A Project report on

Prediction of Disease in Apple leaf using Convolutional Neural Network

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

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CERTIFICATE

This is to certify that the Major Project Phase I report entitled **" Prediction of Disease in Apple leaf using Convolutional Neural Network "** being submitted by B. Ravichandra (20H51A05D7), P. shirisha(20H51A0572), U. Harshith(20H51A05M2) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ABSTRACT

Apple tree diseases can significantly impact fruit quality and yield, making early detection and intervention crucial for orchard management. To avoid the impact on apple production a novel approach is required for the early and accurate prediction of diseases in apple leaves using Convolutional Neural Networks (CNNs). Our proposed system contains a comprehensive dataset of high-resolution images of apple leaves exhibiting various disease symptoms, including common issues like apple scab, apple rust, and powdery mildew. The dataset was carefully annotated to train and validate the CNN model effectively. The proposed CNN model utilizes its ability to automatically learn relevant features from images, making it highly suitable for the task of disease prediction in apple leaves. The neural network architecture consists of multiple convolutional layers and pooling layers, followed by fully connected layers for classification. This model contribute to the field of precision agriculture by offering a cost-effective and efficient tool for apple disease detection. With the potential to be integrated into mobile applications or automated drone-based systems, our model can assist orchard owners in making timely decisions regarding disease management.

CHAPTER 1
INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1. Problem Statement

The objective of this research project is to develop a Convolutional Neral Network (CNN) model for the accurate and early prediction of diseases in apple leaves. Apple cultivation is a significant contributor to the global economy, and the health of apple trees is crucial for maintaining high-quality fruit production. However, diseases like apple scab, fire blight, and apple rust can severely affect apple orchards, leading to crop loss and economic impact.

1.2 Research Objective

- To identify the disease in the leaves based on training and testing
- To identify the type of disease
- To notify the farmers so that early actions can be taken
- Create database of insecticides for respective disease.
- Apply CNN algorithm to data set and generate model for prediction.
- Predict fruit leaf disease from given input image and display disease.
- To provide remedy for the disease that is predicted.
- To explore the scalability and adaptability of the model for use in different apple orchards and under varying environmental conditions.
- To promote the adoption of this technology among apple growers and orchard managers.
- To compare the CNN-based disease prediction model with traditional disease identification methods, such as manual scouting, for performance and cost-effectiveness.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2

BACKGROUND WORK

2.1 MGA-YOLO: A lightweight one-stage network for apple leaf disease detection

2.1.1 Introduction

Apple is one of the most important economic fruits in the world. However, various apple leaf diseases pose great threats to the productivity and the quality of apples, causing significant economic losses. Given available methods for diagnosis, apple leaf disease management still faces great challenges. At present, apple leaf disease diagnosis primarily relies on visual inspection. As the method is subjective, it often leads to misdiagnosis, resulting in low efficiency and insufficient accuracy.

The development of computer hardware and software technology has enabled agriculture and computer engineering technology to be more closely linked. With the help of innovative tools, such as computer vision, machine learning, and deep learning algorithms, smart agriculture applications are flourishing. Such applications typically include precision agriculture, disease diagnosis, and crop phenotyping. As of artificial intelligence, machine learning algorithms are being progressively used in crop leaf disease diagnosis. However, classical machine learning algorithms mostly rely on hand-crafted low-level vision features.This often results in unsatisfactory performance when the captured scene is comparatively complex.

Recently, deep learning models, such as convolutional neural networks (CNNs), have made great progress compared with classical machine learning methods. CNN-based models provide end-to-end pipelines to automatically learn low-level discriminative features and model parameters, making it easier for non-experts to tackle computer vision-based tasks of crop disease diagnosis. To make CNN models more practical and suited for deployment on mobile devices for real-time detection, many lightweight CNNs have been proposed. Lightweight models reduce the number of parameters, but leads to a slight decline in accuracy. To compensate for the accuracy loss of lightweight models, attention mechanisms can be used to distribute different weights to each part of the input feature layers, extract essential features, and improve classification performance.

2.1.2 Merits,Demerits and Challenges

Advantages

- High Detection Accuacy.
- Operates with high inference speed
- It is a Anchor-Free Detection.
- Multi-Granularity Feature Aggregation.
- Potential for Automation.
- It helps in reducing false positive predictions.

Disadvantages

- Less Tolerant to Occlusion.
- Limited Objection Detection Types.
- Difficulty with small or sparse disease regions.
- Not suitable for all environment.
- Dependency on Hardware.
- Complexity for End Users.
- It is model complexity.

2.1.3 Implementation of MGA-YOLO: A lightweight one-stage network for apple leaf disease detection

Apple leaf disease images in our dataset were collected from the public datasets.The apple leaf images were divided into four categories, which included healthy leaves and three types of common leaf diseases: rust, scab, and black rot. Since the majority of the images has a resolution of 4, 000 × 2, 672 pixels, the details of apple leaves are preserved while backgrounds are influenced by shadows and occlusions with complex lighting conditions. This imitates the real application scenarios and potentially enhances the robustness of the trained model. The characteristics of the three apple leaf diseases are significantly different.

