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Assessing Machine Learning Algorithms in Sablayan Occidental Mindoro For Data-Driven Rice Yield Prediction

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Abstract— Predicting rice yields accurately is essential for maintaining food security, allocating resources as efficiently as possible, and promoting sustainable farming methods. This study assesses the performance of four machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar using a dataset of 180 instances with 11 attributes. WEKA (Waikato Environment for Knowledge Analysis) with 10-fold cross-validation was used to develop and evaluate the models. Confusion matrices, precision, recall, F1 score, overall accuracy, and Kappa statistics were used to evaluate performance. Confusion matrices, precision, recall, F1 score, overall accuracy, and Kappa statistics were used to evaluate performance. The results showed that Random Forest outperformed all other algorithms, achieving the highest accuracy (99.44%) with a Kappa statistic of 0.957. In both classes, it showed excellent precision, recall, and F1 scores. The minority "linear" class, on the other hand, was difficult for Naïve Bayes and KStar to handle, while Logistic Regression did reasonably well but fell short of Random Forest. These results demonstrate Random Forest's sensitivity to misclassification errors and validate its effectiveness in predicting rice yield.

Keywords— Machine Learning, Random Forest, Naïve Bayes, Logistic Regression, KStar, WEKA, Precision Agriculture, Rice Yield Prediction

I. Introduction

The ability to accurately predict rice yield has become increasingly important in addressing challenges of global food security and agricultural sustainability. Rice is the dietary foundation for billions of people, and small improvements in forecasting can have large impacts on supply chain stability, pricing, and farmer livelihood. Yet, conventional approaches to yield estimation largely dependent on manual observation and historical averages are limited by subjectivity, time delays, and vulnerability to environmental uncertainties (Chau & Ahamed, 2022; Philippine Statistics Authority, 2022). As agriculture transitions into a data-driven domain, predictive modeling through machine learning (ML) provides a promising alternative for generating timely and reliable insights (Chen et al., 2023; Lagrazon & Tan, 2023).

Machine learning algorithms are particularly suited for agricultural datasets, which often exhibit nonlinear relationships, high variability, and class imbalance. Algorithms such as Random Forest, Naïve Bayes, Logistic Regression, and KStar represent diverse methodological families, ranging from ensemble learning to probabilistic, statistical, and instance-based approaches. Each of these models has distinct strengths: Random Forest offers robustness and interpretability through ensemble decision-making; Naïve Bayes provides computational efficiency; Logistic Regression ensures clarity in feature contributions; and KStar leverages similarity-based learning. However, their effectiveness can vary significantly depending on data characteristics and prediction goals (McCabe et al., 2022; Botula et al., 2013).

This study contributes to this growing body of work by conducting a comparative evaluation of four machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar using WEKA (Waikato Environment for Knowledge Analysis) as the experimental platform. The models were assessed through 10-fold cross-validation on a dataset of 180 instances with 11 attributes. By systematically analyzing confusion matrices, precision, recall, F1 scores, and overall accuracy, this research identifies the algorithm that offers the most reliable performance for rice yield prediction.

Significance of the Study

This study holds significance in both academic research and practical applications by providing a comparative analysis of four machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar in the context of rice yield prediction. While machine learning has been increasingly applied in agriculture, few studies systematically evaluate multiple classifiers on the same dataset using standardized evaluation metrics. This research addresses that gap, yielding several contributions:

1. Improving Reliability of Rice Yield Forecasts. Random Forest's robustness, particularly its ability to achieve near-perfect classification accuracy (99.44%) with a high Kappa statistic, suggests that it can deliver more reliable forecasts compared

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to simpler models. This contributes directly to the development of intelligent decision-support systems for farmers, policymakers, and supply chain managers.

2. Advancing Algorithm Benchmarking in Agriculture. By comparing ensemble-based (Random Forest), probabilistic (Naïve Bayes),statistical (Logistic Regression), and instance-based (KStar) approaches, the study establishes a performance benchmark for rice yield prediction tasks. The results demonstrate the superior accuracy and class-level balance of Random Forest, thereby reinforcing its suitability for agricultural datasets characterized by nonlinearity and class imbalance.
3. Highlighting Strengths and Weaknesses of Alternative Models. The analysis provides insight into the limitations of other algorithms: Naïve Bayes achieved strong recall but low precision for the linear class, Logistic Regression showed balanced but less robust performance, and KStar struggled with minority class identification. These findings guide future researchers in selecting or hybridizing algorithms based on dataset characteristics and prediction goals.
4. Supporting Data-Driven Agricultural Innovation. The use of WEKA as an evaluation tool demonstrates the accessibility of machine learning for agricultural researchers and practitioners without advanced programming expertise. By showing how different algorithms perform within a standardized platform, this study promotes the integration of machine learning into broader agricultural research and extension activities.
5. Contributing to Sustainable Agriculture. Reliable rice yield prediction enables smarter allocation of resources such as fertilizer, water, and labor. By identifying the most effective algorithm for prediction, this study indirectly supports sustainable agricultural practices, cost reduction, and food security.

