Identification of Foliar Diseases on Apple Orchards Using Convolutional Neural Network

Abstract

Apple foliar diseases such as scab and rust can cause significant losses in apple orchards. Early detection using automated image analysis methods can help farmers take timely action and reduce crop losses. This paper proposes using convolutional neural networks (CNNs) for automated detection of apple foliar diseases from leaf images. A dataset of 3642 high-quality RGB images categorized into healthy, scab, rust, and multiple diseases was used. Preprocessing included resizing, rescaling, and augmenting images. Three CNN models were developed - using transfer learning from VGG16 and ResNet50 pretrained weights and designing a novel architecture. The novel CNN model achieved the highest accuracy of 92% on test data, significantly outperforming VGG16 (81%) and ResNet50 (poor performance of 33% due to overfitting). Precision and recall were highest for rust detection. The model struggled with multiple diseases and scab classes. Overall, the study demonstrates the feasibility of using deep CNNs for agricultural disease detection from images. The proposed approach can be extended to build automated warning systems to help farmers identify and treat diseases early. Further work is needed to improve model performance, especially on challenging disease classes.

Introduction

Apples are one of the most popular and consumed fruits in the world, with the growing population and global food shortage, it is paramount to create a system/model that helps in the identification of Foliar diseases in apple trees. Apple orchids are under constant threats from several pathogens and insect attacks. Early detection and appropriate deployment of disease management can help to counteract these threats. Delayed diagnosis can lead to decreased production, increased production costs, excessive or inadequate use of chemicals, and environmental health impacts. These leaf diseases of apples that are commonly found are Scab, Rust, Powdery Mildew amongst others Thapa et al. (2020). Apple scab is a fungal disease caused by Venturia inaequalis. Apple trees' foliage and fruit are both impacted. Dark, scaly sores on the leaves, fruit, and perhaps even the twigs are among the symptoms. The fruit may fracture and develop deformities as a result of these lesions. The severity of apple scab is typically greater in humid and wet climates. Chand et al. (2020). apple rust, induced by the fungal pathogen Gymnosporangium juniperi-virginianae, primarily targets apple leaves and fruit, causing orange or rust-colored spots that release spores, potentially infecting nearby apples (Chand et al., 2020). These foliar diseases can spread rapidly, posing a significant threat to crop yields. In some instances, they can even devastate the entire crop if not promptly controlled (Moinina et al., 2019). Traditionally, disease severity in plants has been assessed by trained professionals visually examining plant tissues, which is costly and inefficient (Dutot et al., 2013). However, with the advancement of digital cameras and information technology in agriculture, expert systems have gained popularity, improving plant productivity (Peng et al., 2006). Nevertheless, these systems heavily rely on expert experience for identifying pest and disease features, resulting in inconsistency and low recognition rates. Researchers have explored automated plant disease diagnosis using machine learning algorithms like random forest, k-nearest neighbor, and Support Vector Machine (SVM) to enhance diagnosis accuracy and speed (Youssef Es-Saady et al., 2016). The application of convolutional neural networks to identify early disease images has emerged as a new research hotspot in agricultural information technology, inspired by the success of the convolutional neural network in image-based recognition. Convolutional neural networks (CNNs) are extensively researched and employed in the field of agricultural disease detection in. This research demonstrate that convolutional neural networks have increased recognition accuracy while simultaneously reducing the need for image preprocessing. Machine learning models learn, recognize patterns, and make decisions with minimal human intervention. Bhateja et al. (2018; Raj et al. 2011). Ideally, machines increase accuracy and efficiency and eliminate the possibility of human error. Zhong and Zhao. (2020). Computer vision models have paved a way for diagnosis of these diseases using a convolutional neural network. This model can be trained to identify various diseases using a large dataset of diseased and healthy plants. Agarwal et al. (2019)

Literature Review

Over the years, research has been made using different machine learning techniques in agriculture to mitigate issues of classifying diseases in the agricultural domain. (Korkut et al.; 2018) using image processing and machine learning methods to automatically detect plant diseases through their leaves and roots. Techniques like Autoencoder: an unsupervised learning algorithm was used to detect diseases in bananas and got an accuracy of 94%. (Pardede et al.; 2018).

The use of machine learning (ML) and deep learning (DL) for detecting plant diseases has grown in recent years. These techniques can be used to identify the correct foliar disease, which can help farmers take the necessary corrective measures. (Muhammad, 2016) Digital images are often used in computer vision to further classify diseases based on their symptoms. (Barbedo, 2014; Dai et al., 2019; Wöhner & Emeriewen, 2019; Sladojevic et al., 2016). The increasing use of machine learning (ML) and deep learning (DL) for detecting plant diseases has made it easier for farmers to identify the correct foliar disease and take the necessary corrective measures. (Muhammad, 2016) Digital images are often used in computer vision to further classify diseases based on their symptoms. (Barbedo, 2014; Dai et al., 2019; Wöhner & Emeriewen, 2019; Sladojevic et al., 2016) It is difficult to detect plant diseases from leaves due to factors such as low resolution, background light, and leaf shadows. Machine learning algorithms, such as ML and Deep Learning, can be used to detect and classify plant diseases from images. This is especially useful in agriculture, where image data processing is common (Jadhav et al. 2020; Amara et al. 2017). Mohanty et al. (2016) trained a deep learning model on a public image dataset of more than 50,000 diseased and non-diseased plants. The goal of this research was to identify 14 crop species and the different insect pests that affect them. The validation accuracy on the dataset was 99.3%. Lu et al. (2017) proposed a method for detecting common rice diseases using a convolutional neural network (CNN). The proposed CNN model achieved an accuracy of 95.48%. The authors used the LeNet architecture, which is a simple but effective CNN architecture, to automate the detection of banana diseases under challenging conditions. Liu et al. (2018) developed a method for detecting four diseases of apple trees. The authors reduced the number of model parameters compared to the standard AlexNet model, which helped to increase the accuracy by 10.83%. The overall accuracy of the model was 97.62%. This unique method enhanced the robustness of the model.

This project is proposed to build a convolutional neural network that correctly identifies apple foliar diseases utilizing the VGG 16 and the inception V3 pretrained weights, with hyperparameter tuning and building a novel hybrid model by expanding on the mentioned pretrained weights to increase accuracy and evaluate the performance in comparison with listed pretrained weights.

