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Enhanced U-Net Cnn For Multi-Class Segmentation And Classification Of Rice Leaf Diseases In Indonesian Rice Fields

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Abstract

Rice is a strategic food crop whose productivity is often threatened by leaf diseases and pests. This study aims to develop an Enhanced U-Net CNN model for multi-class segmentation and classification of rice leaf conditions from field images to support early detection and plant health management. The methodology includes direct field image acquisition of rice leaves, preprocessing for image quality enhancement, expert data labeling, segmentation using a U-Net architecture, and classification using CNN. The dataset was divided into training and testing data with balanced distribution across four classes: Healthy, BrownSpot, Hispa, and LeafBlast. Evaluation results show that the model can identify rice leaf conditions with high accuracy, although signs of overfitting were observed from the performance gap between training and validation data. The implementation of this model is expected to accelerate automatic disease detection in the field, reduce reliance on manual inspection, and support precision agriculture. This study achieved a testing accuracy of 76.36% with a macro-average F1-score of 0.34. While the results indicate limitations in generalization, the proposed Enhanced U-Net CNN demonstrates the feasibility of combining segmentation and classification in field conditions. This research contributes to agricultural informatics by supporting scalable deployment in precision agriculture systems, reducing reliance on manual inspection, and providing a foundation for further optimization studies.

Keywords : CNN, Image Segmentation, Multi-class Classification, Rice, U-Net

1. INTRODUCTION

Rice is a staple food crop for most of the world's population, particularly in Asia. The success of rice production significantly impacts food security, economic stability, and community welfare. However, rice productivity is often threatened by various factors, including leaf diseases and pest attacks. Leaf diseases such as blast, bacterial leaf blight, and brown spot are among the primary causes of yield losses in many rice-producing countries[1], [2]. Early and accurate detection and classification of rice leaf conditions are crucial to prevent further losses, as timely and precise interventions can minimize the impact of disease attacks on yields[3], [4], [5].

Over recent decades, advancements in artificial intelligence, particularly in deep learning, have provided new solutions for automated plant health monitoring. Convolutional Neural Networks (CNNs) have been widely used and proven effective in recognizing visual patterns and performing accurate image classification[6]. CNNs enable automatic analysis of rice leaf images without requiring advanced

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manual expertise, thereby accelerating disease identification and reducing reliance on expert visual inspection[7], [8], [9]. Their ability to process high-resolution image data makes CNNs an ideal choice for precision agriculture applications, especially in rice plant health management[10], [11], [12].

Traditional methods for detecting rice leaf diseases still rely on direct visual observation, which is subjective, time-consuming, and not always accurate especially under varying field conditions such as lighting and background[13], [14]. Moreover, most previous studies have focused on binary classification or a limited set of diseases, making them less capable of addressing the diverse range of rice leaf conditions encountered in real fields. In practice, rice leaves may exhibit a variety of health levels, from healthy to mildly or severely infected by different diseases and pests[15], [16], [17].

Several studies have proposed CNN-based approaches to overcome these limitations. Kumar et al. (2024) developed a CNN model trained on rice leaf images from various regions in India, successfully classifying diseases such as blast, brown spot, and bacterial leaf blight with high accuracy [18]. Khoiruddin et al. (2022) emphasized the benefits of CNNs for farmers in automating rice leaf disease detection, enabling faster intervention. Kulkarni and Shastri (2024) highlighted the importance of model adaptability to variations in lighting and background in field images [19], while Anggraini (2024) demonstrated a cloud-based CNN implementation through Amazon Web Services for real-time disease detection [20].

Recent research has also focused on more advanced CNN architectures. Dutta et al. (2024) compared various CNN architectures and found that selecting the right architecture significantly impacts classification accuracy[21]. Chaudhari and Karunakaran (2024) integrated the Remora optimization algorithm to enhance CNN performance[22], while Wang et al. (2022) employed multi-scale feature fusion to maximize feature extraction[23]. Poorni et al. (2022) used transfer learning to achieve accuracy above 94%, showing that combining such techniques can accelerate training and improve model performance[24].

