linearity is essential for ANN models because it allows the network to learn complex, nonlinear relationships between the input features and the target output. For instance, the interaction between the temperature and humidity, or the combined effect of the rainfall and soil moisture, may not follow a straight line. ReLU activation helps the model adapt to such complexities. By learning these relationships, the hidden layers enable the model to identify more subtle patterns that linear models might miss.

3) Output Layer

The output layer is the final component of the network where the model generates its prediction. In this study, the output layer has a single neuron that forecasts the rice yield. Since this is a regression task, the output layer utilizes a linear activation function, which is suitable for predicting continuous values, such as the rice yield. The linear activation function ensures that the output can take any real value, making it appropriate for tasks where the target is not limited to discrete categories (such as in classification tasks). The output neuron takes the learned patterns from the hidden layers to produce a prediction of the rice yield. The prediction relies on the interaction between the input variables (rainfall, temperature, humidity, rice yield, and harvest area) and the complex patterns learned by the model during training. By leveraging this simple yet effective structure, the MLP model can produce accurate and dependable predictions for the rice yield based on a combination of environmental and agricultural factors.

F. Tuning Hyperparameter

The first step in the model training process is to initialize the ANN model, which is accomplished using the MLP regressor from the scikit-learn library. The ANN model is designed to capture the complex, non-linear relationships between the features in the dataset, such as weather conditions and agricultural data, and the target variable (rice yield). The model is initially trained using a standard configuration, enabling it to learn patterns from the training data. However, the default ANN model's performance can often be enhanced through hyperparameter tuning, including adjusting the number of hidden layers, activation functions, and the learning rate. To enhance the ANN model's performance, GS is deployed to optimize its hyperparameters. GS functions by defining a parameter grid that includes various values for each hyperparameter. It then thoroughly trains the model with all possible combinations of these hyperparameters, assessing the performance with a cross-validation method, usually 10-fold cross-validation. This search aims to find the hyperparameter combination that yields the highest validation performance for the model set. The GS approach systematically trains and evaluates each model configuration across a defined set of hyperparameters, selecting the optimal one based on performance metrics, such as the R², MAE, an MSE. The selection of the best configuration is formally expressed in:

$$\hat{h} = argmax\ Perfomance(h) \quad (2)$$

In this formulation, the GS method exhaustively explores all possible combinations of hyperparameters h within a predefined hyperparameter grid *H*. This grid represents a set of candidate values that each hyperparameter can take. For instance, *H* may include various configurations for the number of the hidden layers, activation functions, or learning rates. GS systematically iterates over each combination in *H*, trains the ANN with the corresponding hyperparameters, and evaluates performance using predefined metrics, such as R², MAE, or MSE. The primary objective is to determine the configuration $\hat{h} \in H$ that maximizes the model performance, thereby determining the optimal set of hyperparameters for the ANN model. In simpler terms, the formula aims to identify the best-performing model by systematically testing all possible hyperparameter combinations and choosing the one that maximizes the performance metric.

Once the hyperparameter grid is defined, GS is employed to train the ANN model using the training dataset, which comprises historical weather and agricultural condition data. During this process, the ANN learns the underlying relationships between the input features and rice yield. Upon identifying the optimal hyperparameters through GS, the refined ANN model is evaluated on the test dataset to assess its predictive performance. The optimized model is expected to outperform the baseline (default) configuration in terms of both accuracy and generalization, as it has been fine-tuned to capture the specific patterns within the dataset. GS contributes to minimizing the prediction errors and enhancing the overall performance of the ANN.

G. Evaluation Metrics

To evaluate the performance of the ANN model, the following evaluation metrics are employed:

- MAE quantifies the average absolute difference between the predicted and actual rice yields [22]. It clearly reflects the model's accuracy, where a lower MAE signifies better performance. The MAE is computed using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i\ | \quad (3)$$

where *n* is the number of samples, yi is the actual value, $\hat{y}i$ is the predicted value, and $|yi{-}\hat{y}i\,|$ is the absolute difference between the actual value and the predicted value.

- MSE quantifies the average of the squared differences between the actual and predicted values [23]. While MSE penalizes larger errors more heavily, MAE offers a more interpretable measure, as it represents the average error in the same units as the target variable and is less sensitive to outliers. The MSE is computed using:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

where y_i denotes the actual value, $\hat{y}i$ represents the predicted value, *n* is the number of observations, and $(\text{yi} - \hat{y}i)^2$ is the squared difference between the actual value and the predicted value.

