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Empowering Precision Agriculture: A Novel ResNet50 based PDICNet for Automated Apple Leaf Disease Detection

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***Abstract:* -** Inspection of plant leaves through the naked eye is difficult and does not guarantee accurate assessment which results in economic loss to the farmers. Biotic or abiotic stress develop lesions on plant leaves and reduce crop quality and yield. This paper presents a novel model that uses RestNet50-based Deep Learning Convolutional Neural Network (DLCNN) classifier. This approach combines the optimization power of ACO with the robustness of ResNet50 to enable effective feature extraction and selection. We verify the efficacy of the strategy by extensive testing on an indigenously built dataset demonstrating its superior performance over other approaches. Our work advances automated methods for apple leaf disease detection and provides a dependable and useful solution for precision agriculture in apple orchards.

Keywords: Automated Disease Detection, ACO, DLCNN, Deep Learning.

I. INTRODUCTION

India's economy is based primarily on agriculture. Since plants are the primary source of food for humans, they must be cared for. Since plant diseases take a toll on the quality and quantity of crop yield, analyzing healthy and unhealthy plants is a crucial step in the development of successful agriculture. To keep uninfected plants safe from infected ones, it is critical to identify the afflicted plants [1]. Since most disease symptoms are evident in the leaves, plant leaves are the primary source for leaf infection detection [2]. The most preferred method of identifying biotic or abiotic stress on plants is by leaf inspection, which involves identifying the symptoms developed by the disease on the surface of the leaf.

Apples are among the most productive fruit varieties globally, owing to their high nutritional and therapeutic value. However, several illnesses, like Apple Alternaria leaf blotch (caused by Alternaria alternata f.sp. mali) and Apple rust (caused by Pruciniaceae glue rust), commonly affect the production of apples. These illnesses harm the quality of the fruits and consequently result in significant financial losses. At the moment, skilled professionals are primarily responsible for inspecting apple leaf diseases. One by one, they must examine each apple leaf. This is a really big task. One apple tree has a huge number of leaves. We don't have enough skilled professionals to complete this kind of inspection work for an entire apple crop. Additionally, a great deal of mistakes will occur when these professionals are fatigued, particularly for some related leaf conditions.

Consequently, to assist farmers in solving this issue, we require an automated solution. Without the assistance of specialists, this solution can enable inexperienced farmers to recognize certain apple leaf diseases accurately. Scab, Alternaria, and Apple mosaic are some commonly known diseases that impact the quality and quantity of apples. These foliar diseases develop symptoms on the leaves, as shown in **Error! Reference source not found.**, and then degrade the quality of the crop.

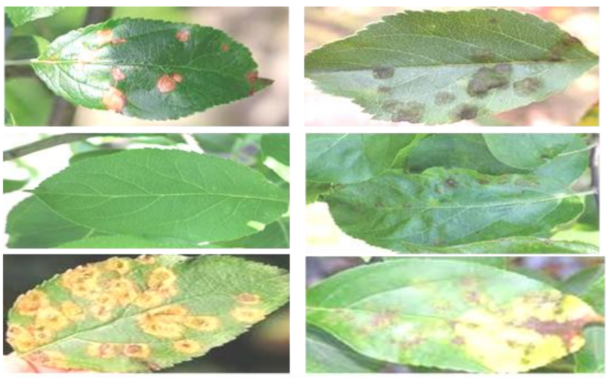

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Fig. 1. Impact of disease on Leaves