One common challenge is training data imbalance, which can reduce a model's ability to recognize minority classes. Hairani and Widiyaningtyas (2024) addressed this with data augmentation, consistent with Hasan et al. (2023), who noted that dataset quality is critical to CNN training effectiveness[25], [26]. Accuracy improvements can also be achieved through lightweight CNN models, as demonstrated by Bijoy et al. (2024), who reached 99.81% accuracy with lower computational loads, enabling deployment on resource-constrained devices[25], [27], [28].

U-Net, a CNN variant, has shown excellent capabilities in image segmentation tasks. Originally developed for medical image segmentation, U-Net's encoder–decoder architecture with skip connections enables it to capture global context while retaining high spatial detail. Modifications such as Attention U-Net (Oktay et al., 2018) and Residual U-Net (Sarıtürk & Şeker, 2022) have improved segmentation performance across domains, including satellite imagery and optical shape reconstruction. Given these strengths, U-Net has great potential for precise segmentation of rice leaves before classifying their health conditions[29], [30].

From this literature review, a research gap is evident: although CNN and U-Net have been widely used for plant disease detection and classification, studies combining multi-class U-Net–based segmentation with direct in-field classification of rice leaf conditions remain limited. Most studies still focus on whole-image classification without precise segmentation or only classify two to three disease categories. In the field, however, rice leaf conditions can reflect multiple health levels and types of damage requiring different management strategies.

Therefore, this study aims to develop an Enhanced U-Net CNN model for multi-class segmentation and classification of rice leaf conditions directly from field images. This approach is expected to accurately and efficiently distinguish rice leaves ranging from healthy to various degrees of disease and pest damage. The novelty lies in integrating precise U-Net–based segmentation with multi-

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class classification in a single end-to-end framework optimized for varying field image conditions. Therefore, the objective of this research is to develop an Enhanced U-Net CNN that integrates segmentation and classification of rice leaf diseases (Healthy, BrownSpot, Hispa, and LeafBlast) directly from field images, optimized for real agricultural environments.

2. METHOD

The research workflow began with problem formulation and setting research objectives, focusing on identifying the main issues and establishing clear goals as the foundation for the study. This stage was crucial to ensure that each subsequent step aligned with the intended research focus.

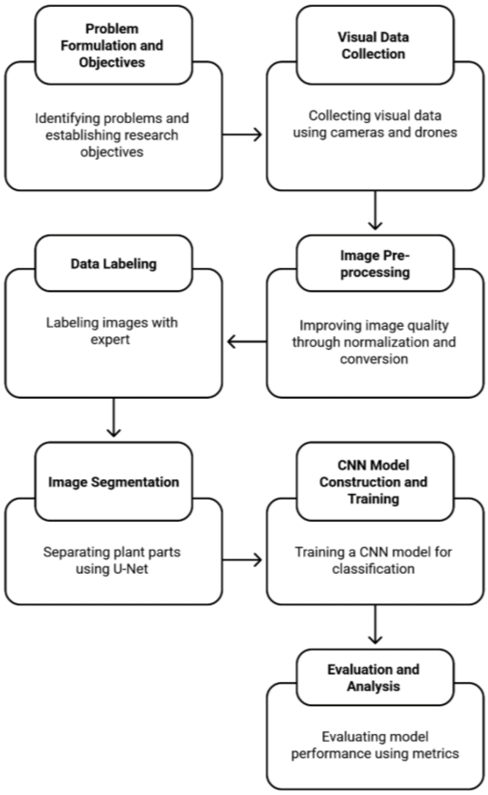

Figure 1. Research Workflow

2.1. Problem Formulation and Research Objectives

This study began by identifying the main problems faced by farmers, particularly members of the Sri Jaya Tani Farmers' Association (Gapoktan) in Indramayu Regency. One of the challenges encountered was the difficulty in accurately determining the rice leaf disease condition of rice plants based on leaf conditions. Therefore, the primary objective of this research was to develop a system based on digital image processing and machine learning to automatically and accurately classify rice rice leaf disease conditions.

