From Pixels to Insights: Plant Classification and Disease Detection

Suchitha Marru
Dept. of ISE
Indiana University
Bloomington, US
sumarru@iu.edu

Manish Reddy Rakasi
Dept. of ISE
Indiana University
Bloomington, US
mrakasi@iu.edu

Hanudeep Marru
Dept. of ISE
Indiana University
Bloomington, US
hanmarru@iu.edu

Vishwa Teja Dusa
Dept. of ISE
Indiana University
Bloomington, US
vishdusa@iu.edu

Abstract - In the realm of mixed agriculture, our project arises from the need to predict plant types and diagnose diseases autonomously, eliminating the need for manual inspections. Embracing drones or robots as technological vanguards, we aim to redefine agricultural surveillance, fostering sustainable practices without human intervention.

I INTRODUCTION

Understanding and categorization of plants heavily relies on interpreting visual cues extracted from their leaves. The complex details captured in leaf images hold crucial insights into plant types and potential diseases. However, accurately predicting these attributes demands sophisticated computational model's adept at processing complex visual data. Leveraging established methodologies such as Convolutional Neural Networks (CNN) and ResNet, our project aims to harness these advanced image analysis techniques. The objective is to precisely predict plant types and diagnose diseases from leaf images, presenting a robust framework for automated agricultural surveillance in mixed farming environments.

II RELATED WORK

As part of Research on plant disease identification, we have explored two main methodologies.

Shape and texture-based identification focused on using attributes that were gathered from leaf photos in terms of color and texture in [1].

Deep learning-based identification of diseases, which uses various CNN architectures in [4].

This method has improved classification accuracy and efficiency with some models reaching 99.4 %, often leveraging data augmentation and pre-trained models. Both methodologies have contributed significantly to the advancements of plant disease identification by employing diverse strategies, to enhance accuracy and efficiency.

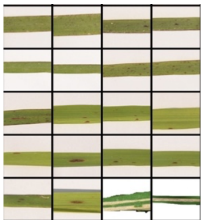
III METHODS

With the scope of our study, we have implemented 3 models Convolutional Neural Networks (CNN), ResNet9, and ResNet50. Each of these models was constructed with the intent to evaluate their respective performances in the task of leaf classification and disease detection.

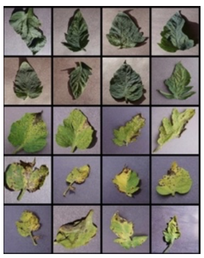
3.1 Dataset

This project uses Kaggle datasets dedicated to predicting plant diseases in rice, tomato, and mango. The rice dataset includes 120 high-resolution images categorized into three classes, each with 40 images. The mango dataset consists of 4000 high-resolution images categorized into 8 classes, including healthy leaves, and the Tomato dataset consists of around 23,000 images categorized into 10 classes, including healthy leaves.

Below are the images from the three of the datasets.


Fig(a): Rice images


Fig(b): Mango images


Fig(c): Tomato


Fig(d): Mango, Tomato mixed farming

3.2 Challenges with the Dataset

Each plant dataset within this project exhibits variations in size, comprising high-resolution images of diverse dimensions. These datasets encompass images with varying resolutions, indicative of the diverse visual characteristics inherent to each plant dataset. Also rice dataset is relatively small so when training the models, it could fail to generalize to new data and could be difficult to build a reliable model.

IV EXPERIMENTAL SETUP

There are numerous approaches to this problem, and below are the approaches we used in this project.

4.1 preprocessing:

We have done reshaping, normalizing, and splitting data into training and testing in the ratio of 80:20. We have also performed data augmentation and saved the class labels to a dictionary.

4.2 Convolutional Neural Networks

Convolutional Neural networks are layers of convolution followed by subsampling and fully connected layers, intuitively speaking, convections and subsampling layers work as future extraction layers, while fully connected layers classify which category current input belongs using extracted features.

4.2 Network architectures

The network architecture we used for training all the datasets is similar. Here the conv2d layer denotes 3 types of convolution layers, and the FC (fully connected) layer represents the linear layers. We tried various architectures and found this architecture to perform better. The activation function used is SoftMax to output a probability distribution over the number of classes.