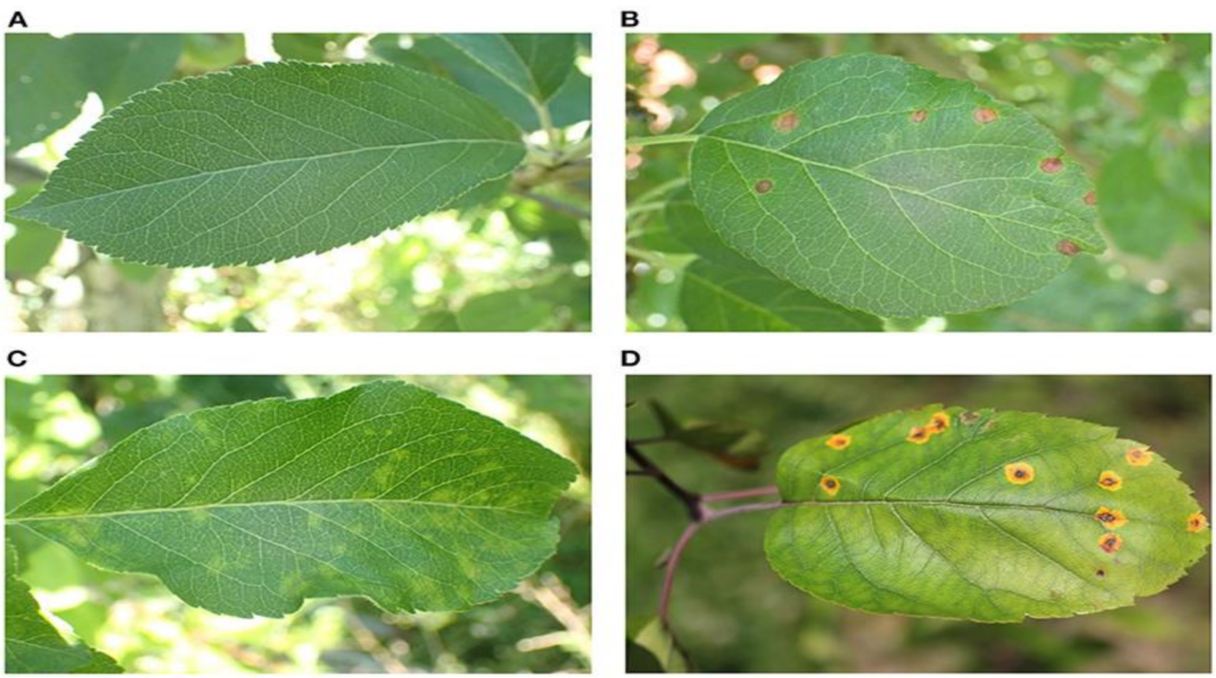

Fig:2.1.3.1 shows the representative images of the four categories.

Image annotation is crucial for building the dataset. The original images from the two public datasets only had class labels for each image, but our method aims to detect each leaf in every image with a class label. Thus, we cannot directly use the original image datasets for training, validation, and testing. We used the annotation tool labeling based on Python to label each leaf in every image with a bounding box and a class label. We annotated entire leaves and drew the smallest circumscribed rectangle of each focused and unobstructed leaf during our labeling process. The number of images in each category is approximately the same to balance the distribution of different labels. It ensured balanced sample distribution and avoided over-fitting caused by the skewness of a specific class.

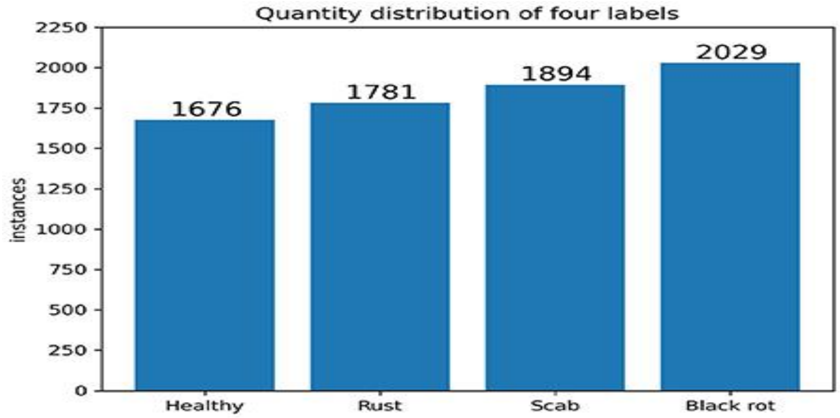

Fig 2.1.3.2: Quantity distribution of four labels of the training and validation datasets.

The number of labels of four categories on the ALDOD training and validation set. In addition to the data formats for training they YOLO network, we also had annotations in PASCAL VOC and MS COCO formats to facilitate the comparison with other state-of-the-art (SOTA) object detection methods. ALDOD has 8,838 images. The training dataset, validation dataset, and test dataset were divided in a ratio of 0.54:0.23:0.23, which correspond to 4,766, 2,036, and 2,036 images in each set, respectively.

To adapt MGA-YOLO to different environmental conditions and reduce the negative impact of photometric distortion,the dataset was first expanded by random HSV adjustments, translations, shearing, rotating, scaling, and horizontal flipping. Mosaic method combines four training images to one in specific ratios. This enriches the background information of detected objects significantly. Based on previous image augmentation techniques, we investigated the effects of Mosaic.

On the testing set with 2,036 images, the MGA-YOLO network accurately identified three apple leaf diseases and healthy leaves, with AP_{50} reaching 96.7% and *mAP* reaching 94.0%. The detection performance of each category is shown in Fig 3 and the confusion matrix of detection results.

