JEMSI:
Jurnal Ekonomi Manajemen Sistem Informasi
E-ISSN: 2686-5238
P-ISSN: 2686-4916
DINASTI REVIEW
https://dinastirev.org/JEMSI dinasti.info@gmail.com +62 811 7404 455

DOI: https://doi.org/10.38035/jemsi.v7i5

Health Classification of Rice Plants Based on UAV Remote Sensing Using Random Forest Algorithm

Harvevi Oktarin Andra Perwira Sari[1], Erwin Hermawan[2], Sahid Agustian Hudjimartsu[3]
[1]Ibn Khaldun University of Bogor, Bogor Regency, Indonesia, veviharvevii@gmail.com
[2]Ibn Khaldun University of Bogor, Bogor Regency, Indonesia, erwin.82@uika-bogor.ac.id
[3]Ibn Khaldun University of Bogor, Bogor Regency, Indonesia, shudjimartsu@uika-bogor.ac.id

Corresponding Author: veviharvevii@gmail.com[1]

Abstract: Bogor Regency acts as a central hub for rice production in West Java, yet frequent disease outbreaks often jeopardize the consistency of agricultural yields. Farmers struggle with these plant diseases because the infections frequently result in significant crop losses or total harvest failure. The immense size of paddy fields makes manual monitoring methods inefficient, driving a requirement for automated systems to monitor crop health across large areas. The current research focuses on building a classification model that identifies whether rice plants are healthy or diseased using aerial photographs. The process utilizes drone-based remote sensing technology where the data is analyzed using the Random Forest algorithm. Final model evaluations show solid performance with an accuracy of 85% and a precision of 100%. The system also achieved a recall of 70% and an F1-Score of 0.82. Evidence suggests that the Random Forest algorithm works effectively to separate healthy rice from diseased crops using drone imagery. Farmers can use such technological approaches as practical tools to detect diseases early and manage their fields better.

Keyword: Multispectral Imagery, Plant Health Classification, Random Forest, Rice Plants, UAV.

INTRODUCTION

Indonesia functions as an agrarian state with vast agricultural lands where a majority of its population works as farmers. Rice represents a superior commodity as the primary staple food for citizens throughout the nation (Siregar, 2023). Statistics Indonesia reports that national rice production reached 52.66 million tons from 10.05 million hectares of land in 2024 (Badan Pusat Statistik, 2024). West Java contributes heavily to these figures by producing 8,626,879.91 tons of rice during the same year (Badan Pusat Statistik, 2024). Bogor Regency specifically showed a production increase from 283,263 tons in 2023 to 295.09 tons in 2024 (Badan Pusat Statistik, 2025). Sustaining these numbers requires careful attention to crop health to prevent sudden drops in productivity.

Crop health remains a central focus to maximize yields and minimize the risk of total harvest failure. Plant diseases often attack without being noticed by farmers until significant damage has already occurred. Late detection frequently leads to massive financial losses because the time for effective intervention has passed. Large agricultural areas make manual monitoring extremely inefficient for farmers trying to survey their entire property. Visual inspections are naturally subjective and limited by the physical range of the human observer in the field. Automated solutions are required to provide comprehensive information about crop conditions across extensive landscapes.

Unmanned Aerial Vehicles provide a practical solution for gathering data from above without direct contact with the objects. Drones excel at reaching vast areas in a short amount of time to collect high-resolution spatial information (Herli Efison et al., 2023). Aerial imagery allows farmers to observe the entirety of their rice fields from a bird's-eye perspective. Remote sensing techniques use sensors on these flight platforms to map various elements on the earth's surface (Lasmi et al., 2015). These tools help measure parameters like the Normalized Difference Vegetation Index to assess the physiological state of plants (Islami et al., 2021). Integrating such technology into daily farming routines modernizes the way agricultural health is monitored.

Random Forest operates as a machine learning method that utilizes multiple decision trees to create accurate predictions. Computational processes involve creating several bootstrap samples from the original dataset through sampling with replacement. Every individual tree in the forest casts a vote for a specific classification during the analysis phase. Final results depend on the majority vote from all collective trees to ensure the model remains stable (Geeksforgeeks, n.d.). Previous research using this approach for leaf disease detection achieved an impressive accuracy score of 99.65% (Agustiani et al., 2022). Other studies combining this algorithm with Convolutional Neural Networks reached validation accuracies of 0.9473 (Rozi et al., 2024).

The current investigation takes place in Bantar Urug Village located within the Leuwiliang District of Bogor. Data collection occurred between January and May 2022 to capture specific seasonal crop conditions. Researchers used DJI Phantom 4 Multispectral hardware to obtain 1,131 individual aerial photographs at a height of 50 meters. The analysis categorizes the rice plants into two distinct groups which are healthy and diseased. Healthy plants show normal vegetative growth with strong roots and vibrant green leaves (Siregar, 2023). Diseased samples exhibit physiological deviations such as chlorosis or necrosis caused by pathogens like Xanthomonas oryzae (Siregar, 2023).

