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Fungus And Bacterial Disease Detection On Leaves Using CNN Based Approach

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Abstract: Leaf diseases in rice and wheat pose a significant threat to global food security by reducing crop yields and quality. Diseases such as leaf rust, bacterial blight, blast, and many more—caused by fungi, bacteria, and viruses—spread rapidly under favourable environmental conditions, leading to severe economic losses. Traditional detection methods, which rely on visual inspection, are often labour-intensive and prone to errors. However, advancements in machine learning, molecular biology, and remote sensing have revolutionized disease detection and management. This paper focuses on the implementation of a technology-driven approach for identifying and classifying leaf diseases in rice and wheat. It examines the causes, symptoms, detection methods, and control strategies while highlighting the role of artificial intelligence and image processing in promoting sustainable agriculture.

***Index Terms*- Deep Learning, Leaf Disease, Convolutional Neural Network (CNN), Precision Agriculture, Image Processing.**

I.INTRODUCTION

Plant diseases present a significant obstacle to global food security, resulting in decreased crop yields and financial losses. Crops like rice and wheat, which are extensively cultivated, are especially prone to diseases such as leaf rust, bacterial blight, and blast, which can spread quickly when conditions are favourable. Conventional disease detection mechanisms rely on tedious, exhausting, and vulnerable to errors manual inspections. However, breakthroughs in artificial intelligence (AI) and deep learning have revolutionized disease identification, allowing for quicker and more precise detection. Convolutional Neural Networks (CNNs) have proven to be highly effective in analyzing leaf images and accurately recognizing diseases. This research explores the use of a CNN-based approach to detect and categorize rice and wheat leaf diseases, offering an automated and effective means of early disease detection. This study promotes the growth of smart agriculture, helping farmers take prompt actions to improve crop health and boost productivity.

II. LITERATURE SURVEY

[1] Convolutional Neural Networks with Transfer Learning for Automated Wheat Rust Disease Classification -This study employs four pre-trained Convolutional Neural Networks (CNNs)—VGG16, HandyNet, InceptionV3, and InceptionResNetV2—to detect wheat diseases. VGG16 achieved a recall of 95% for yellow rust and 100% accuracy for brown rust. The results illustrate how transfer learning enhances early detection of disease and supporting food security.

[2] **AI rooted for assessing the type of wheat yellow rust infestation** -This study classifies the severity of dye rust in wheat by data from the National Agricultural Evaluation
Centre in Peshawar. The accuracy of the Exception and ResNet-50 models is 96%, and diagnostic help can be

Obtained Enhancing Rice Crop Health Assessment: Evaluating Disease Identification with a CNN-RF Hybrid Approach by a ResNet-50-powered device. By providing realistic rust remedies, the tool seeks to assist farmers boost wheat yield and quality.

[3] CNN-based smart agriculture for detecting wheat leaf damage -This article describes a method that uses CNN to detect and identify wheat leaf diseases with 94% accuracy by using photo augmentation to avoid overfitting. It is intended for real-time disease identification, particularly in situations with limited resources. Early disease diagnosis can prevent crop loss and promote sustainable agriculture.

[4] An investigation on picking out and taxonomy of rice plant illnesses -This study reviews 19 articles on identifying rice diseases. It explores data sources, illness categories, splitting, analysis, and classification models, aiming to develop tools for rice disease recognition and classification, providing a foundation for additional study on the identification of plant ailments

[5] Optimizing the appraisal of Rice Crop Gesundheit: Assessing Disease Identification Using a CNN-RF Hybrid Strategy -This research introduces a hybrid RF-CNN model for detecting diseases, specifically rust and leaf spots in rice. The model integrates random forest for classification and CNN for feature extraction, allowing for early and precise disease identification.

[6] Artificial intelligence for Agro-Business in the designation of Rice Pest -This study reviews eight years of research on AI and ML in rice disease diagnosis, focusing on crop pest detection and sapling quality. It analyzes data from Scopus and Web of Science, offering insights on country citations, global trends, and annual patterns to guide future research in rice disease management.

