Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.3, June 2026, pp. 2966~2972
e-ISSN: 2548-6861

Implementation of Hybrid ResNet50 and XGBoost Model for Wheat Plant Disease Classification

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Article Info

Article history:

Received 2026-05-13
Revised 2026-06-03
Accepted 2026-06-11

Keyword:

Image Classification,
Wheat Leaf Disease,
ResNet50,
Wheat Plant,
XGBoost.

ABSTRACT

A hybrid artificial intelligence (AI) system was successfully developed in this study, combining the ResNet50 architecture as an image feature identifier and the XGBoost algorithm for final classification. This model was used to detect six disease variations using 5,505 wheat leaf photographs. To ensure model stability, rigorous testing was conducted using two methods: Stratified 5-Fold Cross-Validation on the entire data set and independent testing using 300 images (equally divided into 50 samples per class).The test results demonstrated very solid performance. The model recorded an average global accuracy of 94.66% (±0.21%) using the K-Fold method, and an accuracy of 94.67% and a Macro F1-Score of 0.9445 in the independent testing. Through confusion matrix mapping, the model successfully classified the Healthy, Black Rust, and Septoria categories perfectly (a score of 1.00). However, there was still a minor error in the case of eight samples being confused between Brown Rust and Yellow Rust due to the visual similarity of the orange-yellowish coloration early in the infection period. Furthermore, the Feature Importance assessment demonstrated that the XGBoost decision base is transparent (Explainable AI). This AI accurately focuses on clinical signs of plants such as chlorosis symptoms and spot texture, while ignoring background objects such as weeds and soil. This combination of methods creates a stable, efficient system with a response time of only 18.5 milliseconds per photo, and a biologically valid decision base.

I. INTRODUCTION

The agricultural sector has a very important role in maintaining food availability and driving economic growth, especially in countries where the majority of the population depends on the agricultural sector as their main source of income.[1]. One commodity that plays a vital role in supporting food needs is wheat. In Indonesia, wheat is the second most important staple carbohydrate source after rice.[2]. Consumption of wheat-based foods in Indonesia continues to increase, as reflected in the high demand for instant noodles, bread, and other similar products. National wheat flour consumption in 2024 is estimated to increase to 7.1–7.2 million metric tons, or an increase of around 5–6% compared to the previous year. This indicates the high public dependence on wheat-based processed products such as bread, noodles, and traditional snacks. Indonesia also remains entirely dependent on imports to meet its wheat needs as a raw material for wheat flour, with wheat and meslin imports reaching 10,586.6 tons in 2023, an increase of 1.22% compared to 2022.[3].

Indonesia's dependence on wheat from 2010 to 2023 shows a continuously increasing trend, with significant implications for national economic resilience, especially in the context of the global crisis, geopolitical pressures, and fluctuations in world food prices. Although wheat can grow in tropical regions such as Indonesia, only spring wheat varieties are capable of producing relatively good yields, provided they are planted in highland areas at altitudes above 1,000 meters above sea level to stimulate the flowering process.[4]. However, field cultivation is not immune to the threat of pests and plant diseases, which can drastically reduce the quality and quantity of harvests.

Over the past decade, developments in Artificial Intelligence (AI) and Machine Learning (ML) have opened up new opportunities for more adaptive and predictive agricultural data management. Machine learning enables computer systems to learn patterns from historical data such as weather, soil conditions, and visual symptoms of crops to build more accurate predictive and diagnostic models. [5][6]. Although computer vision technology has advanced significantly in detecting visual symptoms of plant diseases, its practical implementation in the agricultural sector still faces significant challenges. In real-world environments, extreme variations in natural lighting, the presence of background noise (such as soil or weeds), overlapping leaves, and the early manifestation of disease symptoms often obscure important visual features. Therefore, a model is needed that is not only accurate in the laboratory but also robust to these non-linear disturbances.

Several previous studies have shown that the use of Residual Neural Networks (ResNet50) in plant disease classification yields promising results. For example, research on rice plant classification using ResNet50 proved effective in agricultural image classification, achieving an accuracy of 92.20%.[7][8]. However, using Convolutional Neural Networks (CNN) as a single classifier still has several limitations, particularly in the final decision-making process. In conventional CNN architectures, the final classification process is generally delegated to a Fully Connected (FC) or Dense Layer using the Softmax activation function. However, standard FC layers are often sensitive to parameter explosion, which can lead to the risk of overfitting, especially when dealing with high-dimensional feature representations from moderate-sized datasets.