Objectives

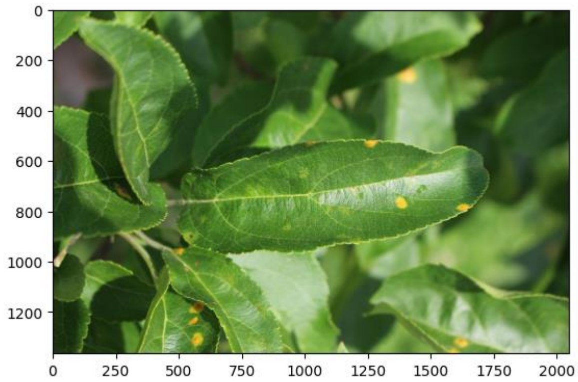
The primary objective of this project is to build an efficient Convolutional neural network that identifies apple foliar diseases using VGG 16 and Inception V3 pretrained weights as a base model and develop a novel model by performing hyperparameter tuning like learning rate, including dropout, Early stopping, batch size, loss function and adjusting the number of convolutional blocks to improve model performance in classifying healthy leaves, from Rust, Scab and multiple foliar diseases.

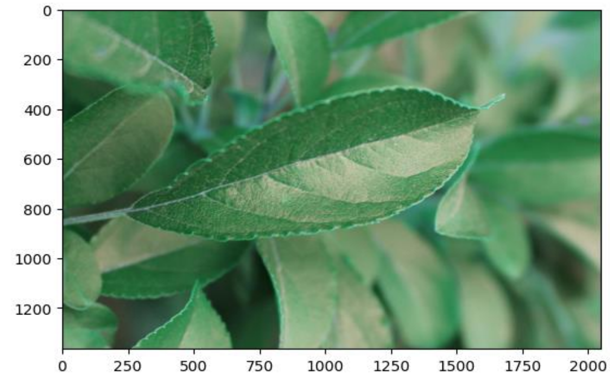
Methodology

Various approaches and methodologies can be used in deep learning initiatives to achieve desired goals. This model utilizes supervised learning approach which entails the use of labeled data to train the model in order to successfully predict the labels (categories of apples foliar diseases) for an unlabeled data.

Data Gathering and Preprocessing

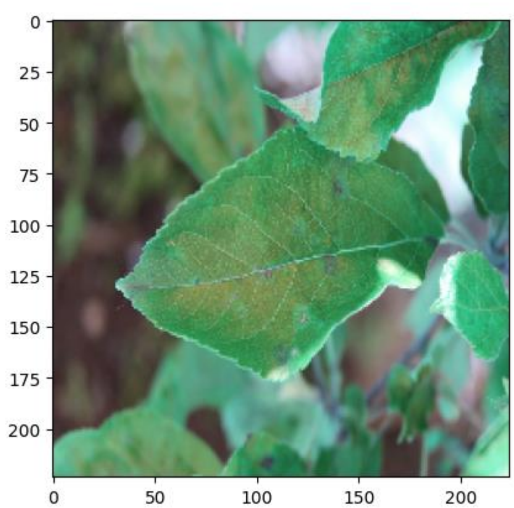
The Dataset was downloaded from Kaggle, and it comprises 3642 images of high quality RGB images of apple foliar diseases which have been categorized in healthy, multiple diseases, Rust and Scab diseases with various illumination angles, surfaces to simulate real life scenarios. Plant Pathology 2020 - FGVC7 (2020). Below are some sample images.

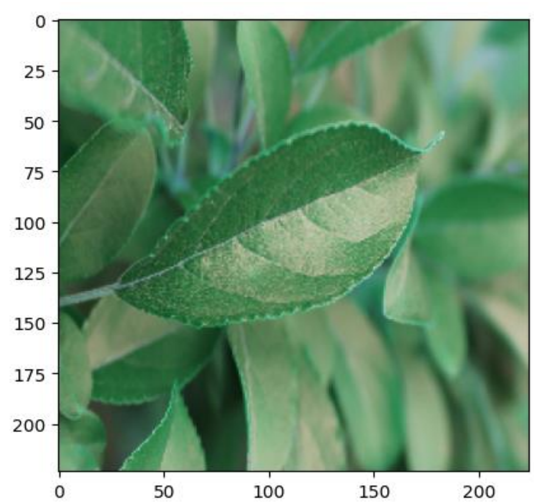




Data Preprocessing

The images were first divided into the four categories namely: healthy, Trust, Scab, and Multiple Diseases using the labeled Csv file from Kaggle. The categorized images were placed in a train folder (directory) while the test images were placed in a test folder (directory). In order to train the model, the images were resized to (224, 224, 3) and rescaled to (0 to 255) in order to have a uniform images size and scale as input for the model. Below is a sample of the rescaled and resized image. The images were also flipped horizontally, vertically, shear range of 20% and zoom range of 20 %. The train data containing all the classes was split into train and validation with validation having 20% of the data. 20% of the validation was further split to get the test data as the test data did not contain labels.



