Study of various deep learning models for lemon disease detection

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Abstract:-

*Agriculture is the backbone of Indian economy. Early detection of plant is very important for preventing the economic losses and increasing the productivity of the lemon fruits. This is the one of the reasons that disease detection in lemon plants plays an important role in agriculture field, as having disease in plants are quite natural. If proper care is not taken in this area then it causes serious effects on plants and due to which respective product quality, quantity or productivity is affected. Detection of plant disease through some automatic method is useful as it reduces a huge work of monitoring in large farms of crops, and at very early phase itself, it detects the symptoms of diseases i.e. when they appear on plant leaves. This paper presents different deep learning (DL) technique for lemon plant disease detection to achieve a great potential in terms of increasing accuracy. In this we have used different conventional neural networks named GoogleNet, ResNet, and SqueezeNet models with and without data augmentation. Dataset used in this is collected from Mendeley data. The dataset of plant images that are collected under categories namely leaves. These images are further categorized using the diseases found in the plant. The dataset considers only the diseases that are common in most of the lemon plants. The dataset contains a total of 609 images and contain 256*256 dimensions with 72 dpi resolution. In each category, 70% images were used for training and 30% images are given into the testing process. The trained models with data augmentation give the best results with 97.83%, 97.42%, and 99.07% for GoogleNet, ResNet and SqueezeNet respectively.*

Keywords: Deep learning; Convolutional Neural Networks; Lemon leaf; Diseased and Healthy leaf; Training; Classification.

1. INTRODUCTION

Agriculture is the backbone of Indian economy. Agricultural image processing is one of the core applications of image processing and the most growing research area. Image processing has been proved to be an effective tool for analysis in various fields, including agriculture. Image processing in agriculture is done by capturing images through cameras. These images are then process and analyze by computers using image processing techniques. It has been simplified by new technological advancements in image capture and data processing to handle numerous agricultural challenges. The following applications of image processing can be found in agricultural applications to take out the infected leaves. Determine the disease by determining the colour, shape, and size of the affected area, then quantify the affected area by disease.

The early detection of lemon plant is very important for preventing the economic losses and increasing the productivity of the fruits. Disease may be identified and detected by using human visual inspection and laboratory tools which are difficult, time consuming methods, and do not give more accurate result. Computer-based analysis and detection is very effective and produces high accuracy result. A number of techniques and methods have been used for detecting the disease and their level. In India, various types of citrus trees are cultivated such as Lime, Lemon, and Orange. Disease control and removal are essential to increase the productivity of the fruits and to get high profit. Different cultural practices are used to reduce the severity of the disease. The removal of diseased foliage, branches and spraying the trees Bordeaux mixture may reduce and cure the lemon disease.

Plant diseases are classified as fungal, bacterial, or viral. The majority of illnesses is fungal in origin and creates visual effects on plant leaves. Fungus can cause diseases such as leaf rust and powdery mildew. Bacterial diseases can cause yellow aura leaf spot. Similarly, viral diseases can cause mosaic leaf patterns or yellowed leaves. While plant diseases cause visual effects in all parts of the plant, such as leaves, stem, and fruits, the most common way for identifying disease-affected plant is to change the colour or shape of the leaves.

Deep learning is now widely utilize in a variety of disciplines, including object identification, signal and speech recognition, biomedical image classification, and segmentation. Deep learning is also being utilized extensively in agriculture for the identification and categorization of plant diseases. Convolutional neural network (CNN) is regard as the most effective deep learning approach. Several CNN architectures such as AlexNet, GoogLeNet and ResNet are utilized to identify and classify plant diseases. Furthermore, there are many researchers who used deep learning models for the identification and classification of citrus diseases.

A Convolutional Neural Network is comprised of a game plan of linked artificial neurons with learnable loads and inclinations that is enclosed in a convolutional network. These neurons communicate with one another by exchanging signals. Associations are burdened with numerical loads that are adjusted throughout the planning cycle, so that when presented with a picture or guidance to perceive, a properly structured association would react appropriately. The association is made up of many layers of neurons that are sensitive to different kinds of features. Each layer has a variety of neurons that react to a variety of different combinations of commitments from previous levels. For example, as seen in Figure 3.1, each layer is designed with the goal of detecting a large number of unpolished models within a given dataset. The second and third levels are designed to identify instances of models, and the fourth layer detects instances of those models.

1.1 CNN Layers

Complex structures, such as CNNs, are used to solve problems with data collection by stacking numerous and different layers on top of one another. Four types of layers are used in image processing convolution layers, pooling/subsampling layers, non-straight layers, and layers that are entirely related. The many levels of CNN are seen in Figure 3.2. It is dealt with by the convolution layer a small portion of the data image. The yield from this layer is sent on to the pooling layer for processing. This is repeated after which there is a completely similar layer that does gathering.