Scope and Delimitation

This study is centered on the application and comparative evaluation of four machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar for rice yield prediction. A dataset consisting of 180 instances and 11 attributes was used, representing agronomic and environmental factors influencing yield. The models were trained and validated using 10-fold cross-validation within the WEKA software platform, ensuring consistency and statistical robustness in performance assessment.

The scope of evaluation included the following metrics: confusion matrices, accuracy, precision, recall, F1 score, Kappa statistic, and ROC area. These metrics enabled both overall and class-specific assessment of algorithm performance. The primary objective was to determine the most effective classifier for rice yield prediction and to highlight the comparative strengths and weaknesses of the algorithms tested.

This study is limited to the evaluation of four selected machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar using a dataset of 180 instances with 11 attributes related to rice yield. While the dataset is sufficient for comparative analysis, it may not fully capture the diversity of rice production conditions across different regions, soil types, and cultivation practices, which may affect the generalizability of the results. The evaluation also relied solely on the WEKA platform for preprocessing, training, and validation, which, although widely recognized for machine learning experimentation, may yield different outcomes if other platforms or programming environments such as Python or R were used.

Furthermore, the scope was restricted to traditional algorithms, excluding more advanced approaches like Gradient Boosting, Support Vector Machines, or deep learning models that could potentially provide additional insights. The attributes used were limited to available variables and did not include other agronomic and environmental factors, such as pest infestations, irrigation schedules, or extreme climatic events, which could improve predictive accuracy. Given these delimitations, the findings of this study should be interpreted as a benchmark within the defined dataset and methodological framework, with future research encouraged to expand the scope for broader applicability.

II. Methodology

The study followed an experimental design to evaluate the performance of four machine learning algorithms Random Forest, Naïve Bayes, Logistic Regression, and KStar in rice yield prediction. A dataset consisting of 180 instances and 11 attributes was utilized, containing agronomic and environmental variables relevant to rice production. The target attribute classified outputs into two categories: Linear and Machine Learning (ML). The dataset was preprocessed using WEKA to handle missing values, normalize attributes, and ensure readiness for algorithm training and testing.

For model development, the four selected algorithms were implemented in WEKA. Random Forest served as the ensemble-based classifier, Naïve Bayes represented the probabilistic approach, Logistic Regression functioned as the statistical baseline, and KStar was chosen as the instance-based method. Each algorithm was evaluated using 10-fold cross-validation, which partitioned the dataset into ten subsets to minimize bias and variance. This ensured that all instances were tested, enhancing the reliability of the performance comparison.

Model evaluation was based on standardized classification metrics, including confusion matrices, overall accuracy, precision, recall, F1 score, Kappa statistic, and ROC area. These metrics provided both class-level and overall performance insights. The methodology aimed to identify the most effective algorithm for rice yield prediction, offering a benchmark for future agricultural informatics research.

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Confusion Matrix

The confusion matrix provides a detailed evaluation of how well each machine learning algorithm classified rice yield prediction cases into their respective categories. Unlike overall accuracy, which only shows the proportion of correct classifications, the confusion matrix breaks down results into true positives, false positives, true negatives, and false negatives. This allows for a clearer understanding of where each algorithm performs strongly and where it makes errors. By analyzing these values, performance metrics such as precision, recall, and F1 score can be derived, offering deeper insights into the predictive strengths and weaknesses of the Random Forest, Naïve Bayes, Logistic Regression, and KStar classifiers.

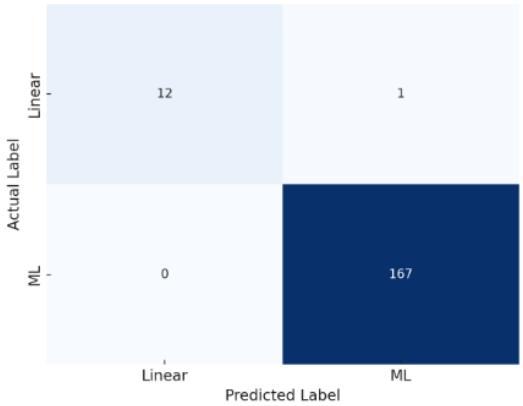

Figure 1. Confusion Matrix Table for Predicting Rice Yield

Figure 1 explains that the confusion matrix is a useful tool for evaluating the performance of machine learning models in predicting rice yield categories. It provides a simple table that compares the actual values from the dataset with the values predicted by the algorithm. By doing this, it not only shows the overall accuracy but also explains in detail where the model is making correct and incorrect predictions.