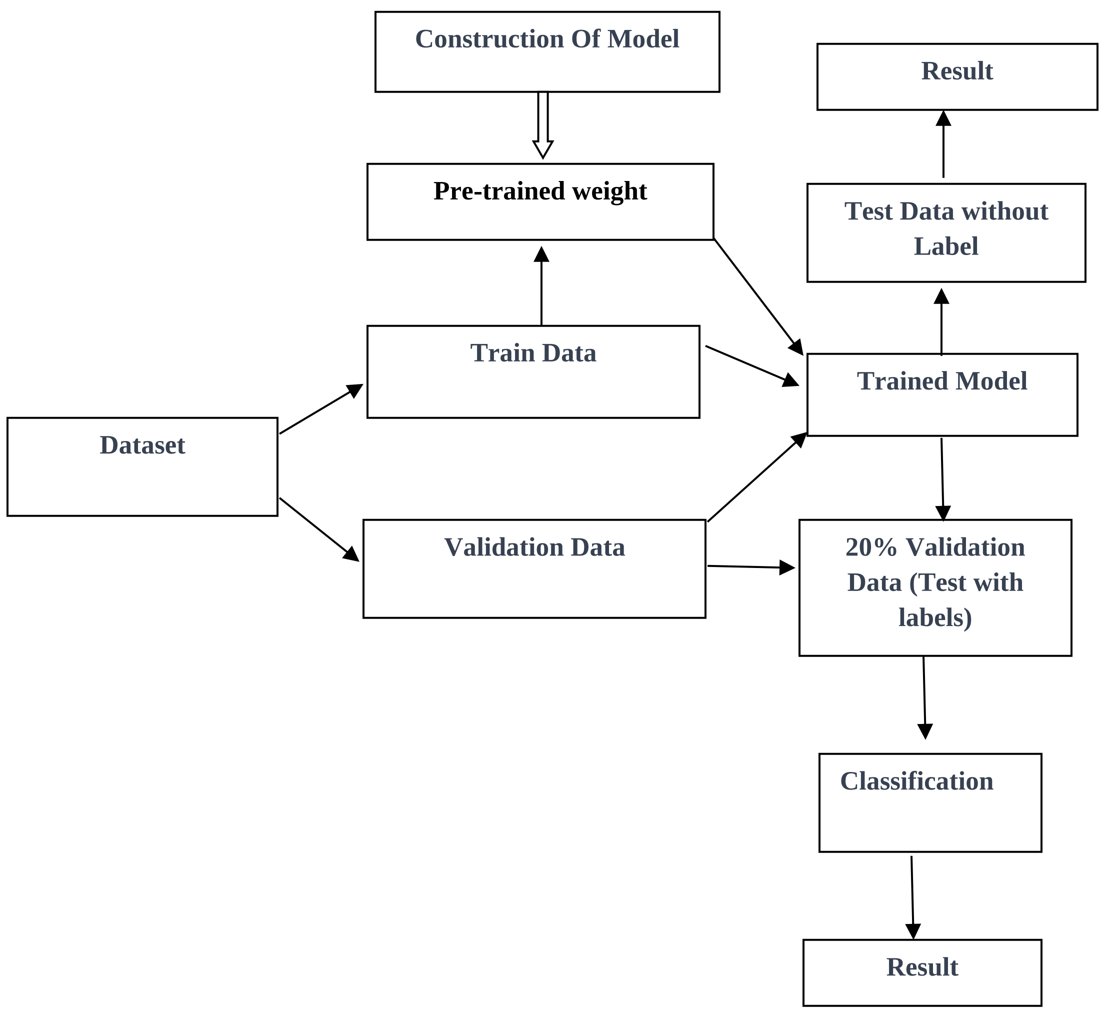


Deep Learning Model

Convolutional Neural Networks (CNN) is a class of deep neural networks that is mostly used for image classification and has proven to be efficient in classification of diseases in agriculture. Agarwal et al. (2019).

Transfer Learning

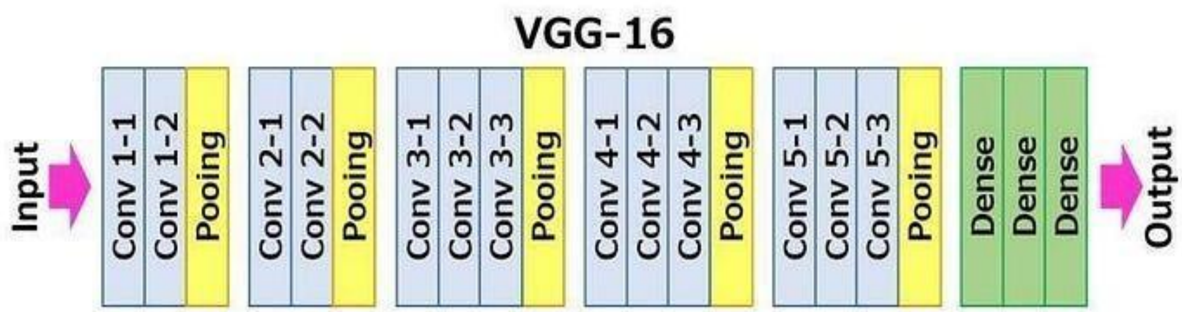
Transfer Learning is a deep learning technique that involves retaining the knowledge acquired from solving a particular problem and applying that knowledge to address a distinct yet interconnected problem.in this project VGG 16 and inception v3 pretrained weights will be used.



Experiments / Implementation of Models

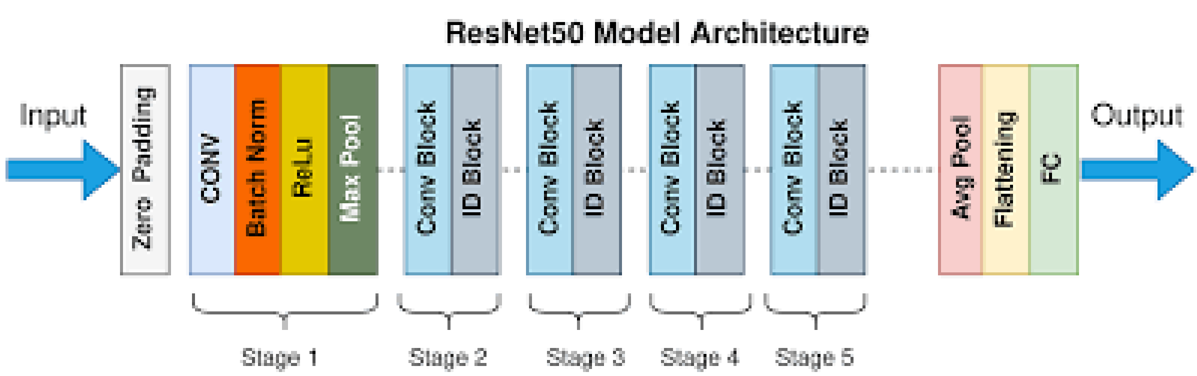
VGG16

VGG16 is a convolutional neural network (CNN) with 16 weight layers. It has 13 convolutional layers, 5 max pooling layers, and 3 fully connected layers. The input tensor size is 224 x 224 x 3. The unique thing about VGG16 is that it uses 3x3 convolution filters with stride 1 and 2x2 max pooling filters with stride 2 consistently throughout the architecture. This makes the model more efficient and easier to train. The first convolutional layer has 64 filters, the second has 128 filters, the third has 256 filters, and the fourth and fifth have 512 filters. The three fully connected layers have 4096 channels each, and the final layer is the SoftMax layer, which outputs 1000 classes. Boesch (2021). VGG16 is a popular CNN architecture that has been used to achieve state-of-the-art results on a variety of image classification tasks. It is also easy to use with transfer learning, which makes it a versatile tool for machine learning practitioners.



