Leaf it to AI: Advanced Disease Detection for Apple Orchards.

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1. INTRODUCTION:

Early detection and diagnosis of apple orchard diseases are crucial for farmers' livelihoods and the global food supply. However, traditional disease detection methods, such as manual inspection, are time-consuming, labor-intensive, and error-prone. Hence, developing an advanced disease detection system for Apple orchards using AI and data science can significantly enhance the efficiency and accuracy of disease diagnosis. The Kaggle dataset on plant pathology, with its large and diverse collection of apple leaf images of diseased and healthy plants, can serve as a valuable resource for building and training machine-learning models for disease detection. Some previous work has been done using computer vision-based models. Still, some limitations need to be addressed, like large variations in visual symptoms of a single disease across different apple cultivars. Hence more research is required to improve the accuracy and robustness of these models, especially in the context of apple orchards.

2. SIGNIFICANCE OF THE SOLUTION:

Developing an advanced disease detection system for apple orchards using AI and data science has significant implications for farmers' livelihoods and the global food supply. By leveraging computer vision-based models and the large and diverse collection of apple leaf images, our solution aims to improve the efficiency and accuracy of disease diagnosis in apple orchards. Identifying diseased plants quickly and accurately can enable farmers to take prompt and targeted actions, such as applying pesticides or removing infected plants, to prevent the further spread of the disease and minimize crop losses. Additionally, one can easily detect and act if and when specific orchards have certain kinds of diseases more in numbers than other diseases.

3. DATASET:

For this project, we used the Plant Pathology 2021 - FGVC8 dataset [2], obtained from the Kaggle platform. This dataset contains 18,600 images of apple orchard leaves, each labeled with a space-delimited list of all the diseases in the image. The dataset includes five different classes of diseases that can affect apple orchard leaves. These classes are: 'scab', 'rust', 'powdery mildew', 'frog eye leaf spot', 'complex', and ‘healthy. The images in the dataset are of varying sizes, with the smallest being 256 x 256 pixels and the largest being 5,760 x 3,840 pixels. Some images also contain multiple diseases, which adds to the complexity of the classification problem.

4. METHODOLOGY:

4.1 IMAGE PREPROCESSING & EDA – Low Risk:

Data preprocessing is an essential step in preparing image data for analysis and training. In this case, the preprocessing steps included removing duplicates and downsizing images for faster computation. Additionally, canny edge detection was used to identify the bounding box around the leaf and isolate the image's relevant portion for training. Exploratory data analysis is also a critical step in understanding the dataset's characteristics and identifying potential issues or biases that may impact analysis. For example, we understood that 3 out of 4 images were non-healthy, reinforcing our project's importance.

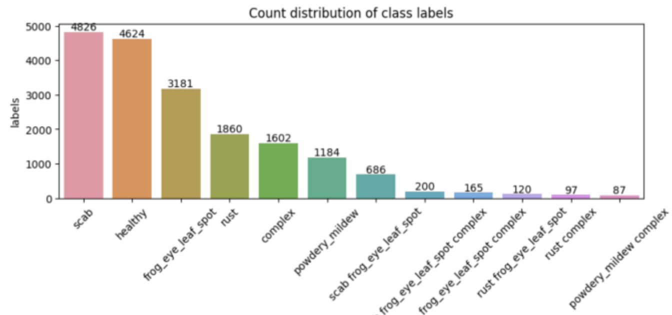

Figure 1 Count plot of class labels

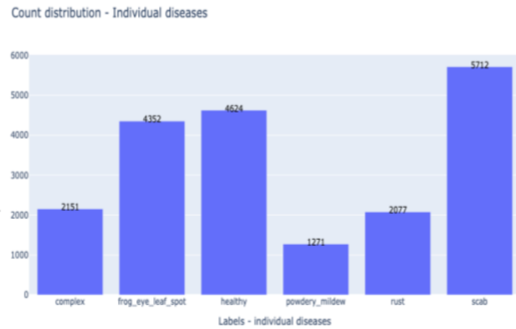

Figure 2 Count plot of individual diseases

4.2 IMAGE AUGMENTATION – Medium Risk:

Image augmentation is a technique used to increase the variety and diversity of training data by applying various transformations to the original images. In this case, three types of image augmentation, namely Random Resize, Flipping the image vertically, and embedding insects in the image, were performed in PyTorch to improve the quality of the training data. Overall, this can lead to better performance and generalization of the apple leaf classification model.