[7] Analysing the Effect of Partition on Camera Vision and Deep Learning-Based Wheat Stripe Rust Disease Classification -Food security is at risk when rust disease diminishes the supply of wheat, a crucial crop for mankind, by 30%. Using Basin splitting methods on rust and wheat adorn data, this study's U2-Net model earns good classification accuracy. It emphasizes how crucial segmentation is to correctly classification diseases.

[8] Enhancing the Recognition of Wheat Leaf Rust Disease by Combining YOLOv5 and Pretrained Models -The article suggests using deep learning. approach using YOLOv5 and pre-trained models for diagnosing wheat leaf rust. Using a dataset of 400 images, VGG16 outperformed VGG19 with an F1 ranking of 92.89%. The method enhances wheat disease diagnosis, improving yield and food security.

[9] A Deep Learning Method for Identifying and Grouping Wheat Leaf Spots Using Help Vector Machines and a Rapid R-CNN - This model achieved 96.33% accuracy for multi-class classification and 96.63% for binary classification, effectively identifying and categorizing wheat diseases to support early disease management and improve crop health.

[10] Using the Global Leaf Coverage Terrain Feature Algorithm uncovers significant illness in rice crops -This project uses image analysis with the Algorithm for Gray Level Co-occurring Matrix Texture Attributes to identify healthy and infected areas in rice crops. By processing 512x512 images, it aims to detect infections early, reducing the 30% crop loss caused by diseases and preventing their spread.

III. RESEARCH METHODOLOGY

3.1 DATA AND SOURCES OF DATA

This study uses a dataset on rice and wheat leaf diseases that was received via Kaggle. The dataset includes captioned pictures of wheat and rice leaves that were divided into ten different classes that included both healthy and sick samples. This dataset, which has been specially selected for the development and assessment of deep learning models specifically, Convolutional Neural Networks (CNNs) aims to improve automated leaf disease diagnosis in precision agriculture. High-resolution field photos, internet picture libraries, and agricultural research institutes were among the several sources from which the images were collected. By using Kaggle as a source, a range of photos taken in various environmental settings are guaranteed, which aids in the creation of reliable and broadly applicable models.

The dataset comprises images of rice and wheat leaves, each labeled with its corresponding disease or designated as "healthy." It likely includes a range of common diseases affecting these crops, with images typically in JPEG or PNG format. The dataset is organized into folders, with each folder representing a specific disease class or healthy leaves, facilitating seamless integration with deep learning frameworks.

Prior to model training, several preprocessing steps were implemented to ensure data consistency and optimize model performance. All images were resized to a uniform resolution of 256x256 pixels. Subsequently, pixel values were normalized to a range between 0 and 1 to promote faster and more stable convergence of the deep learning models. In order to improve model generalization and reduce overfitting, a variety of data augmentation methods were used. These methods included adding Gaussian noise, adjusting image brightness, rotating images at random, and flipping images horizontally. Expert annotation and labeling were performed to guarantee the accuracy.

3.2 THEORETICAL FRAMEWORK

This study employs a Convolutional Neural Network (CNN) architecture for image classification using a deep learning framework to effectively extract hierarchical features. The program is designed to classify rice and wheat leaf diseases based on image data.

3.2.1 Input Processing

The network processes RGB images of 128x128 pixels, maintaining three colour channels (Red, Green, and Blue) to capture essential visual information.

3.2.2 Feature Extraction Using Convolutional Layers

Ten convolutional blocks, each using a 3x3 kernel to extract spatial characteristics, make up the architecture's core. 32 filters are used in the first two blocks, 64 in the next two, 128 in the next two, 256 in the next two, and 512 in the last two. This is a continual increase in the number of filters. The model can learn both low-level and high-level patterns that are crucial for classification thanks to this hierarchical feature extraction. Each convolutional layer receives ReLU activation to add non-linearity and lessen the vanishing gradient issue. While some layers marginally lower the output size, the majority use "same" padding to maintain spatial dimensions.

3.2.3 Dimensionality Reduction with Pooling Layers

Max pooling layers (2x2 filter, stride 2) are incorporated after every two convolutional blocks. These layers downsample feature maps, reducing computational complexity and improving model robustness to slight variations in input images.