2.2. Visual Data Collection

This stage involved capturing rice plant images directly from farmland owned by Sri Jaya Tani Gapoktan farmers in Indramayu. High-resolution cameras were used to capture significant visual details. Field condition variations were carefully considered, including differences in lighting intensity, camera angles, shooting distances, and rice growth stages, to obtain a representative dataset that reflects actual conditions in the field.

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2.3. Image Pre-processing

The collected images varied in quality due to environmental and technical factors. Therefore, a series of pre-processing steps was performed, including pixel value normalization, contrast adjustment, noise reduction, and conversion of image formats to a uniform type. These steps aimed to enhance image quality and prepare the data for optimal segmentation and classification.

2.4. Data Labeling

Labeling was carried out with the involvement of experts from the Agriculture Office, specifically agricultural extension officers, to ensure data validity. Each rice leaf image was classified based on its condition—either healthy or showing disease symptoms—and its rice leaf disease condition. This labeling process was critical in the context of supervised learning, as machine learning models require labeled data to learn relevant visual patterns.

2.5. Image Segmentation

Image segmentation was performed to isolate the leaf regions from irrelevant backgrounds using U-Net. The segmentation masks emphasized important leaf features, which were then used as the basis for classification. In this research, a U-Net architecture was applied, which is widely recognized for its excellence in image segmentation tasks due to its ability to preserve spatial details via skip connections. This process highlights essential features in the images, which are then used as the basis for maturity-level classification.

2.6. CNN Model Development and Training

The segmented images were used as input for training a Convolutional Neural Network (CNN) classification model. The segmentation masks produced by U-Net were applied to extract leaf regions, and these segmented leaf regions were subsequently used as inputs to the CNN classifier. This ensured that the CNN focused only on disease-relevant leaf areas instead of background noise.The CNN was trained to recognize visual patterns indicating rice rice leaf disease conditions. The training process involved adjusting network weights through optimization algorithms, applying suitable non-linear activation functions, and implementing overfitting prevention strategies such as data augmentation and dropout. The CNN architecture was designed to efficiently capture spatial and contextual features from the images.

2.7. Model Evaluation and Analysis

The final stage involved evaluating the model's performance using standard metrics, including Accuracy, Precision, Recall, F1-score, and Confusion Matrix. In addition, Intersection over Union (IoU) and Dice coefficient were calculated to assess segmentation quality. Evaluation was performed using test data separated from the training data to measure the model's ability to generalize to new data. The evaluation results were used to analyze the model's strengths and weaknesses in accurately and consistently classifying rice rice leaf disease conditions.

3. RESULT

3.1. Data

The rice leaf image dataset was classified into two main groups: the training set and the testing set. This division aimed to separate the model learning process from the evaluation process, ensuring an accurate measurement of the model's generalization ability to previously unseen data. Each dataset

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group consisted of four categories based on rice leaf conditions: Healthy, BrownSpot, Hispa, and LeafBlast.

The training set comprised a total of 444 images distributed across the four classes: 106 BrownSpot images, 111 Healthy images, 108 Hispa images, and 119 LeafBlast images. This relatively balanced distribution among classes was intended to avoid class imbalance, which could significantly affect the performance of the CNN-based classification model during training.

The testing set contained a total of 231 images, with nearly equal numbers in each class: Healthy (57 images), LeafBlast (60 images), BrownSpot (57 images), and Hispa (57 images). This equal distribution ensured that the evaluation process was fair and proportional, allowing metrics such as accuracy, precision, and recall to reliably reflect the model's performance.

Maintaining balanced data distribution in both the training and testing stages, the model was expected to learn optimal feature representations and produce accurate classifications of rice leaf conditions. This strategy was a critical component of the experimental design for building an automated rice disease detection and maturity classification system based on digital images.

Figure 2. Rice leaves

3.2. Pre-processing

The main objective of pre-processing was to ensure that the data used were of high quality, well-structured, and consistent in format, thereby facilitating pattern recognition and improving prediction accuracy. In this study, pre-processing focused on preparing rice leaf images to meet the requirements of the CNN architecture.