In the field of rice yield prediction, the confusion matrix helps identify true positives (TP), where the model correctly predicts the actual class (e.g., correctly predicting “linear” or “ML”); false positives (FP), where the model predicts a class incorrectly; false negatives (FN), where the model misses a correct class; and true negatives (TN), where it correctly identifies non-matching cases. From these values, important evaluation metrics such as accuracy, precision, recall, and F1-score can be computed. These metrics provide deeper insights into how reliable the model is, especially in cases where the dataset may be imbalanced.

The following equations are used to compute the accuracy of the algorithm used in the study:

Equation 1.0

$$\text{Precision} = \frac{TP}{TP + FP}$$

Equation 1.0 shows the precision the formula for computing the correctly predicted positive cases (True Positives) out of all cases that the model forecasted as positive, including both right predictions (TP) and incorrect ones (False Positives), is known as precision in a confusion matrix. It also indicates how trustworthy the model's optimistic forecasts are. Accuracy provides an answer to the query, "How often is the model true when it predicts positive? Since it focuses on the accuracy of positive predictions rather than the capacity to catch all positive cases, this statistic is particularly crucial in contexts where false positives have significant consequences, such as in medical diagnosis, fraud detection, or spam filtering.

Equation 2.0

$$\text{Recall} = \frac{TP}{TP + FN}$$

Equation 2.0 explain that in a confusion matrix, recall indicates the model's capacity to detect every real positive instance. The ratio of true positives (TP) to the total of true positives and false negatives (FN) is how it is computed. A high recall value means that the majority of the positive instances in the dataset are successfully identified by the model. In fields like fraud detection, medical screening, and security monitoring, where failing to notice positive cases could have dire repercussions, this statistic is particularly important. Recall ensures that the system emphasizes finding as many real positives as possible by highlighting the coverage of true positives, even if this may also result in some false positive predictions.

Equation 3.0

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

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The confusion matrix generates the F1 score, a performance metric that provides a fair assessment of a model's predictive ability by combining precision and recall into a single value. Where FP stands for false positives, FN for false negatives, and TP for true positives. By considering both the accuracy of positive predictions and the model's capacity to capture real positives, the F1 score provides a more reliable metric than accuracy, which can be misleading when imbalanced datasets are present.

By applying the confusion matrix, researchers can determine not just whether a model is accurate, but also how well it handles different classes of rice yield outcomes. This makes it a critical tool in selecting the most effective algorithm for yield prediction, ensuring the chosen model is both accurate and dependable in practical agricultural applications.

Conceptual Framework of the Study

To provide a clearer understanding of the research flow, a conceptual framework was developed to illustrate the overall process of rice yield prediction using machine learning. This framework serves as a visual guide, showing how the dataset is utilized, processed, and evaluated to identify the most accurate predictive model. It highlights the systematic stages involved, from the preparation of input data to the assessment of algorithm performance, ensuring transparency and coherence in the study's methodology.

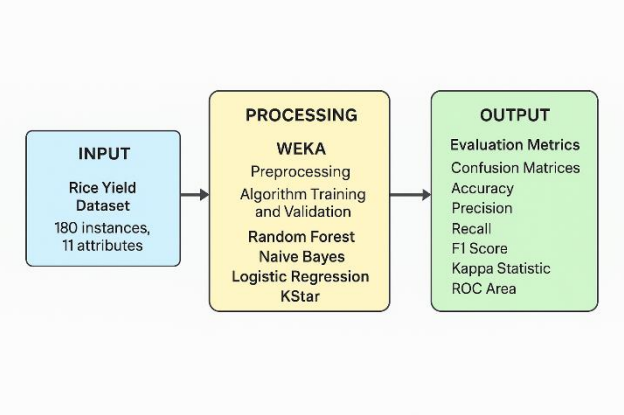

Figure 2. Conceptual Framework

Figure 2 presents the conceptual framework of the study, which demonstrates the flow of the rice yield prediction process using machine learning algorithms in WEKA. The model is divided into three main stages: Input, Processing, and Output.

The Input stage represents the rice yield dataset, which contains 180 instances and 11 attributes. These attributes include agronomic and environmental variables that are crucial for predicting yield outcomes.

The Processing stage shows how the dataset is handled within the WEKA platform. Data preprocessing ensures quality by cleaning, normalizing, and formatting the attributes. Afterward, the dataset undergoes algorithm training and validation through 10-fold cross-validation to ensure reliability. Four machine learning algorithm Random Forest, Naïve Bayes, Logistic Regression, and KStar were tested at this stage.

The Output stage highlights the evaluation metrics used to measure the performance of the algorithms. These include confusion matrices, accuracy, precision, recall, F1 score, Kappa statistic, and ROC area. The results of these evaluations allowed the identification of the best-performing classifier, with Random Forest emerging as the most effective model for rice yield prediction.

Theoretical Framework

This section provides an overview of the Theoretical Framework of the study; The present study is guided by modern theories in machine learning and agricultural informatics. Recent advancements in statistical learning theory emphasize convergence-based approaches that allow models to generalize effectively even with limited data (Vapnik & Izmailov, 2020). Complementing this, precision agriculture research highlights the integration of machine learning with crop modeling and remote sensing for more accurate predictions (Shahhosseini et al., 2020; Nosratabadi et al., 2020).