Therefore, several studies have begun developing hybrid approaches by combining CNNs as feature extractors with conventional machine learning algorithms such as Support Vector Machines or Random Forests to improve classification accuracy.[9]. In this context, the XGBoost (Extreme Gradient Boosting) algorithm is one of the methods that is widely favored because it has high performance, good efficiency, and the ability to handle complex datasets effectively with an independent accuracy level of up to 82% on tabular data.[10]. XGBoost was chosen for the hybrid architecture because it is based on a tree boosting algorithm with powerful internal regularization mechanisms (L1 and L2), and has proven superior in mapping non-linear decision boundaries to visual feature extraction data without burdening deep learning network parameters.

This research aims to develop a wheat leaf disease image detection system using a hybrid machine learning approach that combines ResNet50 as a feature extractor and XGBoost as a classifier. A ResNet50 model pretrained on the large-scale ImageNet dataset is used to extract visual representations of images into high-dimensional feature vectors. The extracted results are then fed directly to XGBoost for the final classification process without undergoing full backpropagation computation. This approach is expected to optimize diagnostic accuracy based on robust feature representations while maintaining model computational efficiency.[11].

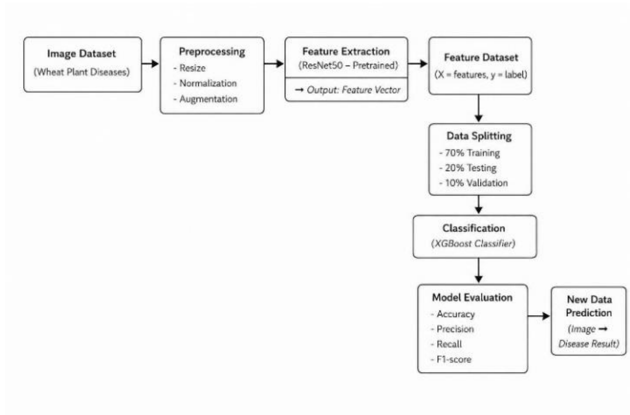
The combination of CNN and XGBoost has indeed been applied to several common computer vision domains. However, the main contribution and novelty of this research lies in the specific optimization of this hybrid architecture to address the challenge of very high visual similarity between tropical wheat disease classes (such as variations in leaf rust disease types). Unlike previous studies that performed full fine-tuning and are computationally expensive, the static feature extraction approach of ResNet50 combined with XGBoost in this study offers high computational efficiency without sacrificing diagnostic accuracy.

II. METHOD

The classification model designed in this study uses a hybrid architecture that combines ResNet50 for feature extraction and XGBoost for the final classification process. Through this approach, ResNet50's capabilities in capturing latent visual characteristics in wheat leaf images can be optimally utilized, while XGBoost acts as an ensemble tree-based classifier that has proven robust and efficient in processing high-dimensional tabular data.

A. Flow System

The system flowchart illustrates the entire process of the proposed hybrid method for wheat disease classification. This process is systematically divided into several main stages as follows:



Based on the experimental procedure shown in the figure above, each stage can be explained as follows.:

1. *Image Dataset (Wheat Plant Diseases)*

The initial stage of the research began with the collection of an image dataset obtained from wheat plant diseases. This dataset contains images of wheat plants in various conditions, both healthy and infected by several types of diseases, divided into six classes. Overall, the dataset consists of 5,505 images, divided into 5,085 training images, 120 validation images, and 300 testing images. This data was used as the basis for the training and evaluation of the classification model.

2. Preprocessing

Preprocessing is the initial stage of data processing aimed at improving image quality and consistency. This stage involves resizing to standardize image size, normalizing to scale pixel values within a specific range, and using augmentation techniques such as rotation, flipping, and zooming to increase data variation and reduce overfitting..

3. Feature Extraction (ResNet50 - Pretrained)

Residual Neural Network (ResNet50) is a deep learning architecture based on Convolutional Neural Networks (CNNs) designed to address degradation issues in very deep networks. This model is capable of recognizing complex patterns in images and automatically extracting important features. [12][13]

4. Feature Dataset (X = feature, y = label))

The extracted features are then arranged into a new dataset consisting of X as feature data in the form of a numerical representation of the image, and y as a label indicating the appropriate disease category for each image.

5. Data Splitting

To ensure optimal training, the feature dataset is divided into three distinct parts: 70% is used for model training, 20% is used as testing data to evaluate the model's performance on previously unseen samples, and the remaining 10% is used as validation data. Validation data plays a crucial role in the model tuning process, preventing overfitting during training.