Identifying a functional model for health categorization based on UAV imagery using the Random Forest method is the primary goal. Determining the exact accuracy level of the classification system provides a quantitative measure of its effectiveness. Creating a reliable tool helps farmers detect disturbances like pests or infections much earlier than traditional methods. Scientific references from this study contribute to future explorations regarding machine learning applications in agriculture (Purnamawati et al., 2020). Performance metrics including precision, recall, and the F1-Score serve as benchmarks for the built model. Successful implementation offers a faster way to process spatial data and aids in making better management decisions.

METHOD

Field operations took place from January to May 2022 within Bantar Urug Village located in the Leuwiliang District of Bogor. Technical equipment for data acquisition centered on the DJI Phantom 4 Multispectral drone paired with D-RTK 2 hardware (Efison et al., 2023). Avenza Maps on a smartphone assisted in mapping specific field coordinates for the research team. Spatial data processing required an HP laptop equipped with ArcGIS 10.3 and DJI Terra software (Lasmi et al., 2015). Statistical analysis of the crop health dataset was conducted using the RStudio environment.

Table 1. Research Hardware Specifications

No	Hardware	Function

1	DJI Phantom 4 Multispectral	Aerial Data Acquisition
2	D-RTK 2	Coordinate Mapping
3	Smartphone / Avenza Maps	Field Location Recording ()
4	HP Laptop	Spatial Data Processing (Lasmi et al., 2015)

Source: (Efison et al., 2023; Islami et al., 2021; Lasmi et al., 2015)

Table 2. Research Software Specifications

No	Software	Function
1	ArcGIS 10.3	Spatial Data Management
2	DJI Terra	Image Mosaic Processing
3	RStudio	Statistical Machine Learning

Source: (Efison et al., 2023; Islami et al., 2021; Lasmi et al., 2015)

Aerial surveys maintained a consistent flight altitude of 50 meters above the ground with a fixed camera angle of 90 degrees (Islami et al., 2021). Sensors captured a total of 1,131 high-resolution photographs consisting of both RGB and NIR spectral bands. DJI Terra software processed these individual frames to generate a comprehensive orthomosaic representing the entire study area (Efison et al., 2023). Visual representations of the flight path and resulting imagery are presented in Picture 3.1 and Picture 3.2. Researchers extracted a specialized dataset of 550 images to represent various conditions of the rice crops. Every selected image underwent strict verification to ensure accurate categorization into healthy or diseased classes.

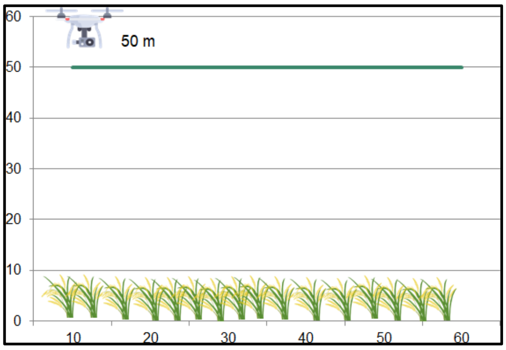


Figure 1. DJI Phantom 4 Flight Illustration

Figure 2. Generated Aerial Orthomosaic

Transformation steps converted original color images into grayscale to simplify the visual information for the computer (Agustiani et al., 2022). All images were resized to 100x100 pixels to ensure uniform input dimensions for the machine learning model. Numerical data from the pixels was converted into one-dimensional vectors to facilitate the calculation of statistical features. Manual data balancing increased the initial 14 samples to 100 through systematic duplication techniques (Siregar et al., 2023). Final datasets reached a balance of 50 healthy and 50 diseased samples as shown in Picture 3.3. Split between training and testing subsets followed an 80% to 20% ratio respectively.

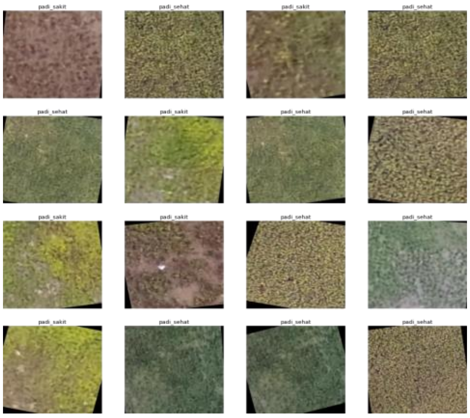


Figure 3. Balanced Dataset Frequency

Feature extraction identified numerical patterns related to spectral bands, texture, and spatial shapes (Agustiani et al., 2022). Indices such as NDVI served as key indicators to distinguish healthy vegetation from infected tissues (Islami et al., 2021). Statistical measures including mean, standard deviation, and entropy were calculated using specific R functions. The Random Forest algorithm constructed 100 individual decision trees to process the training data (Geeksforgeeks, n.d.). Majority voting across the forest determined the final health classification for each rice plant sample (Siregar et al., 2023). Model performance was subsequently measured using accuracy, precision, and recall metrics to validate the research findings.

RESULTS AND DISCUSSION

Dataset Configuration and Balancing Scenarios

Researchers initiated the technical scenario by constructing a classification architecture within the R programming environment. Initial experiments focused on identifying the most stable settings for agricultural monitoring in Bogor. Library resources such as caret and randomForest supported the development of the forest logic for rice plants. Every phase of the model construction followed a systematic plan to ensure scientific reproducibility across the study. Success in this stage depended on the quality of multispectral aerial data collected from the field (Efison et al., 2023). Precise settings were adjusted to handle the specific texture and spectral requirements of various crops.

