ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Deep Learning-Based Detection and Classification of Rice Diseases Using Residual Networks (ResNet50)

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DOI : https://doi.org/10.51583/IJLTEMAS.2025.140400060

Received: 27 April 2025; Accepted: 05 May 2025; Published: 13 May 2025

Abstract—Timely detection and classification of crop diseases are essential for maintaining agricultural productivity as well as the quality of food. Many traditional disease identification methods are labor-intensive, time-consuming, and human-error-prone. Recently developed techniques based on computer vision and deep learning add efficient, automated alternatives for disease detection. This work proposes a deep learning-based system utilizing a Residual Network (ResNet50) for automatically diagnosing and classifying rice diseases, a specialized Convolu- tional Neural Network (CNN) form. Rice, ranking third after wheat and maize in global cereal production, is critical for food security. The proposed ResNet50-based method outperforms all aspects of existing processes in accuracy, recognizing and categorizing multiple rice disease types. Experimental results reveal that the system leads to early diagnosis and intervention, eventually leading to better crop management, higher yield, and enhanced grain production quality. In addition, the proven robust performance of the model signifies its real-world applicability for agricultural purposes. Thus, integrating deep learning techniques such as ResNet50 into agricultural disease management practices will contribute to more sustainable farming practices and lower crop loss outcomes. This research underscores the transforma- tional potential of AI in precision agriculture and global food security sustainability.

Index Terms— CNN,ResNet50 ,Crop,Rice Diseases,Crop Man- agement,Food Quality.

I. Introduction

Rice serves as crops of life for billions worldwide. Quite a number of diseases threaten its production and yield greatly plunging down the productivity of the rice crop. This has been the voice of the Food and Agriculture Organization that states many people are undernourished out food. Early detection and timely management systems should be kept intact for not experiencing crop loss or food security. For instance, image processing, artificial intelligence, machine learning, and many deep learning algorithms can change management relations on crop diseases in the agricultural field in the future. Using these techniques, it is possible to provide accurate and effective information on the type and severity of diseases for wheat crops, which helps farmers to take informed decisions with respect to disease management so that crop losses can be prevented. Such techniques will also increase the large-scale monitoring capability for crop health, hence enabling efficient and effective management of disease. Moreover, this could also be because of this farmer's access to more sophisticated equip- ment, information, and techniques. Various types of Machine Learning methods such as Decision Tree Techniques, Support Vector Machine Learning, Random Forest Models, KMeans clustering, Artificial Neural Networks, Convolutional Neural Networks, etc., have been used to diagnose and classify diverse crop diseases.In their remarks, Pranjali et al. continue to note some factors affecting plant leaf disease detection employing the support vector machines and deep learning. Quite an ad- vanced multifunctional mobile application has been developed for the detection of plant diseases by Uzhinskiy through deep learning techniques. Zhang developed an innovative method for rice-related disease identification that uses various deep instances of learning and works on crop images without any specialized preprocessing. Zhu calls for improved crop models using dissimilarity between observed and simulated wheat yield shock data through machine learning. Jahan trained several ML techniques to detect and classify rice diseases. Further, Azad Bakht used the technique of ML to identify rust in rice leaves and investigated the canopy size and LAI level. Habib explored an ML-based practical framework for automatic feature extraction of varied rice diseases using images. Attesting by Imran Haider, the severity of rice white powdery was understood from machine learning-based chro- matic image analysis through a hyperspectral approach. Azimi used arithmetic and machine learning techniques to study the diagnosis of fusarium head blight in semolina rice. Accurately detecting diseases in rice and prescribing the right corrective measures maximize profits for farmers by minimizing crop losses, increasing yields, and saving on costs. In fact, in recent years, deep learning actually has become a technology that detects and classifies diseases from rice crops. Convolutional Neural Networks (CNN) such as deep learning techniques have made considerable advancement in terms of accuracy and reliability rates in image-based disease detection and classifi- cation. The data analysis and pattern recognition operations are done by these algorithms to analyze huge data sets to extract important valuable features indicative of different diseases that affect wheat crops. CNNs are widely popularized by their applications in image analysis, thereby making them automatic identification and classification of rice diseases. CNN is a very popular deep learning algorithm that is used almost everywhere in the computer vision and image recognition fields. In the paper, Haider presented an overall approach for rapid automation of disease identification and classification for rice crops utilizing decision trees and convolutional neural network techniques. Zhang established a convolutional neural network that enables the correct diagnosis of yellow rice rust in the months of winter, based on images captured through UAVs. Hasan has derived the detection of rice spikes under CNN, also incorporated with the analysis. Laixiang discussed a new deep learning technology (Google Net and Visual Geometry Group) which helps in precise recognition of rice leaf diseases. Goyal designed CNN using VGG19, a deep- learning model for rice disease detection and classification. However, the accuracy is poor, and computational