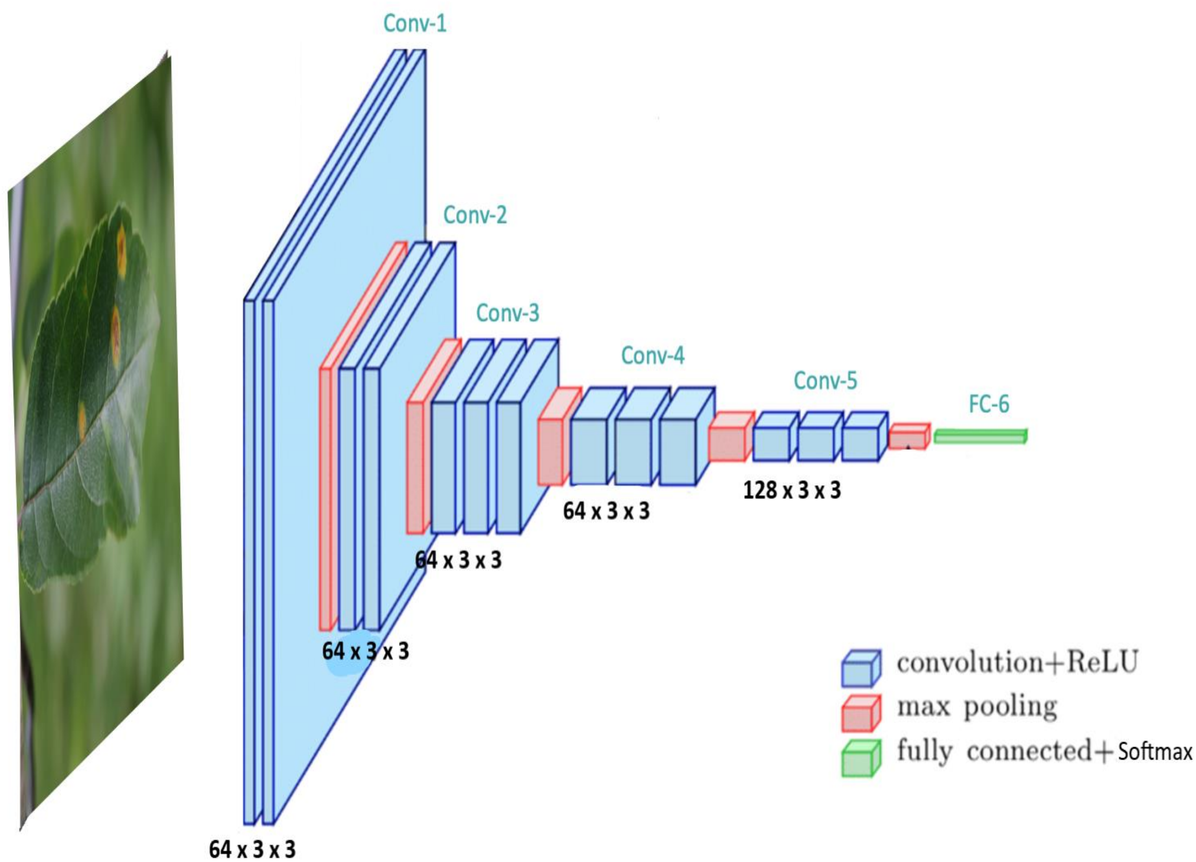
ResNet 50

The ResNet-50 is a convolutional neural network architecture for image classification ResNet-50 architecture consists of four stages each containing residual blocks and shortcut connections that have two convolutional layers each, max-pooling, global average pooling and a fully connected layer for classification using SoftMax activation. The ResNet-50 architecture consists of an input image with a size of 224 x 224 x 3, followed by an initial convolutional layer of 7 x 7 with 64 filters and a stride of 2. Subsequent stages involve max-pooling, residual blocks, and increasing numbers of filters, resulting in a global average pooling layer and finally a fully connected layer with 1000 outputs for classification.

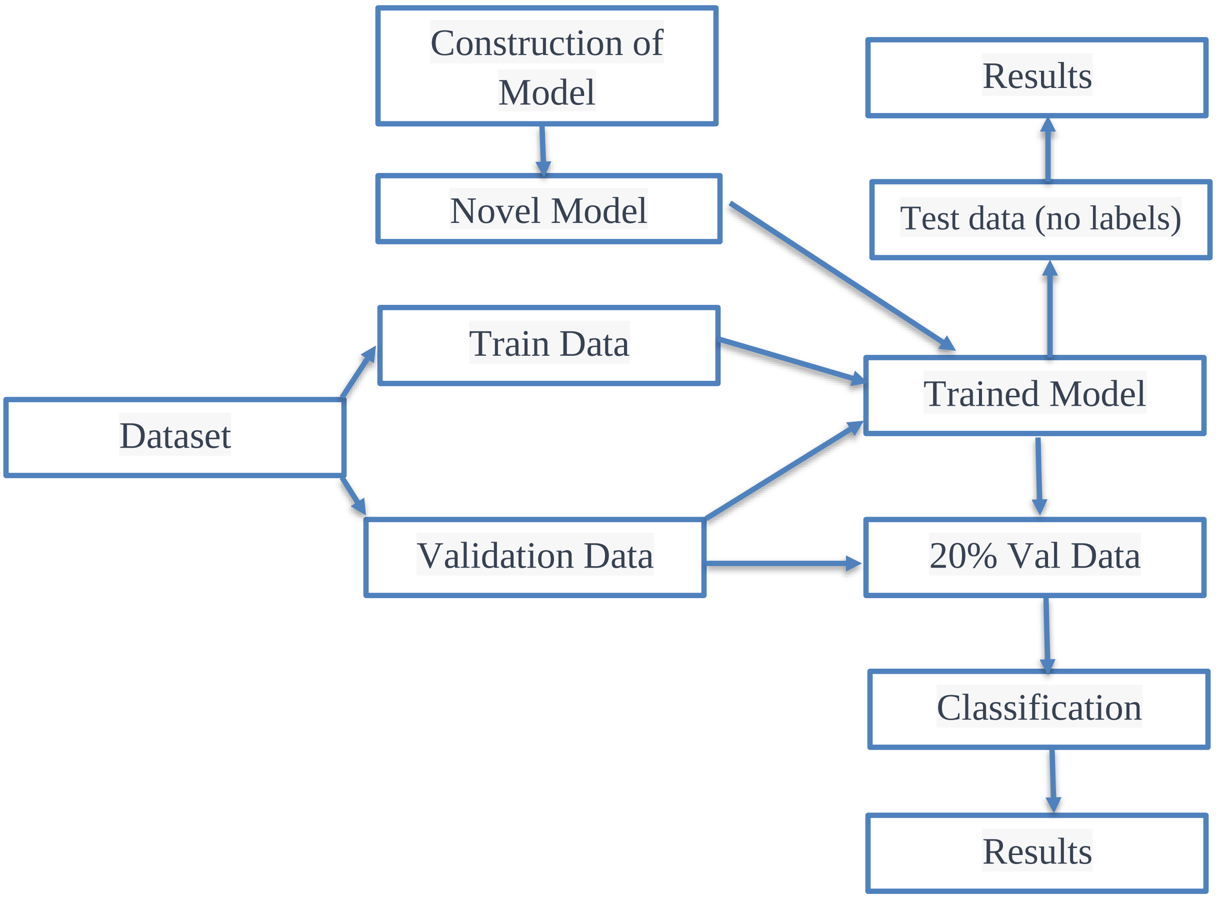


Novel Convolutional Neural Network

The model2 architecture is designed for image classification tasks and comprises a sequence of convolutional and pooling layers, followed by a fully connected layer. It begins with a 64-filter convolutional layer, each filter spanning a 3x3 kernel, utilizing ReLU activation for introducing non-linearity. Subsequently, max pooling is performed using a 2x2 window to reduce spatial dimensions. This pattern repeats with three more convolutional and max-pooling layers, each maintaining 64 filters. The last convolutional layer features 128 filters for more complex feature extraction. After these layers, the feature maps are flattened into a 1D vector to facilitate the transition to the final layer. The fully connected layer, comprising four units, employs a SoftMax activation to provide probabilities for the image belonging to each class. This model architecture leverages convolutional operations to extract hierarchical features from the input images and ultimately classify them into one of the four possible classes.



