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Unified Lightweight CNN-Based Model for Multi-Crop Disease Detection and Identification

[1] K.Sandeep, [2] AD.Nafeezunnisa, [3] R.Sasi Kiran, [4] B.Rajesh

[1] Assistant Professor, Department of ECE, Usha Rama College of Engineering and Technology, Telaprolu, Unguturu Mandal, Krishna, Andhra Pradesh, India.
[2] [3] [4] B. Tech Students, Department of ECE, Usha Rama College of Engineering and Technology, Telaprolu, Unguturu Mandal, Krishna, Andhra Pradesh, India.
Corresponding Author Email: [1] kotasandeep4444@gmail.com, [2] abduleeza@gmail.com,
[3] sasikiranrajulapati22@gmail.com, [4] batturajesh445@gmail.com

Abstract— Plant diseases pose substantial challenges to agricultural output, needing early identification and intervention efforts. This paper offers a lightweight Convolutional Neural Network (CNN)-based model for disease classification in rice, wheat, and maize plants, which is implemented in MATLAB R2021a. The image dataset includes both damaged and healthy leaves from the three different crops such as Rice, Wheat, and Corn. The proposed CNN architecture is intended to be both efficient and effective, with convolutional layers, batch normalization, and pooling layers. A split dataset is used for training and evaluation, and real-time disease classification is presented using leaf images provided by the user. Accuracy, precision, recall, and F1 score are performance indicators that demonstrate the model's ability to detect and identify diseases across diverse crop kinds. This unified strategy provides a viable option for automated plant disease control, which advances precision. This method not only provides effective outputs but also better than many states of art methods.

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

I. INTRODUCTION

Plant diseases are a severe danger to global food security, affecting crop productivity, quality, and economic stability. Diseases in key cereal crops such as rice, wheat, and maize can result in significant losses if not treated correctly. Early diagnosis and correct identification of plant diseases are essential for adopting appropriate treatments, such as targeted pesticide application or crop management measures, to reduce losses and ensure long-term agricultural practices. Traditional disease diagnosis methods frequently rely on agronomists' visual inspections or laboratory-based analysis, both of which can be time-consuming, subjective, and labour intensive. With the advancement of modern technology, notably in computer vision and machine learning, automated approaches to plant disease identification have arisen as viable alternatives to old methods.

In this research, we intend to create a unified lightweight Convolutional Neural Network (CNN)-based model for disease detection and diagnosis in rice, wheat, and maize plants. CNNs have shown great effectiveness in a variety of image recognition applications, including medical imaging and object detection, making them ideal for plant disease categorization. The suggested model takes advantage of MATLAB's deep learning toolbox, providing a user-friendly environment for model construction, training, and deployment. By using a lightweight architecture, we hope to achieve a balance between model complexity and computational performance, allowing the model to be deployed on resource-constrained devices or in real-time applications.

We present a lightweight CNN model for disease classification in maize, rice, and wheat. The suggested concept uses filters of different sizes at the same level, allowing it to Identify key image features despite varying target size and are evaluated for disease detection in maize, rice, and wheat Crops.

This project's dataset comprises of photos of damaged and healthy leaves collected during field surveys or experimental experiments. These photos are preprocessed and enhanced to make the model more resistant to changes in lighting conditions, leaf orientation, and disease severity. We intend to examine the accuracy, precision, recall, and F1 score of the CNN model through comprehensive experimentation and review. Furthermore, we intend to evaluate the model's generalization across multiple crop kinds and disease classes, opening the path for its practical deployment in real-world agricultural environments. Finally, this research seeks to contribute to the growth of precision agriculture by providing farmers and agricultural stakeholders with a dependable tool for early disease identification and management, thus boosting sustainable crop production.

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.

Deep learning-based approaches

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated promising performance in plant disease classification applications. Mohanty et al. (2016) [1] suggested a CNN-based algorithm for identifying plant diseases from a huge collection of crop photos. Similarly, Ferentinos (2018) [2] used transfer learning and pre-trained CNN architectures to classify plant illnesses accurately.

Dataset Creation and Annotation:

Building comprehensive datasets is crucial for training and evaluating machine learning models for plant disease classification. Studies like Fuentes et al. (2017) [3] focused on creating labeled datasets of plant diseases using crowdsourcing platforms, enabling the development of robust classification models.