Category	Labels	Precision	Recall	AP_{50}	mAP
All	2,193	0.955	0.908	0.967	0.940
Healthy	508	0.907	0.856	0.943	0.919
Black rot	603	0.991	0.912	0.977	0.958
Scab	575	0.950	0.901	0.960	0.938
Rust	507	0.970	0.964	0.987	0.945

Fig 2.1.3.3:The detection performance of each category

2.2 Prediction of Apple Tree Leaf Diseases Based on Deep Learning Models

2.2.1 Introduction

Apple trees are a staple of the fruit industry, contributing significantly to global food production. However, the health and productivity of apple orchards are often threatened by various diseases that affect apple tree leaves. Timely detection and management of these diseases are crucial for maintaining crop yields and the economic viability of apple farming. Traditional methods of disease identification, such as manual inspection, can be time-consuming, labor-intensive, and may lack the precision required for early intervention. In response to these challenges, the application of deep learning models has emerged as a promising solution for the automatic and accurate identification of apple tree leaf diseases.

Deep learning, a subfield of artificial intelligence, has demonstrated remarkable capabilities in image recognition and classification tasks. Convolutional Neural Networks (CNNs), in particular, have been widely adopted for their ability to extract intricate patterns and features from images, making them well-suited for detecting subtle symptoms of diseases in apple tree leaves. By leveraging large datasets of images, deep learning models can learn to recognize specific disease manifestations, which can vary in terms of appearance and severity.

It explores the potential of deep learning models for the identification of apple tree leaf diseases. It seeks to address the challenges associated with disease detection, including the need for rapid, accurate, and scalable solutions that can aid farmers in disease management. By harnessing the power of deep learning, this study aims to create a robust system that can automatically analyze images of apple leaves and provide reliable disease diagnoses. The implications of such a system extend beyond the agricultural sector, as it can contribute to sustainable farming practices, reduce pesticide use, and ensure a more secure food supply chain.

2.2.2 Merits,Demerits and Challenges

Advantages

- High Accuracy and Reliability.
- Detecting at early stages
- Reduced Labour cost.
- Reduced pesticide use.
- Speed and Efficiency
- Enhanced crop yields.
- It is a User-friendly application.

Disadvantages

- Data dependency.
- Overfitting to trained data.
- Implementing and fine-tuning deep learning models can be complex.
- Inconsistent Performance.
- Cost of maintainance.
- Limited Adaptability.
- This model may produce false positives.
- Ethical concerns.

2.2.3 Implementation on Prediction of Apple Tree Leaf Diseases using Deep Learning Models

Apple tree leaf disease types vary from season, humidity, temperature, light, and other factors. Apple tree leaves may be infected by pathogenic bacteria from tree sprouts to the leaves falling off**.** A total of 2970 images of ATLDs and healthy leaves were collected. The dataset was evaluated by experts to ensure the validity. The dataset contains five different kinds of diseases and healthy leaves, a total of six types, including Mosaic, Rust, Grey spot, Brown spot, Alternaria leaf spot, and healthy leaves.

Below figure shows that five common diseases have obvious distinguishable visual characteristics.The bright yellow spots of Mosaic spread throughout the leaves.The dark brown herpes of Brown spot is morphologically different from other lesions. Near-round yellowish brown lesions are found in the early stage of Grey spot, and then the lesions turn gray subsequently, therefore, the Grey spot in its early stage is easy to be confused with Alternaria leaf spot. Therefore, it is feasible to classify and identify common ATLDs by visual features.

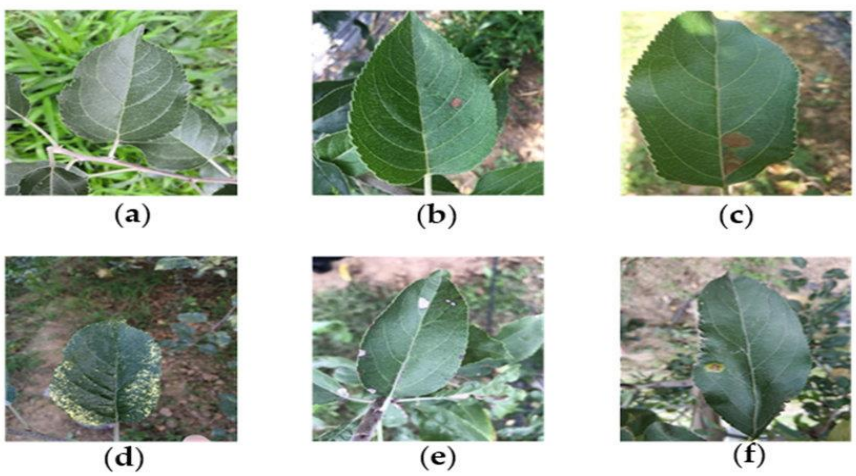

Fig 2.2.3.1:Healthy and diseased apple leaves.

In order to simulate,images are processed by increasing and decreasing the brightness value by 30%, increasing the contrast by 50% and decreasing the contrast by 20%, increasing the sharpness by 100%and decreasing the sharpness by 70%, respectively. By using rotation (90°, 180°,270°),flipping,mirroring and symmetry operation,the actual shooting angles were simulated.In order to simulate the noise that may occur during the image acquisition process, the dataset is further enhanced by adding interference of appropriate Gaussian noise which reduce the overfitting phenomenon in the CNN training stage.In order to improve the CNN convergence speed and learn subtle differences between images, the dataset is normalized.

Xception uses depthwise separable convolutions to reduce model parameters without reducing the model performance. The densely connected dense blocks of DenseNet model increases the model feature reuse capability.

