# Rice Yield Prediction in Sumatra Indonesia Using Machine Learning and Climate Data

2023 3rd International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA) | 979-8-3503-9455-9/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICICyTA60173.2023.10428960

1st Aldian Nurcahyo
*Computer Science Department*
*Bina Nusantara University*
Jakarta, Indonesia
aldian.nurcahyo@binus.ac.id

2nd Haryono Soeparno
*Computer Science Department*
*Bina Nusantara University*
Jakarta, Indonesia
haryono@binus.edu

3rd Lili Ayu Wulandari
*Computer Science Department*
*Bina Nusantara University*
Jakarta, Indonesia
lili.wulandhari@binus.ac.id

4th Widodo Budiharto
*Computer Science Department*
*Bina Nusantara University*
Jakarta, Indonesia
wbudiharto@binus.edu

***Abstract*— Sumatra Island has over 50% of agricultural land in each province, with rice as the dominant food crop. Climate change poses a significant threat to agricultural production, impacting crop patterns, planting times, and yield quality. Rising temperatures and climate variations can further jeopardize agriculture in Sumatra. This study addresses rice yield prediction across eight Sumatran provinces in Indonesia. In this study, four combination climate and crop production data were tested to predict rice yields across eight Sumatran provinces in Indonesia using machine learning (ML) regression-based method. Six regression algorithms are employed for predictive modeling. We employed hyperparameter tunning methodologies such as Grid Search CV or Randomized Search CV for each model to improve its performance. Cross-validation (CV) with k-fold splitting is used to evaluate unbiased models. XGBRegressor appears to be the best-performing model among the six, with 88.48 R2-score, followed by Random Forest Regressor with 86.39 and Support Vector Regressor with 85.21. The XGBRegressor also has the lowest Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which implies it explains more variance and makes more accurate predictions. This indicates its potential as the most dependable model among those examined. The research aims to provide actionable insights to enhance food security in Sumatra amidst climate challenges, aiding both farmers and policymakers in making informed decisions for stable agricultural production and food security in the region.**

**Keywords—*rice yield, prediction, machine learning, regression, Sumatra Indonesia***

## I. INTRODUCTION

The Indonesian population is growing, and this is increasing the demand for rice food crops. Sumatra island in Indonesia, contributes significantly to the agricultural sector of the nation and the nation's rice production. With Indonesian population growing, demand for rice, raw food will rise. However, meeting this demand turns out to be not an easy challenge. Agriculture is a major supporter of the regional economy and food resilience in Sumatra but faces severe challenges as a result of climate change. These challenges are mainly embodied in changing crop patterns, changing planting times, and variations in yield quality. The major threat comes from climate change, characterized by rising temperatures and uncertain weather patterns, threatening agricultural production on the island [1].

Complicated conditions of various climate factors affect the harvest in Indonesia especially Sumatra. Rainfall, humidity, average temperature, wind speed, and climate events like El Nio all play a role in altering the agricultural landscape [2]. Sumatra, Indonesia's largest island, is crucial in the country's agricultural business, contributing significantly to national rice output. Rainfall patterns are an important parameter in considering rice power and variations of such parameters can have a significant impact on harvest yields. Similarly, temperature and humidity levels affect plant development and productivity. Besides, wind speed and periodic El Niño events make an additional layer of complexity in the challenge of rice yield prediction.

Our primary objectives include developing and validating strong predictive models that can effectively predict rice yield in Sumatra, Indonesia. By examining historical climate data covering almost three decades, we aim to build predictive models with an emphasis on reliability and interpretability. Various machine learning algorithms, including Linear Regression (LR), Random Forest (RF), Decision Tree (DT), Support Vector Regression (SVR), K-Neighbors Regression (kNN), and XGBoost Regression (XGB) are employed to create predictive models. Furthermore, we discover the most accurate and dependable outcome predictions. This study provides valuable insights to farmers and policymakers to optimize crop yield prediction, prevent losses, enhance productivity, and strengthen food sustainability in Sumatra, Indonesia.

## II. RELATED WORKS

This section gives insights into the present state of knowledge as well as the approaches used in estimating rice yields using climatic data. Study in southwest Nigeria finds that solar radiation is a significant influence on rice yield, especially during monsoon and post-monsoon periods. This information can help farmers plan crops and select cultivars in the future [3]. This study compares seven algorithms, including machine learning and regression, for rice yield prediction using On-Farm Data Sets with five-hectare plot and multispectral data. K-Nearest Neighbors performed best with a 10.74% error, while Multiple Linear Regression had the highest error of 2712.26 kg-ha-1 [4]. ML models using climate and satellite data, including enhanced vegetation index (EVI), can forecast wheat yields in Australia two months before maturity [5].