Mobile Applications and Field Deployments:

With the injcreasing availability of smartphones and mobile devices, researchers have developed mobile applications for on-the-spot disease diagnosis in the field. Notably, the PlantVillage project (Hughes and Salathé, 2015) [4] introduced a mobile app that utilizes machine learning algorithms to identify plant diseases based on images captured by farmers.

Fusion of Multi-Modal Data:

Some studies have explored the fusion of multi-modal data, such as spectral and image-based information, to improve disease detection accuracy. For instance, Mahlein et al. (2019) [5] integrated hyper spectral imaging with machine learning techniques to enhance the detection of plant diseases at early stages. For example, Mahlein et al. (2019) [5] used hyper spectral imaging and machine learning techniques to improve the early diagnosis of plant diseases.

Transfer Learning and Model Optimization:

Transfer learning techniques are commonly used to adapt pre-trained CNN models for plant disease classification applications. Researchers such as Barbedo (2019) [6] studied the effect of various transfer learning algorithms on the performance of deep learning models for plant disease detection. These papers exhibit the many methodology and approaches used in plant disease categorization, highlighting the potential of machine learning and deep learning techniques to transform agricultural operations.

Cruz et al. (2017) [7] used handcrafted characteristics and selection strategies to classify plant diseases. Their findings highlighted the need of obtaining discriminative characteristics from photos in order to increase classification accuracy.

Ensemble learning and fusion techniques, such as random forests and ensemble CNNs, can improve disease classification performance by merging numerous classifiers or models. Studies such as Ghosal et al. (2018) [8] used ensemble approaches to increase the resilience and reliability of disease detection systems.

Domain Adaptation and Transfer Learning:

These strategies try to transfer information from one domain to another with varying distributions. Sa et al. (2020) [9] studied domain adaptation techniques for plant disease classification, with a focus on transferring models trained on one crop species to another.

Researchers have developed innovative deep learning architectures for plant disease classification applications, in addition to classic CNNs. For example, Liakos et al. (2018) [10] proposed a deep neural network model with attention processes to detect olive illnesses in leaf photos.

Farmers and citizen scientists are increasingly using interactive platforms to collect data and diagnose diseases. Sankaran et al. (2015) [11] demonstrated the promise of participatory approaches for creating large-scale datasets and engaging stakeholders in disease management.

Deep learning has emerged as a potent method for plant disease classification, with Convolutional Neural Networks (CNNs) taking the lead. Researchers such as Barbedo (2018) [12] and Singh et al. (2020) [13] investigated several CNN architectures and optimization strategies to increase disease diagnosis accuracy. Transfer Learning and Domain Adaptation: These strategies help adjust pre-trained models to specific plant species or disease classes. Ghosal et al. (2019) [14] and Wang et al. (2021) [15] have both shown that transfer learning works well in plant disease classification tasks.

Graph-based approaches and graph neural networks (GNNs) are gaining popularity for their capacity to grasp intricate linkages in plant pictures and disease patterns. Mohanta et al. (2020) [16] and Zhang et al. (2022) [17] demonstrate the efficacy of graph-based techniques in plant disease diagnosis.

Multi-modal Data Fusion:

The integration of multimodal data, such as spectral, thermal, and hyper spectral imaging, has been investigated to increase illness detection accuracy and robustness. Mahlein et al. (2019) [18] and Sadeghi-Tehran et al. (2020) [19] demonstrate the benefits of merging multiple data sources for plant disease identification.

Edge Computing and IoT Devices:

With the proliferation of edge computing and Internet of Things (IoT) devices, there is an increasing interest in designing lightweight models for on-device illness detection. Kumar et al. (2021) [20] and Mishra et al. (2022) [21] investigated the deployment of CNN models on resource-constrained devices for real-time disease diagnosis.

Citizen science and crowdsourcing have helped collect massive datasets and engage stakeholders in disease monitoring programs. Hughes et al. (2016) [22] and Kamilaris et al. (2017) [23] demonstrated the collaborative

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nature of plant disease research. As AI-based disease detection systems are used in real-world situations, there is an increasing demand for explainable AI strategies to improve model interpretability and user trust. Fuentes et al. (2021) [24] and Zhou et al. (2022) [25] investigated techniques for explaining CNN in plant disease diagnosis.