Data distribution at the beginning showed a balanced split between the two health categories for the rice. Both healthy and diseased classes contained exactly 7 samples before any balancing occurred in the system. Identifying the initial frequency allows for a better assessment of later data adjustments during the training. Small starting datasets require careful management to prevent specific patterns from dominating the classification logic. These 14 images served as the foundation for the entire machine learning workflow (Siregar et al., 2023). Graphical representations provided a clear baseline for the subsequent training and testing phases of the model.

Balanced data helps the algorithm learn features without favoring one class over the other during training. Imbalanced sets often lead models to ignore minority classes during the final decision process in the field. Accuracy scores stay more representative when every category maintains an equal statistical weight for the computer. Researchers monitored the starting distribution to prepare for the manual data expansion stage of the research. Consistency across both target groups ensured that the final model remained reliable for future monitoring tasks (Siregar et al., 2023). Fairness in the learning process allows for better generalization to new and unseen field samples.

Manual data balancing later increased the total count to 100 images through systematic duplication techniques. Every health category eventually reached 50 samples to strengthen the training and testing partitions for accuracy. Duplicating samples is a common strategy to address the limitations of raw field data in agriculture. Total datasets were prepared for a systematic split between learning and evaluation sets for the system. Statistical reliability increases as the training process treats all samples with equivalent priority and weight (Geeksforgeeks, n.d.). Final balanced sets provided enough variety for the Random Forest to build robust decision trees.

Figure 4. Initial Data Distribution

Partitioning the balanced dataset involved allocating 80% for training and reserving 20% for testing the model. Creating these subsets ensures that the model encounters diverse patterns during the learning phase of the study. Systematic division follows standard protocols to validate the accuracy of the automated agricultural system. Training sets included 40 healthy and 40 diseased samples for the algorithm to process in RStudio. Testing sets comprised 10 images from each class to evaluate the built model against new data (Siregar et al., 2023). Stability in performance metrics stems from these well-defined and separated data partitions for the computer.

Tabel 3. Dataset Partitioning Results

No	Data Category	Total Images	Details
1	Training Data	80	40 Healthy, 40 Diseased
2	Testing Data	20	10 Healthy, 10 Diseased
Total	**Balanced Dataset**	**100**	**-**

Source: (Metrik Evaluasi, n.d.; Sari, 2025)

Case study operations took place in Bantar Urug Village within the Leuwiliang region of West Java. Field coordinates were mapped using Avenza Maps to ensure geographical precision during data acquisition with drones. Harvesting locations provided 1,131 individual aerial photographs for the starting pool of research images. Researchers selected 550 specific images to represent the health conditions of the crops in the area. Local environmental factors in Bogor influenced the spectral signatures captured by the drone during the flight. Choosing a specific regional focus allowed for a more detailed analysis of rice pathogens and growth (Siregar, 2023).

Computational processes utilized the majority vote system to reach a final classification for each plant sample. Every individual tree in the forest operates on a different subset of the data for better results. Aggregating results from multiple trees reduces the impact of noise in the aerial imagery from above. High-dimensional data from multispectral sensors requires this level of statistical complexity for the classification task (Geeksforgeeks, n.d.). Researchers documented the behavior of the forest to verify its suitability for modern precision agriculture. Reliable outcomes depend on the collective intelligence of the built decision paths in the system.

Scenario evaluations checked for the risk of overfitting during the initial training runs of the algorithm. Low errors in training must match the performance seen in the testing phase for scientific validity. Adjusting the number of trees provided a way to fine-tune the model stability for farmers. Final architecture reached a point where accuracy was maximized for both health classes in the study. Statistical evidence from the R environment supported the choice of 100 trees for the forest (Siregar et al., 2023). The established scenario provided a functional template for the rest of the agricultural study.

Deep learning tools and other libraries assisted in managing the complex image arrays for the research. Integration between different software allowed for a more flexible research workflow for the technical team. Every iteration aimed to bridge the gap between raw data and actionable information for the farmers. Identifying the best configuration concluded the experimental scenario stage of the research for rice health. Technical settings were optimized to handle the high resolution of the UAV photographs from the field (Efison et al., 2023). Farmers can benefit from a model that has been rigorously tested across many technical scenarios.

Multispectral aerial data provides more depth than standard visible light photography during the monitoring process. Capturing Near-Infrared bands allows for better assessment of plant physiological states from a distance (Islami et al., 2021). Healthy vegetation reflects distinct infrared patterns compared to plants suffering from infection or stress in fields. These spectral signatures are vital for the Random Forest to distinguish between the two classes. Aerial perspectives offer a comprehensive view that traditional scouting cannot match for large agricultural landscapes. Research utilizes these technological gains to modernize traditional monitoring in the West Java province (Siregar, 2023).