Sri Lankan study uses ANNs to predict paddy yields. LM training excels, offering stable annual predictions amid climate uncertainties, even without seasonal data ANN models help anticipate paddy yields in changing climates [6]. The study's goal was to estimate rice yields using machine learning approaches by experimenting with various combinations of phenology, climate, and geography data [7]. This study found rice yield in China can be predicted accurately one to two months before harvest using LASSO regression, Random Forest (RF), and Long Short-Term Memory Networks (LSTM) [8]. This research using Climate-based rice yield prediction in Sri Lanka using Gaussian process regression [9].

This study examined rice yield prediction in eastern China by evaluating agronomic features and climate data and found that a deep learning model outperformed a traditional model. [10]. Informer, a transformer-based model, beats previous models for rice yield prediction. NIRV, intervals in August and November are key factors. It provides insights into deep learning models for rice yield prediction in India [11]. Nigeria relies heavily on agriculture, and climate change impacts crop yields. This study used data from Katsina state (1970-2017) to build rice yield prediction models. Random Forest and Random Trees outperformed, aiding food security planning [12].

## III. Methods

The methodology we propose is depicted in Fig. 1 below, which consists of data loading, exploratory data analysis, preprocessing, modelling, and model evaluation.

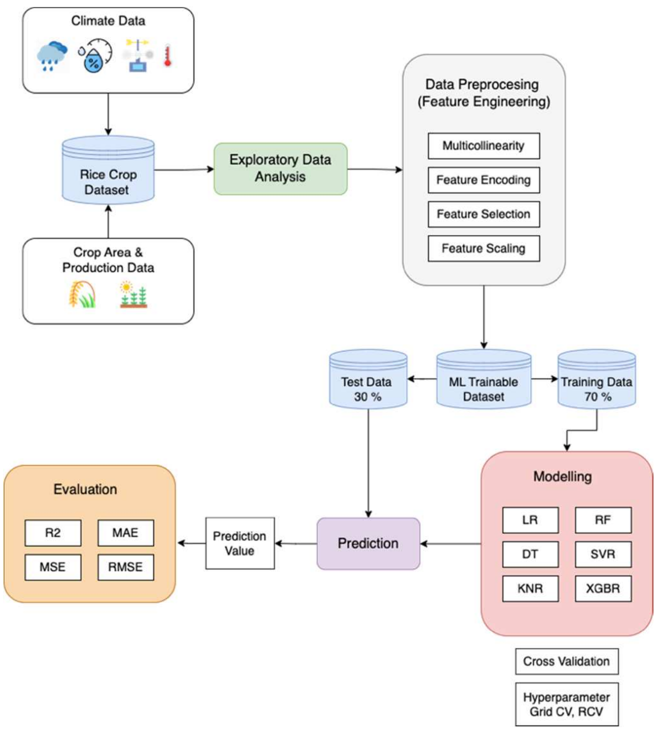


Fig. 1. Methodology for rice yield prediction

### A. Data description

This paper uses a collection of data from eight provinces in Sumatra from 1993 to 2020, namely Nanggroe Aceh Darussalam, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, and Lampung. The following are the features included in the dataset, as shown in Table I. The first four features that consist of crop area and production data come from the Central Statistics Agency (BPS) Database, while the environment and climate date from the Meteorology, Climatology and Geophysics Agency (BMKG) Database. These characteristics give a solid foundation for modeling and analyzing rice yield prediction in Sumatra, Indonesia.