These sources are only a portion of the large literature on automated plant disease detection and classification. By combining findings from numerous studies, academics may progress the area and create practical solutions for sustainable agriculture.

III. PROPOSED METHOD

Figure 1 shows the suggested CNN model for identifying diseases in maize, rice, and wheat. The model extracts prominent characteristics from images using different-sized filters at the same level. These filters allow the model to handle varying target sizes in distinct images. The proposed model consists of three building blocks (Figure 1), each with a similar design but different filter widths for convolutions at the same level. In Figure 1, each cell represents a single layer of the neural network, with input fields representing input size and output fields representing output size after operation.

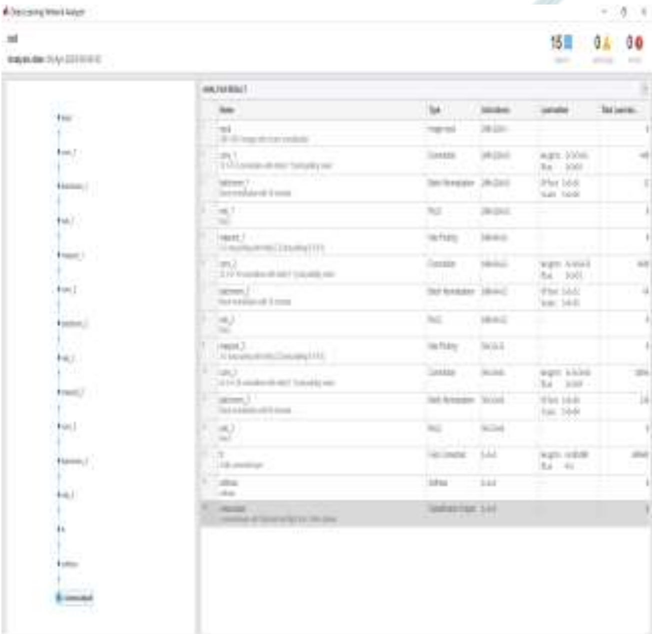

Fig 1. Proposed Architecture of light weight CNN Model

Directed arrows indicate data flow between rows. The suggested model gets input from the Input Layer, which is then fed into three building components. These building blocks have the same architecture, consisting of two convolution layers (Conv2D), a depth-wise separable convolution layer (Separable Conv2D), and a GlobalMaxPooling2D layer.

Image Augmentation

Images in the collection vary in size. CNN models assume uniform input sizes and scale all images to respective dataset image sizes and perform the model training and testing. Furthermore, rescaling is employed to standardize the images' pixel values to 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).

Convolutional Layers:

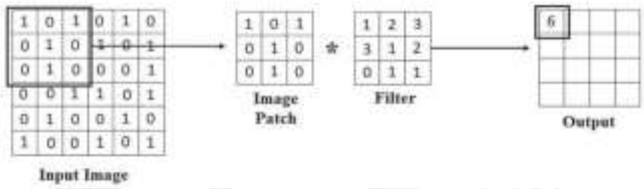

Fig 2. Convolution Operation

Convolutional layers perform feature extraction by applying a set of learnable filters (kernels) to the input image. Each filter detects different features such as edges, textures, or patterns. The number of filters and their dimensions are adjustable parameters. Padding is applied to ensure that the spatial dimensions of the feature maps remain the same. Figure 2 shows the filter operation in a single convolution layer of the proposed model. The model's first building block uses 3 3 filters for convolutions, as shown in equation 1. The 3×3 picture patch uses this filter to accomplish dot product, as seen in Figure 2. The convolution technique generates a matrix that serves as the feature map. Block 2 and Block 3 convolution layers extract feature maps with 5 x 5 and 7 x 7 filter sizes, respectively. The proposed methodology utilizes a Convolutional Neural Network (CNN) architecture for the detection and identification of diseases in rice, wheat, and corn plants. Each layer in the architecture plays a specific role in feature extraction, abstraction, and classification. Let's break down the methodology layer by layer:

The Batch Normalization Layer improves training stability and speed by normalizing the previous layer's activations. It minimizes internal covariate shift by scaling and shifting normalized activations.
The Rectified Linear Unit (ReLU) Layer brings non-linearity into the network by using the rectified linear activation function. ReLU enables the network to learn complicated patterns and correlations in the data.