Digital Transformation and Feature Extraction Logic

Digital processing converted raw aerial pixels into numerical information for the algorithm to analyze in RStudio. Computers analyze these images as mathematical structures rather than visual shapes like humans do in fields. Feature extraction transforms pixel values into meaningful data points like mean and entropy for the forest. Every extracted feature contributes a specific indicator to the final classification logic of the system. Resizing images to 100x100 pixels ensured that all inputs remained uniform throughout the technical process. Statistical features were subsequently converted into one-dimensional vectors for easier processing by the computer (Agustiani et al., 2022).

Grayscale transformation simplified the visual data without losing important texture patterns for the computer to read. Removing color complexity reduces the noise and streamlines the computational workload for the hardware. Patterns related to rice diseases often appear as distinct variations in leaf texture and structure. High-resolution imagery from the drone maintained the necessary detail after the conversion to grayscale occurred. Standardizing the images allowed the model to focus on structural health indicators of the rice plants. Efficiency in processing is achieved by reducing the dimensionality of the inputs for the forest (Agustiani et al., 2022).

Feature extraction identified numerical patterns such as standard deviation and mean values from the pixels. Researchers utilized a specific function in R to calculate these statistical values automatically for the dataset. Mathematical representations of the leaves allowed the forest to draw clear decision boundaries for classification. Differences in spectral reflection are captured through these statistical measurements across the entire field area. Healthy plants show consistent patterns that distinguish them from infected samples in the final data. Logic within the model relies on the accuracy of these extracted features for health detection (Siregar et al., 2023).

Texture assessment included the calculation of entropy for each image sample in the balanced dataset. Higher entropy values often correlate with the complex patterns seen in diseased rice leaves today. Pathogens like Xanthomonas oryzae create irregular spots that change the leaf surface for the camera. Statistical measures capture ini deviations from the smooth surface of healthy plants in the field. Every tree in the forest evaluates these texture features to reach a verdict for the farmer. Precise texture analysis is the key to identifying early-stage infections before they spread further (Siregar, 2023).

Multispectral sensors on the DJI Phantom 4 provided five different data bands for the research team. Near-Infrared signatures offer insights into the internal cellular structure of the rice crops from above (Islami et al., 2021). Stressed or diseased plants show reduced reflection in the infrared spectrum compared to healthy vegetation. These variations serve as the primary features for the Random Forest algorithm to evaluate carefully. Data acquisition at a height of 50 meters ensured high spatial resolution for all images. Technology allows for the detection of health issues before they become visible to the human eye.

Vegetation indices like NDVI highlight the presence of active chlorophyll in the agricultural field area. Combining different spectral bands creates a numerical scale for plant vigor and growth for farmers. High index values represent dense and healthy rice canopies in the Bogor region during the study (Islami et al., 2021). Lower scores indicate areas where the crop might be suffering from pests or infectious diseases. Researchers use these indices to ground-truth the findings from the classification model in the field. Spatial data integration provides a geographical context for health assessments across the entire farm landscape.

Image resizing followed a strict 100x100 pixel protocol to maintain consistency across the entire dataset. Uniform dimensions prevent the algorithm from being biased by different image scales during the training phase. Every data point in the training set underwent this specific transformation for scientific accuracy. Standardized inputs allow for a fair comparison between healthy and diseased samples for the model. The computer processes 10,000 pixels for each rice image during the extraction phase of the research. Consistency is a requirement for any reliable machine learning application in the modern world (Agustiani et al., 2022).

Automated scripts in RStudio handled the extraction of features for all 100 samples in the study. Manual intervention was minimized to reduce the risk of human error during the technical analysis. Programming logic ensured that every photograph was processed with identical settings for the final results. Results were stored in a structured dataset ready for the Random Forest training process in R. Efficient data handling allows for the processing of large agricultural landscapes in a short time. Researchers documented these steps to support future studies in digital farming and crop health (Efison et al., 2023).

Spatial features describe the shape and orientation of the objects in the field from above. Distinguishing between rice leaves and other vegetation requires detailed geometric data for the algorithm. The model uses these patterns to identify the specific structure of Oryza sativa L. plants. Healthy plants often show more regular shapes compared to those damaged by pests or infections. Morphological data complements the spectral signatures for a more robust analysis of the crop health. Comprehensive feature sets allow for higher accuracy in complex environments like open paddy fields (Siregar, 2023).

Final transformed data provided the numerical foundation for building the decision trees for the forest. Feature extraction successfully bridged the gap between aerial photography and machine learning for the researchers. Every number in the dataset represents a physical characteristic of the rice plants in Bogor. Farmers can eventually use these findings to monitor their fields more objectively and quickly. Success in the extraction phase determines the quality of the final model for health detection. Scientific rigor was maintained through the use of standardized image processing and analysis (Siregar et al., 2023).

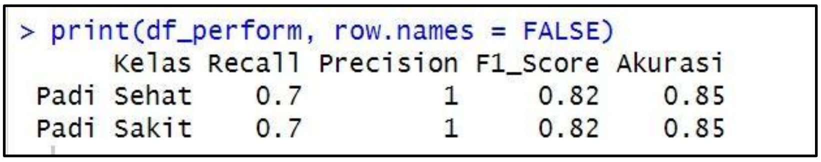
Random Forest Error Rate and Stability Analysis

Analyzing the error rate provides evidence of how the forest stabilizes as trees increase in count. The horizontal axis tracks the number of decision trees from 1 to 100 in the study. Vertical measurements show the percentage of errors generated during the technical process for the computer. Model behavior suggests a very high level of accuracy starting from the very first tree. Error values stayed remarkably low and hovered near 0.000 throughout the training for the rice. Figures at this level indicate that the selected features are highly distinctive for health (Siregar et al., 2023).