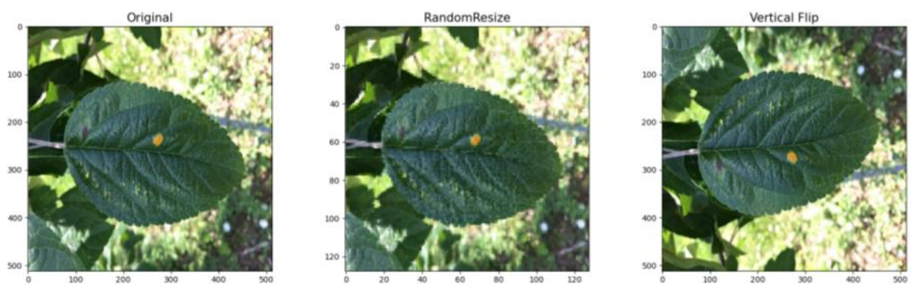

Figure 3 Original Image and Augmentations

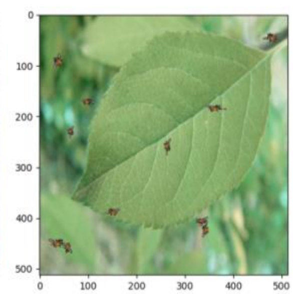

Figure 4 Insect Augmentations

4.3 BUILDING DEEP LEARNING MODELS – High Risk:

Four different CNN models were built for this project: ResNet, VGG, EfficientNet, and a custom CNN model with three convolution layers. All the models were implemented using FastAI libraries in Python and were trained for 20 epochs.

ResNet: The ResNet model was built using transfer learning. We used the pre-trained ResNet50 model, removed the last layer, and added a new layer with five nodes corresponding to the five diseases. The weights of the pre-trained layers were frozen, and only the weights of the newly added layer were trained.
VGG: The VGG model was also built using transfer learning. We used the pre-trained VGG16 model, removed the last layer, and added a new layer with five nodes. The weights of the pre-trained layers were frozen, and only the weights of the newly added layer were trained.
EfficientNet: The EfficientNet model was built using the EfficientNetB0 architecture. The model was trained from scratch using the Adam optimizer and categorical cross-entropy loss function.
Custom CNN Model: The custom CNN model consisted of three convolution layers, followed by max pooling, dropout, and fully connected layers. The model was trained from scratch using the Adam optimizer and categorical cross-entropy loss function.

Activation Map:

The FastAI library provides a convenient API for visualizing the intermediate representations of images as they pass through the convolution layers of a deep learning model. By visualizing these intermediate representations, we can gain insights into how the model extracts and processes features from the input images.

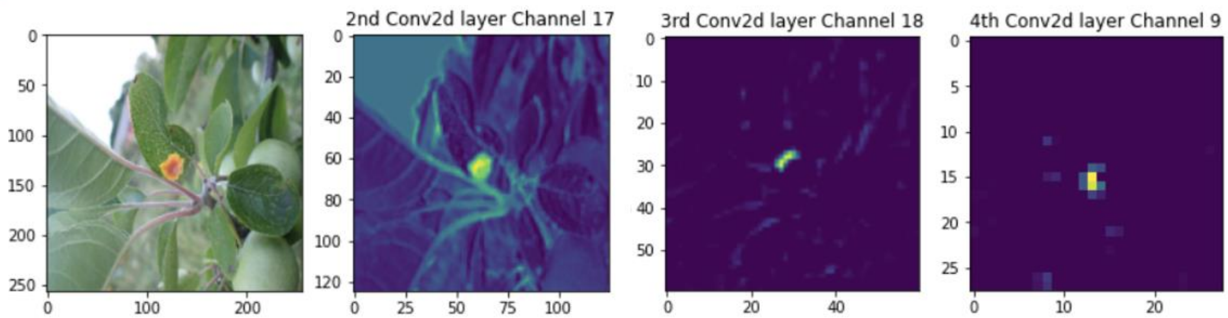

Figure 5 Activation heat map at different convolution layers

In the case of the apple leaf classification model, we can see that as the image flows down through the convolution layers, the main feature that corresponds to the area of the leaf with the disease is highlighted. This indicates that the model correctly identifies and extracts the relevant features important for distinguishing between healthy and diseased leaves.

