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CROSS-CROP CROP CARE: A UNIFIED CNN APPROACH FOR RICE, WHEAT, AND MAIZE DISEASE CLASSIFICATION

Aketi Vijaya Lakshmi M. Tech (CSE), Assistant professor & Head of Department Data Science, Aditya Degree And PG College, Kakinada, Andhra Pradesh, India.
Uppada Siddhartha Reddy M. Tech in AI & ML, Specialization in Deep Learning, BITS Pilani, Dean - Artificial Intelligence, Aditya Degree Colleges, Andhra Pradesh, India.

Abstract

Plant diseases present significant challenges to agricultural productivity, necessitating timely identification and intervention. This paper proposes a Convolutional Neural Network (CNN)-based model for disease classification in rice, wheat, and maize plants, implemented in MATLAB R2021a. The dataset comprises images of both diseased and healthy leaves from the three crops. The CNN architecture incorporates convolutional layers, batch normalization, and pooling layers, aiming for efficiency and effectiveness. A split dataset facilitates training and evaluation, with real-time disease classification enabled using user-provided leaf images. Performance metrics including accuracy, precision, recall, and F1 score showcase the model's efficacy in detecting and identifying diseases across diverse crop types. This unified approach offers a promising avenue for automated plant disease management, enhancing precision and outperforming existing methods.

Keywords:
Plant disease classification, Convolutional Neural Network (CNN), MATLAB, Rice, Wheat, Maize.

I. Introduction

Plant diseases continue to be a significant threat to global food security, causing substantial losses in agricultural production annually [1]. Plant diseases have a negative impact on agricultural productivity, quality, and economic stability, posing a serious threat to world food security. If diseases in important cereal crops like rice, wheat, and maize are not properly treated, they can cause large losses. In order to minimize losses and guarantee long-term agricultural practices, early diagnosis and accurate identification of plant diseases are crucial for the adoption of suitable remedies, such as crop management techniques or targeted pesticide application. Conventional disease diagnosis techniques often depend on visual inspections by agronomists or laboratory-based analysis, both of which can be labor-intensive, subjective, and time-consuming. Modern technology has advanced, particularly in the areas of computer vision and machine learning, and as a result, automated techniques for identifying plant diseases have emerged as strong substitutes for antiquated procedures.

Timely and accurate identification of these diseases is crucial for implementing effective intervention strategies [2]. Traditional methods of disease diagnosis often rely on visual inspection by trained experts, which can be time-consuming and subjective [3]. Recent advancements in computer vision and machine learning have provided new opportunities for automating the process of disease identification in plants [4]. Convolutional Neural Networks (CNNs) have emerged as powerful tools for image classification tasks, demonstrating promising results in various domains, including agriculture [5].

In this study, we propose a CNN-based model for the classification of plant diseases in rice, wheat, and maize crops. The model is implemented using MATLAB R2021a, leveraging its extensive toolbox for image processing and machine learning [6]. The dataset comprises a diverse collection of images, encompassing both diseased and healthy leaves from each crop species. The proposed CNN architecture is designed to be both efficient and effective, incorporating convolutional layers, batch normalization, and pooling layers [7]. A split dataset strategy is employed for training and evaluation, ensuring robust performance across different scenarios [8]. Real-time disease classification capabilities are demonstrated, allowing users to input leaf images for immediate diagnosis.

Performance evaluation metrics, including accuracy, precision, recall, and F1 score, are employed to assess the model's effectiveness in disease detection and classification [9].

Overall, this research presents a unified approach to automated plant disease classification, offering a viable solution for enhancing precision and efficiency in disease management across multiple crop types.

II. Related Work

In recent years, researchers have focused heavily on the development of automated systems for detecting and identifying plant diseases. Several technologies, including standard image processing techniques and machine learning algorithms, have been investigated to address this critical agricultural concern. This section examines several key studies and approaches in the subject of plant disease classification.