TABLE I. SUMMARY OF FEATURES

| Feature Name | Description | Unit Value | Range | Type |
|---|---|---|---|---|
| Province | The province's name | Text | Varies by province | Categorial |
| Crop Area | Agricultural land area | Hectare (Ha) | 63142-872737 | Numerical |
| Year | Rice production | Numeric | 1992-2020 | Numerical |
| Yield | Annual rice production | Tons per hectare (Ton/Ha) | 42938-4881089 | Numerical |
| Rainfall | Annual rainfall average | Millimeter (mm) | 222-5522 | Numerical |
| Humidity | Annual humidity average | Percent (%) | 54-90 | Numerical |
| Average Temp. | Annual temperature average | Degree Celsius (°C) | 22-30 | Numerical |
| pH | Soil pH | pH unit | 4 - 7.5 | Numerical |
| Crop | Name of Crop (rice) | Text | Rice | Categorial |

### B. Exploratory Data Analysis

A useful tool for analyzing data on rice yield in Sumatra, Indonesia, is exploratory data analysis (EDA). Python has been utilized by us to analyze data. It is an interactive, interpreted, object-oriented programming language. With a wealth of libraries as MATplotlib, Seaborn, and Pandas, it is open source [13]. We have examined the relationships between temperature, humidity, rainfall, and rice production using a variety of chart kinds and parameter sets. Machine learning models can be created to estimate rice yield using this data.

### C. Data Preprocessing

*1) Correlation matrix:* When independent and dependent variables in a regression model have a strong connection, it affects model stability. Province and Crop are categorical variables. In regression analysis, correlation between dependent and independent variables is necessary, while correlation between independent variables is undesirable [14]. High correlations (greater than 0.8) between numerical independent and dependent variables indicate multicollinearity. The matrix shows (Fig. 2) that there is no multicollinearity in this scenario.

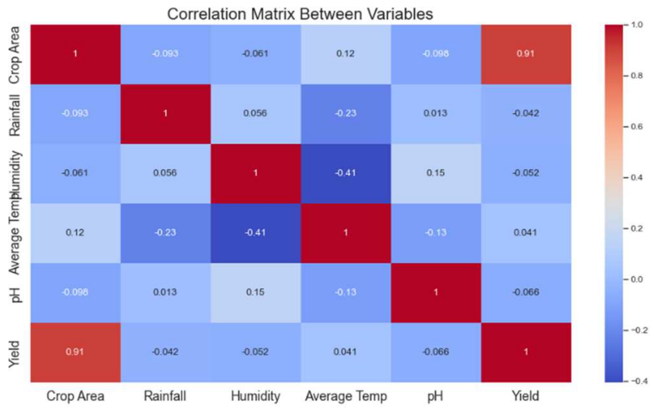


Fig. 2. Multicollinearity

*2) Feature encoding*: Categorical data, such as 'Province' in this dataset, has labels rather than numerical values. Numeric inputs are required by many machine learning methods. To improve prediction, 'Province' is converted into a binary array using one-hot encoding. In the matrix, each category is represented by a binary column.

*3) Feature selection:* We used correlation analysis to identify highly correlated features and remove them from the dataset [15]. The purpose of the feature selection procedure is to discover the most important features for predicting rice yield. Dropping specific columns improves the predictive performance and interpretability of the model. The "Year" column has been removed from the dataset because it contains time-related information and is not directly connected to the rice yield prediction task. The emphasis is on climatic characteristics. To avoid utilizing the target variable as a predictor of itself, the "Yield" column is not used as an input feature in feature selection.

*4) Train and test:* The dataset is divided into two parts, for training data (70%) and for testing data (30%). The training dataset is used to train the machine learning algorithm, while the test dataset is used to make predictionand evaluate its performance. This division ensures objective evaluation.

*5) Feature scaling:* The dataset contains features with widely disparate magnitudes, units, and ranges. High magnitude features will weigh far more heavily in distance estimates than low magnitude objects. To counteract this impact, we must bring all features to the same magnitude level. This can be accomplished through scaling using the StandardScaler function.

## *D. Modeling*

*1) Model selection:* Six algorithms are employed for predictive modeling: Linear Regression, Random Forest, Decision Tree Regression, Support Vector Regression (SVR), K-Neighbors Regression, and XGBoost Regression. These models were chosen because they are all well-suited for predicting rice yield and have been shown to be effective in previous studies [3][4][7]. We implemented all models using Python libraries Sklearn.

*2) Cros validation*: In order to guarantee an impartial and equitable evaluation, we employed a 10-fold cross-validation (CV) methodology, which nine are used for testing and the tenth for training. Every subset is utilized as the test set once during the ten repetitions of this process. This method offers a more reliable measure of generalization performance while assisting in the reduction of overfitting [16].