3.2.4 Frequentization via Dropout

Dropout layers are incorporated across the network to stop overfitting. Each convolutional block is followed by a 25% dropout rate, however the fully connected layers are applied first at a higher 40% rate. Dropout improves model generalization by randomly deactivating neurons during training.

3.2.5 Flattening of Features

Before moving on to the classification phase, the feature maps that were retrieved from the convolutional and pooling layers are flattened into a one-dimensional vector.

3.2.6 Fully Connected Classification Layers

The classification module consists of 66 output layers with softmax activation after a dense layer with 1500 neurons and ReLU activation. Accurate classification of rice and wheat leaf diseases is made possible by the softmax layer, which creates a probability distribution across ten disease classes.

This CNN architecture follows a hierarchical feature learning strategy, where convolutional layers extract key patterns, pooling layers reduce dimensionality, and fully connected layers perform classification. Dropout regularization enhances generalization by reducing overfitting. The increasing filter depth across convolutional blocks allows the model to learn progressively complex features, ultimately improving its capability to accurately identify and classify leaf diseases in wheat and rice crops.

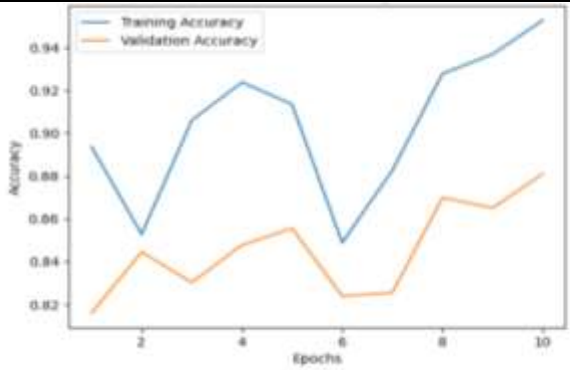

Fig 1. Accuracy v/s Epoch graph for CNN

The graph Fig1 shows that training accuracy increases over epochs but fluctuates, while validation accuracy remains lower. This indicates that the model is learning but may be overfitting, performing well on training data but struggling with unseen data. Reducing overfitting requires techniques like regularization, data augmentation, or more training data.

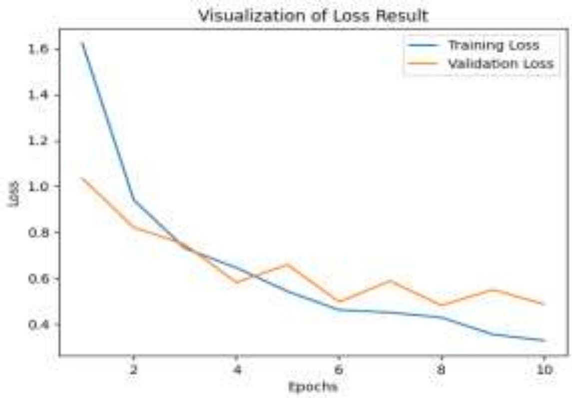

Fig 2. Loss v/s Epoch graph for CNN

The graph Fig 2 illustrates a steady decrease in training loss, indicating effective learning. However, the fluctuating validation loss suggests variance issues or overfitting. To improve generalization, techniques like Dropout, L2 regularization, or increasing dataset size can be applied. These insights align with the model's training, evaluation, and visualization process in the code.

3.3. EVALUATION METRICS

This study evaluates the effectiveness of a Convolutional Neural Network (CNN) in classifying rice and wheat leaf diseases. The model's performance was analyzed across ten distinct classes, encompassing both healthy and diseased leaves. Standard evaluation metrics, including precision, recall, F1-score, and accuracy, were used to assess its classification capabilities.