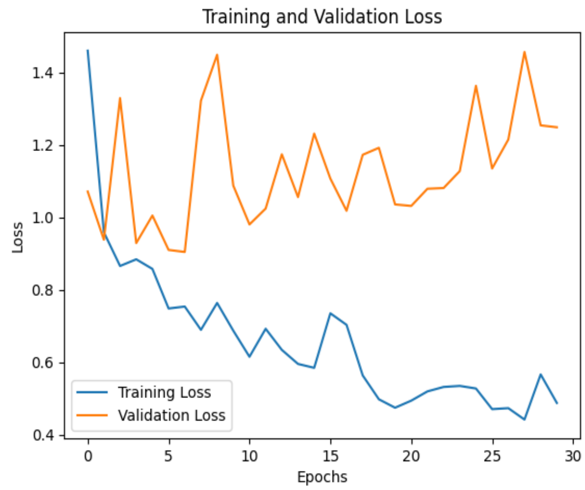
Model Process Flow Diagram

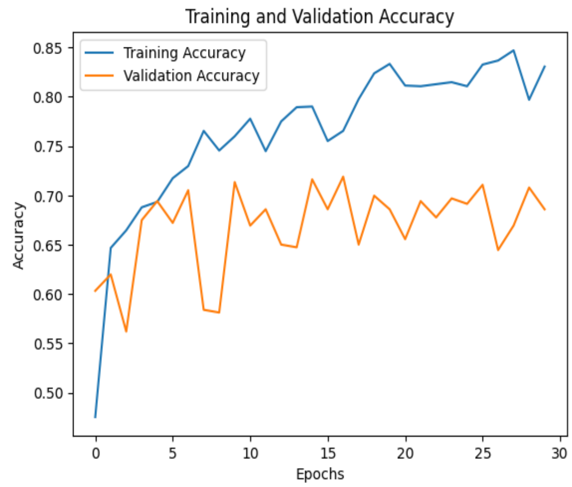


Results

Model	Accuracy (%)	Loss (%)	Validation Accuracy (%)	Validation Loss (%)	Epochs
Novel Model	86	38	86	39	30
VGG 16	81	52	68	124	30
ResNet 50	99	0.14	89	54	30

The performance of the model using VGG 16 with data augmentation, dropout and with 30 epochs gave an accuracy of 0.8121 (81%), loss of 0.5223 (52%), validation accuracy of 0.68 (68%) and validation loss of 1.2481 (124%) which indicates that the model has accurately predicted 67% of that the model had 33 % off predictions. The high validation loss signifies that the model isn't generalizing well or overfitting on the dataset.





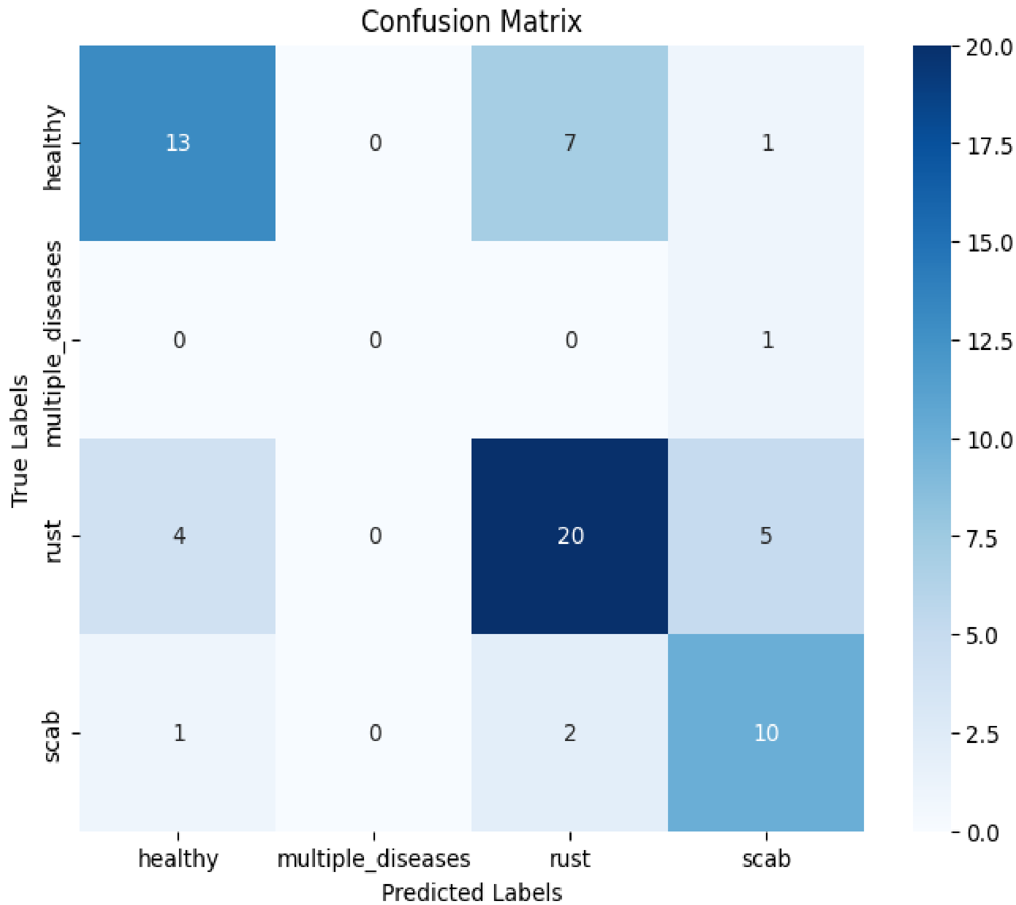
The model achieved a moderate overall accuracy of 67% in classifying images of healthy plants and those with rust, scab, or multiple diseases. Its precision and recall were highest for the rust category, indicating decent performance at identifying this disease and not mislabeling other classes. However, it failed completely on the multiple diseases class, suggesting difficulty distinguishing combinations of diseases. For the remaining classes, precision ranged from 0.59 to 0.72 and recall from 0.62 to 0.77, showing the model can identify them well but still makes some mistakes. To improve, collecting more training data, using augmentation techniques, trying different model architectures, and increasing the training set size could help boost precision and recall across all classes from the current moderate levels.

```
2/2 [==============================] - 0s 315ms/step
Classification Report:
                   precision    recall  f1-score   support

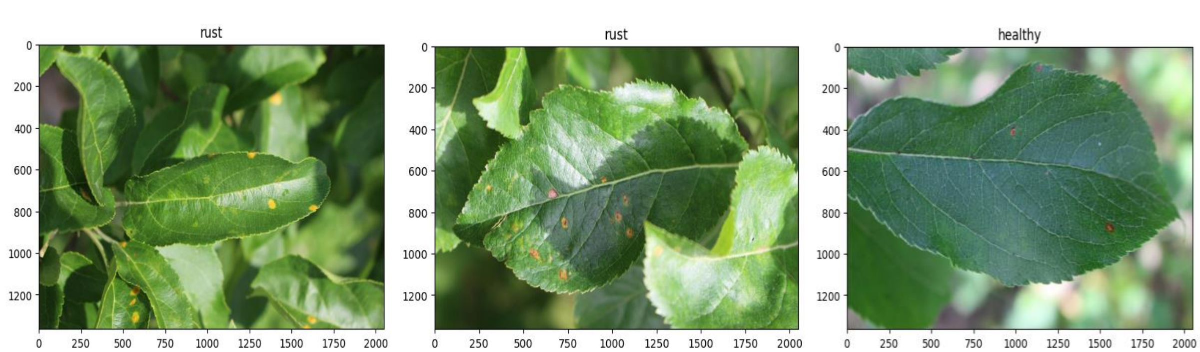
          healthy       0.72      0.62      0.67        21
multiple_diseases       0.00      0.00      0.00         1
             rust       0.69      0.69      0.69        29
             scab       0.59      0.77      0.67        13

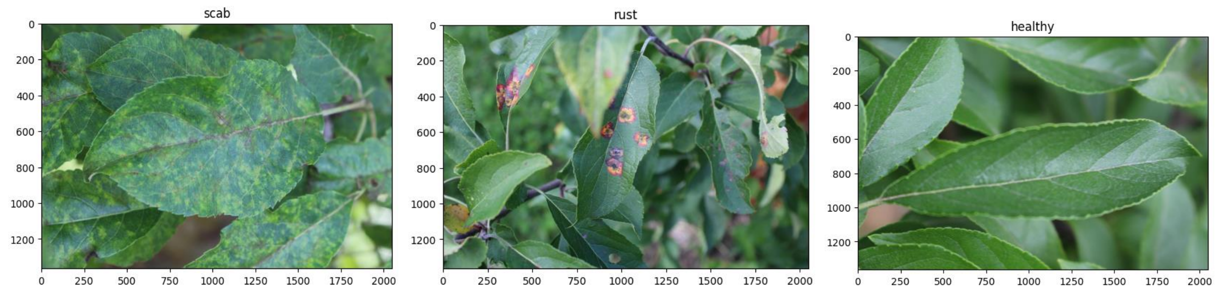
         accuracy                           0.67        64
        macro avg       0.50      0.52      0.51        64
     weighted avg       0.67      0.67      0.67        64
```