Loss of normal green color or yellowing known as Chlorosis, Powdery mildew, Cereal rust or Stem rust in wheat, Leaf rust in corn, Sclerotinia, Leaf spot or septoria or brown spot and Birds-eye spot on berries are a few mutual signs of disease in plants [3]. In the fields of image processing and computer vision, the Convolutional Neural Network (CNN) is the most widely used classifier, which has demonstrated accurate image grouping and filtering [4]. CNNs are the artificial Neural Networks that are used for the classification of images. Leaf disease diagnosis is also accomplished by image processing techniques [5]. Convolutional Neural Networks (CNNs) are effective for image classification tasks due to their ability to learn hierarchical features from input images. They use convolutional filters to detect patterns like edges, textures, and simple shapes. Pooling layers reduce computational load while preserving important features. The introduction of non-linearity, which is made possible by non-linear activation functions such as ReLU, enables the model to grasp complicated features from the input. The spatial dimensions are flattened into a vector for fully connected layers, which make predictions based on learned features. A softmax activation function is used as an output layer to select

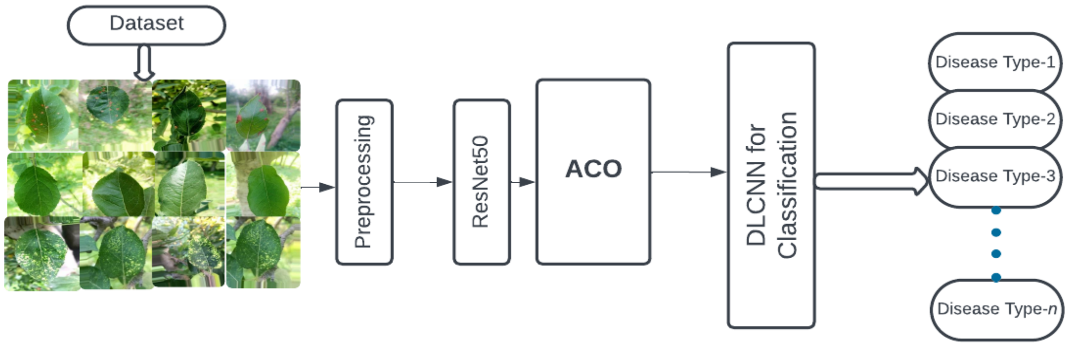

Fig. 1. Architecture of the PDICNet model

the class with the highest probability [6]. A collection of machine learning techniques that depend on huge datasets is called deep learning. Unlike machine learning, deep learning techniques do not require the grouping of features. While other plant disease techniques have had positive outcomes in the past, they are less moldable and are more time-consuming [7]. This study presents a novel model based on ResNet50 coupled with DLCNN powered by Ant Colony Optimization for a more precise classification of stress in apple leaves.

II. Related Works

Computer vision is widely used in conjunction with the deep learning approach to diagnose plant diseases. The paper [8] analyses the plot train and test visualization. It makes use of 35000 photos of both healthy and sick plants. This approach yields a 96.5% accuracy rate, however, the suggested approach achieves a 100% accuracy rate and detects sick leaves across a range of plant diseases. With the use of a convolution neural network, it identified 31 distinct plant variants and plant illnesses. A substantial amount of data is required for this method for accurate classification. By analyzing and classifying the photos from various phases into predetermined groups, deep learning technology is used for leaf disease detection.

A technique called clustering and picture segmentation is proposed in the research [10] as a means of detecting tomato leaf disease through image processing. The hierarchical features in this case are extracted using the CNN method, which maps the pixel concentrations of the input photos and compares them to the training images. It makes use of hybrid techniques, fuzzy logic, and the potential for organizing an artificial neural network. Using Grey Level Co-occurrence Matrix- GLCM the leaf picture has been divided into groups based on different stages.

In the manuscript [11], a leaf is extracted from the input photos using a YOLOv3 object identification. The implementation of deep learning systems with higher accuracy could aid in the identification of diseases. The human eye is incapable of recognizing this level of detail [12]. The optimal discriminating structure for the detection of distinct classes is found by using the ant colony optimization to examine the feature inspection interplanetary. A set of possible individualities, including figure, morphology, color, and texture, are extracted from the leaf photos to locate a feature examination planet.