- The R² evaluates how effectively the model explains the variance observed in the actual data [23]. An R² value approaching 1.0 indicates that the model accounts for most of the variance in the target variable, whereas a value near 0 suggests a poor explanatory power and limited model fit. The R² is computed using:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}i\,)^2}{\sum_{i=1}^{n}(\text{yi} - \bar{y}i)^2} \quad (5)$$

where yi denotes the actual (observed) value, $\hat{y}i$ denotes the predicted value produced by the model, $\bar{y}$ is the average of the actual values, $\sum(\text{yi} - \hat{y}i)^2$ represents the Residual Sum of Squares (RSS), which quantifies the total squared error between the predicted and actual values, $\sum(\text{yi} - \bar{y}i)^2$ is the Total Sum of Squares (TSS), indicating the total variance present in the observed data.

The use of these three metrics is appropriate, as the target variable (the amount of rice harvested) is a continuous and numerical variable. The combination of MSE, MAE, and the R² provides a comprehensive evaluation framework. MAE and MSE capture the model's prediction accuracy, while R² reflects its ability to explain the variance in the observed data, thereby enabling a complete and objective assessment of the model performance.

III. RESULT AND DISCUSSION

A. Data Collection

The data utilized in this study were obtained from two primary sources: the BMKG and local agricultural departments. The weather data provided by BMKG encompass key environmental variables known to influence the the agricultural productivity, particularly rice yield. These variables include the average temperature (°C), relative humidity (%), and rainfall (mm), all of which are critical for analyzing the effects of the climatic conditions on the rice growth and yield. The BMKG dataset spans the period from 2009 to 2024 and offers periodic records (monthly or annual) of these parameters, thereby enabling the investigation of both the seasonal patterns and long-term climate trends relevant to the rice production. The collected data are structured into input features and output variables. Input features, which influence the rice yield but are not affected by other factors in the model, include the average temperature, humidity, rainfall, and harvest area. The output variable is the rice production, which is dependent on these inputs and serves as the target for prediction. Table I lists the variables employed in the current study for forecasting the rice yield using the ANN model, distinguishing between the input features and the output variable.

TABLE I. USED VARIABLES

Category	**Variable name**	**Description**	**Unit**
Input feature	Average temperature	Average temperature for the season	°C
	Relative humidity	Average temperature for the season	%
	Rainfall	Total rainfall during the growing season	mm
	Harvest area	Area of land used for rice cultivation	Hectares/ HA
Output (target)	Rice yield	Total rice yield for the season (target variable)	Tons

B. Data Preprocessing

Effective data preprocessing is a critical step in ensuring that the dataset used in the ANN model is both high-quality and analytically suitable. The data preprocessing steps include:

1) Data Cleaning

The first step in data preprocessing is to clean the data, ensuring that they are free from inconsistencies. Table II illustrates the data cleaning process applied to the dataset, focusing on handling the missing values, duplicates, and outliers to ensure data consistency. In Table II, the "Original value" column shows the initial data for each variable, while the "Imputed value (mean/median)" column displays the corrected or imputed data after using imputation methods. For example, the variable "Temperature" initially had a value of 22.5, which was replaced with 23.0 based on the mean or median of the column. For the "Rainfall" variable, a missing value (indicated by NULL or 8888) was imputed with 120.0, a value calculated from the average rainfall data. Regarding "Humidity," no missing values were found, and the original value of 78.2 remained the same. Table II illustrates how the missing values are efficiently handled through imputation, ensuring that the dataset remains complete and ready for analysis without impacting the model's results.

TABLE II. DATA CLEANING PROCESS

Variable	**Original value**	**Imputed value (mean/median)**
Temprature	22.5	23.0
Rainfall	Null (8888)	120.0
Humidity	78.2	78.2

2) Data Extraction and Transformation

Data transformation and extraction are crucial steps in preparing the dataset for the ANN model. During data extraction, only the relevant features from both the weather and agricultural datasets are selected, ensuring that the unnecessary variables are removed, and thus reducing the redundancy, which enhances the model efficiency. This includes key environmental factors, such as temperature, rainfall, and humidity, as well as agricultural variables, including the harvest areas. The data transformation process then begins, standardizing the dataset's format. This involves converting the categorical variables into numerical values through encoding and standardizing measurement units for consistency across the dataset, such as ensuring that the rainfall is measured in mm and temperature in degrees Celsius/°C. These combined steps ensure that the data are both streamlined and consistent, making them ready for model training.