*3) Hyperparameter Grid CV or Randomized CV:* A critical step in maximizing the effectiveness of ML models is hyperparameter tuning. Using strategies such as Grid Search CV or Randomized Search CV, hyperparameter adjustment is critical for each model to increase its performance. Whereas Randomized CV selects a subset of hyperparameter values at random, Grid CV evaluates a predetermined grid of hyperparameter values in a methodical manner [17][18].

*4) Fit the model:* We next use the complete dataset to fit the chosen regression model after determining the ideal hyperparameters. In order to do this, the model must be trained using all of the training data in order for it to discover the underlying trends and connections between the input characteristics and the desired variable, or "yield."

*5) Make prediction:* We use the trained model to predict the test data after the model has been fitted. This involves feeding the test data into the model, which generates predictions for rice yield based on the learned relationships from the training data.

*6) Visualize the prediction:* To gain insights into the model's performance and identify potential patterns, we used the Seaborn 'kdeplot' function tool to visualize the comparison between the actual and predicted distribution of rice yield.

*7) Check the R2 score of the model:* With the R-squared score we calculated we can assess the overall effectiveness of the model. This metric quantifies the percentage of the target variable's volatility (rice yield) that the model can account for. A higher R-squared value denotes a more robust prediction ability and better model fit to the data.

## *E. Model Evaluation*

We evaluated the model performance using the following statistical metrics. The relation coefficient ($R^2$), Mean Absolute Error (MAE), Mean Squared Error (MSE) and the root mean square error (RMSE) were used to evaluate the model performances [19]. A higher R2-score suggests that the model fits the data better. A lower MAE indicates better model accuracy. MSE calculates the average of the squared discrepancies between anticipated and actual values. A lower MSE indicates better accuracy but is more sensitive to outliers. A lower RMSE is better. These metrics are used to assess the performance of different regression models in predicting rice yields based on climate data. Higher R2 and lower MAE, MSE, and RMSE values indicate better model performance.

Numerous studies have been conducted to evaluate the performance of regression models for rice yield prediction. This paper predict error parameters of the artificial neural network (ANN) model to assess the model's performance on predicting rice yield. ANN model predict rice yield more precisely than regression analysis which has a low RMSE and high R2[20]. This paper presents an analysis of rice crop prediction using ML algorithms and multilinear regression. The best performing algorithm was kNN with MAE 10.74%

[4]. ML methods outperformed traditional regression methods in predicting rice yields by integrating phenology and climate data. SVM and RF performed better than backpropagation neural network (BP), achieving lower RMSE and higher R2 scores [7].

## IV. Experiment Result

### A. *Exploratory Data Analysis*

For 28 years, the average yield in 8 provinces was 1,679,700.887 tons, with the lowest yield being 42938 tons and the maximum yield being 4,881,089 tons. The average agricultural land area is 374,350 hectares. Each attribute's mean and median values are not significantly different. As a result, the data can be said to be regularly distributed. Fig. 3 shows that North Sumatra has the highest yield output based on historical data and annual rice production in tons across eight Sumatra provinces.

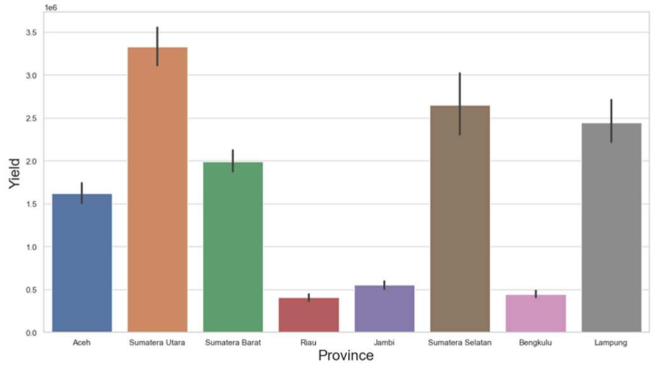


Fig. 3. Annual rice production in tons

Fig. 4 indicates that the year with the largest rice production was in 2017. However, in the following years, rice production experienced a significant decline.