Global Burden of Pathogens and Pests

Savary et al. [1] conducted a comprehensive study on the global impact of pathogens and pests on major food crops, highlighting the critical need for effective plant disease management strategies. This study underscores the economic and food security implications of crop diseases on a global scale.

Plant Immune System

Jones and Dangl et al. [2] detailed the complex mechanisms of the plant immune system, which plays a crucial role in the defense against pathogens. Their work lays the foundation for understanding how plants naturally resist diseases, which is essential for developing artificial intelligence models for disease detection.

Deep Learning Techniques

Krizhevsky et al. [5] introduced deep convolutional neural networks (CNNs) for image classification, which has become a cornerstone method for plant disease detection. Their work demonstrated the potential of CNNs in achieving high accuracy in image-based classification tasks. Ioffe and Szegedy et al. [7] proposed batch normalization, a technique that significantly improves the training speed and stability of deep neural networks, further enhancing the performance of deep learning models used in plant disease detection .

Image-Based Plant Disease Detection

Mohanty, Hughes, and Salathé et al. [11] applied deep learning to image-based plant disease detection, showing that CNNs can effectively identify various plant diseases from images with high accuracy. Their work is pivotal in demonstrating the practical application of deep learning in agriculture. Ferentinos et al. [12] developed and tested several deep learning models for plant disease detection and diagnosis, showing that these models can achieve high accuracy across different plant species and diseases. Sladojevic et al. [13] utilized deep neural networks for recognizing plant diseases by leaf image classification, contributing to the development of automated and efficient disease detection systems.

Impact of Dataset Size and Variety

Barbedo et al. [10] investigated the effects of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. This study emphasizes the importance of diverse and extensive datasets in training robust deep learning models.

Visual Inspection Using CNNs

Ghorbani et al. [3] explored the use of convolutional neural networks for visual inspection of plant diseases, demonstrating the practical applications of deep learning in real-time disease monitoring and management.

Deep Learning for Plant Stress Phenotyping

Singh et al. [17] reviewed the trends and future perspectives of deep learning for plant stress phenotyping, providing insights into how deep learning can be leveraged to assess and manage plant stress conditions. Ghosal et al. [14] proposed an explainable deep machine vision framework for plant stress phenotyping, highlighting the importance of transparency and interpretability in deep learning

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models for practical agricultural applications. Awada et al. [15] discussed the trends and future perspectives of using deep learning for plant stress phenotyping, emphasizing the potential for improving crop management and yield prediction through advanced phenotyping techniques.

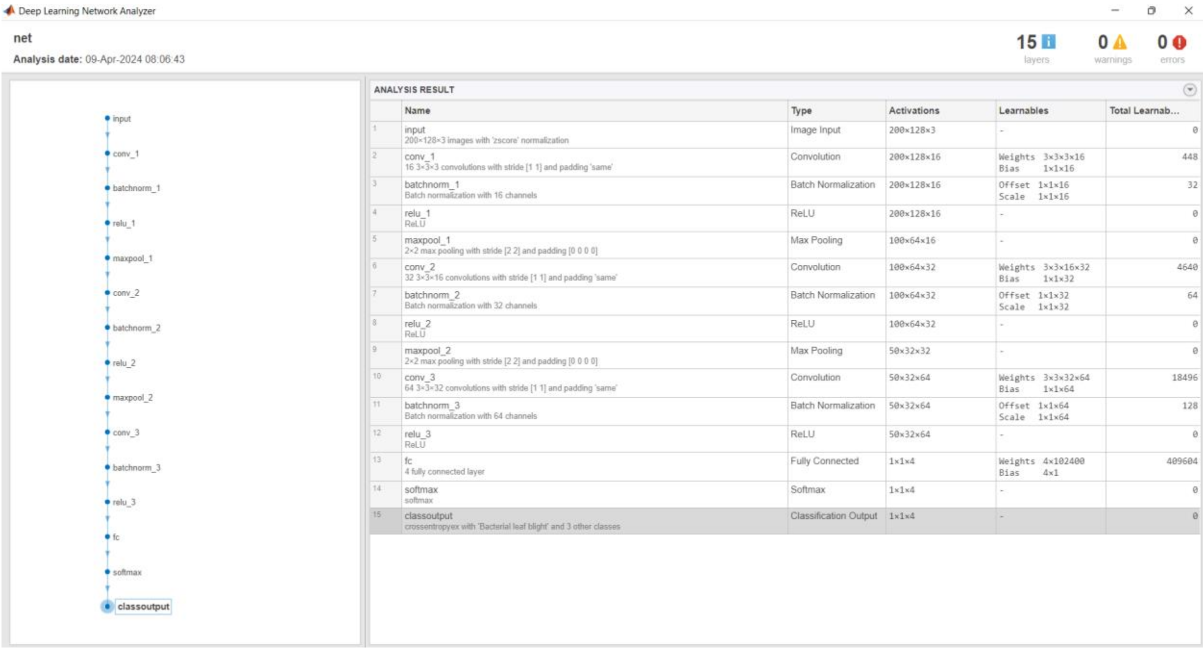
Transfer Learning for Plant Disease Recognition