CNNs usually consist of three parts: a convolutional layer, a pooling layer, and a fully connected layer. Convolutional and pooling layers act as feature extractors for the input image, while fully connected layers act as classifiers. The basic purpose of convolution is to automatically extract features from each input image. Compared with traditional feature extractors (SIFT, Gabor, etc.), the strength of CNN lies in its ability to automatically learn the weights and biases of different feature maps, so as to generate powerful feature extractors with specific tasks.The activation function is executed after each convolution. Rectified linear units (ReLU) function is a very popular non-linear activation function that introduces non-linearity into CNN.

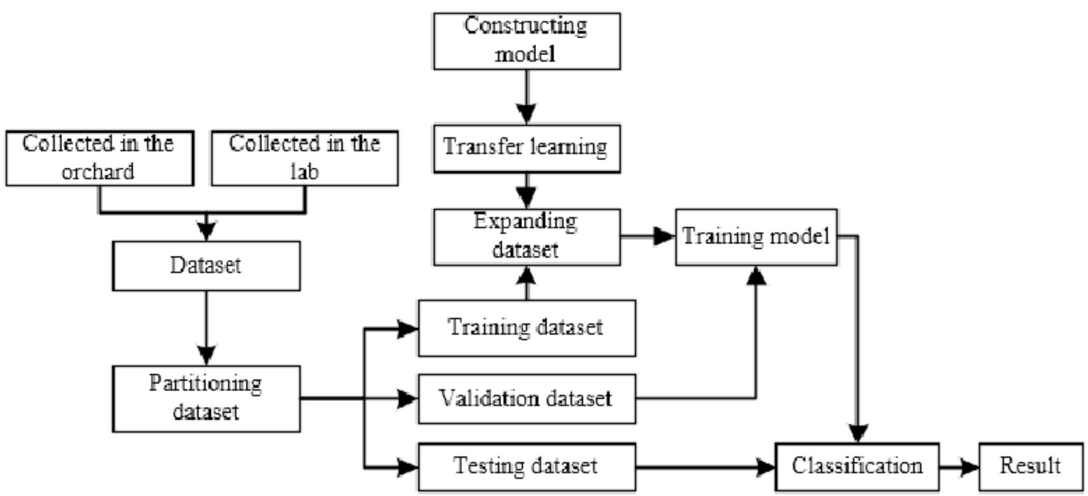

Fig 2.2.3.2 :Disease detection process

ATLDs detection process is shown in Figure5.Firstly, we collect images of diseased leaves and healthy leaves of apples from both laboratory and orchard fields. The original dataset was classified according to the disease categories by experienced professionals, and the dataset is divided into training, validation, and testing dataset. After that, we perform data augmentation on the training dataset and all images were normalized. Then, the XDNet model proposed in this paper was pre-trained on a subset of PlantVillage dataset, and then the training model was migrated to the ATLDs dataset collected earlier. Finally, the specific disease type of each image in the testing dataset was detected by the model.

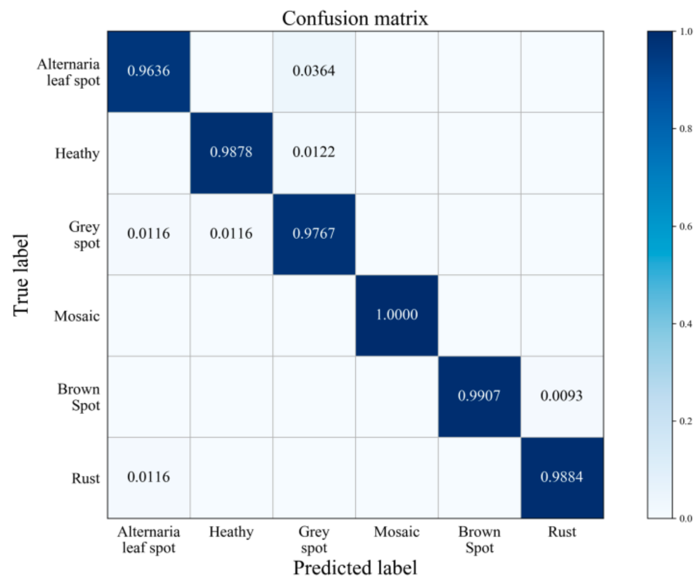

Fig 2.2.3.3 : Confusion matrix

In order to test the generalization performance and stability of the XDNet model, this paper performs the cross-validation five times. A total 20% of the dataset is selected as the testing dataset, and the remaining 80% of the dataset is divided into training dataset and validation dataset with a ratio and the remaining 80% of the dataset is divided into training dataset and validation dataset with a and the laboratory background in each subset is consistent.

2.3 Apple Leaf Disease Identification through Region-of Interest-Aware Deep Convolutional Neural Network

2.3.1 Introduction

Apple leaf diseases can have a detrimental impact on apple orchards, leading to reduced yields and compromised fruit quality. Timely and accurate identification of these diseases is crucial for effective disease management and prevention. In recent years, the field of computer vision and artificial intelligence has made significant strides in revolutionizing agriculture by automating various tasks, including the detection and diagnosis of plant diseases. "Apple Leaf Disease Identification through Region-of-Interest-Aware Deep Convolutional Neural Network" is a cutting-edge approach that leverages the power of deep learning and computer vision to address this critical agricultural challenge.

Apple leaf diseases often manifest as subtle visual symptoms such as discoloration, spots, or irregularities in the leaf texture. Conventional methods of disease identification can be time-consuming and prone to errors. The proposed system employs a deep convolutional neural network (CNN) that is not only capable of recognizing disease patterns but is also region-of-interest (ROI) aware. This means that it can pinpoint specific areas on the apple leaves where diseases are likely to manifest and focus its analysis there. By doing so, it significantly improves the accuracy and efficiency of disease detection.