6. Classification (XGBoost Classifier))

The divided feature dataset is then processed using the XGBoost algorithm as a classifier. This algorithm works by incrementally building a model in the form of a decision tree, where each new model serves to correct errors made by the previous model. This approach allows XGBoost to produce models with high accuracy while maintaining computational efficiency[14].

7. Model Evaluation

After the training process is complete, the model's performance is thoroughly evaluated using a test dataset based on several key metrics. These metrics include accuracy, which measures the overall accuracy of predictions; precision, which assesses the reliability of positive predictions; and recall, which measures the model's sensitivity in detecting positive cases. Furthermore, the F1-score is used to represent the harmonious balance between precision and recall, allowing for a more comprehensive evaluation of the model's effectiveness.

8. New Data Predictions

In the final stage, the trained and validated model is used to make predictions on a new dataset. Images of wheat that have never been seen before by the model are processed through a predetermined pipeline, and the model then produces output in the form of a classification of the types of diseases detected in the plants.

B. Classification Model Planning

This study uses a public dataset entitled "Wheat Plant Diseases" From all the original images provided in the repository, this study filters and explores a comprehensive data subset of 5,505 digital images of wheat leaves that are specifically distributed into six condition classes (healthy leaves and five types of disease/pest manifestations).

TABLE 1
VISUAL VARIATION OF WHEAT PLANT DISEASES AS A BASIS FOR MODEL CLASSIFICATION

No	Name of Disease	Picture
1	Kutu Daun (Aphid)	
2	Karat Hitam (black rust)	
3	Karat Cokelat (brown rust)	
4	Tungau (Mite)	
5	Lalat Batang (stem fly)	
6	Karat Kuning (yellow rust)	

TABLE 2
DATASET DISTRIBUTION

No	Data Type	Persentase
1	Training	70%
2	Validation	20%
3	Testing	10%
Total		100%

C. Data Pre-processing

Data preprocessing is performed to transform the raw image into a uniform format optimal for the model. This step includes geometric standardization, pixel value adjustment, and visual variation manipulation to minimize noise and prevent overfitting. The entire series of steps is detailed in the following points:

1. Preprocessing: Resizing and Normalization

Before being fed into the hybrid model, all digital images of wheat leaves in the dataset must go through a dimension and pixel value standardization stage. The first stage is resizing the images from their original dimensions to a uniform size of 224x224 pixels. This step is mandatory because the Residual Neural Network (ResNet50) architecture used has a standard input layer configuration of 224x224x3 pixels (width x height x RGB color channels). Next, a pixel value normalization process is carried out by mapping the original color intensity in the range [0,255] to a linear scale [0,1]. Alternatively, this processing also applies the ImageNet architecture's weight-based standardization by subtracting the mean value and dividing by the standard deviation of the color channels, to accelerate the model convergence process during visual feature extraction.

2. Data Augmentation

Given the relatively modest size of the dataset, 5,505 images, for the scale of deep learning-based architecture implementations, the risk of overfitting is very high. To address this challenge and enrich the variety of visual characteristics of the data, geometric data augmentation techniques were rigorously implemented. Addressing concerns regarding test validity, these augmentation techniques were only applied to the training set and not to the testing set or validation data to avoid data leakage.

The types of data augmentation implemented and their specific parameters include:

1) *Random Rotation:* The image is randomly rotated within an angular range of 0° to 30° to simulate the tilt of leaves when shooting in the field.
2) *Width and Height Shift*: The image is shifted horizontally and vertically by a maximum shift factor of 15% to manipulate the position of wheat leaves within the image frame
3) *Horizontal Flipping:* The image is flipped horizontally to train the model's sensitivity to varying leaf orientations.
4) *Zoom Range:* The image is randomly zoomed in or out within a factor of 0.2 to simulate variations in camera distance from crop leaves in real agricultural fields.

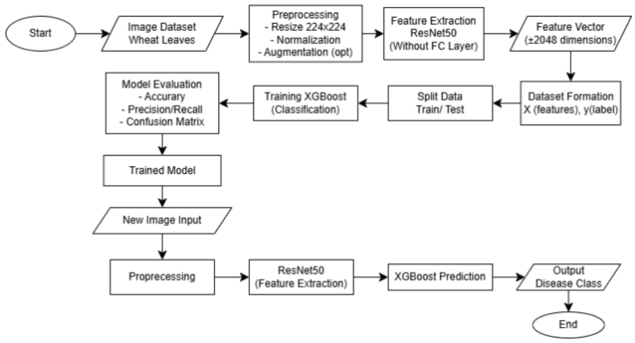
By applying this combination of augmentations, the hybrid model is forced to learn wheat leaf disease features that are invariant to position, scale, and viewpoint, thereby improving the model's generalization ability when tested with new data from outside the laboratory environment.