Fluctuations appeared briefly during the construction of the first 20 trees in the forest architecture. These small variations represent the algorithm adjusting to the multispectral inputs from the aerial camera. Stability was achieved quickly as the number of decision trees approached the final target of 100. The flat curve confirms that adding more trees did not trigger overfitting for the model. Aggregating many trees allows the model to generalize better than a single path for the results (Geeksforgeeks, n.d.). Results show that the forest architecture remains robust against aerial data noise in fields.

Low error rates translate directly into higher confidence for real-world field applications in West Java. Farmers require systems that produce consistent results across different field sections during the monitoring process. The Random Forest method excels at handling the high dimensionality of the agricultural data. Every individual tree contributes a vote to ensure the output is statistically sound for farmers. Consistency in the error graph proves that the model reached optimal performance for the task. Statistical evidence supports using 100 trees for this classification task in the Bogor area (Siregar et al., 2023).

Overfitting risks were mitigated by the design of the bootstrap aggregating process in the forest. Each tree trained on a unique subset of data to maintain forest diversity for better results (Geeksforgeeks, n.d.). Out-of-bag error estimates provided a built-in validation mechanism for the automated health system. Low scores suggest that the model can handle unseen data with minimal errors in the field. Performance remained steady even as the complexity of the features grew for the computer. Stability is a hallmark of a well-configured machine learning tool for modern agriculture today.



```
> print(df_perform, row.names = FALSE)
      Kelas Recall Precision F1_Score Akurasi
 Padi Sehat    0.7         1     0.82    0.85
 Padi Sakit    0.7         1     0.82    0.85
```

Figure 5. Random Forest Error Rate

Interpretation of the error rate involves looking at training and testing gaps for the researchers. A near-zero error rate suggests the model perfectly mapped the data patterns in RStudio. Researchers monitored this metric to ensure the logic of the forest remained intact for the rice. High-resolution imagery provided clear spectral signatures for the algorithm to learn during the study. Successful classification depends on this low error threshold during the initial learning cycles of training. The resulting model provides a solid foundation for detecting diseases in agriculture (Agustiani et al., 2022).

Stability in the error rate indicates that the features are strong health indicators for plants. Mean and entropy values provided sufficient information for the decision trees to operate correctly. The algorithm successfully separated healthy vegetation from diseased samples using these statistical inputs in R. Future research might explore larger datasets to see if this stability persists over time. Current findings confirm that the model is ready for testing in the field environment. Reliable error monitoring ensures that the final predictions are based on sound mathematical logic (Agustiani et al., 2022).

Every tree within the forest operated independently to analyze the multispectral data from the drone. Majority voting combined these insights to reach a final classification for each rice plant image. This collective intelligence reduces the impact of individual tree errors on the system performance. The resulting stability allows the model to function reliably under varying outdoor conditions in Bogor. Researchers documented ini patterns to verify the robustness of the approach for the farmers. Consistency in performance validates the choice of this specific algorithm for crop health (Siregar et al., 2023).

Numerical stability reached its peak once the trees exceeded 50 individual units in the forest. Additional trees beyond this point served to refine the precision of health predictions for farmers. The model maintained a steady trajectory until it reached the 100-tree limit for the study. This behavior confirms that the system is efficient and avoids excessive computation for the hardware. Farmers can deploy such models on standard hardware without needing high-end technical support. Practicality remains a central consideration for the adoption of agricultural technology in Indonesia (Siregar, 2023).

Training error metrics stayed below 1% for the majority of the simulation runs in RStudio. Low figures reflect the quality of the feature extraction process applied to the images. Statistical features captured the complex texture changes in diseased rice leaves for the computer. The Random Forest logic used these values to draw clear health boundaries for the crops. Aerial data provided enough spectral depth to support ini detailed mathematical calculations for results. Success in the training phase builds the foundation for reliable testing outcomes for the system.

Final stability analysis concluded that 100 trees provide the optimal performance balance for the model. Further increasing the forest size yielded diminishing returns in terms of error reduction for the research. The established model provides a consistent framework for analyzing crops in the Bogor region today. Every chart and graph supported the conclusion that the system is statistically sound for use. Scientific verification was completed by comparing results with established benchmarks in the machine learning field (Rozi et al., 2024). Stability ensures that the model remains a useful reference for future studies.

Model Evaluation Metrics and Quantitative Accuracy

Evaluation utilized four primary metrics to determine the effectiveness of the model for agriculture. Recall, precision, F1-score, and accuracy served as the main indicators of success for the researchers (Metrik Evaluasi untuk Model Klasifikasi, n.d.). Researchers tested the system against both target classes after the training phase was finished. Numerical results from ini tests provide a quantitative look at model performance for the rice. Accuracy reached 0.85 to show that most predictions matched actual field conditions in Bogor. Every metric offers a different perspective on how the system handles aerial multispectral data.