In the paper [13], a new method for identifying plant leaf diseases is proposed. It involves several phases, like feature extraction, classification, picture acquisition, and segmentation. Here, Disease detection has been accomplished by BPNN-Back Propagation Network, Support Vector Machine (SVM), cluster-based classification models (CCM), Stochastic Gradient Descent approaches, Ottusu's algorithm, K-means clustering. The detection of leaf disease takes longer. This procedure involves many different activities, one of which is automating the identification system by employing composite photos captured in outside illumination and penetration environments. Various classification techniques that rely on the input data are presented in the study [14]. The classification techniques employed in the paper include Support Vector Machine and k-mean clustering. In [15], the Convolution Neural Network has been utilized to detect diseases in coffee crop. In the stages of picture categorization and pattern identification, Convolutional Neural Networks have proven to be accurate and successful. The primary goal of this approach is to identify coffee leaf disease with a high degree of precision. [16] Proposes a pre-trained LSTM-based convolution Neural Network (MLP-CNNs) to detect plant disease. Convolutional Neural Networks were used to extract deep features, which were then applied to an LSTM classifier. The study has presented a novel technique for detecting plant diseases and pests using deep neural networks. The LSTM classifier produced superior results than the others in terms of feature extraction and classification. [17] tries to uncover the factors that influence the application of deep neural networks to phytopathology.

III. Materials And Methods

Apple is a nutritious fruit that is consumed largely in the world, however, the impact of biotic or abiotic stress tends to reduce its quality and market value. As the manual approach does not assure accuracy and thereby results in misuse of control measures, deep learning is widely used for incorporating the much-needed reliability in the diagnosis. This work aims to offer an efficient model for classifying apple leaf diseases accurately. We use PDICNet as shown in **Fig. 1** for apple leaf disease detection. We apply preprocessing to make the dataset better for the purpose. Subsequently, with the application of ResNet50 we do segmentation and feature extraction. Optimal feature selection is done by ACO. We use an indigenous dataset constructed by collecting images from apple cultivation fields of Jammu and Kashmir for training and testing of the model.

3.1 Date set

A data set has been constructed keeping in view the local conditions. The dataset contains more than 7000 images in three categories as indicated in Table-I. This data set has been constructed by image acquisition from the apple orchards in Kashmir Valley in India using different types of capturing devices as shown by the procedure in **Fig. 2**. The images have been captured in varying lighting conditions to add diversity to the dataset. As the application of CNN models on raw data does not yield good classification results, segmentation has been applied.
As preprocessing improves the quality of a dataset and therefore enhances the performance of a neural network the following techniques have been used for preprocessing the dataset.

3.1.1 Normalization

Image normalization allows for the most accurate comparisons across different texture instances and data-collecting methods. When imaging modalities don't measure actual physical quantities, it's best to normalize the pixel values (intensity). The samples are normalized using the z-score method by subtracting the mean value from the pixel value and dividing by the standard deviation as shown below.

$$z = (x - \mu)/\sigma \qquad (1)$$

3.1.2 Resizing

As the images have been captured using different devices, the variation in images results in a prolonged training time. To eliminate this discrepancy and incorporate size consistency, useful scaling techniques like cropping large images and padding zeros in smaller images have been used. In this study, 256x256 pixel size has been used across the data set to make the mages suitable for most of the CNN model.