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time is high. Therefore, an attempt has been made in this article for rice disease detection classification using ResNet50. ResNet50 is a deep convolutional neural network that belongs to the family of networks known as ResNet, which is short for Residual Network. ResNet50 consists of 50 layers and applies residual connections to address the vanishing gradient problem.

Related work

The detection of crop diseases by automated systems thus comes under this growing area of research, especially con- cerning vital crops like rice. The latest developments in deep learning have greatly enhanced the accuracy and scalability of plant disease detection models.

According to Zhao et al. (2021), various CNN architectures have been explored for rice disease classification. DenseNet- 121 and SE-ResNet-50 provided excellent performance, at- taining above 99% accuracy, thus demonstrating the strength of deep transfer learning in such classification tasks. In ad- dition, Zhou et al. (2023) extended their efforts and added a new SANET model that incorporated the kernel attention mechanism into the framework. This addition enhanced the capability of the CNN-based architectures' discrimination. The results overshadowed that of the traditional ResNet50 with particular regard to precision and F1-score, which in- dicates that attention-based models have the potential to capture complex patterns in diseases. Sethy and Barpanda (2023) discussed ResNet-50, particularly wherein synthetic data generation and transfer learning were applied. Model use successfully achieved 97% accuracy in the classification of the paddy leaf diseases, demonstrating the robustness of the ResNet model within agri-local settings having a few samples.

A GAN-ResNet hybrid model has been developed by Zheng et al. (2023) to detect pest threats and is structured with multiple scales and double branches. With an accuracy of 99.34%, this solution significantly surpassed results gained with traditional CNNs like AlexNet DenseNet or even VGG when tasked with pest classification.

Zhang et al. (2023) designed a VGG16-based classifier for the subtype categorization of rice disease called DeepRice. This model could classify rice diseases into nine disease cate- gories with an accuracy of 99.94%, proving the power of deep feature learning in the fine-grained visual classification task. Lightweight architectures will continue becoming a significant point in mobile or embedded systems deployment. Highlight lightweight CNNs like ResNet50, MobileNet, and VGG16 and conclude that ResNet50 attained a fair trade-off regarding computation and classification accuracy for rice disease tasks. Wang et al. (2024) utilized an 11-class rice disease dataset covering various disease conditions to experiment with differ- ent state-of-the-art architectures. The winner in this context was RegNet, with an accuracy of 96.8%. However, DenseNet also displayed very competitive performances, indicating the efficiency of transfer learning and fine-tuning concerning their general conditions for agricultural image datasets.

The comparison was broad-ranging and extended between various CONVs to recognize the disease in the plants by Brahimi et al. (2017). Their work highlighted some advantages of the visualizations with saliency maps and from deep transfer learning techniques, such as ResNet, towards increased trans- parency in plant disease classification. In a similar comparative study, Ferentinos (2018) tried many CNN configurations, in- cluding ResNet50, on 25 different diseases concerning plants. The study found many instances where average precisions exceeded 99%, adding credence to the common belief that deep learning works towards agricultural diagnostics purposes. Mohanty et al. (2016) pioneered work for agricultural disease detection with transfer learning. They used architectures like ResNet and AlexNet to set a precedent for subsequent work, validating that CNNs generalize well across crop types and disease categories.