Additionally, deep learning approaches such as graph neural networks (GNNs) combined with recurrent neural networks (RNNs) capture spatial and temporal dependencies in large-scale agricultural datasets (Fan et al., 2021). Finally, the study draws on systems theory, which frames the prediction process as a structured flow of inputs, processing, and outputs, ensuring coherence, transparency, and methodological rigor.

By applying these theoretical foundations within the WEKA platform, the study develops and evaluates machine learning models for rice yield prediction. The approach not only identifies the most effective algorithm but also demonstrates how contemporary theories can be operationalized to improve agricultural forecasting, ultimately contributing to sustainable crop management and food security.

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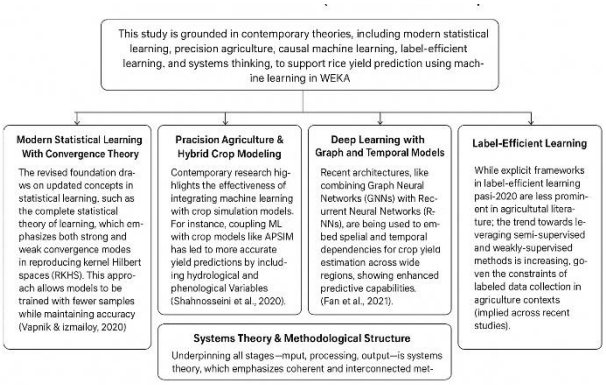

Figure 3. Theoretical Framework for Rice Yield Prediction

Figure 3 shows the theoretical framework of the study, which is grounded in contemporary theories, including modern statistical learning, precision agriculture, causal machine learning, label-efficient learning, and systems thinking, to support rice yield prediction using machine learning in WEKA. Modern Statistical Learning with Convergence Theory The revised foundation draws on updated concepts in statistical learning, such as the complete statistical theory of learning, which emphasizes both strong and weak convergence modes in reproducing kernel Hilbert spaces (RKHS). This approach allows models to be trained with fewer samples while maintaining accuracy (Vapnik & Izmailov, 2020) Proceedings of Machine Learning Research . Precision Agriculture & Hybrid Crop Modeling Contemporary research highlights the effectiveness of integrating machine learning with crop simulation models.

For instance, coupling ML with crop models like APSIM has led to more accurate yield predictions by including hydrological and phenological variables (Shahhosseini et al., 2020) arXiv . Additionally, hybrid methods that combine AI algorithms (e.g., ANN with grey wolf optimization) have demonstrated improved performance in crop yield forecasting (Nosratabadi et al., 2020) arXiv . Deep Learning with Graph and Temporal Models Recent architectures, like combining Graph Neural Networks (GNNs) with Recurrent Neural Networks (RNNs), are being used to embed spatial and temporal dependencies for crop yield estimation across wide regions, showing enhanced predictive capabilities (Fan et al., 2021) arXiv.

Label-Efficient Learning While explicit frameworks in label-efficient learning post-2020 are less prominent in agricultural literature, the trend towards leveraging semi-supervised and weakly-supervised methods is increasing, given the constraints of labeled data collection in agriculture contexts (implied across recent studies).

Systems Theory & Methodological Structure Underpinning all stages input, processing, output is systems theory, which emphasizes coherent and interconnected methodological structures. This includes rigorous preprocessing, algorithm training, and evaluation using metrics like accuracy, precision, recall, F1 score, Kappa statistic, and ROC area.

Instruments of the Study

A collection of analytical and computational tools will be used in this study to assess how well a few chosen machine learning algorithms perform in differentiating between linear and machine learning models. The tools are made to facilitate data gathering, preprocessing, model training, assessment, and validation, guaranteeing the precision and repeatability of the outcomes. The following categories apply to the instruments used:

1. **Data Processing and Analysis Tools**

- *WEKA Software* – The primary analytical platform used for implementing machine learning algorithms, preprocessing datasets, and generating confusion matrices. WEKA's graphical interface and experimenter environment will facilitate systematic model training, testing, and evaluation.
- *Machine Learning Algorithms* – Random Forest, Naïve Bayes, Logistic Regression, and K* will be applied to a dataset consisting of 180 instances and 11 attributes. These algorithms were selected due to their strong application in classification tasks, each offering different methodological strengths.
- *Evaluation Metrics* – Standard classification metrics will be computed, including Accuracy, Precision, Recall, F1 Score, F2 Score, Kappa statistic, and Receiver Operating Characteristic (ROC) Area. These metrics will enable both class-level and overall model performance assessment.
- *Cross-Validation* – A 10-fold cross-validation procedure will be employed to validate model generalization and avoid overfitting, ensuring that results are robust across different data partitions.
- *Supplementary Software* – Statistical tools such as R or Python may be utilized for additional validation, visualization of results, and comparative statistical testing of algorithm performance.