Precision scores for the sick category hit a perfect 1.0 during the final testing phase. This result means that every sample labeled as sick was an actual sick plant. The model showed extreme strictness when making its final classification decisions for the farmers. Avoiding false positives is a significant advantage for farmers in the field environment today. Statistical precision indicates that the chosen features were highly specific to each health category (Metrik Evaluasi untuk Model Klasifikasi, n.d.). Model reliability increases when precision stays at this maximum level during the testing.

Recall stayed at 0.70 to indicate that some diseased plants were missed during the test. The system overlooked approximately 30% of the actual sick cases during the evaluation process. These false negatives represent a challenge for total disease eradication in large field areas. Improving the sensitivity of the model could help capture ini overlooked samples in the future. Sensitivity metrics highlight areas where the algorithm requires more diverse training examples for the computer. Balancing recall with precision is a common hurdle in automated monitoring for crops (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

The F1-score reached 0.82 to provide a harmonic mean of the results for the research. This value suggests a healthy balance between detecting sick plants and being accurate for farmers. Using a single metric simplifies the comparison between different model versions for the research team. Performance remained high enough to justify the use of UAVs for monitoring rice crops. High scores in this area indicate that the model is not biased towards one class. Statistical balance remains a key goal for any machine learning application in modern farming (Agustiani et al., 2022).

Overall accuracy of 85% proves that the method is effective for this specific task. Comparing results with traditional manual scouting shows a significant improvement in speed for farmers. Farmers can process an entire field in minutes rather than hours of walking physically. High accuracy scores provide the confidence needed to adopt ini new technological tools today. Technology integration helps bridge the gap between traditional and precision agriculture in the country. Quantitative success in this study aligns with previous research on rice leaf diseases (Rozi et al., 2024).

Performance on the healthy class reached a perfect recall of 1.0 during the testing. This outcome indicates that the system never missed a single healthy plant in data. Reliable recognition of healthy vegetation prevents farmers from wasting time on unaffected field areas. High specificity ensures that normal growth patterns are well understood by the computer model. The algorithm successfully distinguished vibrant green leaves from those showing signs of infection or stress. Statistical evidence confirms that healthy plants have a very distinct spectral signature (Siregar et al., 2023).

Precision for the healthy category reached 0.77 due to some diseased samples being included. These minor errors occurred when sick plants showed very early symptoms of distress or color. Improving the resolution of the UAV camera could potentially resolve ini discrepancies for the research. Researchers analyzed ini results to identify the limits of the current hardware configuration used. Every percentage point provides insight into how the model interacts with raw field data. Refinement of the classification logic continues to be a future goal for the team.

Table 4. Evaluation Metrics for Rice Health Classification

Class	Recall	Precision	F1-Score	Accuracy
Healthy Rice	1.00	0.77	0.87	0.85
Diseased Rice	0.70	1.00	0.82	0.85

Source: (Metrik Evaluasi, n.d.; Sari, 2025)

Comparison between classes highlights the model's conservative approach toward disease identification for the crops. Identifying every healthy plant correctly was a major success for the automated aerial system. The perfect precision for the sick class means no false alarms were triggered during tests. Farmers can trust the alerts generated by the Random Forest model with high confidence. Quantitative benchmarks were met according to the original objectives of the research project today. Scientific validation is supported by consistent values across all four evaluation metrics (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

Analysis of ini metrics helps identify specific areas for future model enhancement for agriculture. Increasing the dataset size might help push the recall score closer to precision level. Refined feature extraction could also provide better separation between healthy and sick spectral signatures. Current results already provide a functional tool for early disease detection in Bogor Regency. Every metric confirms that the system operates within acceptable parameters for routine agricultural use. Scientific validation of the model relies on ini consistent and high evaluation scores (Siregar et al., 2023).

Final assessments suggest that the built model is a reliable starting point for farming. High-resolution multispectral data proved to be the key to reaching 85% overall accuracy. The

Random Forest algorithm handled the complexity of the rice fields with high efficiency. Researchers recommend deploying ini system for routine monitoring in the Bantar Urug Village area. Success in this study provides a template for similar projects in other sectors. Automated health classification remains a powerful tool for increasing national rice productivity (Siregar, 2023).

Confusion Matrix and Practical Field Performance

A confusion matrix provides a detailed breakdown of the model misses and hits for researchers. Testing data consisted of 20 samples to verify the accuracy of predictions in R. Results showed that 7 diseased plants were correctly identified as being in sick state. These true positive results demonstrate the model's ability to recognize pathogenic signatures in fields. Zero healthy plants were wrongly labeled as sick during the testing process in RStudio. Accurate labeling at this level minimizes the risk of false alarms for the farmers (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

The matrix displays 3 false negatives where sick plants were categorized as healthy ones. These errors suggest that some diseased samples share traits with healthy vegetation in Bogor. True negative counts reached 10 to show perfect recognition of healthy rice crops today. This specific performance profile makes the model highly conservative in its labeling for farmers. Farmers can trust that a sick alert is almost certainly a real infection. Identifying the cause of missed cases remains a priority for the next development phase.