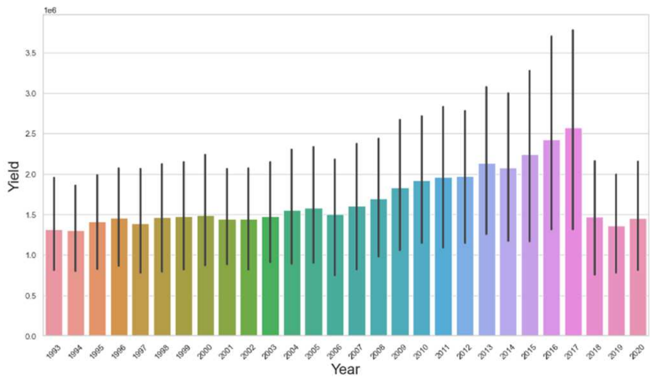


Fig. 4. Rice production from 1993-2020

Fig. 5 shows that peak rice production occurs in the 27-28°C temperature range, which is optimum for crop growth and better yields. Temperature cultivars and more precise understanding are needed to lessen the negative impacts of high temperatures on rice output and the effects of climate change on rice productivity and quality [21]. Deviations from this range may have a negative impact on output. This temperature interval is considered optimal for fostering robust crop growth and, consequently, enhancing overall yield outcomes.

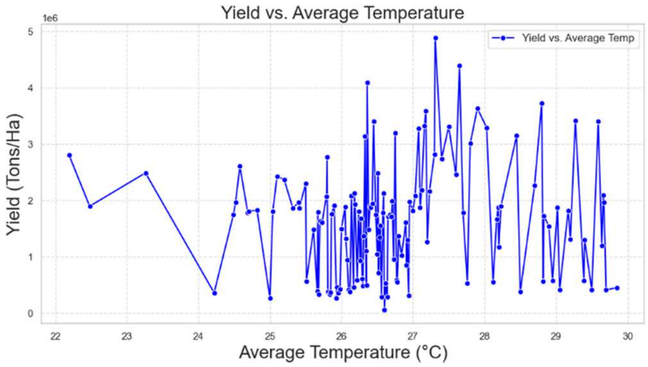


Fig. 5. Rice yield in sumatra vs Average Temp.

Fig. 6 show The highest average temperature was ever achieved in the year 2000-2005, which was more than 29 degrees Celsius, but in the following years it tended to be stable in the temperature range of 27 degrees Celsius.

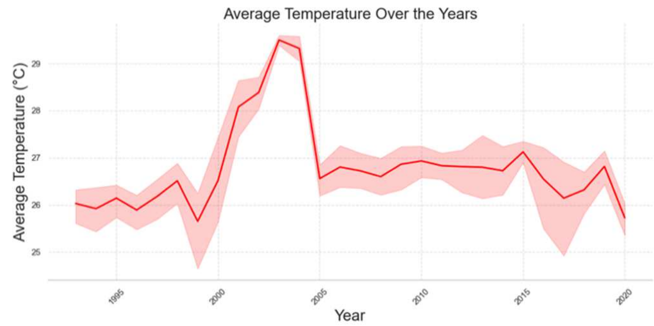


Fig. 6. Average temp. over the years

According to this study [22], there is a correlation between climate variables (rainfall, mean, minimum, and maximum temperatures, relative humidity) and the rice field productivity. The information depicted in Fig. 7, there appears to be a discernible relationship between the stability of rice yield production and a specific climatic factor, namely, the annual precipitation levels. In particular, the data suggests that rice yield stability is closely associated with the presence of a moderate amount of rainfall, which, in this context, is estimated to be approximately 2500 millimeters per year. This observation indicates that variations in rice yield performance may be influenced or even regulated by the availability of this specific level of annual rainfall.

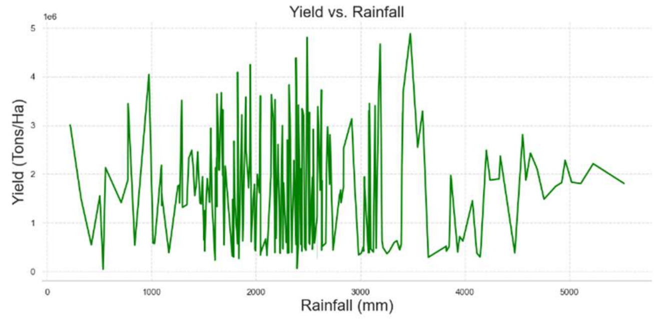


Fig. 7. Rice yield in sumatra vs rainfall

Fig. 8 provides a visual representation of the relationship between humidity levels and rice production. It illustrates that within the range of 80-85% humidity, rice cultivation appears to exhibit characteristics of an optimal and consistent nature.