The confusion matrix provides insights into how well your model classified different apple foliar diseases. The varying shades of blue represent the number of images correctly classified by the model. Darker shades indicate higher accuracy. Notably, the model excelled in classifying "rust" images, surpassing other diseases. This analysis highlights areas of strength and potential improvement in disease classification.

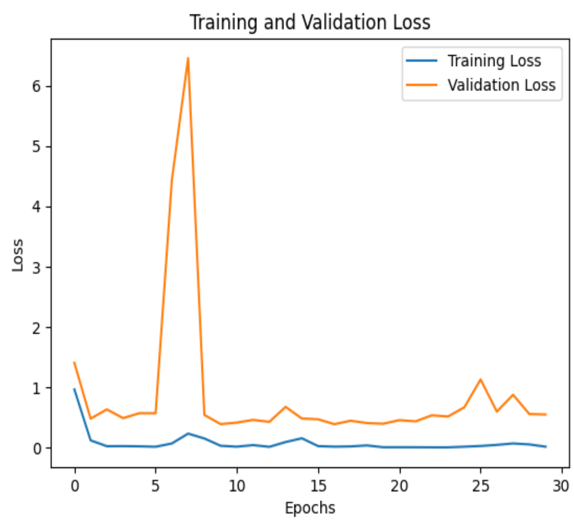


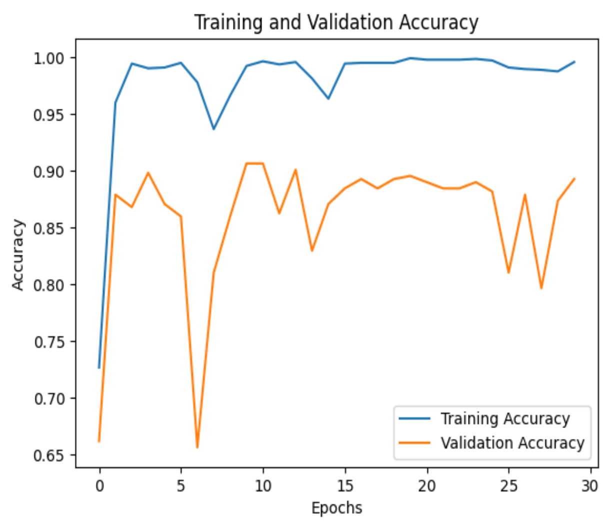
The VGG-16 pretrained weight model was employed to classify the initial images from the unlabeled test dataset. Impressively, it accurately classified most of the images. However, there were instances of misclassification, such as the third image, where a slight rust disease presence was erroneously classified as healthy. This underscores the model's proficiency while also highlighting areas where it can benefit from refinement to better discern subtle disease manifestations.





The pretrained ResNet-50 model, with its top layer frozen, demonstrated impressive performance on the training data, achieving a remarkable 99% accuracy and a minimal loss of 0.0141. However, this high accuracy did not generalize well to the validation dataset, where it achieved an 89% accuracy but suffered from a significantly higher loss of 54%. This discrepancy suggests the model may be overfitting to the training data.