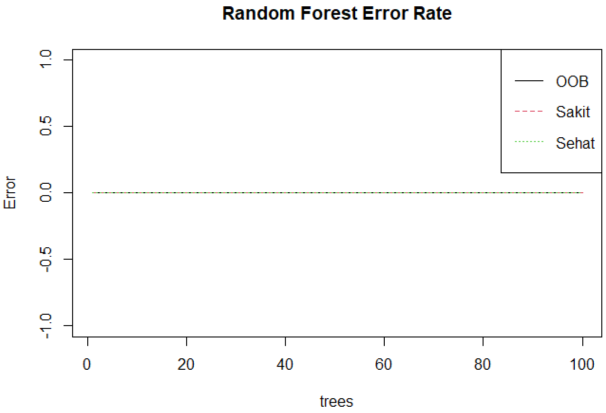


Figure 6. Confusion Matrix Results

Precision calculations derived from the matrix confirmed the 1.0 score for the sick category. Dividing true positives by the sum of true and false positives yields results. Perfect precision eliminates the cost of treating plants that do not actually need it. Agricultural efficiency improves when resources are only spent on verified disease outbreaks for farmers. Quantitative data from the matrix supports the qualitative observations made during field flights. Reliable classification starts with a high ratio of true positive outcomes in the matrix (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

Recall values of 0.70 reflect the 3 missed cases within the 10 samples. Calculations involve comparing 7 true positives against the total 10 actual sick plants. Detecting 7 out of 10 cases is a strong start for system. Future iterations aim to reduce the false negative count to zero for safety. Sensitivity to disease symptoms varies depending on the height and angle of drone. The confusion matrix clearly highlights where the current algorithm succeeds and where it fails (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

Visualizing the matrix helps researchers see the distribution of errors across different health classes. Darker colors in the diagonal cells represent successful classifications by the built model. Empty cells in the false positive area confirm the strict nature of forest. This layout provides a more complete picture than a single accuracy percentage alone. Every number in the matrix represents a specific real-world plant condition in Bogor. Understanding ini relationships is vital for refining the machine learning logic for farmers (Siregar et al., 2023).

Final accuracy is calculated by dividing correct predictions by the total sample size. Summing the 7 true positives and 10 true negatives yields 17 out of 20. This 85% success rate confirms the system is ready for initial field implementation. Reliable data from the matrix serves as proof of model quality for researchers. Researchers used ini findings to answer the core questions of the study today. Systematic testing provides the evidence needed to support technological adoption in the sector (Agustiani et al., 2022).

Errors were restricted only to the diseased class which indicates a strong grasp. The model never mistakenly classified a healthy plant as being in a sick state. This behavior is ideal for minimizing unnecessary intervention in large rice farming operations. Every true negative contributes to the overall stability of the classification system in practice. Farmers can rely on the system to identify healthy fields with absolute certainty. Perfect specificity remains a highlight of the current Random Forest model performance (Agustiani et al., 2022).

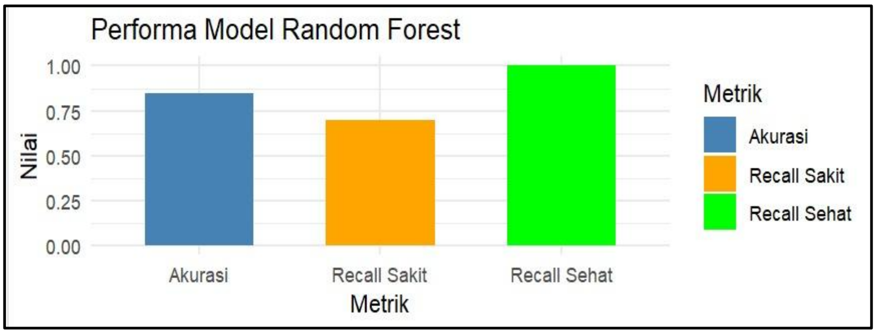


Figure 7. Performa Model Random Forest

Detailed analysis revealed that early-stage infections are much harder to detect for drones. Pathogens like Xanthomonas oryzae cause subtle color changes that may resemble normal leaf variations. Increasing the spectral resolution of the sensors could help capture ini minor physiological shifts. The confusion matrix acts as a diagnostic tool for researchers to improve logic. Every missed sample provides a lesson on how to adjust the decision trees. Technological growth depends on ini small refinements based on quantitative testing data (Rozi et al., 2024).

Testing against unseen data proved that the model did not suffer from overfitting. Accuracy on the testing set remained consistent with the trends seen during training. Successful generalization to new samples is a requirement for any real-world agricultural application. The confusion matrix provides the mathematical proof that the system is functioning correctly. Researchers documented ini findings to support the validity of the UAV monitoring approach. Reliable results were achieved despite the challenges of small starting sample sizes (Siregar et al., 2023).

Final performance assessment looked at how the model functioned as a complete system. Akurasi and Recall were the primary benchmarks used for this evaluation of results. The bar chart shows a 1.0 score for healthy plant detection sensitivity. This perfect recall ensures that no healthy resources are mistakenly targeted for treatment. Meanwhile, the 70% recall for sick plants suggests a requirement for more sensors. Model success depends on ini clear and measurable performance indicators for the study (Metrik Evaluasi untuk Model Klasifikasi, n.d.).