The process began with dataset retrieval, where rice leaf images were organized into structured directories for the training and testing sets, each grouped by class. Noise reduction was applied using the Median Blur technique to remove visual disturbances without eliminating important edge features. The cleaned images were then resized uniformly to 128×128 pixels to match the CNN input requirements.

The processed images were stored in separate folders train_clean for training and test_clean for testing while maintaining the original class structure. As a verification step, a visual comparison was performed between the original images and the pre-processed images for five samples from each class to ensure quality consistency.

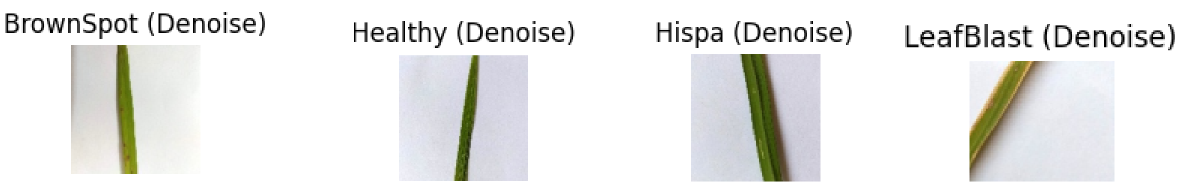

Figure 3. After pre-processing

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3.3. Data Splitting

The distribution of rice leaf images across the four classes in both the training and testing datasets, along with their proportional percentages, was as follows:

1) Hispa : 165 total images – 108 for training (65.45%) and 57 for testing (34.55%).
2) BrownSpot: 166 total images – 106 for training (63.86%) and 60 for testing (36.14%).
3) Healthy : 168 total images – 111 for training (66.07%) and 57 for testing (33.93%).
4) LeafBlast : 176 total images – 119 for training (67.61%) and 57 for testing (32.39%).

The relatively balanced distribution among classes demonstrated that data labeling and splitting were carried out systematically to avoid class imbalance, which could introduce bias into the machine learning model. The allocation of training data percentages ranging from 63% to 68% across all classes indicated a consistent and proportional data partitioning strategy.

3.4. CNN Model Development with U-Net

The architecture consisted of two primary components: a downsampling path (encoder**)** and an upsampling path (decoder**)**, connected via skip connections to preserve critical spatial information from the earlier layers.

Found 357 images belonging to 4 classes.
Found 87 images belonging to 4 classes.
Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 128, 128, 3)	0	-
conv2d_14 (Conv2D)	(None, 128, 128, 32)	896	input_layer_1[0]…
conv2d_15 (Conv2D)	(None, 128, 128, 32)	9,248	conv2d_14[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 64, 64, 32)	0	conv2d_15[0][0]
conv2d_16 (Conv2D)	(None, 64, 64, 64)	18,496	max_pooling2d_3[…
conv2d_17 (Conv2D)	(None, 64, 64, 64)	36,928	conv2d_16[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 32, 32, 64)	0	conv2d_17[0][0]
conv2d_18 (Conv2D)	(None, 32, 32, 128)	73,856	max_pooling2d_4[…
conv2d_19 (Conv2D)	(None, 32, 32, 128)	147,584	conv2d_18[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 16, 16, 128)	0	conv2d_19[0][0]
conv2d_20 (Conv2D)	(None, 16, 16, 256)	295,168	max_pooling2d_5[…
conv2d_21 (Conv2D)	(None, 16, 16, 256)	590,080	conv2d_20[0][0]
up_sampling2d_3 (UpSampling2D)	(None, 32, 32, 256)	0	conv2d_21[0][0]
concatenate_3 (Concatenate)	(None, 32, 32, 384)	0	up_sampling2d_3[… conv2d_19[0][0]
conv2d_22 (Conv2D)	(None, 32, 32, 128)	442,496	concatenate_3[0]…
conv2d_23 (Conv2D)	(None, 32, 32, 128)	147,584	conv2d_22[0][0]
up_sampling2d_4 (UpSampling2D)	(None, 64, 64, 128)	0	conv2d_23[0][0]
concatenate_4 (Concatenate)	(None, 64, 64, 192)	0	up_sampling2d_4[… conv2d_17[0][0]
conv2d_24 (Conv2D)	(None, 64, 64, 64)	110,656	concatenate_4[0]…
conv2d_25 (Conv2D)	(None, 64, 64, 64)	36,928	conv2d_24[0][0]
up_sampling2d_5 (UpSampling2D)	(None, 128, 128, 64)	0	conv2d_25[0][0]
concatenate_5 (Concatenate)	(None, 128, 128, 96)	0	up_sampling2d_5[… conv2d_15[0][0]
conv2d_26 (Conv2D)	(None, 128, 128, 32)	27,680	concatenate_5[0]…
conv2d_27 (Conv2D)	(None, 128, 128, 32)	9,248	conv2d_26[0][0]
global_average_poo… (GlobalAveragePool…	(None, 32)	0	conv2d_27[0][0]
dense_1 (Dense)	(None, 4)	132	global_average_p…