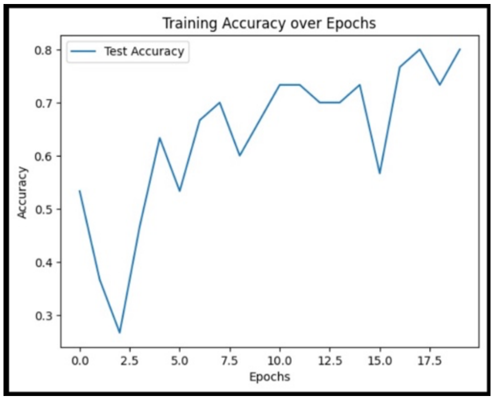
Layers type	**Shape**
Conv2D layer1	(16,3)
MaxPooling2D	-
Conv2D layer2	(32,3)
MaxPooling2D	-
Conv2D layer 3	(64, 3)
Flatten	-
FC L1	128
FC L2	num_classes

4.2.2 Hyper Parameters

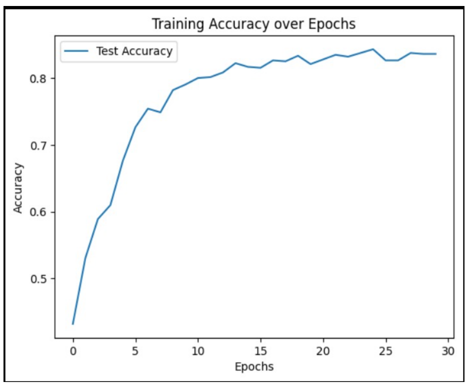
In our project, we used the Adam optimizer, which is favored for its ability to dynamically adjust learning rates and its superior performance with complex datasets. For our loss function, we chose 'sparse categorical cross-entropy' because it's well-suited for image classification tasks where class labels are integers. We trained the models around 20-30 epochs (varied them accordingly)

Hyperparameter	**Value**
Loss	Sparse categorical cross entropy
Optimizer	Adam
Epochs	20 (but varies accordingly)
Learning rate	0.001

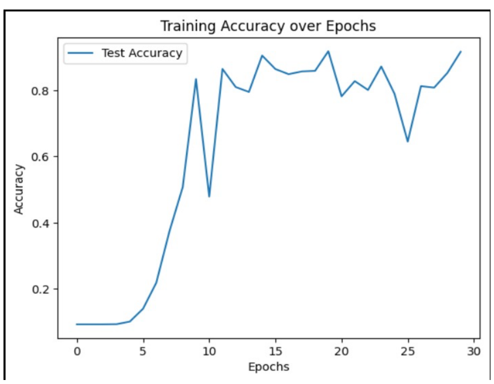
Test-Accuracy plots of the CNN model on different datasets are as below:



1. Test-Accuracy plot on the rice dataset

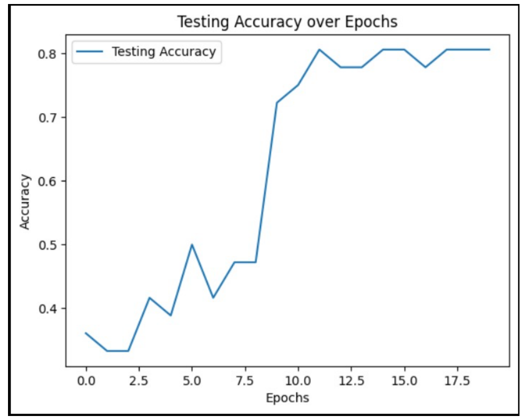


2. Test-Accuracy plot on the rice dataset(augmented)



3. Test-Accuracy plot on the tomato dataset

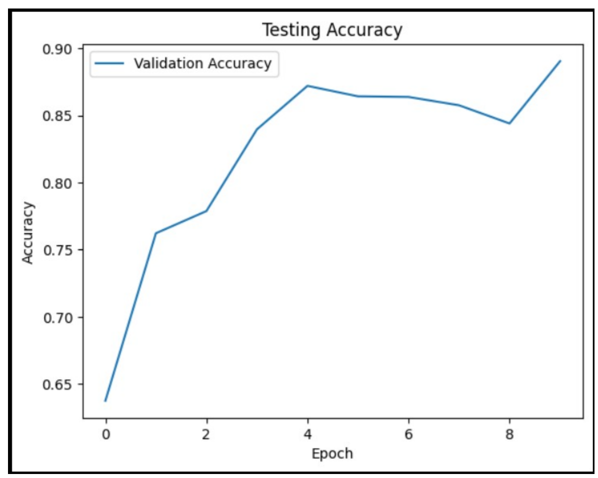
4. Test-Accuracy plot on the mango dataset



5. Test-Accuracy plot on the manually combined dataset.

4.2.3 handling the data imbalance.

We used weight balancing with compute_ sample_ weight because of dataset imbalances: Tomato (23,000 images), Mango (4,000), and Rice (120). This technique prioritizes less frequent samples, ensuring fair attention across all datasets and enhancing overall model performance. This method achieved around 90% (89.04) of accuracy.



6. Test-Accuracy plot with sampled weights

4.3 ResNet9

We experimented with a custom ResNet9 model, which included an initial convolutional block, a second convolutional block, a first residual block, multiple convolutional blocks, a second residual block, and a classifier block. However, the runtime of the epoch time was slow, we thought maybe it was something faulty with our architecture, so, we decided to stick with the standard ResNet50 due to its effectiveness and short training time.