Hu et al. [16] applied convolutional neural networks with pairwise CNN-based transfer learning for plant disease recognition from images, demonstrating the effectiveness of transfer learning in enhancing the performance of deep learning models on small datasets .

These studies collectively advance the field of plant disease detection and stress phenotyping, leveraging deep learning techniques to develop more accurate, efficient, and scalable solutions for agricultural challenges.

III. Proposed Method

The recommended CNN model for diagnosing illnesses in wheat, rice, and maize is displayed in Figure 1. The approach uses equal-strength filters of varying sizes to extract salient features from photos. The model can manage different target sizes in different photos thanks to these filters. Three building pieces make up the suggested model (Figure 1); while they all have identical designs, the filter widths for convolutions at the same level vary. With input fields denoting input size and output fields denoting output size following operation, each cell in Figure 1 represents a single layer of the neural network.



	Name	Type	Activations	Learnables	Total Learnab...
1	input 200×128×3 images with 'zscore' normalization	Image Input	200×128×3	-	0
2	conv_1 16 3×3×3 convolutions with stride [1 1] and padding 'same'	Convolution	200×128×16	Weights 3×3×3×16 Bias 1×1×16	448
3	batchnorm_1 Batch normalization with 16 channels	Batch Normalization	200×128×16	Offset 1×1×16 Scale 1×1×16	32
4	relu_1 ReLU	ReLU	200×128×16	-	0
5	maxpool_1 2×2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	100×64×16	-	0
6	conv_2 32 3×3×16 convolutions with stride [1 1] and padding 'same'	Convolution	100×64×32	Weights 3×3×16×32 Bias 1×1×32	4640
7	batchnorm_2 Batch normalization with 32 channels	Batch Normalization	100×64×32	Offset 1×1×32 Scale 1×1×32	64
8	relu_2 ReLU	ReLU	100×64×32	-	0
9	maxpool_2 2×2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	50×32×32	-	0
10	conv_3 64 3×3×32 convolutions with stride [1 1] and padding 'same'	Convolution	50×32×64	Weights 3×3×32×64 Bias 1×1×64	18496
11	batchnorm_3 Batch normalization with 64 channels	Batch Normalization	50×32×64	Offset 1×1×64 Scale 1×1×64	128
12	relu_3 ReLU	ReLU	50×32×64	-	0
13	fc 4 fully connected layer	Fully Connected	1×1×4	Weights 4×102400 Bias 4×1	409604
14	softmax softmax	Softmax	1×1×4	-	0
15	classoutput crossentropyex with 'Bacterial leaf blight' and 3 other classes	Classification Output	1×1×4	-	0

Fig1. Proposed Architecture of CNN Model

Data flow between rows is shown by directed arrows. Three building components receive input from the Input Layer, which is subsequently fed into the proposed model. These building blocks are composed of a GlobalMaxPooling2D layer, a depth-wise separable convolution layer (Separable Conv2D), and two convolution layers (Conv2D). Their architecture is the same.