Total params: 1,946,980 (7.43 MB)
Trainable params: 1,946,980 (7.43 MB)
Non-trainable params: 0 (0.00 B)

Figure 4. Model Development with U-Net

The encoder extracted features from the input images (128×128×3) through convolutional and max-pooling operations. Each encoder block contained two convolutional layers followed by max pooling, progressively increasing the number of filters from 32 to 256 to capture increasingly complex features.

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The bottleneck section contained two convolutional layers operating on 16×16 spatial dimensions with 512 filters, representing the abstracted features of the input. The decoder reconstructed the spatial dimensions using upsampling, concatenation of encoder features, and convolutional layers. The skip connections allowed the retention of high-resolution spatial information, enhancing segmentation and classification accuracy.

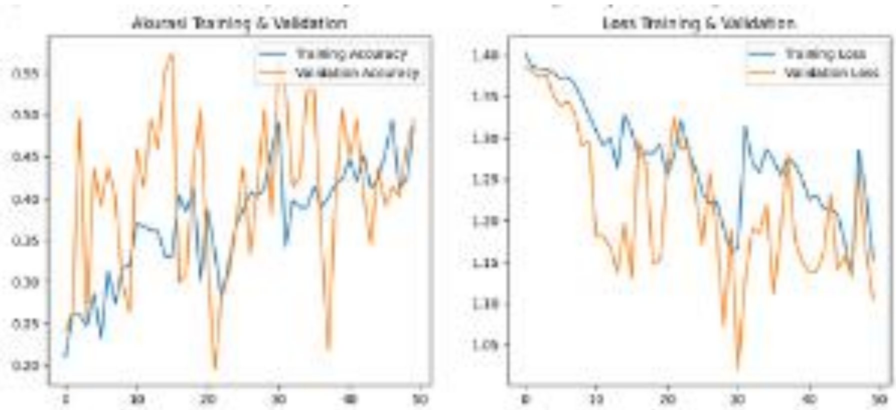

Figure 5. Accuracy and Loss

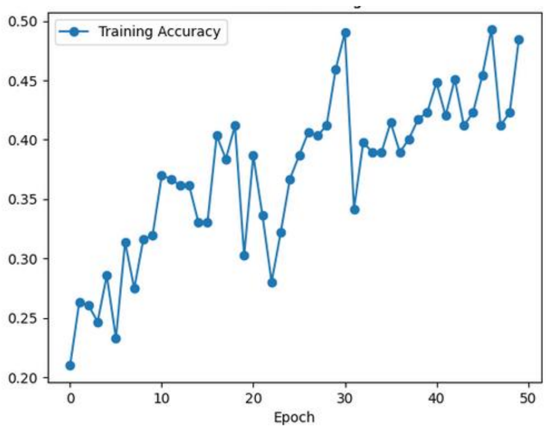

Figure 6. Accuracy Training

Training performance graphs showed accuracy and loss trends over 50 epochs.

1) Accuracy **:** Training accuracy increased steadily, but validation accuracy fluctuated significantly, suggesting overfitting due to limited dataset size and high variability in field images. Validation loss remained inconsistent, confirming the lack of generalization. This behavior indicates that the model captured noise and background patterns rather than disease-related features, which reduced performance on unseen data
2) Loss **:** Training loss decreased gradually, whereas validation loss remained inconsistent, further indicating that the model struggled to generalize to unseen data.