3.3.1 Standard Performance Metrics

The CNN model's classification performance was measured using the following key metrics:

3.3.1.1 Precision:

The ratio of correctly predicted positive instances to the total predicted positives, computed as:
Precision=True Positives/(True Positives+False Positives)

3.3.1.2 Recall (Sensitivity):

The proportion of actual positive cases correctly identified by the model, given by:
Recall=True Positives/(True Positives+ False Negatives)

3.3.1.3 F1-Score:

The harmonic mean of recall and precision, ensuring a balanced evaluation, calculated as:
F1-Score=2×((Precision×Recall) / (Precision+Recall))

3.3.1.4 Support:
The number of instances per class, with each class containing 63 samples, ensuring a balanced dataset.

3.3.1.5 Accuracy:
The overall proportion of correctly classified instances, determined as:
Accuracy=(True Positives+True Negatives)/Total Samples

3.3.1.6 Macro Average:
The unweighted mean of precision, recall, and F1-score across all classes.

3.3.1.7 Weighted Average:
The mean of these metrics, weighted by the number of samples in each class.

The CNN model achieved an **overall accuracy of 88%**, demonstrating its robustness in classifying rice and wheat leaf diseases. Table 1 provides a detailed breakdown of its performance per class, showcasing its effectiveness in distinguishing between healthy and diseased leaves.

	precision	recall	f1-score	support
Rice_Bacterial_leaf_blight	1.00	0.97	0.98	63
Rice_BrownSpot	0.74	0.86	0.79	63
Rice_Healthy	0.82	0.95	0.88	63
Rice_LeafBlast	0.84	0.65	0.73	63
Rice_LeafScald	0.95	0.94	0.94	63
Rice_NarrowBrownSpot	0.89	0.87	0.88	63
Wheat_BrownRust	0.98	0.84	0.91	63
Wheat_Healthy	0.94	0.81	0.87	63
Wheat_Septoria	0.89	0.94	0.91	63
Wheat_YellowSmut	0.82	0.98	0.89	63
accuracy			0.88	630
macro avg	0.89	0.88	0.88	630
weighted avg	0.89	0.88	0.88	630

Table 1 CNN Model Evaluation Metrics Results

The model exhibited high precision and recall for several classes, particularly Rice_Bacterial_leaf_blight and Rice_LeafScald, achieving values close to or exceeding 90%. This indicates strong classification accuracy for these diseases. However, some classes, such as Rice_BrownSpot and Rice_LeafBlast, showed relatively lower recall, suggesting potential challenges in detecting all instances of these diseases.

The consistently high F1-scores across classes reflect a well-balanced trade-off between precision and recall. Additionally, the macro and weighted averages, both approximately 88%, further validate the model's reliability. The close alignment of these averages suggests that the model performs consistently across all disease categories, benefiting from the balanced dataset used in training and evaluation.
Overall, the results indicate that the CNN model effectively classifies rice and wheat leaf diseases with high accuracy, precision, recall, and F1-scores, making it well-suited for real-world agricultural disease detection. Future enhancements could focus on improving recall for specific disease classes and expanding the dataset with more diverse samples to further refine classification performance.

3.3.2. Confusion Matrix Metrics:
The confusion matrix provides a visual representation of the model's classification performance, where each row represents actual classes, and each column corresponds to predicted classes. Correct classifications appear along the diagonal, while misclassifications are indicated by off-diagonal elements, highlighting cases where the model struggled to distinguish between certain disease categories.

However, certain diseases, such as Rice_LeafBlast, exhibit misclassification trends, often being confused with Rice_BrownSpot and Rice_NarrowBrownSpot. This suggests that these diseases share overlapping visual characteristics, making differentiation more challenging for the model.

The confusion matrix also highlights instances of false positives (incorrectly classified diseases) and false negatives
(missed cases of actual diseases). Such errors can impact the model's practical effectiveness, particularly in agricultural settings where accurate disease identification is essential for timely intervention.