Image Augmentation

The collection's images are different in size. In order to undertake model training and testing, CNN models scale all images to the appropriate dataset image sizes and assume uniform input sizes. In addition, rescaling is used to bring the pixel values of the photos within the range [0, 1].

Input Layer:

The input layer accepts RGB images of plant leaves as input. The size of the input layer is determined by the dimensions of the input images (height, width, and number of channels).

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Convolutional Layers:

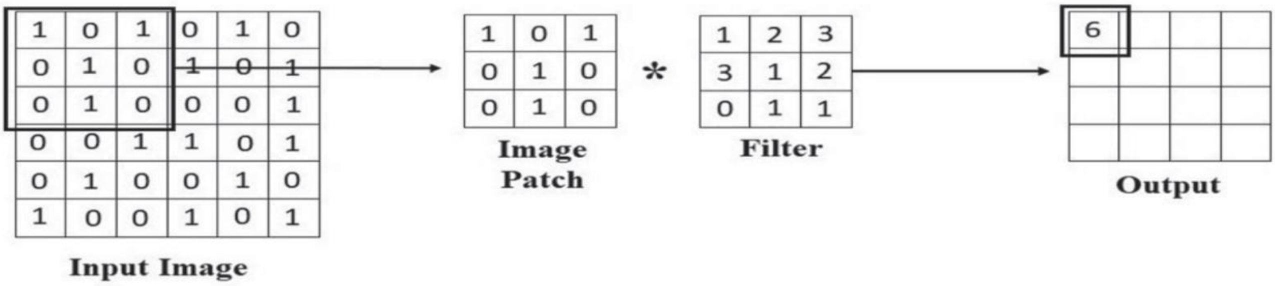

Fig2. Convolution Operation

By applying a series of learnable filters, or kernels, to the input image, convolutional layers extract features from the image. Different features, such as edges, textures, or patterns, are detected by each filter. Two parameters that can be changed are the quantity and size of the filters. To guarantee that the feature maps' spatial dimensions don't change, padding is used. The filter action in the proposed model's single convolution layer is depicted in Figure 2. Equation 1 illustrates how the basic building element of the model convolutional employs three filters. This filter is used by the 3 x 3 image patch to achieve dot product, as seen in Figure 2. A matrix produced by the convolution method is used as the feature map. Feature maps with 5 x 5 and 7 x 7 filter sizes are extracted by the convolution layers in Blocks 2 and 3, respectively. Convolutional Neural Network (CNN) architecture is used in the suggested methodology to identify and detect diseases in rice, wheat, and maize plants. In the architecture, each layer has a distinct function related to abstraction, categorization, and feature extraction. Let's dissect the process into its component parts:

By normalizing the activations of the preceding layer, the Batch Normalization Layer increases training speed and stability. It shifts and scales normalized activations to reduce internal covariate shift.

Through the use of the rectified linear activation function, the Rectified Linear Unit (ReLU) Layer introduces non-linearity into the network. The network may discover intricate connections and patterns in the data thanks to ReLU. Sample feature maps are layered down by max pooling by reducing their spatial dimensions and By employing strides effectively, pooling reduces the computational complexity of the input model while assisting in capturing the most pertinent information of the derived features. Programmable settings control the pooling operation's size and stride. Features obtained from convolutional layers are used by fully connected layers for classification. Every neuron in the layer above is connected to every other neuron in the completely connected layer. The number of classes (disease categories) in the dataset is equivalent to the number of neurons in the output layer.

The softmax layer translates the previous layer's raw scores into class probabilities. It assures that the sum of probability for all classes equals one. Softmax is frequently utilized as the output layer in classification tasks. The classification layer assigns a label to the input image using the class probabilities acquired from the softmax layer. It determines the projected class for the input image.