The heart of this innovative approach lies in the neural network's ability to learn from large datasets of annotated apple leaf images, which encompass healthy leaves as well as those affected by various diseases. As the network processes these images, it extracts features and patterns that enable it to distinguish between healthy and diseased leaves. Furthermore, the region-of-interest awareness empowers the system to eliminate background noise and irrelevant information, enhancing the precision of disease identification.

Apple Leaf Disease Identification through Region-of-Interest-Aware Deep Convolutional Neural Network promises several benefits for apple orchard management. By automating the detection process, it reduces the need for manual inspection and the associated labor costs.

Moreover, it allows for early disease detection, enabling prompt intervention, such as targeted pesticide application or removal of infected leaves, which can prevent the spread of diseases and minimize yield losses.

2.3.2 Merits,Demerits and Challenges

Advantages

- This approach enables early detection of diseases.
- Achieves in High-level of accuracy.
- Reduced Labour costs.
- Increased productivity.
- Large-scale monitoring.

Disadvantages

- Algorithm sensitivity.
- Maintainance and updates
- Decision making not easily interpretable.
- It produces false positives and negatives.
- Hardware and infrastructure costs.
- Privacy concerns.

2.3.3 Implementation on Apple Leaf Disease Identification through Region-of Interest-Aware Deep Convolutional Neural Network

The primary idea is that leaf disease symptoms can be detected only in the leaf area whereas the background region contains no information about them. During DCNN training, the additional use of a region of interest (ROI) feature map including three areas: leaf area, background, and spot area. Symptoms can be detected only in the leaf area whereas the background region contains no information regarding leaf diseases. Therefore, the additional use of the predicted ROI feature map that contains the leaf area, background, and spot area can teach the DCNN regarding which features in the ROI map are more important and which features should have a decisive role in classifying leaf diseases. Hence, an additional subnetwork to predict the ROI feature map from an input image is designed, and subsequently combined with the conventional VGG network.

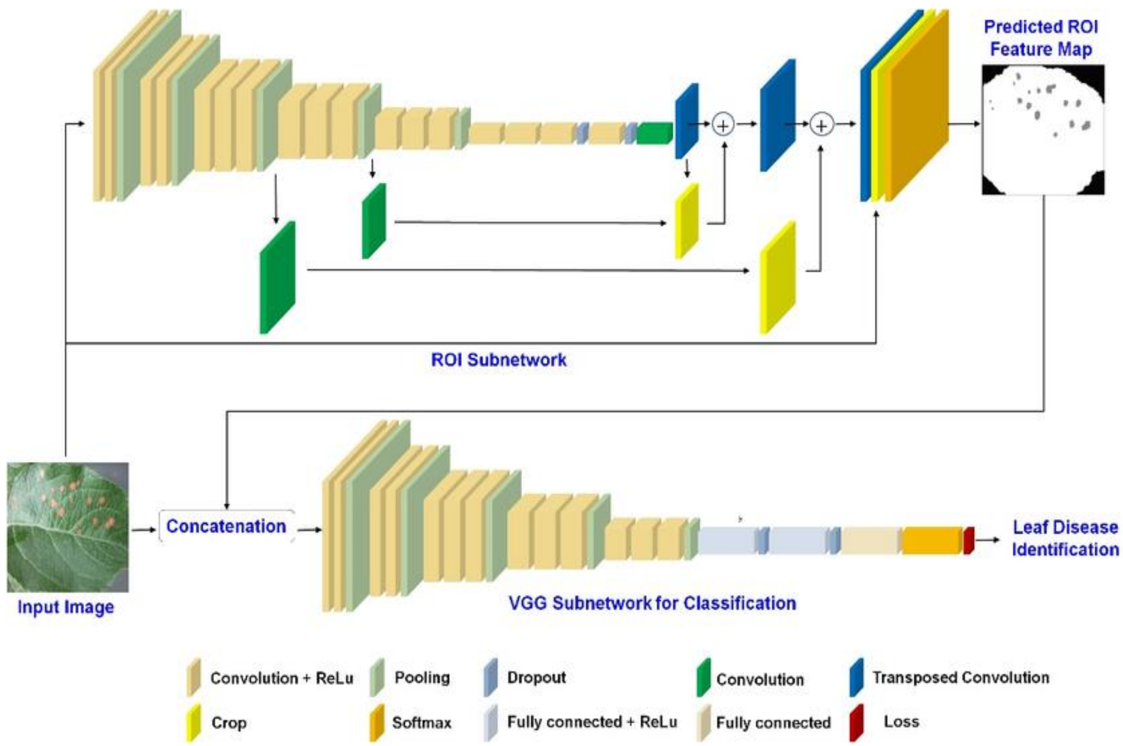

Fig 2.3.3.1:ROI-aware DCNN for leaf disease identification

The architecture of the ROI subnetwork in Fig. 7 is inspired by the semantic segmentation. However, the goal of this study is different from that.In other words, our goal is not to divide the input image into multiple regions, but to achieve apple leaf disease identification. In the proposed architecture, the ROI subnetwork is pretrained with a new training set that contains ground truth ROI maps; subsequently, this subnetwork is combined with the pretrained VGG subnetwork through the concatenation layer to complete a whole network to be trained in an end-to-end manner. Therefore, the purpose of using the ROI subnetwork is to predict the ROI feature map and subsequently teach the VGG subnetwork regarding which features in the ROI map should have a decisive role in classifying leaf diseases. The ROI subnetwork serves as a guide to achieve a more accurate leaf disease identification. As shown in Fig. 7, the proposed architecture is different from those of TL-based methods because two types of subnetworks are connected to create a whole network that is subsequently trained in an end-to-end manner.