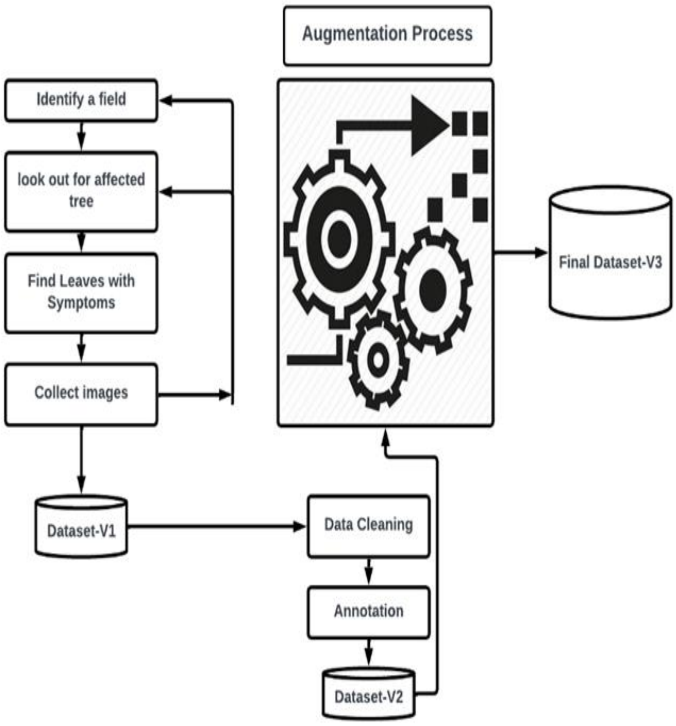

Fig. 2. Procedure adopted for creating the dataset

3.1.3 Outlier rejection

Images having mechanical damage due to hail storms rather than disease symptoms or overlapping symptoms were out rightly removed from the database as damaged samples.

3.1.4 De-noising

Gaussian noise mainly emanates during image acquisition due to varying levels of illumination and is represented mathematically as:

$$y = x + n \qquad (2)$$

Where y is considered as the noisy image with noise n added to the clean image x. The Gaussian filter has been used to eliminate the noise without changing the minute details of the images in the data set.

3.1.5 Augmentation

To make the dataset more suitable for any deep learning model augmentation techniques like brightness change, geometrical transformations, Zoom, flipping, rotation, and shearing have been used using the ImageDataGenerator class of the Keras toolkit. Augmentation does not only make a dataset bigger, it also makes the target dataset better by reducing overfitting and enhancing data diversity, model resilience, and translation invariance [18]. After applying the augmentation techniques a dataset containing more than 7000 images has been built as shown below in Table I.

Table I: Data Set

Type of Image	*No. of Images*
Healthy-Images	2500
AppleMosaic	2500
Alternaria	2500
Total-Images	***7500***

A sample of images from each category is given in **Fig. 3**, **Fig. 4** and **Fig. 5**.
The data set has the following advantages in comparison to publicly available data sets like PlantPathology Data-set-2020 [19].

- It contains samples specific to the Indian region.

- Models trained on this dataset do not suffer from performance degradation when tested in the real field. This is because the dataset contains images with non-uniform backgrounds and includes all possible variations in the real field.
- The classification of images has been done by experts in the field of agriculture.
- Image data has been pre-processed by applying geometric, intensity, and other transformations using the Keras/PIL library of Python.
- The data set being authentic has a huge potential to help researchers working on phytopathology.

3.2 Feature extraction with Resnet50

The different variations of ResNet are ResNet18, ResNet34, RestNet50, RestNet101 and RestNet152. The ResNet50, being fifty layers deep, stacks residual blocks to make a network. This model is extensively used for the analysis of image data with amazing accuracy. As deeper neural