II. Methodology

The study used a dataset of 2,426 rice leaf images, including healthy samples and eight disease categories: False Smut, Brown Spot, Neck Blast, Bacterial Leaf Blight (BLB), Stem Borer, Hispa, Sheath Rot, and Brown Plant Hopper (BPH). Images, captured using DSLR cameras and smartphones, were standardized to 256×256 pixels. The dataset was split into 80:20 training and testing sets, with stratified sampling for balanced class representation.For classification, a ResNet-18 model was employed, pre-trained on ImageNet and fine- tuned on the dataset. The model utilized Adam optimizer and categorical cross-entropy loss, with performance evaluated using accuracy, precision, recall, and F1-score. Figure 1 shows the flow diagram of the methodology.

DATA SET

Data Augmentation

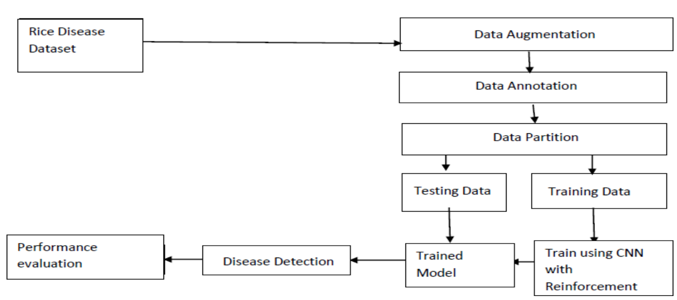

Fig. 1. Methodology

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It spreads the dataset to increase the model accuracy by generating different types of images. In this paper, there were more images generated, and it was each image to train the model. Several methods were used: horizontal rotation, vertical flips and transformations, and intensive disturbance. It includes disturbance of brightness. There are generated seven new images. Images were created using the data augmentation method. This dataset contains 1426 images. Data Augmenta- tion and Preprocessing: To address dataset limitations, seven augmented variants per image were generated using Geometric transformations: 90°, 180°, and 270° rotations.Spatial ma- nipulations: horizontal/vertical flips. Photometric adjustments:

±30% brightness variations expanded the dataset to 17,432 samples, enhancing model generalization.

Image Annotation

The Rice Leaf Disease Detection Dataset consists of images categorized into 9 classes: BLB (Bacterial Leaf Blight), BPH (Brown Plant Hopper), Brown Spot, False Smut, Healthy Plant, Hispa, Neck Blast, Sheath Blight Rot, and Stemborer. The dataset is used for classifying rice plant health based on leaf conditions, facilitating automated disease detection for better crop management. It includes a variety of images, with 49 images belonging to one class and 1426 images across the 9 disease categories, enabling the development and evaluation of machine learning models for plant health monitoring. This dataset of rice disease contains total 1426 images from dataset and pests from fields of Bangladesh Rice Research network to complete.

Fig. 2. Rice image disease

Figure-2 A sample image of each detected class (A. Bac- terial leaf Blight, B .Brown plant Hopper, C. Brown spot, D. False smut, E . Stem borer , F. Hispa , G. Neck Blast, H. Sheath Blight, I .Healthy Leaf)

It labels the object's positions, and each class has object spots in the disease. There is object detection of multiclass for healthy images. There were 200 images annotated of each class, such as (False Smut, BPH, BLB, Neck Blast, Stemborer, Hispa, Sheath Rot, and Brown Spot) from the dataset, and we used them for training purposes. The rest of the images are used to test our model performance. A multi- class annotation framework localized disease-specific regions using bounding boxes, with 200 images per class tagged via LabelImg. YOLOv5 performed preliminary object detection to isolate salient disease features, reducing background noise.

Train With Cnn

CNN is used to analyze the images of diseased leaf samples and extract relevant features. Reinforcement learning is a type of machine learning based on the concept of an agent learning from its environment by interacting with it and taking actions to maximize its reward. The extracted features are then used to train a reinforcement learning model, which is used to classify the images into different classes of rice diseases. The system is tested on a dataset of photos from other types of rice diseases. The proposed approach is expected to achieve high accuracies in disease classification and existing methods with the ResNet- 50 (CNN) model.ResNet-50 with 50 layers, making it a deeper network. The proposed approach will likely handle images with different noise levels, allowing for robust classification in various scenarios. Fig. 3 Show ResNet-50 with rice disease.