Before training the whole network in an end-to end manner, as shown in Fig. 7, two subnetworks were first pretrained. To train the ROI subnetwork, ground truth ROI maps are required. In this study, ground truth ROI maps were generated manually through image editing (Photoshop) to divide them into three areas: background, leaf area, and spot area.The ground truth ROI maps, the ROI subnetwork was trained using mini-batch gradient descent optimization.Fig. 8 shows the ground truth ROI maps.

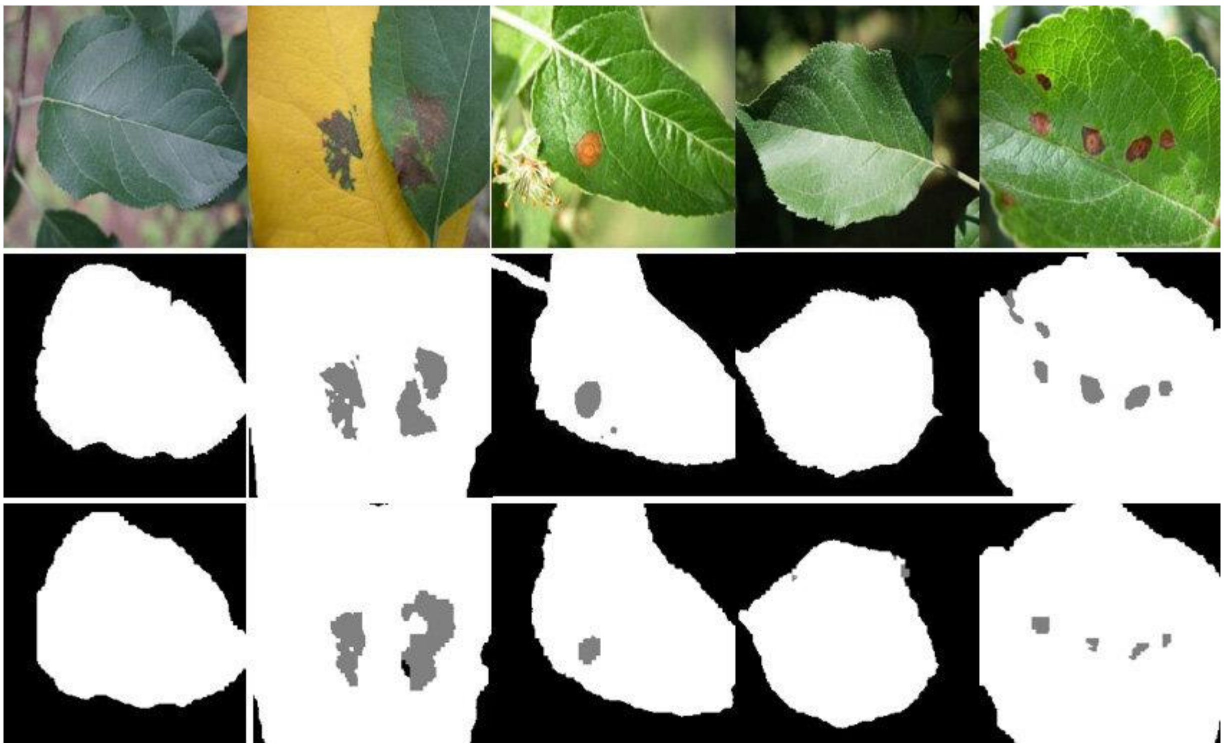

Fig 2.3.3.2: Leaf images, ground truth ROI maps, and predicted ROI maps

Next, to train the VGG subnetwork, the last three layers of the subnetwork were removed, and subsequently added with a fully connected layer, softmax layer, and log loss layer. Given a new training image set with three labels, the VGG subnetwork was trained using gradient descent optimization. The experimental result indicates that the VGG subnetwork obtains the correct recognition accuracy of 74.7%. Finally, to train the whole network in Fig. 4, the last loss layer of the pretrained ROI subnetwork was removed; subsequently, the softmax layer was connected to the pretrained VGG subnetwork through the concatenation layer that stacked the predicted ROI map on the top of the input image. Subsequently, the whole network was trained with the new training image set in an end-to-end manner.

Methods	Correct recognition accuracy
Clustering-based feature extraction	43.9%
TL method using VGG network	74.7%
TL method using ResNet network	74.6%
DCNN-based bilinear model	80.6%
Proposed ROI-aware DCNN	84.3%

Table 1 : Performance evaluation

Table 1 presents the correct recognition accuracy results for the proposed method and conventional state-of-the-art methods. By comparing the proposed method and the TL method using the VGG network, it is verified that the additional use of the ROI subnetwork increases the recognition accuracy by 9.6%. Hence, it is concluded that the ROI subnetwork can teach the VGG subnetwork regarding which features in the ROI feature map should have a decisive role in classifying apple leaf diseases. In other words, the ROI subnetwork had served as a guide for a more accurate leaf disease identification. It is also shown that the proposed ROI-aware DCNN demonstrates the best performance among all the methods.