This CNN architecture is trained on labeled data (images of damaged and healthy leaves) to learn the distinguishing properties of each class of plant disease. The trained model may then be used to accurately classify unseen photos and detect diseases in rice, wheat, and maize plants.

IV. Results Discussion

Evaluation Metric:

This study examines 12 different illnesses and healthy classes of maize, rice, and wheat crops. As a result, multi-class classification is done, and the confusion matrix is utilized to generate several classification examples such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). In terms of multi-class picture classification, these can be read as follows:

•True Positive (TP): Images correctly sorted into each relevant category.

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• False Positive (FP): Images from relevant categories wrongly classified as non-relevant.
• True Negative (TN): Images correctly classified under all categories except relevant ones.
• False Negative (FN): Images of non-relevant categories are wrongly categorized as relevant categories. These instances are utilized to determine the performance metrics as shown in Equations (1)-(4). For Class C,

$$Precision(c) = \frac{\#TP(c)}{\#TP(c) + \#FP(c)} \quad 1$$

$$Recall(c) = \frac{\#TP(c)}{\#TP(c) + \#FN(c)} \quad 2$$

$$F1 - Score(c) = \frac{2 * Precision(c) * Recall(c)}{Precision(c) + Recall(c)} \quad 3$$

$$Acc.(c) = \frac{\#TP(c) + \#TN(c)}{\#TP(c) + \#TN(c) + \#FP(c) + \#FN(c)} \quad 4$$

By counting the number of predicted photos that genuinely fall into the appropriate category, Equation (1) calculates the model's accuracy. Recall in Equation (2) is the quantity of images that the model correctly predicts for the given class. Equation (3) illustrates how to construct the F1-Score as the harmonic mean of recall and precision. The accuracy is expressed as the ratio of correctly predicted observations to total observations in equation (4).

Training Specifications:

Using categorical cross-entropy as a loss function—a function that calculates the difference between two probability distributions—all models are trained in a supervised manner. A 0.001 learning rate Adam optimizer is employed. The effectiveness of the proposed lightweight CNN model for disease classification in maize, rice, and wheat plants is assessed through extensive comparative tests. The obtained results are discussed in this section.