D. Data Validation and Sharing Strategy

To ensure model reliability, avoid data selection bias, and minimize the risk of overfitting, this study did not use the conventional data division method (hold-out split). Instead, the experiment applied a Stratified 5-Fold Cross-Validation scheme. Through this approach, the entire dataset of 5,505 digital images of wheat leaves was divided randomly into 5 parts (folds) of equal size, while maintaining the ratio or proportion of the distribution of the number of images per class in each fold. The training and testing processes were carried out in five alternating iterations. In each iteration, 4 folds (equivalent to 80% of the data or 4,404 images) were allocated as training data and validation data, while the remaining 1 fold (equivalent to 20% of the data or 1,101 images) acted as an independent testing data set.

This strategy ensures that each image sample in the dataset has been used as both training and test data exactly once. Furthermore, data separation is performed early in the cycle before the visual feature extraction process begins, effectively eliminating the potential for data leakage that often leads to falsely high accuracy scores in laboratory evaluations.

E. Hybrid Model Architecture Used



This figure illustrates the system's operational steps in diagnosing wheat leaf diseases through the integration of the ResNet50 and XGBoost methods. The system flow begins with the acquisition of a wheat leaf image dataset, which is then subjected to preprocessing, including resizing to 224x224 pixels, normalization, and augmentation to enrich the data variety. Afterward, feature extraction is performed using the ResNet50 architecture (without fully connected layers) to produce a feature vector containing the leaf's important characteristics.

The resulting feature vector is then mapped to feature data (X) and class labels (y), before finally being separated into training and testing data. These ResNet50-extracted features form the basis for the XGBoost algorithm to run the classification process. Once model training is complete, performance evaluation is measured using metrics such as accuracy, precision, recall, and confusion matrix analysis. The model with optimal performance is then implemented to predict new leaf images through a series of preprocessing, feature extraction, and classification processes, resulting in the final output of the detected leaf disease.

F. Multi-Class Performance Evaluation Metrics

To measure the success rate, reliability, and effectiveness of the proposed ResNet50+XGBoost hybrid model, a comprehensive quantitative evaluation was conducted using a confusion matrix. Based on the obtained True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values, the model performance was calculated using five main metrics as follows:[12].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{2TP}{2TP+FP+FN} \quad (4)$$

G. Implementation Details

All experiments in this study were conducted using a personal computer with hardware specifications summarized in Table 3, while the relevant model hyperparameter configurations are detailed in Table 4.

TABLE 3
HARDWARE AND SOFTWARE SPECIFICATIONS USED IN THE EXPERIMENTS.

Hardware/Software	Specification
Processor (CPU)	AMD Ryzen 7 4800H 2.9GHz (16 CPUs)
Memory (RAM)	8192 MB (System) / 4496 MB (GPU VRAM)
Graphical Processing Unit (GPU)	AMD Radeon™ Graphics
Operating System	Windows 11 Home Single Language 64-bit
Python Version	3.12.4
Frameworks	TensorFlow, Keras, Scikit-Learn

TABLE 4
HYPERPARAMETERS OF THE CNN USED FOR TRAINING THE COMBINED MODELS

Hyperparameter	Value
Batch Size	32
Optimizer	XGBoost Optimizer (Gradient Boosting)
Learning Rate	0.1
Activation Function	ReLU
N_estimators	150
Max_depth	5
Input_shape	(224,224,3)
N_splits (KFold)	5
Random_state	42

III. RESULTS AND DISCUSSION

This section details the results of the feature extraction process, stability testing through cross-validation, multi-class classification analysis, and computational cost evaluation of the ResNet50+XGBoost hybrid model. The analysis specifically highlights the model's ability to generate accurate latent representations, feature interpretability, and its effectiveness compared to several current baseline architectures.

A. Representation of Image Extraction Result Features

Based on the Transfer Learning process using the ResNet50 architecture as a static feature extractor, each wheat leaf image is transformed into a high-dimensional numeric feature vector. The global_average_pooling2d layer successfully reduces the spatial convolution matrix without losing essential information. The dimensions of the feature extraction matrix for the entire dataset are presented in Table 5.