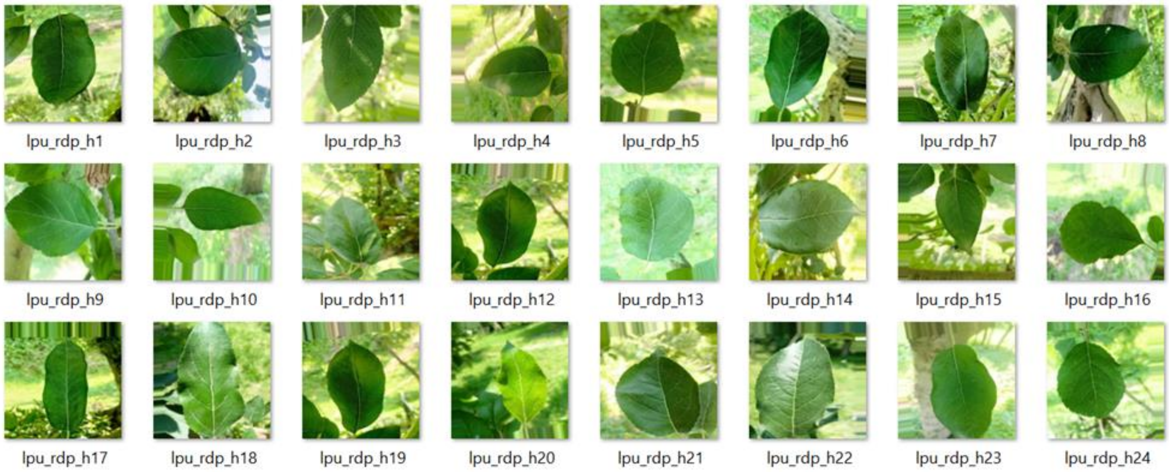

Fig. 3. Sample images (Healthy)

networks are difficult to train ResNet resolves the problem by making use of skip connections. These skip connections deal with the vanishing gradient by introducing an alternate route for the gradient to pass through and also by using an identity function. By this approach, it becomes possible to train much deeper networks than what was previously possible. The model for segmentation and feature extraction is shown in **Fig. 6**.

Using the information obtained from solving one problem to tackle another problem that is related to the first problem is an example of Transfer Learning. The neural networks pre-trained on large datasets such ImageNet are re-trained on smaller datasets through hyper-parameter fine-tuning. The pre-trained models having acquired extensive hierarchical representations of characteristics from the huge dataset, make this method beneficial for tasks that are similar to it. Compared to training from scratch, fine-tuning requires less training time and data since the model adapts its learned characteristics to the current task. Transfer learning models address the issue of gradient vanishing and gradient explosion of Deep learning models caused by their prolonged training time. The ResNet50 generates the segmented map of an input image by dividing it into 8x8 blocks which are individually examined at pixel level to highlight the regions of interest. This is followed by the extraction of seismic features for subsequent analysis. ResNet50 employs an Identity Mapping Module (IMM) and Residual Convolution Module (RCM) to address the vanishing gradients.

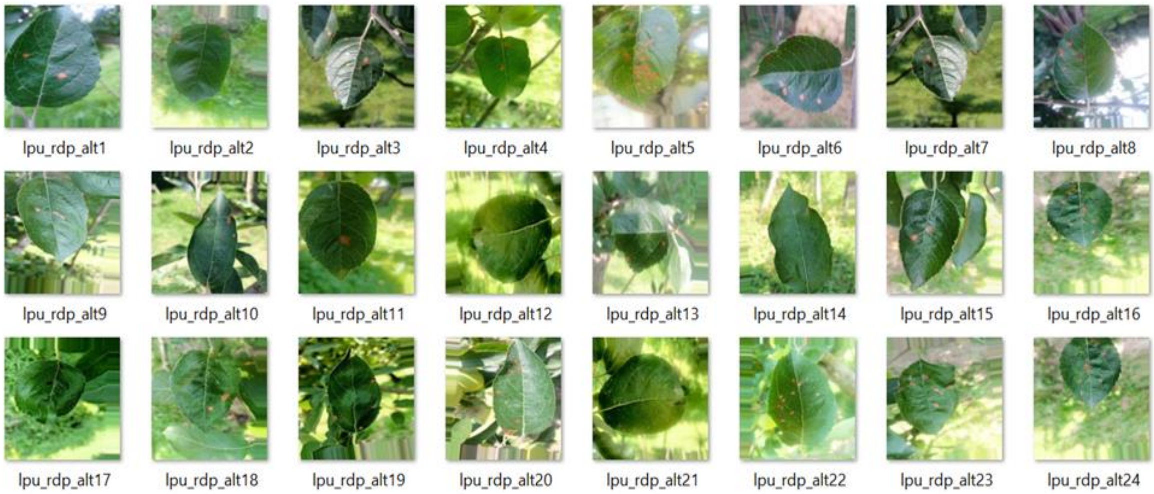

Fig. 4. Sample Images (Alternaria)