5. RESULTS & CONCLUSION:

Model performances of all the models are summarized in the table below. The VGG-16 model achieved the highest accuracy among the four models, with a value of 0.87. The ResNet and EfficientNet models followed closely with accuracies of 0.83 and 0.85, respectively. The CNN-based model achieved the lowest accuracy with a value of 0.81.

In terms of the F1 score, the VGG-16 model performed the best with a score of 0.73, followed by the EfficientNet model with a score of 0.70. The ResNet and CNN-based models had F1 scores of 0.69 and 0.68, respectively.

Regarding precision, the VGG-16 model had the highest precision value of 0.71, followed by the ResNet and EfficientNet models with values of 0.68 and 0.67, respectively. Finally, the CNN-based model had the lowest precision value of 0.64.

Model	Accuracy	F1-score	Precision
VGG-16	0.87	0.73	0.71
ResNet	0.83	0.69	0.68
EfficientNet	0.85	0.70	0.67
CNN-base	0.81	0.68	0.64

Table 1: Comparison of Models Performance

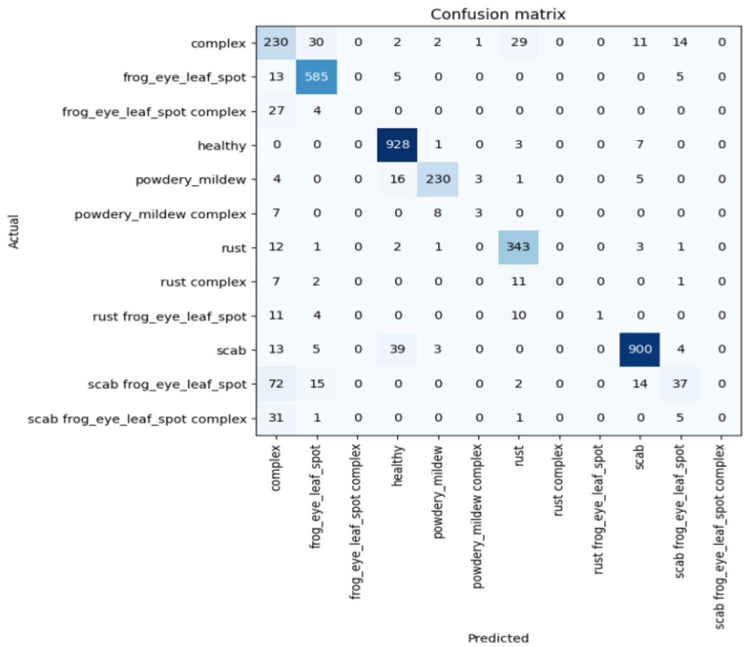

Figure 6 Confusion Matrix of VGG-16 model

Based on the confusion matrix in Figure 1, we found that our models could accurately predict healthy leaves accurately. Additionally, leaves with 'scab' disease, which is the most common disease, were classified with high accuracy as well. However, our models needed help with correctly classifying leaves with less prevalent diseases, resulting in a higher misclassification rate. Additionally, leaves with multiple diseases were often misclassified, indicating the need for more robust models to handle these cases.
Overall, while our models demonstrated strong performance in detecting common diseases on apple orchard leaves, there is still room for improvement in detecting less prevalent diseases and leaves with multiple diseases.

6. FUTURE WORK

Given the limited computing resources available for this project, we only used a subset of available image augmentation techniques to train our models. However, further improvements in model performance can be achieved by incorporating more advanced augmentation techniques, such as shearing and random scaling. In addition, there is scope for extending this project beyond detecting diseases on apple orchard leaves. We can explore using similar models to detect diseases on other plant species, such as tomatoes, cucumbers, and potatoes, which can provide a more comprehensive solution to agricultural disease detection. Moreover, this project can be extended to leverage drone technology equipped with cameras that can capture images of entire fields of crops. By integrating the models developed in this project with drone technology, we can achieve early detection and rapid response to disease outbreaks, which can minimize crop losses and improve overall yield.

REFERENCES

1. https://docs.fast.ai/
2. https://www.kaggle.com/competitions/plant-pathology-2021-fgvc8/data
3. Check out our deployed app here!
   https://huggingface.co/spaces/Chamanthi/Capstone_Leaf_it_to_AI