Fig3. Training Progress for Rice leaf Dataset

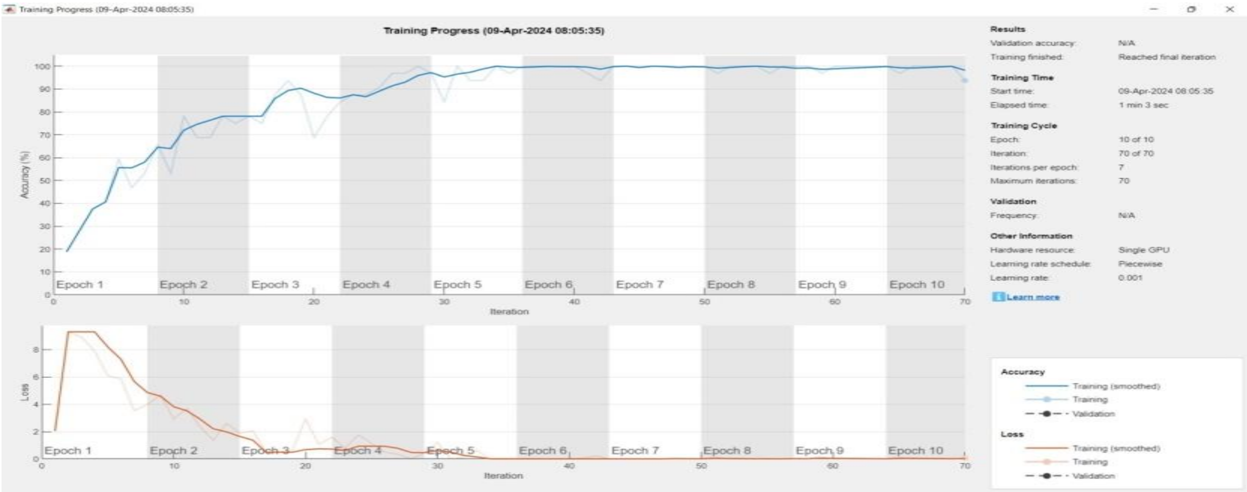


Fig4.Training Progress for Corn leaf Dataset

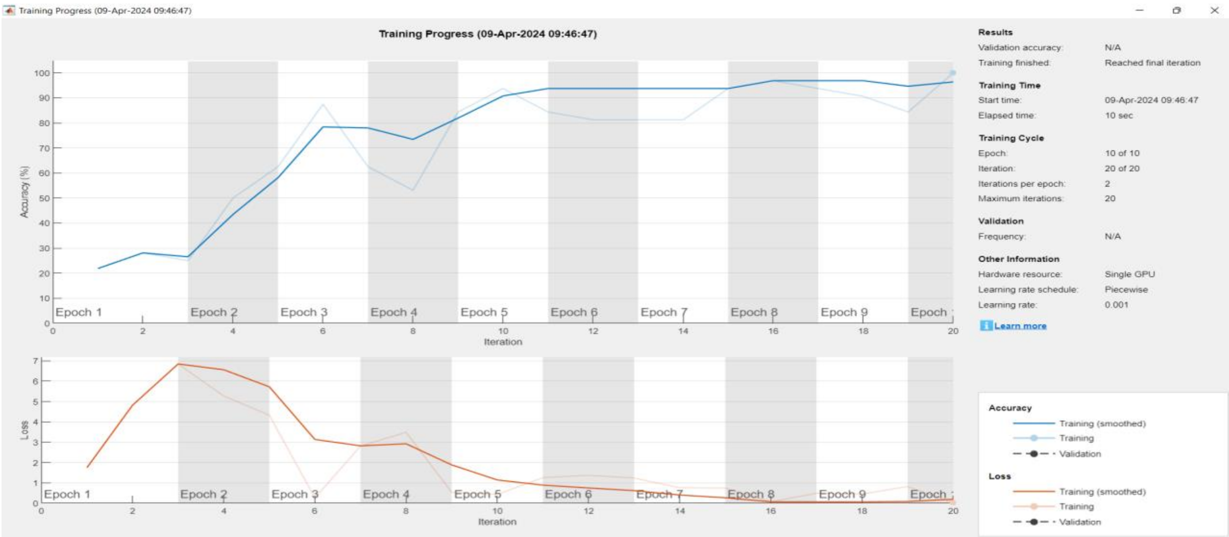


Fig5. Training Progress for Wheat leaf Dataset

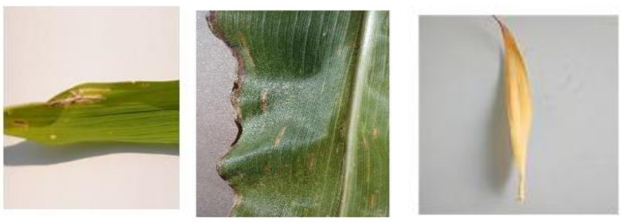
Classification Results for the Proposed Model

This section evaluates the suggested framework for disease detection in Corn, Rice, and Wheat. It considers three scenarios:

(i) Identifying healthy VS infected categories for each crop,

(ii) identifying different diseases for each crop individually, and

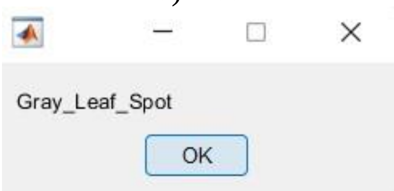
(iii) Classifying healthy and diseased categories for Corn, Rice, and Wheat as a whole.