The convolutional (CONV2D) layer extracts features by applying spatial kernels on the input image. The result so obtained is integrated with the channel-wise information from the feature map to highlight the regions of interest. The feature map is made more suitable and manageable for further processing by down-sampling through pooling. Both the Batch Normalization (BN) layer and the CONV2D layer are utilized in simultaneously to normalize the feature map that is generated by the CONV2D layer. This is done to achieve training stability and to speed up convergence. ReLU aids in feature selection by activating the most relevant neurons. It assists the network in selecting important features from the input data by selecting both higher-order and lower-order characteristics. This makes it possible to effectively learn significant features while suppressing less significant ones, which eventually enhances the performance of the model.

In Neural Networks, downsampling is frequently used at the MaxPool layer to reduce the number of network parameters by a factor of two and the spatial size of the input data by a factor of two. MaxPool assists in maintaining important information while lowering computational complexity and memory needs by choosing the most salient features. This procedure effectively manages computational resources while preserving the network's capacity to identify pertinent

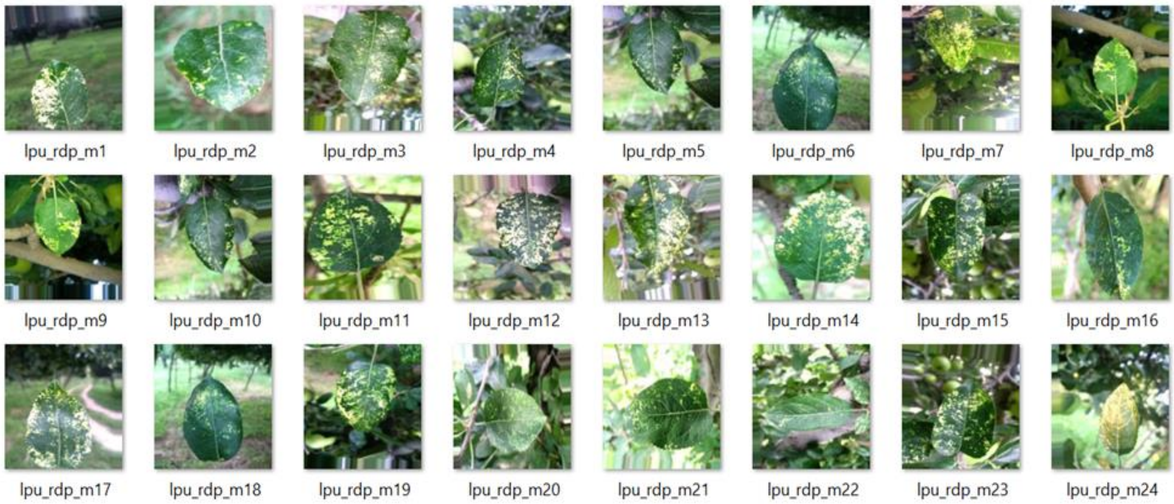

Fig. 5. Sample Images (Apple-Mosaic)

patterns and structures within the data. In ResNet50 IMM provides shortcut or skip connections to enable direct information flow between shallow and deep layers which resolves the issue of gradient vanishing. It also prevents performance degradation that may occur through excessively deep networks involving a series of CONV2D layers. In both the RCM and the IMM, a stack consisting of three convolutional layers is utilized. As a result of the reduced dimensions of both the input and output, the third layer functions as a bottleneck, and the RCM is accountable for first decreasing and then restoring the dimensions. RCM is limited to capturing multilayer texture data at a single scale for structures. As a result, feature extraction improves in accuracy at the expense of fewer computations and features extracted.