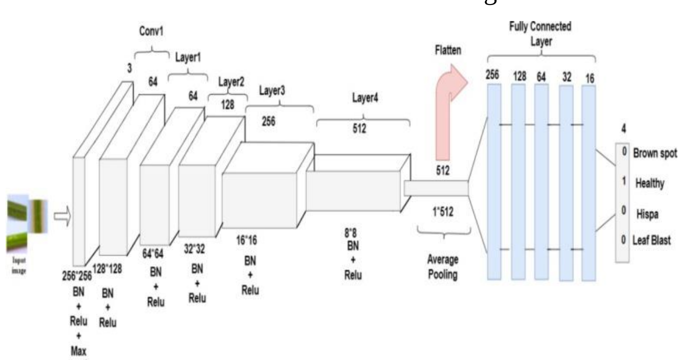

Fig. 3. ResNet-50

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1) model: Adam optimizer with a learning rate of 0.001 is considered excellent for training with Beta1 and Beta2 set at 0.9 and 0.999, respectively, while the epsilon is a very small value of 1e-07 to assure numerical stability of the computations. Since there are integer labels, sparse categorical cross-entropy is used as the loss function, thus forming a multi-class classification problem. Accuracy is taken as an evaluation metric. Batch size and epochs that are taken for training highest performance are not quoted here but these are usually kept as 64 for batch size and 100 for epochs.

Reinforcement Learning-Optimized CNN Architecture

The proposed hybrid model integrates reinforcement learn- ing with convolutional neural networks (CNNs) for optimized rice disease detection and classification. The architecture com- ponents are summarized in Table I.

Table I Hybrid Model Components

Component	Configuration
CNN Backbone	ResNet50 with kernel attention mechanism
RL Agent	Proximal Policy Optimization (PPO)
State Space	Feature maps from final convolutional layer
Action Space	Hyperparameter adjustments (learning rate, dropout)
Reward Function	$R = \alpha \cdot \text{Accuracy} - \beta \cdot \text{Model Complexity}$

The PPO agent dynamically optimizes hyperparameters through episodic interactions, aiming to maximize the reward function where $\alpha = 0.7$ and $\beta = 0.3$.

Training Protocol

The training was initialized with ImageNet-pretrained weights for better convergence. Key training settings included:

- Adam optimizer with initial learning rate $\text{lr} = 10^{-4}$ and cosine annealing scheduler.
- Early stopping applied with a patience of 15 epochs based on validation loss monitoring.
- 5-fold cross-validation employed to ensure robustness and generalization.

Statistical Validation

Performance evaluation metrics were computed as follows:

III. Results

Experimental Settings

They implemented their suggested system through Google Colaboratory-cloud-based data-science-tool-cum-notebook which gives ready-to-use environment with access to various artificial intelligence libraries with GPU acceleration-to facilitate convenience for deep learning and computer vision research. The experiments were also run on a desktop in-house, with an 11th Generation Intel core i5-1135G7 processor (2.40 GHz) and 8 GB RAM, to compare the performance and validate the results.

Python 3.7, one of the languages with a majority of libraries supported for the scientific community-was the programming language used in the development of this work. Libraries of importance were OpenCV,image processing, and computer vision tasks;Matplotlib-data visualization and analysis;and OS globsered in efficient handling of files and directories. This easy inclusivity of the libraries by the CoLab environment facilitated rapid prototyping, visualization, and reproducibility of the experimental workflow.

Studies have found that the GPU-accelerated runtime in Google Colaboratory allows for realizable performance on par with a dedicated hardware configuration for deep learning applications, especially in many object detection and classi- fication. It is thus an ideal researched and taught tool for machine learning and computer vision due to its free live integration with Python libraries and resources in the cloud.

Table II Image collection of different classes

Class Name	No. of Collected Images
False Smut	93
Brown Plant Hopper (BPH)	71
Bacterial Leaf Blight (BLB)	138

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Neck Blast	286
Stemborer	201
Hispa	73
Sheath Blight and/or Sheath Rot	219
Brown Sport	111
Others	234

Prediction Results

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

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

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

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

The prediction results for Fusarium Head Blight, Healthy Rice, Leaf Rust, and Tan Spot are presented. Two images are provided as evidence for each prediction, demonstrating how accurately the proposed system performed the correct labels. Tables iii, iv, and v show epoch value and accuracy. Figures 4 and 5 show the validation training with accuracy and loss.