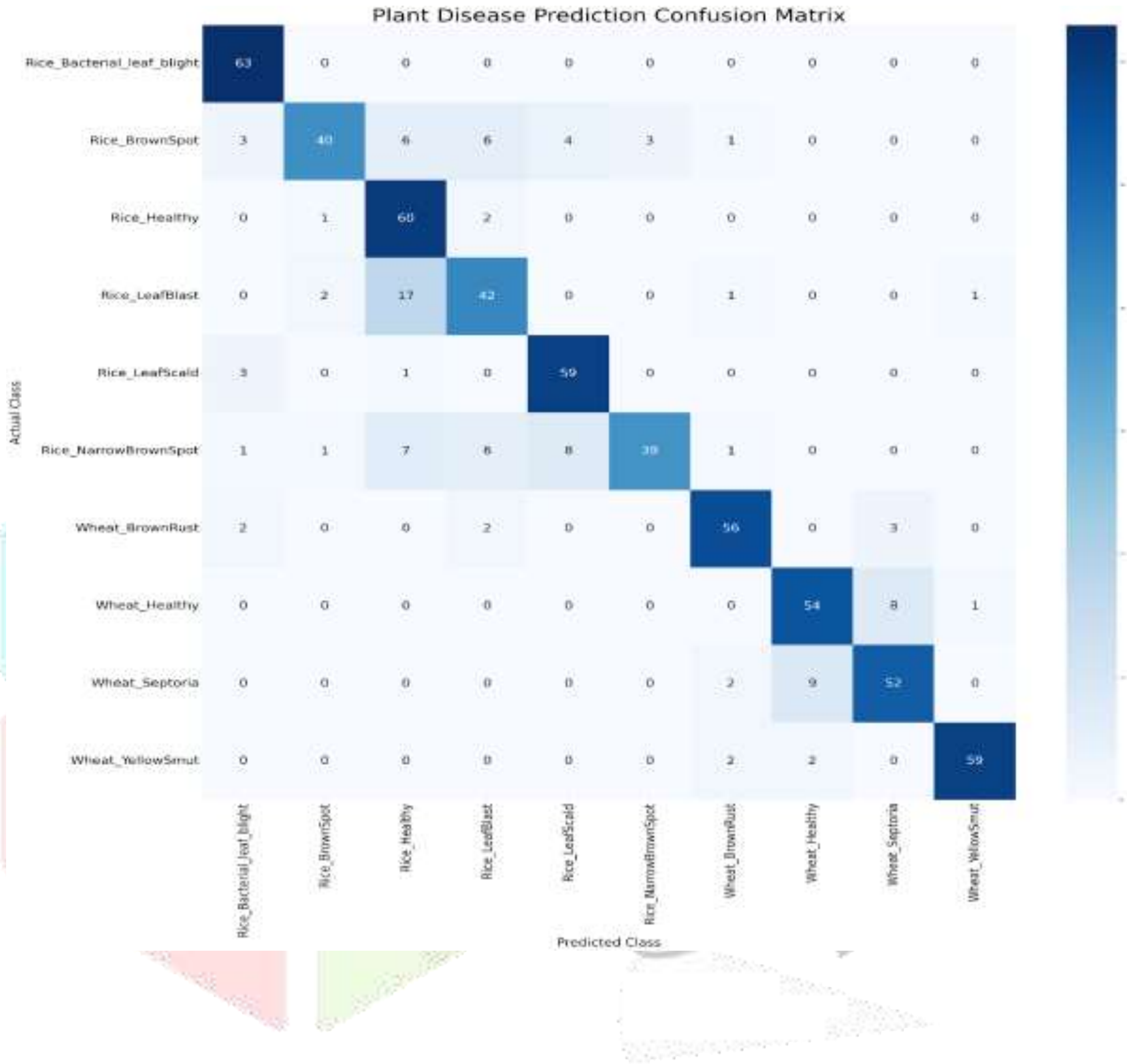

Fig 3. Confusion Matrix of Predicted class vs Actual Class

Additionally, potential class imbalances may influence prediction outcomes, with majority classes being more accurately classified, while minority classes experience slightly lower accuracy. These variations in prediction distribution are reflected in the confusion matrix, indicating areas where the model's classification performance could be further refined.

The CNN model demonstrates strong classification performance, achieving an overall accuracy of 88% and consistently high precision, recall, and F1-scores. Its ability to distinguish between healthy and diseased leaves makes it a valuable tool for precision agriculture. However, further improvements, such as enhancing recall for specific disease classes and incorporating a more diverse dataset, could further strengthen its effectiveness. The comprehensive evaluation metrics and balanced dataset ensure a reliable assessment, supporting its potential for broader deployment in real-world agricultural disease detection.

An analysis of the confusion matrix as shown in Fig. 3 reveals that the model performs exceptionally well in classifying diseases such as Rice_Bacterial_leaf_blight and Wheat_YellowSmut, with minimal misclassification errors. The high concentration of correct predictions along the diagonal reinforces the model's reliability in accurately distinguishing various disease categories.