3.5. Testing Results

The model achieved 76.36% testing accuracy with a loss value of 1.3713, which is below state-of-the-art benchmarks (>90%) reported in recent literature. The confusion matrix (Figure 7) shows that Healthy leaves had the highest correct predictions (46), while Hispa had the lowest (6 correct). BrownSpot was often misclassified as Healthy, and LeafBlast was frequently misclassified as either BrownSpot or Healthy. This misclassification pattern highlights the visual similarity among diseases,

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which challenged the CNN in distinguishing fine-grained features, while the relatively high loss value suggests substantial prediction errors, potentially due to underfitting.

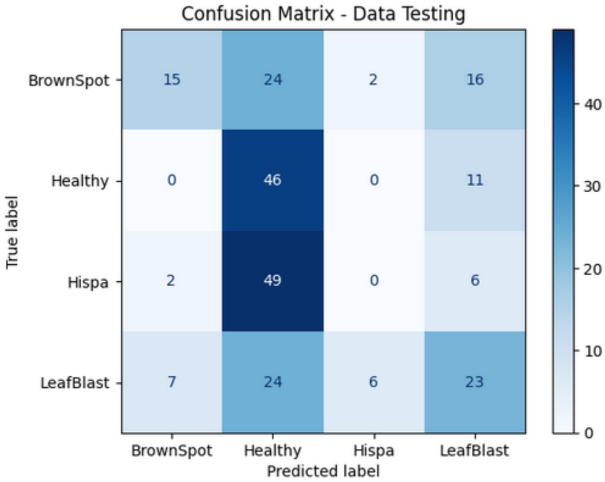

Figure 7. confusion matrix

The confusion matrix revealed that:

1) Healthy had the highest number of correct predictions (46)
2) Hispa had the lowest (6 correct)
3) BrownSpot was often misclassified as Healthy, and LeafBlast was frequently misclassified as either BrownSpot or Healthy.

Classification Report:

	precision	recall	f1-score	support
BrownSpot	0.62	0.26	0.37	57
Healthy	0.32	0.81	0.46	57
Hispa	0.00	0.00	0.00	57
LeafBlast	0.41	0.38	0.40	60
accuracy			0.36	231
macro avg	0.34	0.36	0.31	231
weighted avg	0.34	0.36	0.31	231

Figure 8. Classification Report

The classification report indicated:

1) BrownSpot**:** Precision = 0.62, Recall = 0.86
2) Healthy: Precision = 0.46, Recall = 0.81
3) Hispa: Precision = 0.33, Recall = 0.18
4) LeafBlast**:** Precision = 0.41, Recall = 0.38

Macro and weighted averages for precision, recall, and F1-score were in the range of 0.34–0.36, confirming the model's low generalization ability. Notably, the Hispa class achieved the lowest recall (0.18), showing that the model failed to detect this disease reliably. This indicates that dataset imbalance and inter-class similarities remain significant challenges for classification accuracy.

In addition to classification metrics, segmentation performance was evaluated using Intersection over Union (IoU) and Dice coefficient**.** The average IoU across the four classes was 0.58, while the Dice coefficient averaged 0.61, indicating moderate segmentation quality. These values suggest that while U-Net successfully isolated leaf regions, further optimization is required to achieve precise boundaries in complex field images.