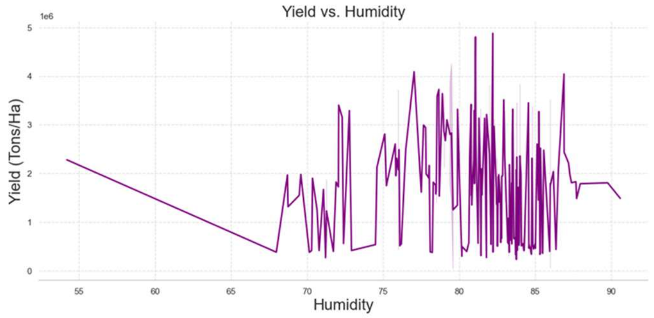


Fig. 8. Rice yield in sumatra vs humidity levels

Based on the purpose of this study, the attribute that will be the output is the annual rice production (column = Yield). The QQ-plot depicts the Yield variable's distribution. It compares theoretical quantile values to variable quantile values to determine the data distribution. Because the lines appear almost straight, the plot shows a rather typical distribution in Fig. 9.

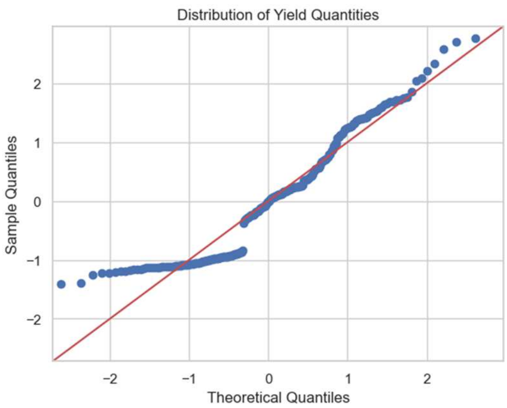


Fig. 9. Rice yield variables distributions

The vertical boxplot representation of the Yield output variable's distribution is displayed in Fig. 10. The center 50% of the data, or the interquartile range (IQR), is shown by the box. With outliers excluded, the whiskers reach the lowest and maximum values. When a point is outside the range of less than 1.5 IQR or above the median, an outlier occurs. The fact that there are no outliers in the Yield distribution suggests that the data is relatively clean and normally distributed. It means that the regression analysis results are more likely to be trustworthy.

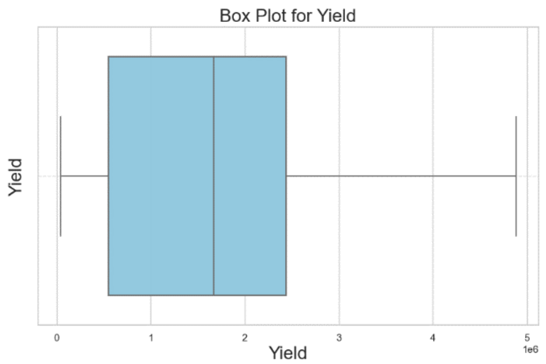


Fig. 10. Rice yield in sumatra visual boxplot

## *B. Regression Model Performance*

In the context of the performance of the regression models on both the training and test datasets, and considering their respective average cross-validation scores, Linear Regression and Random Forest Regression demonstrate relatively balanced performance. These two models have reasonably good generalization capabilities, as indicated by the similarity between their training and test scores, and they both have average cross-validation scores of around 83.0 (Fig. 11).

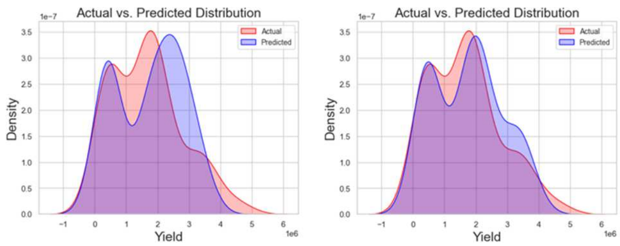


Fig. 11. Actual vs. predicted linear regression and random forest

## *C. Model Evaluation*

Herewith the performance metrics for various predictive models used in rice yield prediction (Table II). The score is obtained after we carry out Hyperparameter Tuning for each model. The R2-score, a measure of how well the models explain the variance in the data, is shown for each model. A higher R2-score indicates a better fit to the data.