IV. RESULTS AND DISCUSSIONS

4.1 RESULTS

The CNN model achieved an 88% accuracy in classifying rice and wheat leaf diseases, proving its effectiveness in automated disease detection. It excelled in identifying Rice Bacterial Leaf Blight and Rice Leaf Scald, with precision and recall exceeding 90%. However, differentiating between Rice Brown Spot and Rice Leaf Blast was more challenging due to their similar visual features, leading to lower recall. The confusion matrix showed a high rate of correct classifications, though some misclassifications resulted in false positives and false negatives. With macro and weighted average scores around 88%, the model demonstrated consistent performance across all disease categories. Enhancing recall for specific diseases, diversifying the dataset, and addressing class imbalances could further improve its accuracy. These refinements would enhance the model's reliability, making it a valuable tool for precision agriculture and early disease detection in crops.

Fig 4. Test Image of Healthy Leaf   Fig 5. Predicted Image as Rice Healthy Leaf

Fig 6. Test Image of Bacterial Leaf Blight   Fig 7. Predicted Image as Rice Bacterial Leaf Blight

The CNN model demonstrated an 88% accuracy in classifying rice and wheat leaf diseases, highlighting its effectiveness in automated disease detection. It particularly excelled in identifying Rice Bacterial Leaf Blight, as shown in Fig 6 (Test Image of Rice Bacterial Leaf Blight) and Fig 7 (Predicted Image of Rice Bacterial Leaf Blight), achieving precision and recall values above 90%. Additionally, it successfully classified Healthy Rice Leaves, as seen in Fig 4 (Test Image of Healthy Rice Leaf) and Fig 5 (Predicted Image of Rice Healthy Leaf).

Fig 8. Test Image of Brown Rust Leaf   Fig 9. Predicted Image as Wheat Brown Rust Leaf

Fig 10. Test Image of Healthy Leaf of Wheat

Fig 11. Predicted Image as Wheat Healthy Leaf

When analyzing wheat diseases, the model performed well in classifying Wheat Brown Rust Leaf, as shown in Fig 8 (Test Image of Wheat Brown Rust Leaf) and Fig 9 (Predicted Image of Wheat Brown Rust Leaf). The model also successfully identified Healthy Wheat Leaves, as depicted in Fig 10 (Test Image of Healthy Wheat Leaf) and Fig 11 (Predicted Image of Wheat Healthy Leaf). With macro and weighted average scores around 88%, the model exhibited consistent performance across both rice and wheat disease categories.

To further improve the model's accuracy, enhancing recall for specific diseases, diversifying the dataset, and addressing any class imbalances would be beneficial. These refinements would make the model even more reliable, offering a valuable tool for precision agriculture and early disease detection in crops.

4.2 CONCLUSION

This study demonstrates the effectiveness of deep learning, specifically CNNs, in accurately classifying rice and wheat leaf diseases, achieving 88% accuracy. The model excelled in detecting diseases like Rice Bacterial Leaf Blight and Rice Leaf Scald, though it faced challenges in distinguishing similar conditions such as Rice Brown Spot and Rice Leaf Blast. Despite some misclassifications, its consistent precision, recall, and F1-scores across all classes confirm its reliability for early disease identification. Future enhancements should focus on improving recall for certain diseases, increasing dataset diversity, and addressing class imbalances to enhance overall performance. Integrating this approach with real-time monitoring systems could enable early disease detection, minimize crop losses, and contribute to sustainable farming practices.

4.3 FUTURE SCOPE

The future scope of this study includes enhancing disease classification using advanced deep learning models like Vision Transformers (ViTs) and CNN-RNN hybrids for improved accuracy. Integrating IoT and edge computing can enable real-time disease detection, reducing reliance on cloud processing. Expanding the dataset to include more crops and utilizing hyperspectral imaging can refine detection accuracy. Developing mobile applications for farmers will make AI-driven disease identification more accessible. Collaboration with agricultural experts and policymakers can drive the adoption of these technologies, promoting precision agriculture, sustainable farming, and global food security.

V. ACKNOWLEDGEMENT

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