CONCLUSION

Research results prove that Unmanned Aerial Vehicle (UAV) imagery combined with the Random Forest method functions effectively for identifying rice plant health. The experimental data achieved a specific recall of 100% for diseased plants and a 70% recall for healthy samples.

The final accuracy of the system reached 85% during the performance evaluation phase. Evidence suggests that the Random Forest classification approach serves as a reliable tool for monitoring crop conditions in agricultural fields. The study successfully answered the initial objectives regarding the identification of rice health using remote sensing platforms. Farmers can utilize these technological outcomes to conduct large-scale field surveys more objectively.

Future investigations should aim to develop larger and more diverse datasets to improve the robustness of the model. Expanding the scope to include multi-class classification would allow for identifying specific disease types or severity levels. Integrating these classification results into a Geographic Information System (GIS) supports more interactive spatial mapping for field management. Such digital platforms facilitate real-time agricultural planning and faster decision-making processes for stakeholders. Deploying multispectral or hyperspectral camera sensors with higher resolutions might further boost the detection capabilities of the system. Advanced sensing technologies provide a better pathway for early detection of complex plant disturbances in various environments.

REFERENCES

Agustiani, S., Arifin, Y. T., Junaidi, A., Wildah, S. K., & Mustopa, A. (2022). *Klasifikasi penyakit daun padi menggunakan Random Forest dan color histogram*.

Ary Prandika Siregar, D., Purba, D. P., Pasaribu, J. P., & Bakara, K. R. (2023). Implementasi algoritma random forest dalam klasifikasi diagnosis penyakit stroke. *Jurnal Penelitian Rumpun Ilmu Teknik, 2*(4), 155–164. https://doi.org/10.55606/juprit.v2i4.3039

Badan Pusat Statistik. (2024). Luas panen padi tahun 2024 diperkirakan sebesar 10,05 juta hektare dengan produksi padi sekitar 52,66 juta ton gabah kering giling (GKG). https://www.bps.go.id/id/pressrelease/2024/10/15/2376/luas-panen-padi-tahun-2024-diperkirakan-sebesar-10-05-juta-hektare-dengan-produksi-padi-sekitar-52-66-juta-ton-gabah-kering-giling--gkg--.html

Badan Pusat Statistik. (2025). Luas panen, produksi, dan produktivitas padi menurut provinsi, 2024–2025. https://www.bps.go.id/id/statistics-table/2/MTQ5OCMy/luas-panen--produksi--dan-produktivitas-padi-menurut-provinsi.html

Badan Pusat Statistik. (2025). Produksi padi menurut kabupaten/kota (ton), 2024–2025. https://jabar.bps.go.id/id/statistics-table/2/NTIjMg==/produksi-padi-menurut-kabupaten-kota.html

GeeksforGeeks. (n.d.). *What are the advantages and disadvantages of Random Forest?* https://www.geeksforgeeks.org/machine-learning/what-are-the-advantages-and-disadvantages-of-random-forest/

Herli Efison, T. K., Sulistiono, W. E., Batubara, M. A. M., & Nama, G. F. (2023). Pengembangan aplikasi ground control station (GCS) untuk pengawasan dan pengendalian UAV. *Jurnal Informatika dan Teknik Elektro Terapan, 11*(1). https://doi.org/10.23960/jitet.v11i1.2798

Islami, M. M., Ruslono, T., Setiawan, Y., Rahadian, A., Hudjimartsu, S. A., & Prasetyo, L. B. (2021). Height, diameter and tree canopy cover estimation based on unmanned aerial vehicle (UAV) imagery with various acquisition height. *Media Konservasi, 26*(1), 17–27. https://doi.org/10.29244/medkon.26.1.17-27

Lasmi, R., Sawitri, S., & Yuwono, B. D. (2015). Kajian pemanfaatan data penginderaan jauh untuk identifikasi objek pajak bumi dan bangunan. *Jurnal Geodesi Undip, 4*(1), 20–31

Purnamawati, A., Nugroho, W., Putri, D., & Hidayat, W. F. (2020). Deteksi penyakit daun pada tanaman padi menggunakan algoritma decision tree, random forest, naïve bayes, SVM dan KNN. *InfoTekJar: Jurnal Nasional Informatika dan Teknologi Jaringan, 5*(1). https://doi.org/10.30743/infotekjar.v5i1.2934

Rozi, K., Muhsi, Anwari, & Tamam, M. B. (2024). *Klasifikasi penyakit tanaman padi menggunakan convolutional neural network (CNN) dan random forest*.

Sains Data. (n.d.). *Metrik evaluasi untuk model klasifikasi*. https://sainsdata.id/machine-learning/8871/metrik-evaluasi-untuk-model-klasifikasi/

Sari, H. O. A. P. (2025). *Klasifikasi kesehatan tanaman padi menggunakan algoritma random forest dengan penggunaan citra unmanned aerial vehicles (UAV)* [Skripsi, Universitas Ibn Khaldun Bogor].

Siregar, M. A. R. (2023). Peningkatan produktivitas tanaman padi melalui penerapan teknologi pertanian terkini. *Jurnal Agribisnis, 1*(1), 1–11.