CHAPTER 3

RESULTS AND DISCUSSION

CHAPTER 3

RESULTS AND DISCUSSION

The deep CNN reduces the need of additional feature engineering processes. The kernels applied at different layers generate the ‘‘activation maps’’ or generally called ‘‘feature maps’’. The feature maps obtained at different convolutional and pooling layers for an apple leaf infected with Cedar Rust. The early convolutional layers learn the features like edges, corners, and simple texture and preserving the most of the information in the input image. Pooling layers downsample the feature maps. Figure 3.2 illustrate 32 feature maps generated at first convolutional block (conv1+ pool1). It can be observed from the figures that orange, pale yellow lesions are highlighted within the leaf image. But, deeper layers defines an abstracted form of original image and encodes high level information such as disease spots and complex texture. Moreover, the feature maps get sparser at more deeper layers that detect specific information about patterns and shapes. Figure 3.3 shows 8 features maps related to third convolutional block (conv3+pool3). These feature maps represent only the complex information such as lesion shape and size.

3.1 Accuracy analysis

In this experiment, the proposed CNN model is evaluated for its accuracy. The training accuracy is plotted along with validation accuracy against the number of epochs in Fig.(x). It can be observed that there is only a small difference in training and validation accuracy curves. It declare that the proposed model fits well for the addressed problem. It can also be observed from the graph that model accuracy initially increases sharply with increasing epochs. Later it improves slowly.

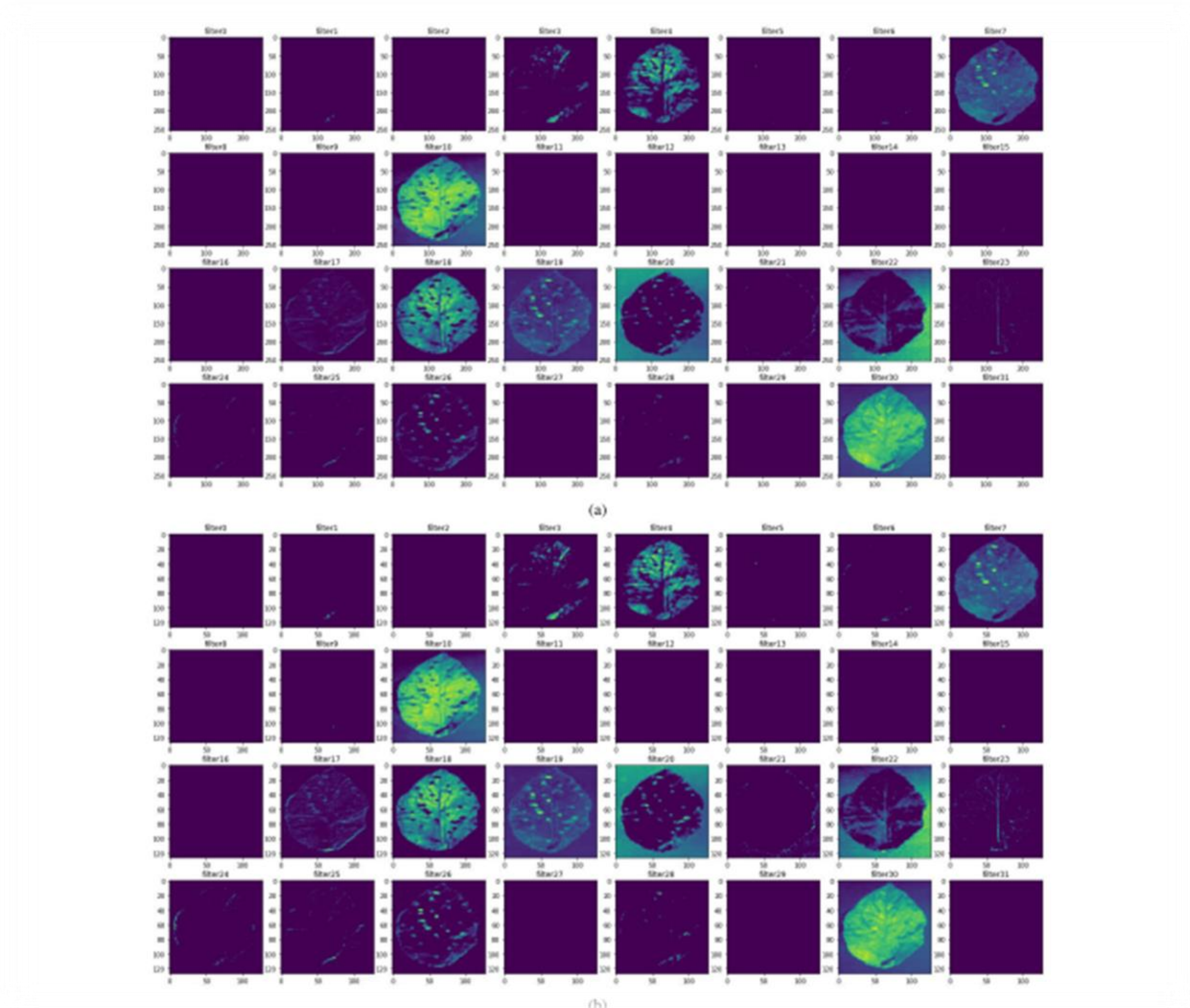

Fig 3.2: Feature maps generated at (a) first convolutional layer, and (b) second convolution layer in deep CNN model.