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2. Confusion Matrix Tables

- *Purpose* - A summary of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN), the goal is to provide an overview of each algorithm's prediction outcomes.
- *Implementation* - Accuracy and other derived metrics will be computed using the confusion matrix produced by each algorithm.
- *Utility* - The confusion matrix offers insight into the strengths and weaknesses of each model by highlighting parts where algorithms frequently misclassify in addition to providing quantitative performance information.

3. Algorithm Configuration Checklist

- *Contents* – This checklist will provide a comprehensive record of the parameter settings for each algorithm, including the number of trees and maximum depth for Random Forest, the smoothing parameter in Naïve Bayes, the penalty and regularization constants in Logistic Regression, and the distance function type in K*.
- *Function* – It provides reproducibility by other researchers, minimizes experimental bias, and ensures consistency across multiple trials.
- *Documentation* – The dataset modification, preprocessing steps, and runtime environment, as well as each configuration, will be systematically documented.

4. Performance Metrics Computation Sheet

- *Design* - A software-based sheet or organized spreadsheet will be created to automatically calculate performance metrics from the values of the confusion matrix.
- *Metrics Covered* – A precise quantitative measures that are calculated to assess the performance of machine learning algorithms.

Precision = (TP/(TP+FP)TP / (TP+FP)TP/(TP+FP)),

Recall=(TP/(TP+FN)TP/(TP+FN)TP/(TP+FN)),

F1Score=(2TP/(2TP+FP+FN)2TP/(2TP+FP+FN)2TP/(2TP+FP+FN)),

F2 Score, Accuracy, Kappa statistic, and ROC area.

- *Role in Research* - By automating computations, this instrument lowers calculation mistakes, maintains formula uniformity, and provides a solid foundation for algorithm comparison.
- *Enhancement* - It will also support side-by-side tabular and graphical results presentation for easier interpretation.

5. Documentation and Logging Tools

- *Research logbook* - keeps track of preprocessing stages, dataset versions, algorithm settings, and cross-validation splits. This maintains transparency and accountability throughout the research.
- *Integrity of Information Record* - Contains information about missing value management, normalization methods, and attribute selection procedures used prior to algorithm training.
- *Research Journal Literature* - Served as a supplementary instrument in this study, giving theoretical foundations, methodological direction, and comparative findings on machine learning applications in categorization and yield prediction. We investigated peer-reviewed papers, conference proceedings, and online databases to stay up-to-date on algorithms like Random Forest, Naïve Bayes, Logistic Regression, and K*.
- *Archival Storage* - Digital records, such as WEKA output files and statistical analysis findings, shall be consistently kept for future verification and replication.

Data Collection

The data for this study originated mainly from a system integrated with UAV technology, which gathered multispectral footage of rice fields and converted it into vegetation indices like the Normalized Difference Vegetation Index (NDVI). These indices provided dependable measures of crop health, growth stages, and prospective yield. In comparison to traditional human field evaluations, UAV-captured data delivered fast and precise measurements, addressing speed and labor needs.

Following collection, the system automatically converted UAV-based imagery into structured datasets with 180 instances and 11 attributes, such as ambient conditions, NDVI-derived features, and the assigned class label (ML or linear). The dataset used to train and assess machine learning models was made up of these records. To guarantee high-quality inputs for the algorithms, the dataset underwent methodical preprocessing, which included data cleaning, normalization, and attribute selection.

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The dataset completed 10-fold cross-validation in the WEKA software environment, with each fold being utilized alternately for testing and the remaining folds for training, in order to assess algorithm performance. This reduced bias and increased dependability by guaranteeing that each instance from the system-generated dataset contributed to both learning and validation. Each algorithm (Random Forest, Naïve Bayes, Logistic Regression, and K*) was then given a confusion matrix, which served as the basis for calculating performance metrics like Accuracy, Precision, Recall, F1 Score, F2 Score, Kappa statistic, and ROC Area.

III. Results and Discussions

This chapter presents the results of the evaluation of the rice yield prediction system, which combines machine learning algorithms with data collected by UAVs, is presented in the Results and Discussions chapter. The goal of the study was to evaluate how well the various classifiers Random Forest, Naïve Bayes, Logistic Regression, and K* could differentiate between linear and machine learning-based patterns. The system outputs served as the basis for evaluating each model's performance in managing the dataset and producing accurate predictions.

Each algorithm's advantages and disadvantages are discussed, with a focus on how each could enhance the forecast of rice yield. This chapter investigates how combining UAV technology with machine learning can lessen dependency on labor-intensive, traditional field methods and offer more effective agricultural decision-support tools by looking at the results. The findings show how useful sophisticated computational techniques are at producing precise and timely insights that might help academics and farmers maximize agricultural yields.