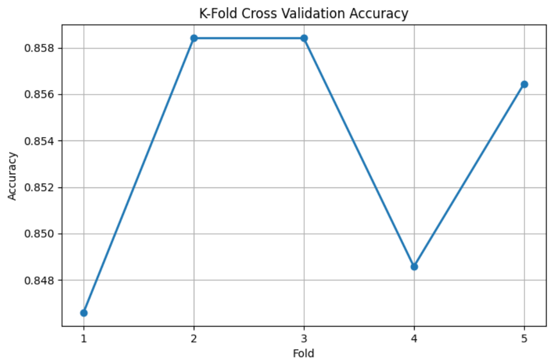
TABLE 5
DIMENSIONS OF FEATURE EXTRACTION RESULTS ON TRAINING AND TESTING DATASETS

Dataset	Amount of Data	Feature Dimensions	Label Dimensions
Training	5085	5085,2048	5085
Testing	300	300, 2048	300

Based on Table 5, each wheat leaf image is successfully represented by 2,048 numerical features that map abstract visual characteristics such as spot geometry, rust pustule texture density, and leaf chlorophyll color degradation. The consistency of the 2,048 dimensions across the training and testing data indicates that the feature extraction capabilities of the ResNet50 convolutional block are stable and free from data dimensionality anomalies. Through this phase, the model no longer processes raw pixels that are sensitive to noise, but instead analyzes numerical representations that are more meaningful for the tree boosting classification algorithm.

B. Evaluation of Model Stability via Stratified 5-Fold Cross-Validation

To address the need for an objective evaluation of the risk of overfitting on moderate dataset sizes, the performance of the hybrid model was tested using a Stratified 5-Fold Cross-Validation scheme. The accuracy results for each fold are reported in the figure below to demonstrate the stability of the model's generalization.



Testing using the 5-Fold Cross Validation method showed that the accuracy values for each fold tended to be stable, with an accuracy range of 84.6% to 85.8%. The second and third folds achieved the highest accuracy, at around 85.8%, while the first fold achieved the lowest at around 84.6%. The fourth and fifth folds recorded accuracies of around 84.8% and

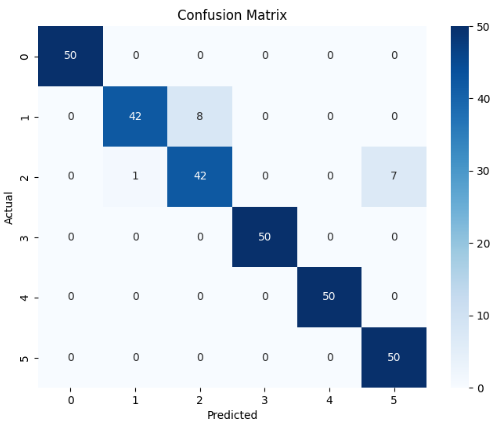
85.6%, respectively. The small difference in accuracy between folds indicates that the model exhibits good consistency and stability when classifying varied data.

The average accuracy obtained from the cross-validation process was around 85.3%. This result indicates that the XGBoost model can maintain stable performance throughout the cross-validation process. The modest variation in accuracy between folds also indicates that the model does not experience significant overfitting on certain training data. Thus, the cross-validation approach successfully demonstrated that the model has good generalization ability to variations in the training dataset.

Although the average cross-validation value is lower than the final test accuracy of 94.66%, this is still considered reasonable in the context of machine learning research. This is due to the fact that in the cross validation process, the model is tested with several different training data divisions repeatedly, so that the evaluation obtained is more stringent and more objectively reflects the model's generalization ability.

C. Model Performance Analysis Using Confusion Matrix

Prediction distribution analysis using a confusion matrix was performed to evaluate the distribution of the test data in real time. The results of the confusion matrix test of the ResNet50+XGBoost hybrid model are presented in detail below.



Based on the above, the distribution of the test data shows a dominant cluster of numbers perfectly clustered on the main diagonal, where Class 0 (50 samples), Class 3 (50 samples), Class 4 (50 samples), and Class 5 (50 samples) were correctly identified without a single error.