4.4 ResNet50

ResNet50 is a deep learning model that's deep, with 50 layers, and it's smart because it uses shortcuts (residual blocks) to skip over some parts of the network, which stops the learning from getting stuck. which effectively prevents the vanishing gradient problem. Its pre-trained on the ImageNet database, ResNet50 is widely employed for advanced image classification tasks.

4.4.1 Network Architecture and Hyperparameters:

We used the ImageNet weights and proceeded to update the weights with characteristics related to plants as we moved from dataset to dataset by unfreezing layers to specialize it for plant disease detection by using this ResNet50 architecture.

Tomato Dataset: We begin with the ResNet50 model which is pre-trained on ImageNet dataset features. Custom layers (GlobalAveragePooling2D, Flatten, Dense) were added. Image augmentation techniques were applied to enhance generalization. Rather than freezing all layers, as is common in transfer learning, the last four layers were unfrozen to update the model with tomato-specific features. Now, this model's weights are a combination of ImageNet and tomato features.

Hyperparameter	**Value**
Loss	categorical cross entropy
Optimizer	Adam
Epochs	5
Learning rate	0.0001

Mango Dataset: The tomato-trained model is used as the base model with its updated weights. Seventeen layers were unfrozen to refine the model weights for mango disease features, number of layers was chosen based on experimental results.

Hyperparameter	**Value**
Loss	Sparse categorical cross entropy
Optimizer	Adam
Epochs	5
Learning rate	0.00001

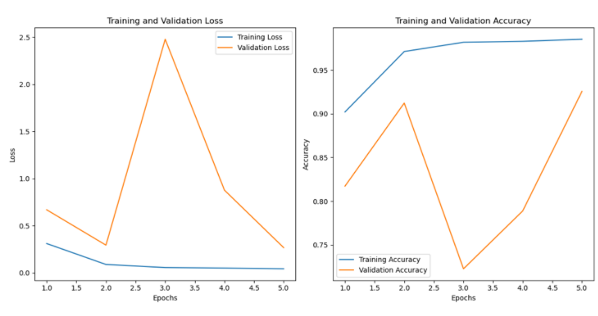
Rice Dataset: Due to a limited dataset, 30 layers were unfreezed. This model was further trained to identify rice diseases. Despite concerns of overfitting, the focus was on extracting weights for the final model. Now the weights of this model, which are the combination of ImageNet, tomato, mango, and rice features are used for the final model.

Hyperparameter	**Value**
Loss	Sparse categorical cross entropy
Optimizer	Adam
Epochs	30
Learning rate	0.0001

Combined Model: Employed the rice-trained weights to build a comprehensive model addressing all three plant types, integrating features specific to each plant's diseases. In this model, the dataset we used is a combination of rice, mango, and tomato which is a relatively large dataset when compared to the dataset we used in the CNN model.

Hyperparameter	**Value**
Loss	categorical cross entropy
Optimizer	Adam
Epochs	5
Learning rate	0.0001

Plots of training and validation loss, training, and validation of the ResNet model:



V Results:

5.1 CNN model

Datasets	***CNN Test Accuracy (%)***
Combined or plant leaf classification	80.56
Tomato	92.21
Rice	80.00, Aug test (65.63) Aug train and test (83.61)
Mango	94.20

The above is the accuracy of the CNN model on different datasets. We tested the model by giving the random low-dimensional image downloaded from Google and it was able to predict it accurately. This shows that the Tomato and Mango datasets have better accuracy than the Combined and Rice datasets because the dataset size is minimal.

5.2 ResNet Model

Datasets	***ResNet Test Accuracy (%)***
Combined or plant leaf classification	92.79
Tomato	76.82
Rice	46.66
Mango	38.40

The above data indicates varying performance levels of the ResNet model across different datasets, with notably higher accuracy in the combined dataset compared to individual plant-specific datasets like Tomato, Rice, and Mango because the combined model was trained with the features or weights of the individual datasets. We tested the model by giving the random low-dimensional image downloaded from Google and it was able to predict it accurately.

VI Conclusion

After exploring both the models (CNN and ResNet50) for plant classification and disease detection, our project established that sophisticated image processing models could be finely tuned to the intricacies of agriculture. The ResNet50 model with its deep residual framework, outperformed the CNN model, even with the different data complexities and sizes. Notably, resnet50 achieved higher accuracy than the CNN model.

VII Future scope

- we want to expand our dataset by including the species and diseases. This will enhance the model's robustness and accuracy.
- We aim to enhance the reliability of ResNet9 by optimizing its performance.
- we want to develop a real-time application that will provide farmers with real-time, actionable insights to improve agricultural productivity and disease management.

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