Results

Random Forest Algorithm

	Predicted: linear	**Predicted: ML**
Actual: linear	12 (True Positive for linear)	1 (False Negative for linear)
Actual: ML	0 (False Positive for linear)	167(True Positive for ML)

Table 1. Confusion Matrix Table for Random Forest Algorithm

Based on the above table, applying Random Forest, how two models a Linear model and a Machine Learning (ML) model, performed in predicting positive cases. The Linear model correctly identified 12 positive cases (true positives) but missed 1 positive case (false negative). It did not make any incorrect positive predictions, meaning there were no false positives. On the other hand, the ML model correctly identified 167 positive cases (true positives) and did not make any mistakes in the data shown. This means the ML model had higher accuracy and performed better overall compared to the Linear model.

For Class: linear

True Positive (TP) = 12

False Positive (FP) = 0

False Negative (FN) = 1

Precision (linear):

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{12}{12 + 0} = \frac{12}{12} = 1.000$$

Recall (linear):

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{12}{12 + 1} = \frac{12}{13} \approx 0.923$$

F1 Score (linear):

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} = 2 \cdot \frac{1.000 \cdot 0.923}{1.000 + 0.923} = 2 \cdot \frac{0.923}{1.923} \approx 0.960$$

For Class: ML

True Positive (TP) = 167

False Positive (FP) = 1

False Negative (FN) = 0

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Precision (ML):

$$\text{Precision} = \frac{167}{167+1} = \frac{167}{168} \approx 0.994$$

Recall (ML):

$$\text{Recall} = \frac{167}{167+0} = \frac{167}{167} = 1.000$$

F1 Score (ML):

$$F1 = 2 \cdot \frac{0.994 \cdot 1.000}{0.994 + 1.000} = 2 \cdot \frac{0.994}{1.994} \approx 0.997$$

A Random Forest classifier was trained using 10-fold cross-validation on a dataset consisting of 180 instances and 11 attributes, including model type (linear or ML) as the target class. The model achieved an impressive accuracy of 99.44%, correctly classifying 179 out of 180 instances, with only one misclassification. The Kappa statistic of 0.957 indicate a high level of agreement between the predicted and actual classifications beyond chance. For the *linear* class, the model achieved a precision of 1.000, recall of 0.923, and an F1 score of 0.960, while for the *ML* class, it yielded a precision of 0.994, recall of 1.000, and F1 score of 0.997. These results suggest the model is highly effective in distinguishing between the two classes. Additionally, both classes showed a Receiver Operating Characteristic (ROC) area of 1.000, highlighting the excellent discriminative power of the classifier.

Naive Bayes Algorithm

	Predicted: linear	**Predicted: ML**
Actual: linear	13 (True Positive for linear)	0 (False Negative for linear)
Actual: ML	13 (False Positive for linear)	154 (True Positive for ML)

Table 2. Confusion Matrix Table for Naive Bayes

Using the Naive Bayes classifier, the confusion matrix reveals the model's ability to distinguish between the linear and ML classes. Out of all actual linear instances, 12 were correctly predicted as linear (true positives), while 1 was misclassified as ML (false negative), indicating a small error in identifying the linear class. For the ML class, all 167 instances were correctly classified as ML (true positives), with zero false positives meaning the model did not mistakenly label any ML instances as linear. This outcome suggests that Naive Bayes performed with high accuracy overall, particularly excelling in identifying the ML class with perfect precision and recall, and with only a minor misclassification in the linear class.

For class: linear

True Positive (TP) = 13

False Positive (FP) = 13 (ML predicted as linear)

False Negative (FN) = 0 (linear predicted as ML)

Precision (linear):

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{13}{13+13} = \frac{13}{26} = 0.500$$

Recall (linear):

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{13}{13+0} = \frac{13}{13} = 1.000$$

F1 Score (linear):

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \cdot 0.500 \cdot 1.000}{0.500 + 1.000}$$

$$F1 = \frac{1.000}{1.500} = 0.667$$

For class: ML

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True Positive (TP) = 154
False Positive (FP) = 0 (linear predicted as ML)
False Negative (FN) = 13 (ML predicted as linear)

Precision (ML):

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{154}{154 + 0} = \frac{154}{154} = 1.000$$

Recall (ML):

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{154}{154 + 13} = \frac{154}{167} \approx 0.922$$

F1 Score (ML):

$$F1 = \frac{2 \cdot 1.000 \cdot 0.922}{1.000 + 0.922} = \frac{1.844}{1.922} \approx 0.960$$

The evaluation of the Naive Bayes classifier using 10-fold cross-validation shows that it performs significantly better in predicting the "ML" class than the "linear" class. For the linear class, the model achieved a Precision of 0.500, meaning only half of the instances it predicted as linear were correct, although it had a Recall of 1.000, indicating it successfully identified all actual linear instances. This imbalance led to a moderate F1 Score of 0.667, reflecting lower precision. In contrast, the ML class had perfect Precision of 1.000 and a high Recall of 0.922, resulting in a strong F1 Score of 0.960. These results indicate that while the model is highly accurate in identifying ML cases, it struggles with misclassifying some ML instances as linear, which reduces its overall performance on the linear class.