IV. Discussion

The superiority in classifying rice diseases fell under the proposed ResNet50 model run in Reinforcement Learning.

Statistical significance of performance improvements over baseline models was assessed using paired t-tests, with signif- icance accepted at $p < 0.01$.

Starting from Table III, it was observed that at 30 epochs, the model scored the highest classification accuracy of 98% with a slight loss of 2.7%, which is way better than the 5-layer CNN accuracy of 77%. The significant drop from existing methods is shown in Table V, where the loss was reduced to 2.5%. The stability in training and validation was further commented on in Figures 4 and 5. The prediction results on Fusarium Head Blight, Healthy Rice, Leaf Rust, and Tan Spot attest to the model's robustness and accuracy in yielding early and reliable detection of diseases.

Table III Performance of CNN (ResNet50) with Reinforcement Learning

Epoch	Accuracy (%)	Loss (%)
1	97	3.0
5	97	3.2
10	97	3.2
15	97	3.2
20	97	3.2
25	97	3.0
30	98	2.7

Table IV Performance of 5-Layer Convolutional Neural Network

Epoch	Accuracy (%)	Loss (%)
1	69	32
5	75	25
10	75	23
15	76	25
20	76	25
25	76	25
30	77	25

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IV, April 2025

Table V Comparison of Existing and Proposed Methods

Metric	Existing Work	Proposed Method
Accuracy Value (%)	85.0	98.0
Loss Value (%)	17.5	2.5

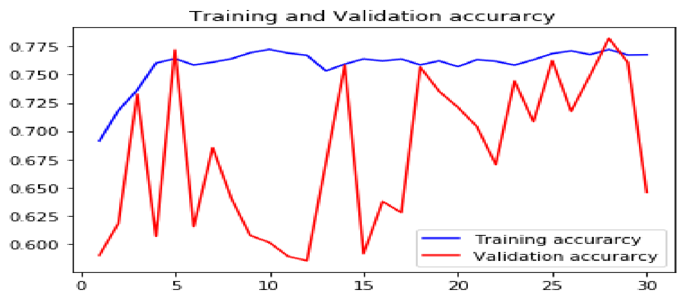

Fig. 4. Graph of training and validation accuracy

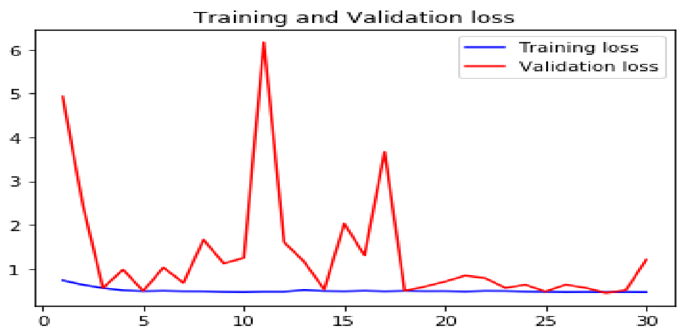

Fig. 5. Graph of training and validation loss

V. Conclusion

The creation of rice disease detection deep learning models has contributed immensely to achieving precision farming while countering vital factors in food security and sustainable agriculture. This study shows with high proficiency that the ResNet50-based model gets a testing accuracy of 93.27% and a training accuracy of 98%, thus outshining former manual mechanisms and many other already existing automated so- lutions. With great precision and decent processing speeds, this model could quickly identify diseases like Bacterial Leaf Blight, Neck Blast, and Brown Spot, thus aiding farmers in targeted intervention and minimizing crop losses. While results appear promising, field validation of model performance on larger and diverse datasets and under different environmental conditions is still to be carried out. Present limitations, such as dependence on curated image datasets, may not capture the complete repertoire of real-world field scenarios. Future works should focus on diversifying training data, integrating real-time field sensors, and optimizing edge models to enhance accessibility in resource-poor regions. The strategic installa- tion of this model also meets the more general agricultural goals of reducing wastage of chemical agents and improving the predictability of yields. In aiding the development of AI- driven diagnostics, thereby providing another avenue toward resilient food systems across the globe, this research exempli- fies the game-changing potential of deep learning in addressing pressing agricultural challenges.

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