3) Z-score Normalization

Normalization standardizes the input features to have a mean of 0 and a standard deviation of 1. This process ensures that all features contribute equally to the learning process, which is particularly important in ANN models, where differing scales can adversely affect the convergence and model performance. Table III displays the application of Z-score normalization to the selected environmental features used in predicting the rice production. Table III, the "Original value" column shows the raw values of each feature before normalization, while the "Z-score normalized value" column shows the transformed values. For instance, the original temperature value of 22.5 was transformed to a Z-score of -0.75, indicating that it is 0.75 standard deviations below the mean temperature of the dataset. Similarly, the rainfall value of 120 was normalized to a Z-score of 1.25, meaning it is 1.25 standard deviations above the mean. The humidity value of 78.2 was transformed to -0.20, which is slightly below the mean of the humidity variable, and the soil pH value of 5.8 was normalized to 0.10, showing it is slightly above the mean. This normalization process brings all features (temperature, rainfall, humidity, and soil pH) to a common scale. This helps the ANN model learn more effectively and identify the meaningful relationships between these variables and rice production. Without standardization, the features with larger scales, like rainfall, might overshadow others and hinder learning. Using Z-score normalization enables the model to handle all features more effectively, resulting in improved prediction accuracy.

TABLE III. Z-SCORE NORMALIZATION

Feature	Original value	Z-score normalized value
Temperature	22.5	-0.75
Rainfall	120	1.25
Humidity	78.2	-0.20
Harvest Area	619	-1.20

4) Split Data

Data splitting is essential in preprocessing because it enables the model to generalize effectively to unseen data. The dataset is typically divided into two parts: one for training and one for testing. The training set, usually 70-80% of the total, is used for the model to learn patterns and relationships from the input features and output variables. Its goal is to enable the model to adjust its parameters, learn from the data, and improve performance by minimizing errors during training. The remaining 20-30% of the data is set aside as the testing dataset. This subset is crucial because it evaluates how well the model performs on new data. Using a separate test set prevents overfitting, ensuring that the model learns to recognize general patterns rather than just memorizing training data. This unbiased evaluation estimates the model's accuracy, robustness, and capacity to handle variations it has not seen before.

C. Modeling and Evaluation

This section provides a comprehensive evaluation of various machine learning algorithms employed to forecast rice yields in Malang City, Indonesia. The main models analyzed are the ANN and an optimized version of the ANN that uses GS for hyperparameter tuning. These models were chosen for their ability to manage complex regression problems, particularly their strengths in modeling the non-linear relationships and their robustness when working with large, multidimensional agricultural datasets. The ANN was selected as the primary model due to its proven ability to capture the complex, non-linear relationships between the target variable (rice yield) and various input features, including environmental factors, such as rainfall, temperature, and soil conditions. ANNs are widely used across different fields due to their flexibility and adaptability, particularly in cases where traditional linear models may not effectively represent the data.

The performance of each model was evaluated using the metrics: R^2 score, MAE, and MSE. The models were trained and evaluated utilizing a training and testing dataset split, with the same set of features for all models. This ensures a fair comparison between the algorithms. To address overfitting and improve the generalization of the models, GS was applied to tune the hyperparameters of the ANN model. The ANN model obtained the best parameters of 1 hidden layer, such as 200 hidden layers, activation = "relu", learning_rate = "constant", solver = "adam" and alpha = 0.0001. The results presented in Table IV show an improvement in the model performance after applying GS optimization to the ANN. The R^2 value increased from 96.89% to 97.41%, indicating a 0.52% improvement in the model's ability to explain variance in the rice yield. Furthermore, the MAE decreased by approximately 9.78% (from 849.71 to 766.69), and the MSE decreased by 25.77% (from 2,504,538.96 to 1,858,857.06), demonstrating improved accuracy and reduced error after optimization. These results clearly show that GS optimization significantly improves the accuracy and efficiency of the ANN model for the rice yield prediction.

TABLE IV. MODEL PERFORMANCE RESULTS

Model	R^2	MAE	MSE
ANN default with MLP	96.89%	849.71	2,504,538.96
ANN-pptimized	**97.41%**	**766.69**	**1,859,857.06**

Besides the quantitative metrics, Figure 3 provides a visual representation of the model's prediction performance. In the plot for the default ANN model, the predicted values (represented by the solid line) exhibit noticeable discrepancies from the actual values (represented by the dashed line), indicating significant errors in the predictions. This gap suggests that the default ANN model, although somewhat accurate, still struggles to fully comprehend the complexities of the data. However, when looking at the optimized ANN plot, the predicted values align much more closely with the actual values (Figure 4). This improved match between the predicted and actual distributions demonstrates how hyperparameter optimization enhances the model's ability to generalize from training data to new, unseen data.