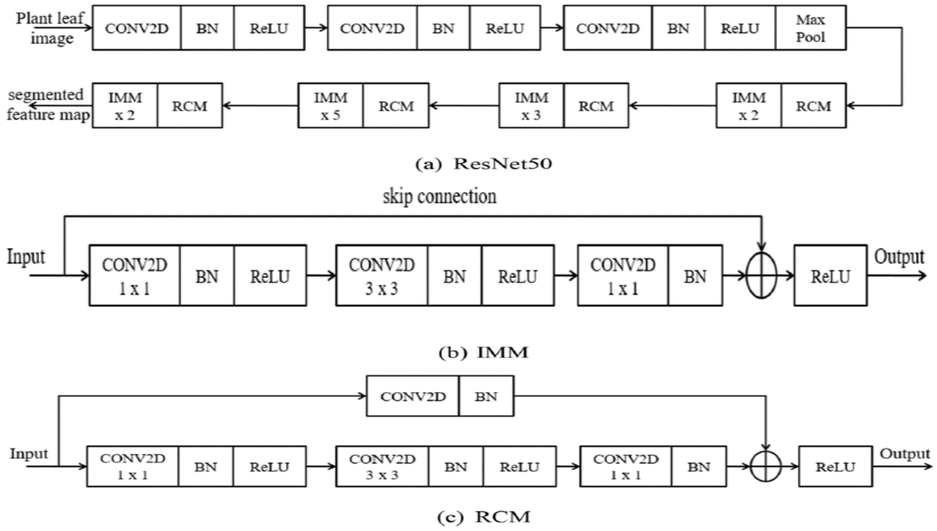

Fig. 6. Architecture of ResNet50 [[20]]

3.3 Feature selection with ACO

Before applying DCNN optimal feature selection is done by Ant Colony Optimization (ACO). ACO treats the feature subsets as solutions and uses ants' search behavior as to explore the solution space. Ants look for food by first randomly exploring the area around their nest because they do not know where food is located in their surroundings. An ant that sees a food source quickly assesses the volume and quality of the food and then carries some of it back to the nest. The ant leaves behind a chemical called pheromone on the earth as it makes its way back. The quantity and quality of the diet affect the amount of pheromone that is deposited. This will direct additional ants toward the food supply. ACO technique employs approximate optimization by mimicking
the seeking behavior of ants by which they determine the shortest path between their nest and the food source through indirect communication. The generic ACO algorithm consists of several steps, including initializing the pheromone, building a solution, and updating the pheromone. Until a terminal condition (all pixels have been visited) is reached, the solution development and pheromone updating procedure is carried out repeatedly. The technique is implemented by using pheromone rate as a variable that helps in differentiating between the healthy leaf and the infected leaf. Every pheromone component of the feature analysis is represented by a matrix (h) with a size of G*G, where G is the number of rows and columns that represent all of the unique feature vectors. The experimental function given in equation (3) is calculated and the parameters for the optimization technique are recalibrated to the best values through successive iterations.

$$n_j(n+1) = (1-S)n_j(n) \qquad (3)$$

The lesion or the symptoms on a leaf is located by using the transition probability which is mathematically expressed as:

$$Q_m(S) = \frac{S_m(S)}{\sum_{i=1}^{d} S_i(S)} \qquad (4)$$

Where *s represents* the pheromone evaporation rate.

IV. Results And Discussion

DLCNN shown in **Fig. 7Fig. 7.** Deep CNN Model is used for the classification. The model has several convolutional layers. Through the utilization of a collection of filters, these layers determine how convolution is carried out over the entire set of input features. Multiple convolutional layers make up this design, and each one learns various traits that differentiate between various plant leaves. Upon completion of each gradient update on a batch of data, DLCNN sees distinct feature information from the preceding layer. The data distribution of this input feature map is highly variable, partly due to the many modifications made to the parameters of the previous layers in the training process. As a result, training time is significantly reduced, and different optimization techniques need to be used to figure out how to initialize the parameters in the training set. The ReLU activation function mimics real neural behavior by simulating a real neuron's dormancy in response to particular impulses. It introduces non-linearity by replacing negative values with zero as governed by the following function.

$$f(x) = \max(0, x) \tag{5}$$

It is referred to as a subset layer because the max-pooling layer only activates a portion of the neurons that are contained inside the feature map for processing. A 2x2 filter with a stride of two is utilized for every block to reduce the spatial dimensions. The output layer uses the SoftMax function as an activation function to predict a disease based on multinomial probability distribution. The model was trained and tested by using 80:20 as splitting ratio as shown in Table II.