TABLE II. MODEL EVALUATION SCORE

| No | Model | R2 Score | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | XGBRegressor | 88.48 | 227,871.54 | 140838095080.65 | 375,284.02 |
| 2 | Random Forest | 86.39 | 228,328.35 | 175422207775.73 | 418,834.34 |
| 3 | SVR | 85.21 | 275,596.06 | 180764477737.42 | 425,164.06 |
| 4 | Liner Regression | 84.95 | 282,956.81 | 183982367802.32 | 428,931.66 |
| 5 | K-neighbors | 82.40 | 311,685.34 | 215114998835.69 | 463,804.91 |
| 6 | Decision Tree | 80.84 | 291,400.01 | 234169607560.34 | 483,910.74 |

- The XGBRegressor has the highest R2-score at 88.479%, indicating that it explains the most variance in the target variable. The Decision Tree model has the lowest R2-score at 80.845%.
- The XGBRegressor has the lowest MAE at 227,871.54, making it the most accurate in terms of absolute error. The K-Neighbors model has the highest MAE at 311,685.34.
- The XGBRegressor has the lowest MSE at 140,838,095,080.65. The Decision Tree model has the highest MSE at 234,169,607,560.34.
- The XGBRegressor has the lowest RMSE at 375,284.02, making it the model with the smallest

typical error. The Decision Tree model has the highest RMSE at 483,910.74.

In summary, XGBRegressor have the highest R2 scores and provide the best overall fit to the data, followed by Random Forest, SVR, Linear Regression, K-Neighbors, and Decision Tree in descending order of R2 score. Our experiment has result that the XGBoost algorithm achieved the highest R2 Score with 2.0 9 % compared to Random Forest and 3.27 % compared to SVR.

## V. CONCLUSSION

Because of the important of crop management strategies in a variety of climate situations, this study proposed regression model aiming at the predictive models for rice yield prediction in Sumatra, Indonesia. In our approach, all the models are adjusted with hyperparameter to increase its performance. Furthermore, CV with k-fold splitting is used for unbiased model evaluation. As a result, XGBRegressor appears to be the top-performing model across all metrics in this analysis with the highest R2-score at 88.48% and the the lowest MAE at 227,871.54, MSE at 140,838,095,080.65 and MSE at 140,838,095,080.65. This indicates the purposed method of this study is useful. Some of the interpretation and explanatory which has been presented has gain insight for the rice yield-influencing factors.

Our future research will add weather, environmental and soil health features. We will also try it for different types of plants and test it with the model we have created. We intend to include interpretable tools to increase model transparency and enable informed decision-making. This technique can aid in our understanding of climate-crop interactions, allowing us to improve food security and sustainability in a changing environment.

## REFERENCES


[1] R. R. H. Teapon, Harianto, H. Siregar, and Widyastutik, "Impact of Climate Change and Technology on Food Availability in Sumatera, Indonesia," *Int. J. Sci. Soc.*, vol. 4, no. 3, pp. 411–422, 2022, doi: 10.54783/ijsoc.v4i3.533.

[2] A. Ansari *et al.*, "Evaluating the effect of climate change on rice production in Indonesia using multimodelling approach," *Heliyon*, vol. 9, no. 9, 2023, doi: 10.1016/j.heliyon.2023.e19639.

[3] P. G. Oguntunde, G. Lischeid, and O. Dietrich, "Relationship between rice yield and climate variables in southwest Nigeria using multiple linear regression and support vector machine analysis," *Int. J. Biometeorol.*, vol. 62, no. 3, pp. 459–469, 2018, doi: 10.1007/s00484-017-1454-6.

[4] and O. M. Oscar Barrero, Sofiane Ouazaa, Camilo Ignacio Jaramillo-Barrios, Mauricio Quevedo, Nesrine Chaali, Sair Jaramillo, Isidro Beltran, "Rice Yield Prediction Using On-Farm Data Sets and Machine Learning," *Int. Conf. smart Inf. Commun. Technol.*, pp. 422–430, 2019, doi: 10.1007/978-3-030-53187-4_68.

[5] Y. Cai *et al.*, "Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches," *Agric. For. Meteorol.*, vol. 274, pp. 144–159, 2019, doi: 10.1016/j.agrformet.2019.03.010.

[6] V. Amaratunga, L. Wickramasinghe, A. Perera, J. Jayasinghe, U. Rathnayake, and J. G. Zhou, "Artificial Neural Network to Estimate the Paddy Yield Prediction Using Climatic Data," *Math. Probl. Eng.*, pp. 1–11, 2020, doi: 10.1155/2020/8627824.