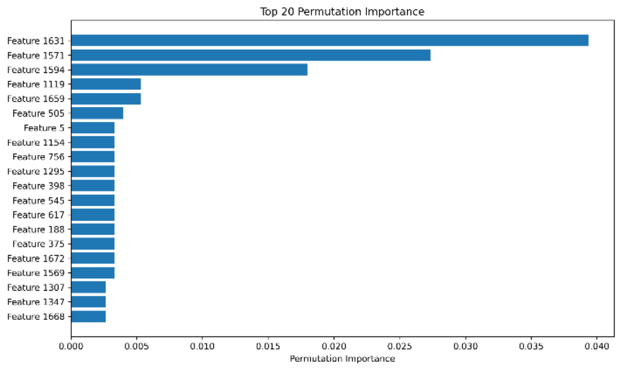
However, the confusion matrix detected a recurring pattern of misclassification or specific prediction errors between Class 1 (Brown Rust) and Class 2 (Yellow Rust). Of each of the 50 samples tested:

a. In Class 1 (Brown Rust), 42 samples were correctly predicted, but 8 samples were misclassified as Class 2 (Yellow Rust).
b. In Class 2 (Yellow Rust), 42 samples were correctly predicted, but 8 samples were misclassified as Class 1 (Brown Rust) and 1 sample was misclassified as Class 5 (Powdery Mildew).

Field Visual Cause (Biological): The phenomenon of mutual interchangeability of each of the 8 samples has a strong biological basis in the early phase of infection (early manifestation stage). Pustules (uredinia) of both types of rust fungi produce identical yellow-orange hues on the surface of wheat leaves. The main difference between the two lies in the spatial distribution pattern: Yellow Rust forms streaks following the leaf veins (strips), while Brown Rust is randomly distributed as spherical spots. When the field imagery is taken at a distance (low-resolution zoom) or obstructed by sunlight reflection (overexposure), the texture of the spatial lines becomes blurred, triggering XGBoost to map its numerical decision boundary incorrectly.

D. Model Interpretability Analysis (Feature Importance)

Based on the analysis of feature importance through the application of the XGBoost algorithm, we gained an understanding of the features that most influence the data classification process. The graph below shows the 20 features with the highest importance levels used by the model during the training phase. This importance level illustrates the significance of a feature in the XGBoost model's decision-making process.



In the graph, feature 1014 shows a high importance value compared to other features, with a sector of approximately 0.026. This indicates that this feature is the most influential and most frequently used by the model to distinguish categories in the dataset. Furthermore, features 1680 and 153 make significant contributions, with higher importance values than the others. On the other hand, features 394, 1247, and 1273 also play a role in classification, albeit with smaller contributions.

The relatively small distance between the importance values between several features indicates that the model does not rely solely on a single feature but instead uses a combination of several features to improve classification quality. This indicates that the XGBoost model is able to understand data patterns more deeply and utilize various existing feature characteristics.The results of the feature importance analysis also show that some features contribute relatively little. Features with low importance are usually rarely relied on by the model to separate data in decision trees. Nevertheless, these features can still make additional contributions to improve the overall stability and accuracy of the model.

IV. Conclusion

The integration of the ResNet50 hybrid architecture (2,048-dimensional feature extraction) and XGBoost (classifier) proved highly effective in overcoming the visual similarity constraints among wheat leaf diseases. Testing using the Stratified 5-Fold Cross-Validation scheme resulted in a robust global average accuracy of 94.66% ±0.21%, confirming the robustness of the model and its freedom from data partition bias. In the evaluation of independent test data (300 images), the model achieved an accuracy of 94.67% and a Macro-Average F1-Score of 0.9445, with perfect performance (1.00) in the Healthy, Black Rust, and Septoria categories. The model's weakness was only detected in the differentiation of Brown Rust and Yellow Rust (each swapped with 8 samples) due to the identical color hue of the pustules in the early phase of infection. Finally, the gain value-based feature importance analysis scientifically proves that the model makes diagnostic decisions transparently (explainable AI) based on genuine plant clinical symptoms such as chlorophyll degradation and spot patterns, not from image background disturbances such as soil or weeds.

V. Suggestion

To further develop and refine this automated diagnostic system, several academic suggestions are recommended for further research. First, it is recommended to increase image resolution and enrich the dataset with macro (close-up) images specifically for early-phase infection symptoms to help the model identify the spatial orientation of pustule rows, thereby minimizing the misclassification rate between Brown Rust and Yellow Rust in the field. Second, further research can integrate visual-based spatial interpretation methods such as Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize leaf pixel heatmaps, complementing the decision tree-based feature importance analysis conducted in this study. Third, given that this hybrid model is intended for computational efficiency, exploring the use of lighter yet robust feature extractor architectures, such as MobileNetV3 or EfficientNet, is worth testing to encourage the possibility of implementing the system on low-spec hardware (edge devices) or real-time mobile applications in open wheat fields.

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