Table II: Data set splitting

Type of Image	No. of Images	Training Set (80%)	Testing Set (20%)
Healthy-Images	2500	2000	500
AppleMosaic	2500	2000	500
Alternaria	2500	2000	500

The performance yielded by the model is depicted in Table-III. The train and test accuracy is plotted in **Fig. 8**.

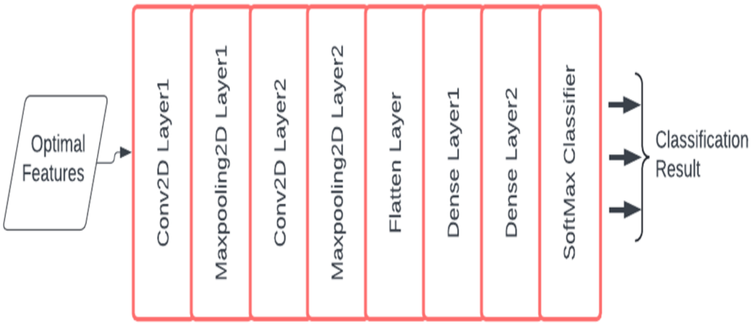

Fig. 7. Deep CNN Model

Table III: Performance Measures

Accuracy	Recall	F-Measure
97.7	96.95	96.05

For the purpose of evaluating the performance of the model, the following metrics were utilized.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{6}$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100 \tag{7}$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100 \tag{8}$$

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \tag{9}$$

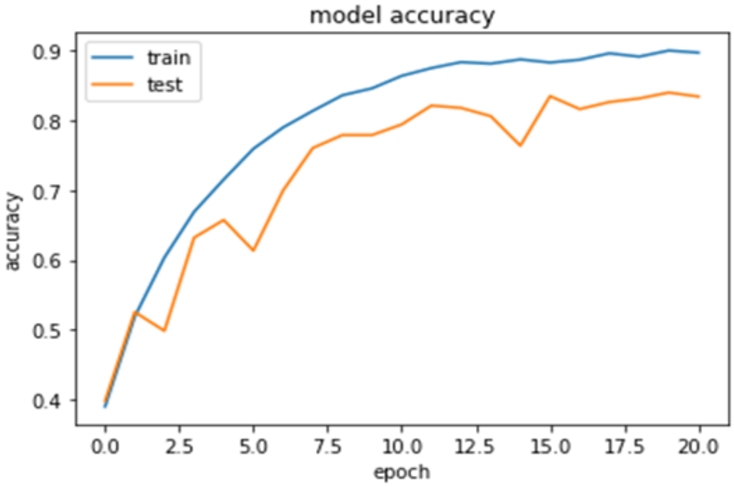

Fig. 8. Performance of the model

V. Conclusion

Plant disease detection at an appropriate stage is important for preventing economic loss. The traditional approach of detection and diagnosis done through the naked eye limits accuracy to the knowledge of the farmers or agricultural experts. Moreover, such approaches are not available to people in hard-to-reach areas. This study proposes an efficient model for automated disease detection and classification of apple leaves. It uses ResNet50 for feature extraction and ACO for optimal feature selection before using a DLCNN for classification of the detected disease. To achieve the best classification accuracy locally constructed data set has been used after applying preprocessing operations. The approach presented in the study yields better results as compared to the ML, DL and CNN-based approaches.

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