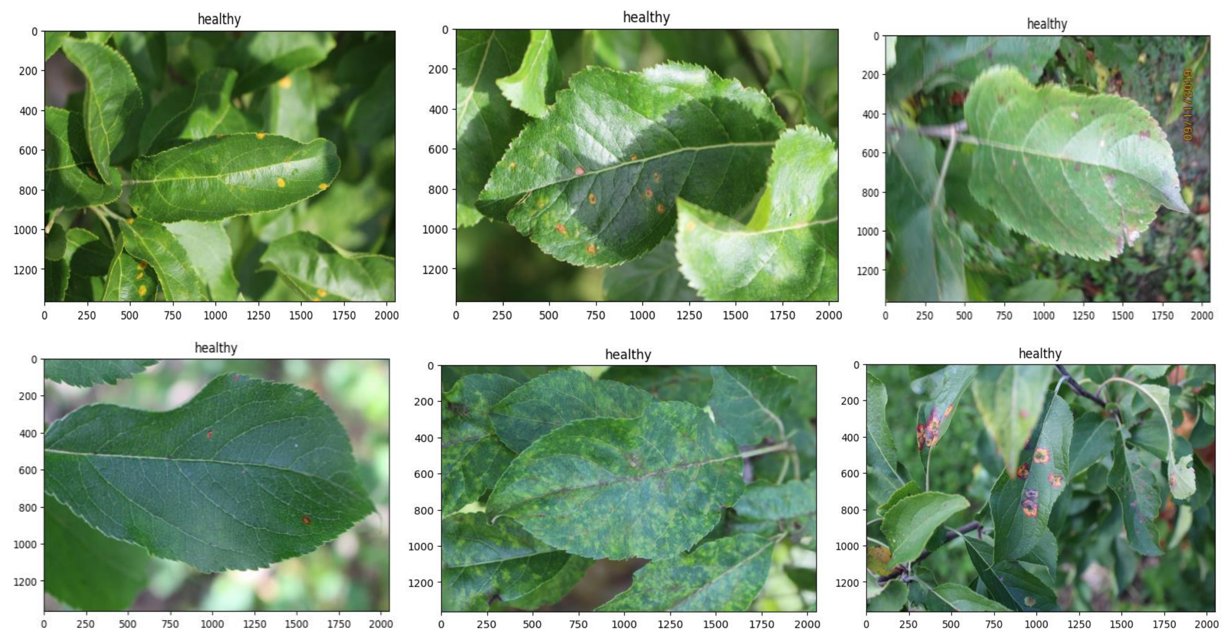


The model's ability to accurately classify plant diseases has deteriorated dramatically, with overall accuracy dropping to 33% indicating near random guessing. Precision is now 0 across all disease classes besides healthy, showing the model makes frequent incorrect predictions and mislabels images. Recall reaches 1.0 for healthy but 0 for all other classes, meaning the model simplistically labels every sample as healthy while failing to identify any other diseases. Correspondingly, F1 scores are very poor at 0 for all classes except a weak 0.49 for healthy. This significant decline suggests the model is likely overfitting training data rather than learning generalizable patterns.

```
2/2 [==============================] - 0s 310ms/step
Classification Report:
                  precision    recall  f1-score   support

         healthy       0.33      1.00      0.49        21
multiple_diseases       0.00      0.00      0.00         1
            rust       0.00      0.00      0.00        29
            scab       0.00      0.00      0.00        13

        accuracy                           0.33        64
       macro avg       0.08      0.25      0.12        64
    weighted avg       0.11      0.33      0.16        64
```



Result of Novel Model

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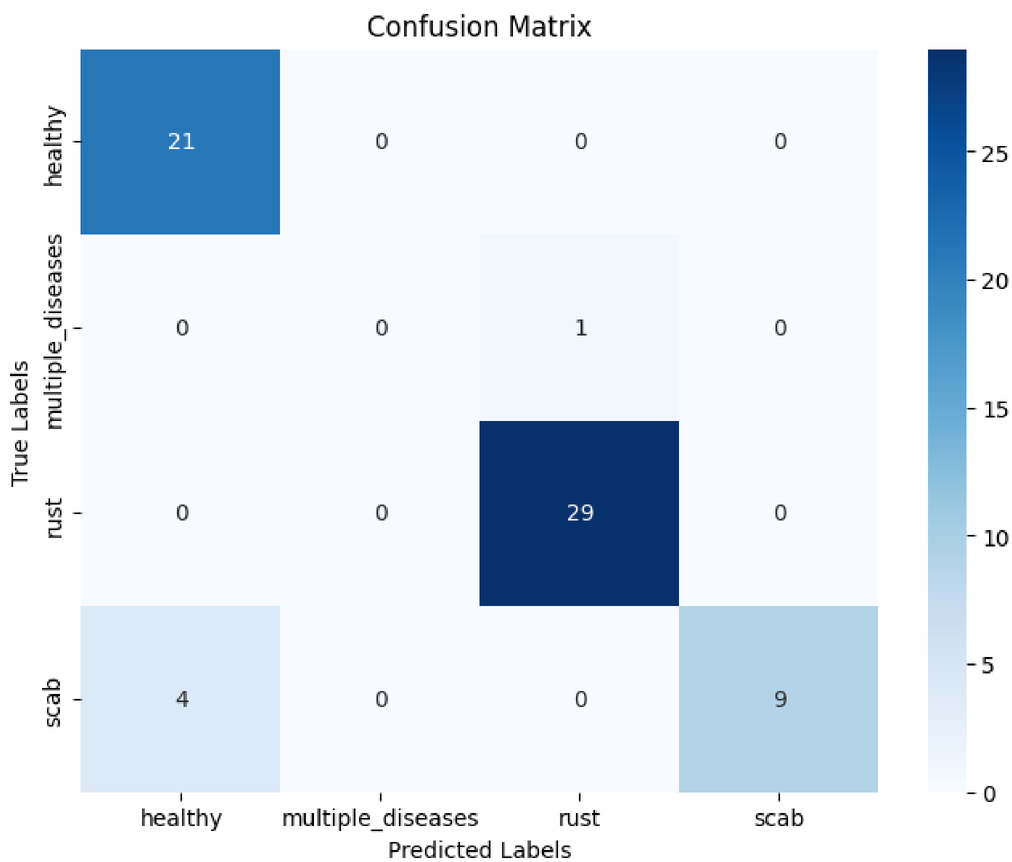
2/2 [==============================] - 0s 8ms/step
Classification Report:
                  precision    recall  f1-score   support

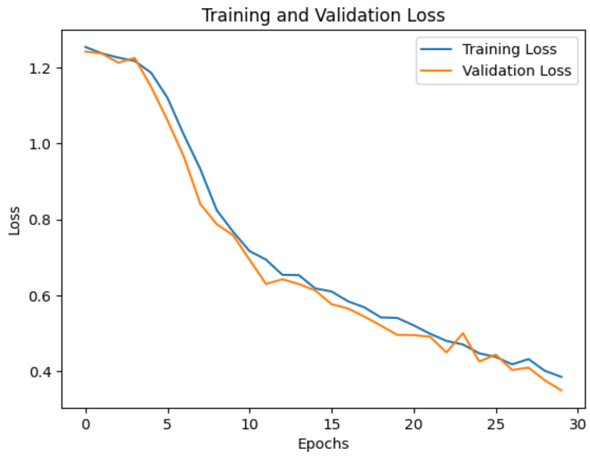
         healthy       0.84      1.00      0.91        21
multiple_diseases       0.00      0.00      0.00         1
            rust       0.97      1.00      0.98        29
            scab       1.00      0.69      0.82        13