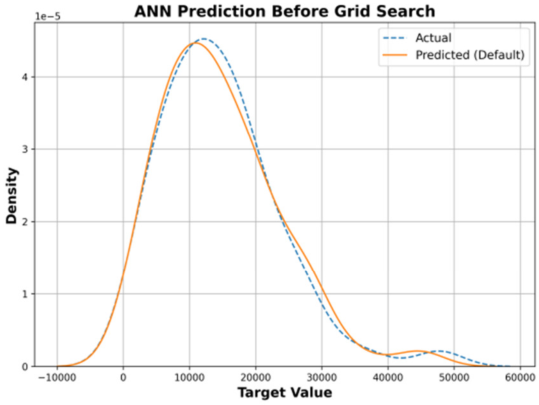

Fig. 3. ANN actual versus predicted values on default model.

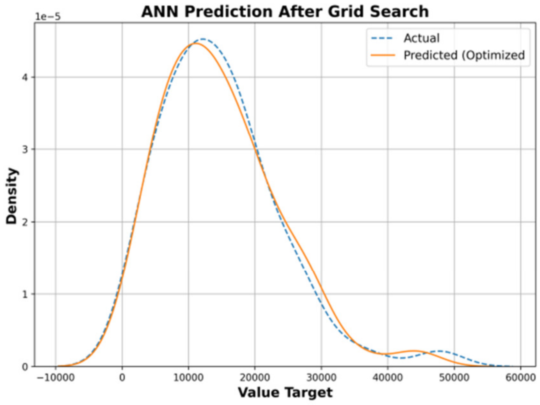

Fig. 4. ANN actual versus predicted values on GS optimization.

The ANN model optimized using GS demonstrates the best performance in predicting the rice harvest yields compared to the model without hyperparameters. This highlights the importance of HT in enhancing the model performance, particularly for complex tasks, such as predicting the agricultural yields. The ANN model's ability to handle non-linear relationships, combined with the systematic optimization process provided by GS, enables it to achieve higher prediction accuracy, making it a valuable tool for forecasting the agricultural outcomes. Additionally, the actual versus predicted plots verify the model's enhanced performance, visually showing the accuracy of the predictions made by the optimized ANN. These findings strongly support the use of ANN in agricultural forecasting, offering a reliable and efficient method to aid decision-making in the agricultural sector. This study is limited by the small size of the dataset, which may impact the model generalization, highlighting the need for additional data to improve both the model performance and generalization.

A comparison of the ANN model's performance before and after the GS optimization shows a clear improvement. Before optimization, the model had an R^2 score of 96.89%, an MAE of 849.71, and an MSE of 2,504,538.96, using default parameters, such as activation="relu", hidden_layer_sizes=100, and solver="adam". After the optimization with GS, the R^2 score increased to 97.41%, indicating a more effective ability to explain the data variability. Additionally, the MAE decreased to 766.70, and the MSE dropped notably to 1859857.06, indicating an enhanced prediction accuracy. The optimal parameter identified was the hidden layer_sizes=200, while other configurations remained unchanged. This enhancement in performance was primarily attributed to expanding the number of neurons in the hidden layer from 100 to 200, hence augmenting the model's capacity to learn complex data patterns. The results demonstrate that the variations in the number of neurons have a significant influence on the model's performance. Conversely, other parameters, such as the activation function and solver, remain unchanged, indicating that alterations to these elements do not significantly affect performance.

IV. CONCLUSION

This study demonstrates that Artificial Neural Networks (ANNs), particularly the Multilayer Perceptron (MLP) architecture, are effective tools for predicting the rice yields in Indonesia under fluctuating climatic conditions. By integrating weather variables (e.g., rainfall, temperature, humidity) with agricultural data (e.g., harvest area, rice yield), the model successfully captured the complex, nonlinear relationships between the environmental factors and rice productivity. Comprehensive data preprocessing, including data cleaning, feature extraction, and Z-score normalization, ensured that the ANN model was trained on high-quality and consistent data, thus enhancing the predictive accuracy. Furthermore, the application of Grid Search (GS) for hyperparameter optimization significantly improved the model performance. The optimized ANN achieved a coefficient of determination (R^2) of 97.41%, highlighting its robustness and predictive capability. The accuracy and robustness of the optimized ANN model underscore the model's potential to support agricultural decision-making, particularly in addressing the challenges posed by climate variability. However, the study is limited by the relatively small dataset size, which may restrict the model's generalizability. Future research should incorporate larger datasets, ideally sourced from public repositories or governmental agencies, to further validate and strengthen the model's reliability and applicability.

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