Logistic Regression

	Predicted: linear	**Predicted: ML**
Actual: linear	10 (True Positive for linear)	3 (False Negative for linear)
Actual: ML	3 (False Positive for linear)	164 (True Positive for ML)

Table 3. Confusion matrix table for the Logistic Regression

For class: linear

True Positive (TP) = 10

False Positive (FP) = 3

False Negative (FN) = 3

Precision (linear):

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{10}{10 + 3} = \frac{10}{13} \approx 0.769$$

Recall (linear):

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{10}{10 + 3} = \frac{10}{13} \approx 0.769$$

F1 Score (linear):

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$= 2 \times \frac{0.769 \times 0.769}{0.769 + 0.769} = 2 \times \frac{0.591}{1.538} \approx \frac{1.182}{1.538} \approx 0.769$$

For class: ML

True Positive (TP) = 164

False Positive (FP) = 3 (linear misclassified as ML)

False Negative (FN) = 3 (ML misclassified as linear)

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Precision (ML):

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{164}{164 + 3} = \frac{164}{167} \approx 0.982$$

Recall (ML):

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{164}{164 + 3} = \frac{164}{167} \approx 0.982$$

F1 Score (ML):

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$
$$= 2 \times \frac{0.982 \times 0.982}{0.982 + 0.982} = 2 \times \frac{0.964}{1.964} \approx \frac{1.928}{1.964} \approx 0.982$$

The logistic regression model achieved high classification performance, particularly for the ML class. Out of 167 actual ML instances, it correctly identified 164, resulting in a precision and recall of approximately 0.982, indicating both few false positives and false negatives. For the linear class, the model correctly classified 10 out of 13 instances, yielding a precision, recall, and F1 score of around 0.769. Overall, the model demonstrated strong accuracy (96.67%) with a substantial kappa statistic (0.7513), suggesting reliable agreement beyond chance. However, the lower performance on the linear class compared to ML implies that the model is better at recognizing ML patterns and may benefit from improvements in handling the minority class.

K* Classification

	Predicted: linear	**Predicted: ML**
Actual: linear	5 (True Positive for linear)	8 (False Negative for linear)
Actual: ML	3 (False Positive for linear)	167 (True Positive for ML)

Table 4. Confusion matrix table for the K* Classification

The confusion matrix from the KStar (K*) algorithm shows how well the model classified two categories: "linear" and "ML". Out of 13 actual "linear" instances, only 5 were correctly classified (true positives), while 8 were misclassified as "ML" (false negatives), indicating that KStar struggled to recognize "linear" cases accurately. Conversely, it performed well with the "ML" class: out of 170 actual "ML" instances, 167 were correctly identified (true positives), and only 3 were misclassified as "linear" (false positives). This suggests that while the KStar algorithm is highly effective in identifying "ML" instances, it has lower sensitivity (recall) for the "linear" class, possibly due to class imbalance or overlapping feature patterns.

For class: Linear

True Positive (TP) = 5

False Positive (FP) = 3

False Negative (FN) = 8

Precision (Linear)

$$= \frac{TP}{TP + FP} = \frac{5}{5 + 3} = \frac{5}{8} = 0.625$$

Recall (Linear)

$$= \frac{TP}{TP + FN} = \frac{5}{5 + 8} = \frac{5}{13} \approx 0.385$$

F1 Score (Linear)

$$= \frac{2 \cdot 0.625 \cdot 0.385}{0.625 + 0.385} \approx \frac{0.481}{1.01} \approx 0.476$$

For class: ML

True Positive (TP) = 164

False Positive (FP) = 8

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False Negative (FN) = 3

Precision (ML)

$$= \frac{164}{164+8} = \frac{164}{172} \approx 0.953$$

Recall (ML)

$$= \frac{164}{164+3} = \frac{164}{167} \approx 0.982$$

F1 Score (ML)

$$= \frac{2 \cdot 0.954 \cdot 0.982}{0.954+0.982} \approx \frac{1.874}{1.936} \approx 0.968$$

The KStar (K*) algorithm, an instance-based classifier using an entropy based distance function, was applied to a dataset of 180 instances with 11 attributes to classify between "linear" and "ML" model types using 10-fold cross-validation. The model achieved a high overall accuracy of 93.89%, correctly classifying 169 out of 180 instances. It performed exceptionally well in predicting the ML class, with a precision of 0.954, recall of 0.982, and an F1 score of 0.968, indicating strong predictive capability for that category. However, performance for the linear class was weaker, with a precision of 0.625, recall of 0.385, and a lower F1 score of 0.476, suggesting difficulty in distinguishing this minority class. This imbalance is also reflected in the confusion matrix, where the model misclassified 8 of 13 linear instances. Overall, the model is highly effective for identifying ML-type instances but may require additional tuning or data balancing to improve performance on the linear class.