[7] Y. Guo *et al.*, "Integrated phenology and climate in rice yields prediction using machine learning methods," *Ecol. Indic.*, vol. 120, p. 106935, 2021, doi: 10.1016/j.ecolind.2020.106935.

[8] J. Cao *et al.*, "Integrating Multi-Source Data for Rice Yield Prediction across China using Machine Learning and Deep Learning Approaches," *Agric. For. Meteorol.*, vol. 297, p. 108275, 2021, doi: 10.1016/j.agrformet.2020.108275.

[9] L. Wickramasinghe, R. Weliwatta, P. Ekanayake, and J. Jayasinghe, "Modeling the Relationship between Rice Yield and Climate Variables Using Statistical and Machine Learning Techniques," *J. Math.*, pp. 1–9, 2021, doi: 10.1155/2021/6646126.

[10] Y. Guo, H. Xiang, Z. Li, F. Ma, and C. Du, "Prediction of rice yield in east China based on climate and agronomic traits data using artificial neural networks and partial least squares regression," *Agronomy*, vol. 11, no. 2, p. 282, 2021, doi: 10.3390/agronomy11020282.

[11] Y. Liu *et al.*, "Rice Yield Prediction and Model Interpretation Based on Satellite and Climatic Indicators Using a Transformer Method," *Remote Sens.*, vol. 14, no. 19, p. 5045, 2022, doi: 10.3390/rs14195045.

[12] E. A. Jiya, U. Illiyasu, and M. Akinyemi, "Rice Yield Forecasting: A Comparative Analysis of Multiple Machine Learning Algorithms," *J. Inf. Syst. Informatics*, vol. 5, no. 2, pp. 785–799, 2023, doi: 10.51519/journalisi.v5i2.506.

[13] K. Sahoo, A. K. Samal, J. Pramanik, and S. K. Pani, "Exploratory data analysis using python," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 12, pp. 4727–4735, 2019, doi: 10.35940/ijitee.L3591.1081219.

[14] J. I. Daoud, "Multicollinearity and Regression Analysis," *J. Phys. Conf. Ser.*, vol. 949, no. 1, p. 012009, 2018, doi: 10.1088/1742-6596/949/1/012009.

[15] H. Mamdouh Farghaly and T. Abd El-Hafeez, "A high-quality feature selection method based on frequent and correlated items for text classification," *Soft Comput.*, vol. 27, no. 16, pp. 11259–11274, 2023, doi: 10.1007/s00500-023-08587-x.

[16] B. Das, B. Nair, V. K. Reddy, and P. Venkatesh, "Evaluation of multiple linear, neural network and penalised regression models for prediction of rice yield based on weather parameters for west coast of India," *Int. J. Biometeorol.*, vol. 62, no. 10, pp. 1809–1822, 2018, doi: 10.1007/s00484-018-1583-6.

[17] Y. Sun, S. Ding, Z. Zhang, and W. Jia, "An improved grid search algorithm to optimize SVR for prediction," *Soft Comput.*, vol. 25, no. 7, pp. 5633–5644, 2021, doi: 10.1007/s00500-020-05560-w.

[18] X. Zhou, Y. Kono, A. Win, T. Matsui, and T. S. T. Tanaka, "Predicting within-field variability in grain yield and protein content of winter wheat using UAV-based multispectral imagery and machine learning approaches," *Plant Prod. Sci.*, vol. 24, no. 2, pp. 137–151, 2021, doi: 10.1080/1343943X.2020.1819165.

[19] C. J. Willmott *et al.*, "Statistics for the evaluation and comparison of models," *J. Geophys. Res. Ocean.*, vol. 90, no. C5, pp. 8995–9005, 1985, doi: 10.1029/jc090ic05p08995.

[20] J. K. Park, A. Das, and J. H. Park, "Integrated model for predicting rice yield with climate change," *Int. Agrophysics*, vol. 32, no. 2, pp. 203–215, 2018, doi: 10.1515/intag-2017-0010.

[21] S. Fahad *et al.*, *Rice responses and tolerance to high temperature*. Woodhead Publishing, 2019. doi: 10.1016/B978-0-12-814332-2.00010-1.

[22] S. Chairani, "The Correlation between Rainfall, Temperature, Relative Humidity, and Rice Field Productivity in Aceh Besar," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1071, no. 1, p. 012030, 2022, doi: 10.1088/1755-1315/1071/1/012030.