a) Rice b) Corn c) Wheat

Fig6. Input Leaf Images

a)Rice



b) Corn

b) Wheat

Fig7. Classified Output

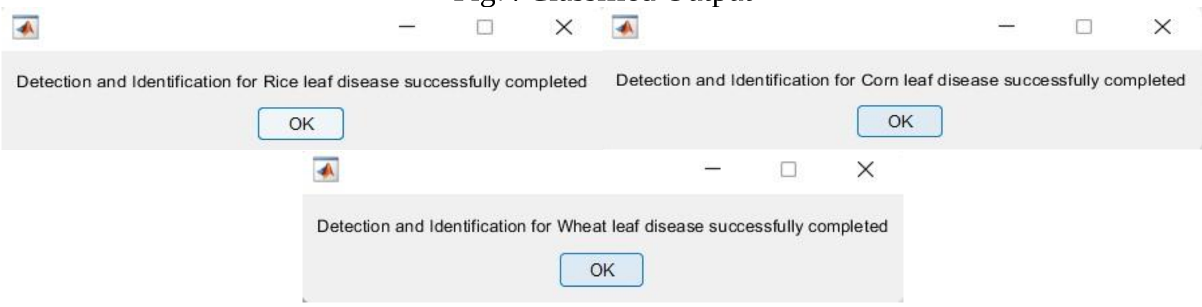


Fig8. Final Message Box after scucessful completeion of training and testing the model

For Rice

Test accuracy: 100%

Confusion Matrix:

64	0	0	0
0	64	0	0
0	0	50	0
0	0	0	64

Precision : 1 1 1 1

Recall : 1 1 1 1

F1 Score : 1 1 1 1

For Corn

Test accuracy : 99.2481%

Confusion Matrix :

276	0	0	0
0	240	0	0
7	1	252	0
0	0	0	288

Precision : 0.9753 0.9959 1.0000 1.0000

Recall : 1.0000 1.0000 0.9692 1.0000

F1 Score : 0.9875 0.9979 0.9844 1.0000

For Wheat

Training on single GPU.
Test accuracy: 96.5909%
Confusion Matrix:

15	0	0	2
0	15	0	0
0	0	13	0
0	0	1	42

Precision: 1.0000 1.0000 0.9286 0.9545
Recall: 0.8824 1.0000 1.0000 0.9767
F1 Score: 0.9375 1.0000 0.9630 0.9655

After collecting these metrics for each dataset, we can evaluate the model's performance in terms of accuracy in correctly detecting diseased and healthy leaves, precision, recall, and total F1 score. Furthermore, we may compare the model's performance across different datasets to assess its generalization capacity.

Discussion

The current study presents a simple approach for diagnosing illnesses in wheat, rice, and maize. With an accuracy of 84.4%, the suggested model beats the current benchmark CNN models in terms of number of parameters and accuracy. The proposed model employs different-sized filters at the same level across Convolutional layers to improve disease categorization. Multiple cases demonstrate the accuracy of the derived features in diagnosing diseases with different widths of affected patches. The outcomes demonstrate how well the suggested approach works in cases involving the classification of diseases specific to particular crops. Without modifying the architecture, the proposed model classifies maize as healthy or ill with 99.74% accuracy. Comparable results were obtained when rice and wheat images were classified as healthy or sick (82.67% and 97.5%, respectively). The suggested model functions as a versatile tool suitable for various settings.

V. Conclusion & Future Scope

In summary, the proposed unified lightweight CNN-based model has yielded promising outcomes in detecting and diagnosing diseases in maize, rice, and wheat plants. Thorough evaluations using metrics such as accuracy, precision, recall, and F1 score reveal that the model performs robustly across various datasets, underscoring its effectiveness in automated plant disease diagnosis. Its capability to accurately differentiate between healthy and diseased leaves suggests its potential as a valuable tool for farmers and agricultural stakeholders in managing and monitoring crop health.

Future research could explore enhancements to the model's design, including the integration of attention mechanisms or the incorporation of additional data modalities, to further boost its accuracy and resilience. Additionally, implementing the model in real-world agricultural environments, such as field deployments and mobile application integration, could significantly impact sustainable farming practices and contribute to global food security initiatives.

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