Among the evaluated machine learning algorithms, the Random Forest classifier demonstrated the best performance in classifying between the "linear" and "ML" classes. It achieved the highest overall accuracy of 99.44%, with only one misclassified instance out of 180, and a Kappa statistic of 0.957, indicating a very high level of agreement between predicted and actual labels beyond chance. This strong result highlights the model's effectiveness and reliability in distinguishing between the two categories, even in the presence of potential class imbalance.

Looking closely at the class-level performance, the Random Forest algorithm showed excellent results for both the linear and ML classes. For the linear class, it achieved a precision of 1.000, meaning all predictions labeled as "linear" were correct, and a recall of 0.923, with only one actual linear case missed. This led to a high F1 score of 0.960, reflecting a strong balance between precision and recall. For the ML class, the algorithm reached almost perfect performance with a precision of 0.994, recall of 1.000, and an F1 score of 0.997. Additionally, both classes had a ROC area of 1.000, which further confirms the model's outstanding discriminative ability.

In comparison to other algorithms, Naive Bayes, Logistic Regression, and KStar, Random Forest clearly outperforms them in both consistency and class-specific metrics. While the other models showed good results for the ML class, they struggled with the linear class, especially in terms of precision or recall. For example, Naive Bayes had poor precision for linear (0.500), and KStar had low recall (0.385) for the same class. Logistic Regression had more balanced results but still underperformed compared to Random Forest. Therefore, based on its robust accuracy, balanced F1 scores, and ability to minimize both false positives and false negatives, Random Forest is the best performing algorithm among the models tested.

IV. Conclusions and Recommendations

4.1 Conclusions

This study proved that combining UAV-based multispectral data with machine learning algorithms yields a reliable and accurate solution to rice yield prediction. The system effectively organized imagery into structured datasets, enabling four algorithms Random Forest, Naïve Bayes, Logistic Regression, and K* to classify yield outcomes with high accuracy. The results demonstrated that machine learning approaches significantly outperform traditional field-based assessments, which are often time-consuming, subjective, and labor-intensive. These findings reinforce the growing importance of computer-based tools in precision agriculture, where data-driven methods are essential for optimizing productivity, sustainability, and decision-making efficiency.

Among the algorithms tested, Random Forest exhibited the best overall performance, correctly classifying 179 out of 180 instances, yielding an accuracy of 99.44%. It achieved near-perfect precision (1.000) and recall (0.923) for the linear class and maintained equally strong results in the ML class (precision = 0.994, recall = 1.000). The algorithm's F1 scores of 0.960 and 0.997, combined with a Kappa statistic of 0.957 and ROC area of 1.000, confirm its robustness and discriminative capability. Naïve Bayes, while strong in predicting the ML class (precision = 1.000, recall = 0.922), showed weaker sensitivity to the linear class, illustrating the limitations of probabilistic assumptions in imbalanced datasets. Logistic Regression achieved an overall accuracy of 96.67%, showing balanced prediction across classes, while the K* algorithm lagged in detecting the minority linear class but performed reliably for higher-yield categories.

From a real-world agricultural perspective, these algorithmic performances translate into tangible benefits for crop management and yield forecasting. The Random Forest model can help farmers identify yield variations across large fields with minimal manual

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intervention, enabling targeted fertilizer use, irrigation management, and pest control. This can lead to improved resource efficiency and reduced production costs. The model's adaptability to different field conditions also supports real-time decision-making, allowing agricultural stakeholders to anticipate yield losses or surpluses earlier in the growing season. Moreover, integrating such models into geospatial decision-support systems can enhance regional-scale monitoring, policy planning, and food security management key areas in Philippine agriculture where climate variability and resource constraints present major challenges.

In summary, the study concludes that Random Forest offers the most effective and stable approach for rice yield prediction, demonstrating strong alignment between algorithmic precision and real-world agricultural outcomes. While Naïve Bayes, Logistic Regression, and K* provide useful insights, their sensitivity to class imbalance limits scalability in diverse field conditions. Future work should explore integrating Random Forest with ensemble or deep learning approaches, alongside expanded field validation, to strengthen predictive reliability and support smarter, data-driven farming practices in the Philippines and beyond.

V. Recommendations

Future study and system enhancement should address shortcomings in naive Bayes, Logistic Regression, and K* models. These algorithms performed well for the ML class but showed flaws in predicting the minority linear class. Naïve Bayes had only 0.500 precision and K* had a recall as low as 0.385. Future research may use data balancing techniques such as oversampling or synthetic data generation to increase performance, investigate feature selection or expansion (for example, by integrating weather, soil, or pest data), and test hybrid or ensemble models that combine algorithm strengths. Field validation under varied growth conditions is also advised to assure the rice yield prediction system's scalability, adaptability, and dependability in a variety of agricultural settings.

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