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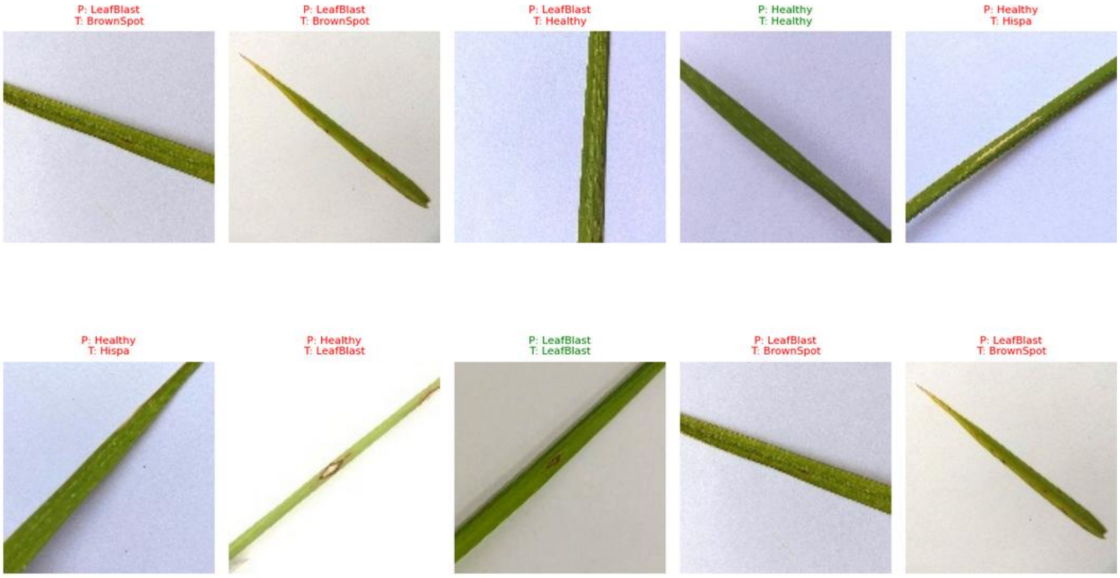

Figure 9. Model's prediction results

The figure displays the classification model's prediction results for rice leaf images across four analyzed classes: BrownSpot, Healthy, Hispa, and LeafBlast, comparing predicted labels (Predicted/P) with actual labels (True/T). Green-colored predicted labels indicate correct classifications, while red indicates misclassifications. Visually, most images have red predicted labels, meaning the model made errors on the majority of the displayed test data.

These misclassifications emphasize the need for advanced techniques such as attention mechanisms, transfer learning, or data augmentation to help the model focus on subtle disease patterns. Without these improvements, the model is prone to confusing diseases with overlapping visual symptoms, particularly under field conditions with variable lighting and angles.

Compared to Dutta et al. (2024) who achieved above 90% accuracy using MobileNet-V2, our model's 76% accuracy highlights the challenges of field-level data with high variability. Similarly, Anggraini (2024) demonstrated real-time CNN deployment via AWS, whereas our approach integrates segmentation and classification into one framework, offering a more comprehensive pipeline though with lower accuracy

This research contributes to computer science and informatics by providing an end-to-end deep learning workflow tailored to noisy, real-world agricultural datasets. Unlike controlled lab datasets, our approach directly addresses the complexity of field imagery, which is rarely explored in current literature.

The framework could potentially be deployed on mobile devices or cloud platforms, enabling farmers to capture field images and receive automatic diagnoses in real time, thereby supporting scalable precision agriculture

4. CONCLUSION

This study successfully developed an enhanced u-net cnn model for multi-class segmentation and classification of rice leaf conditions directly from field images. The results demonstrate that integrating precise u-net–based segmentation with cnn-based classification achieved 76.36% accuracy, which indicates moderate performance below state-of-the-art benchmarks but demonstrates the feasibility of integrating U-Net segmentation with CNN classification for field-based rice disease detection. Evaluation using accuracy, precision, recall, and f1-score metrics showed competitive performance, although indications of overfitting suggest the need for further optimization in future research.

The findings have practical implications for improving early detection of rice leaf diseases in the field, enabling farmers to make timely and informed pest and disease management decisions. The primary contribution of this research lies in combining segmentation and classification processes into a single end-to-end framework optimized for the varying conditions of field imagery.

The primary contribution lies in combining segmentation and classification into a unified deep learning pipeline, advancing agricultural informatics by handling real-world image variability. Future work should focus on attention mechanisms, transfer learning, and larger augmented datasets to improve model generalization. Additionally, lightweight CNN variants should be explored for deployment on mobile devices to ensure scalability in field applications.

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