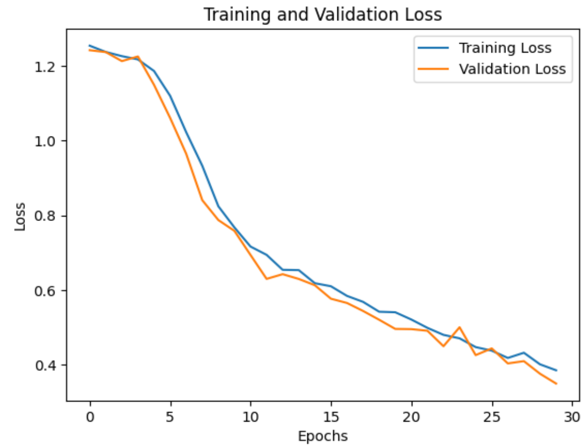
        accuracy                           0.92        64
       macro avg       0.70      0.67      0.68        64
    weighted avg       0.92      0.92      0.91        64
```

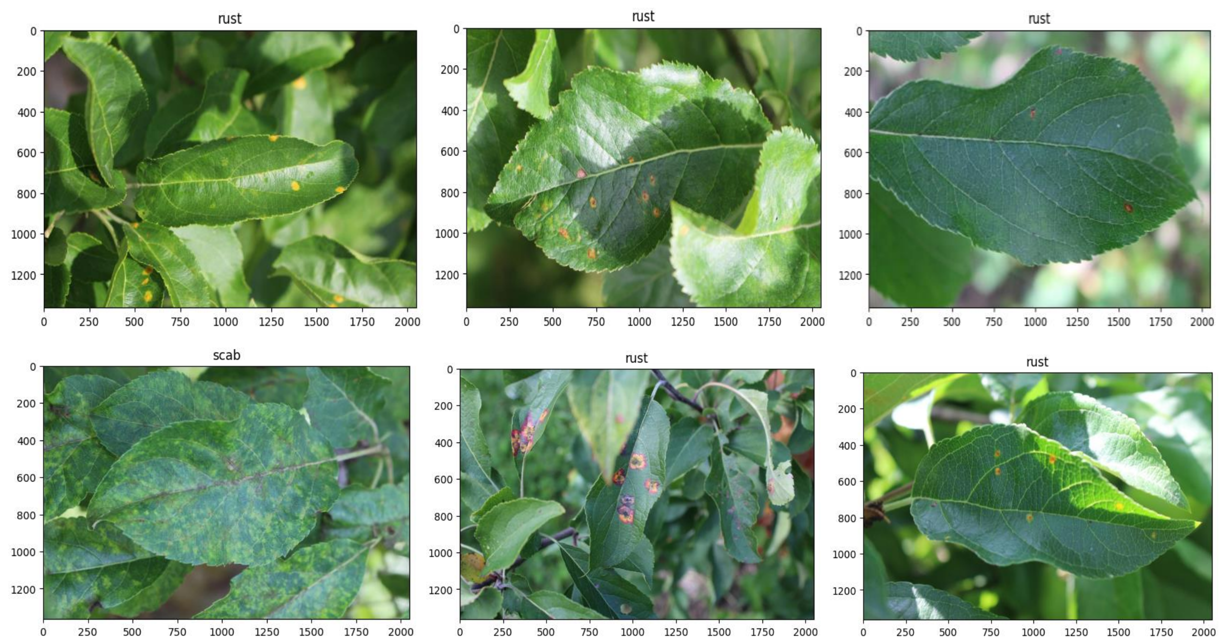
The provided classification report offers insights into the performance of a machine learning model on a multi-class classification task involving the prediction of plant disease categories: "healthy," "multiple diseases," "rust," and "scab." The report highlights varying levels of precision, recall, and F1-Score for each class. The model demonstrates strong performance in accurately identifying "healthy" and "rust" instances, achieving high precision and recall. However, it struggles with the "multiple diseases" and "scab" classes, evident from low precision and/or recall values. The overall accuracy of 92% suggests that the model generally performs well, but the macro average F1-Score of 0.68 indicates room for improvement in achieving a balanced performance across all classes. Despite this, the weighted average F1-Score of 0.91 signifies a generally robust model performance, though further efforts could be directed towards enhancing accuracy for classes with lower precision and recall values.



The confusion matrix provides insights into how well your model classified different apple foliar diseases. The varying shades of blue represent the number of images correctly classified by the model. Darker shades indicate higher accuracy. Notably, the model excelled in classifying "rust" images, surpassing other diseases. This analysis highlights areas of strength and potential improvement in disease classification.







The model architecture is designed for image classification tasks and comprises a sequence of convolutional and pooling layers, followed by a fully connected layer. It begins with a 64-filter convolutional layer, each filter spanning a 3x3 kernel, utilizing ReLU activation for introducing non-linearity. Subsequently, max pooling is performed using a 2x2 window to reduce spatial dimensions. This pattern repeats with three more convolutional and max-pooling layers, each maintaining 64 filters. The last convolutional layer features 128 filters for more complex feature extraction. After these layers, the feature maps are flattened into a 1D vector to facilitate the transition to the final layer. The fully connected layer, comprising four units, employs a SoftMax activation to provide probabilities for the image belonging to each class. This model architecture leverages convolutional operations to extract hierarchical features from the input images and ultimately classify them into one of the four possible classes (healthy, scab, rust and multiple) apple foliar diseases with an accuracy of 92% which performed better than pretrained weights at 67% (VGG 16) and 33% (ResNet 50) in the classification report. The ResNet 50 architecture performed well with the train data but learnt to classify only the healthy images only which led to the poor performance of the model during classification on the test data which require more investigation.

Conclusion

The goal of the project was to build a convolutional neural network (CNN) to identify apple foliar diseases from images. The four disease classes were healthy, rust, scab, and multiple diseases. A supervised learning approach was used with a labeled image dataset. Data preprocessing included resizing, rescaling, and augmenting the images. Three models were developed - using transfer learning with VGG16 and ResNet50 pretrained weights and designing a novel CNN architecture. The novel CNN model achieved the best accuracy of 92%, significantly outperforming VGG16 (81% accuracy) and ResNet50 (99% train accuracy but only 33% test accuracy). Analysis of classification reports and confusion matrices provided insights into model performance.

The novel model excelled at identifying the rust class but struggled more with multiple diseases and scab. Overall, the project demonstrated the potential of deep learning and CNNs for agricultural disease detection from images. Next steps were proposed to further improve model performance.

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