Max pooling layers down sample feature maps by lowering their spatial dimensions and Pooling helps to capture the most relevant information of obtained features, while lowering the computational complexity of input model by using strides in effective way. The size and stride of the pooling operation are programmable parameters.

Fully connected layers use convolutional layers' derived features for categorization. Each neuron in the completely connected layer connects to every neuron in the previous layer. The number of neurons in the output layer is equal to the number of classes (disease categories) in the dataset.

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 (pictures 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.
- 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,

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

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

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

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

Equation (1) measures the model's precision by determining how many of the predicted images actually belong to the relevant category. In Equation (2), recall refers to the number of photos successfully predicted by the model for the relevant class. The F1-Score is calculated as the harmonic mean of precision and recall, as shown in equation (3). Equation (4) represents accuracy as the ratio of accurately predicted observations to total observations.

Training Specifications:

All models are trained in a supervised way utilizing categorical cross-entropy as a loss function, which computes the difference between two probability distributions. An Adam optimizer with a learning rate of 0.001 is used.

Extensive comparison experiments are undertaken for evaluating the performance of the suggested light-weight CNN model for disease classification in maize, rice and wheat plants. This section discusses the acquired results.

Fig 3. Training Progress plot for Rice leaf Dataset

Fig 4. Training Progress plot for Corn leaf Dataset

Fig 5. Training Progress plot 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

Fig 6. Input Leaf Images

a)Rice

b) Corn

b) Wheat

Fig 7. Classified Output

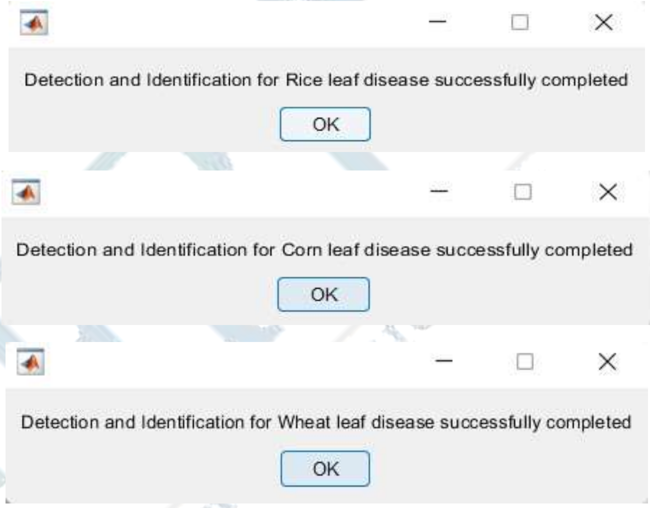

Fig 8. Final Message Box after scucessful completeion of training and testing the model

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 research reveals a lightweight model for identifying diseases in maize, rice, and wheat. The proposed model outperforms existing benchmark CNN models in terms of accuracy and number of parameters, achieving 84.4%. The suggested model improves disease categorization by using different-sized filters across Convolutional layers at the same level. The derived features accurately diagnose diseases with varying widths of diseased areas, as evidenced by multiple cases.

The results highlight the efficacy of the proposed model in crop-specific disease categorization scenarios. The suggested model achieves 99.74% accuracy in categorizing maize as healthy or diseased, without requiring any changes to the architecture. The classification of healthy and sick pictures of rice and wheat yielded similar results (82.67% and 97.5%, respectively). The proposed model serves as a versatile tool suitable for various settings.

V. CONCLUSION & FUTURE SCOPE

In conclusion, the suggested unified lightweight CNN-based model has shown promising results in disease detection and diagnosis in maize, rice, and wheat plants. Through rigorous examination using accuracy, precision, recall, and F1 score criteria; the model has demonstrated solid performance across numerous datasets, demonstrating its effectiveness in automated plant disease diagnosis. The model's ability to accurately distinguish between damaged and healthy leaves indicates its potential as a useful tool for farmers and agricultural stakeholders in monitoring and managing crop health.

Future study could look into improving the model design, such as incorporating attention mechanisms or adding more data modalities, to improve its accuracy and robustness. Furthermore, efforts to implement the model in real-world agricultural settings, such as on-field implementations and integration with mobile applications, could have a substantial impact on sustainable crop production methods and contribute to global food security efforts.

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