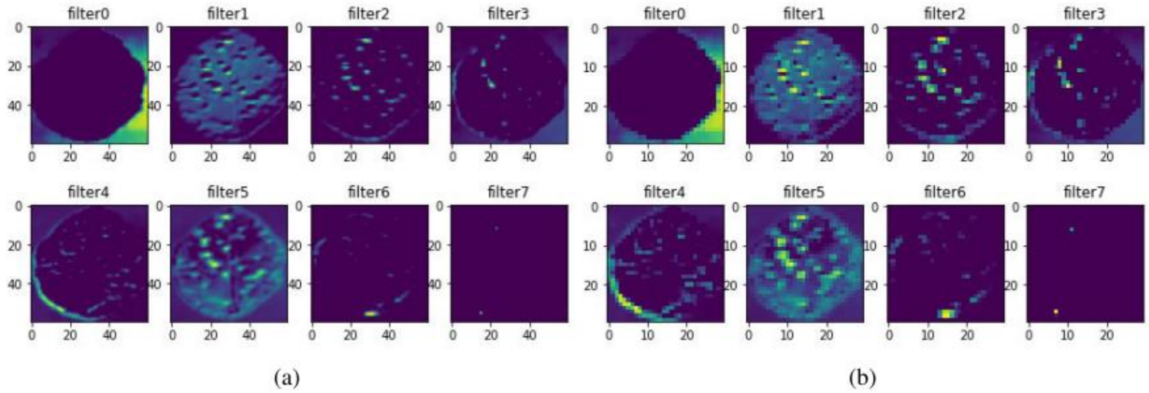

Fig 3.3 : Feature maps generated at (a) third convolutional layer, and (b) third pooling layer in deep CNN model.

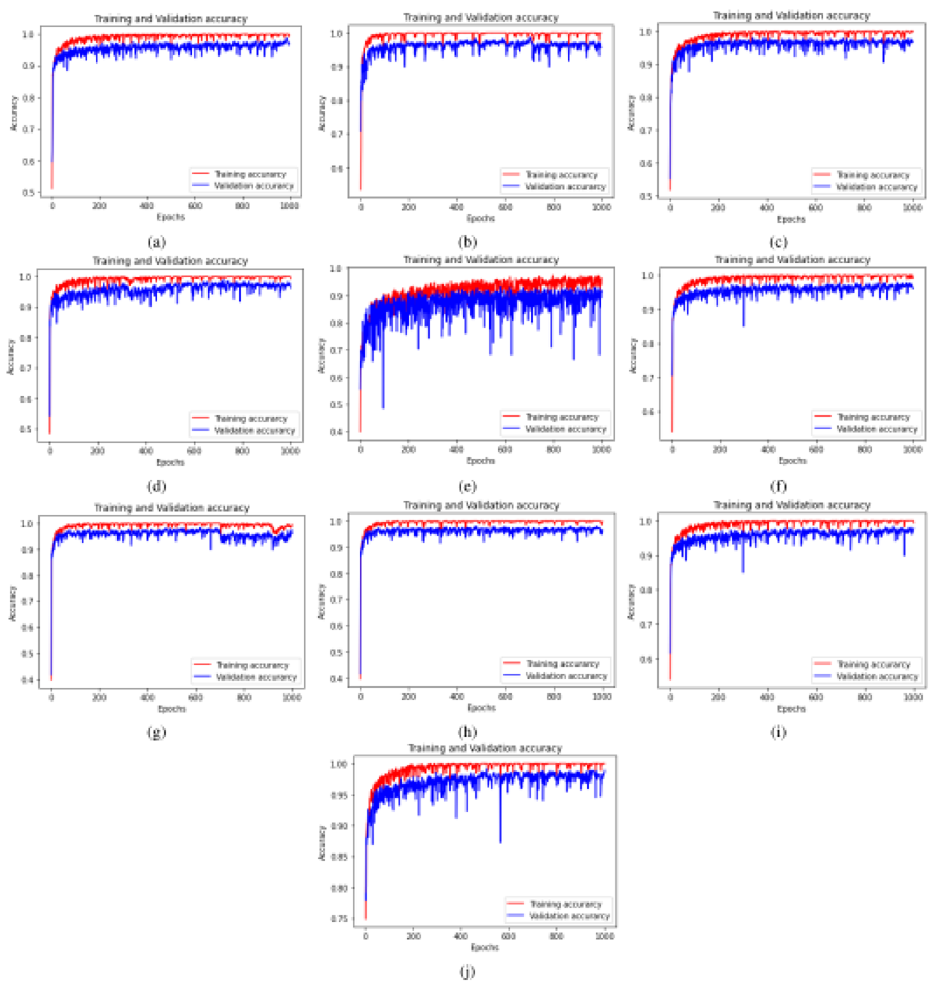

Fig 3.4: Accuracy versus epochs

CHAPTER 4
CONCLUSION

CHAPTER 4

CONCLUSION

An automated Apple leaf disease prediction model is developed using segmentation and classification algorithms. Algorithms for Machine Learning now have potential to improve leaf disorder early diagnosis. It can assist people make real-time prediction of disease in leaf. This study aided in the development of a system for Apple leaf disease identification. A deep CNN model was proposed in this work to identify diseases in apple crops with the help of leaf images. It can assist the non-expert farmers in apple orchards and lower the stress on plant pathologists. The model was trained on 3171 apple leaves for 1000 epochs. The accuracy of the model was evaluated to 98% on PlantVillage dataset. The rigorous investigation manifests the proposed model to be better than various pre-trained CNN models. The method was also found better than some other existing methods on the basis of various parameters including accuracy and memory requirements. The model achieves good accuracy for differ balanced the accuracy and precision. The large dataset with improved image variability would allow more rigorous experiments helping to improve the model to detect diseases at different stages for a variety of apple crops.

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GitHub Link

1. https://github.com/Ravi8295