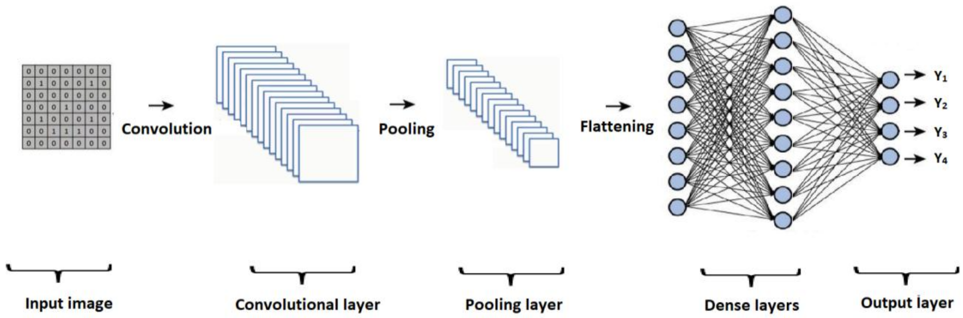


Figure 1. Architecture of CNN

1.2 Convolutional Layer

Different characteristics of the data are removed as a result of the convolution operation. A low-level feature such as edges, lines, and corners is removed by the first convolution layer of the algorithm. More raised level layers destroy more key level characteristics as the number of raised level layers increases. The pattern of 3D convolution employed in CNNs is seen in Figure 3.3. The data has the dimensions N x N x D and is convolved with H bits, which are all of the dimensions k x k x D and are all freely convolutional. The convolution of a commitment with one section results in one yield incorporate, while the convolution of a commitment with H parts results in H features. In order to shift each segment, each portion must be moved from left to right, starting with the top left corner of the data and progressing downwards. The piece is moved one segment downward after reaching the top right corner, and then it is moved one segment from left to right, repeating this process for each segment until the upper right corner is reached. Until the spot arrives in the bottom right corner of the screen, this cycle is repeated.

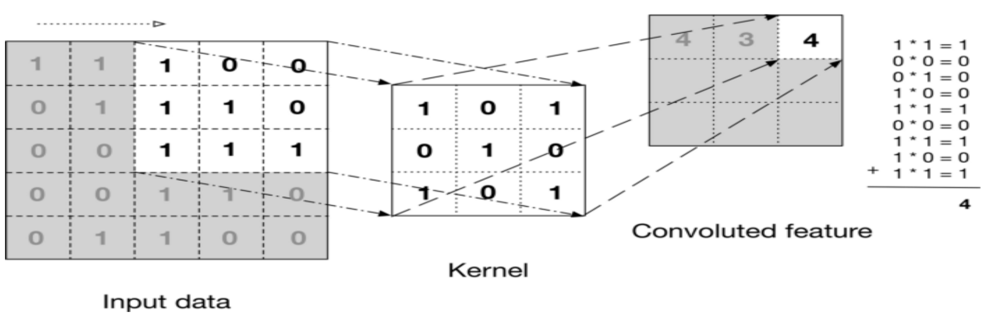


Figure 2. Representation of Convolutional Process

Consider the case when N = 5 and k = 5, which means that the segment may take 5 different conditions from left to right and 5 different circumstances from beginning to finish. The yield will comprise 28x28 (i.e., (N-k+1) x (N-k+1) segments in contrast to the places in which they are found in the previous two positions. To measure the position of the part in a sliding window measure, segment by segment copy and gather k x k x D segments of data and k x k x D segments of kernel are copied and collected for each position of the part. As a result, in order to cause one segment of one respect to integrate, k x k x D copy accumulate assignments are necessary for each segment of one respect.

1.3 Pooling Layer

The pooling layer contributes to the reduction of the overall target of the highlights. The following are the two distinct methods of carrying out pooling activity, maximum pooling and normal pooling respectively. In all situations, the information is divided into sub-districts that do not cover the whole state.

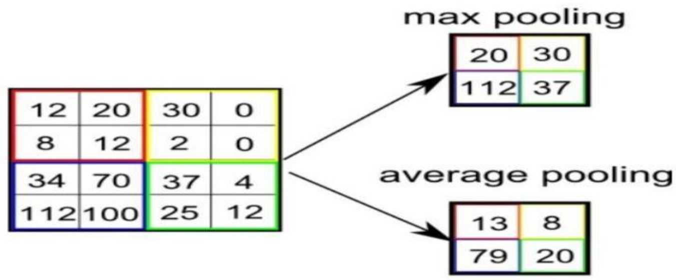


Figure 3. Representation of Max Pooling and Average Pooling

The pooling cycle is further explained in detail in Figure1.3. The data is divided into four non-covering networks, each of which is 2x2 in size, and they are represented by the colours green, yellow, red, and blue in the information image of size 4x4. A result of the maximum pooling action, the yield is determined by taking the best evaluation of the four features in the 2x2 matrix (37 from the green grid, 30 from the yellow system, 20 from the red organization, and 112 from the blue organization) and averaging them. Regardless, the ordinary of the four characteristics (20 from the green structure, 8 from the yellow matrix, 13 from the red grid, and 79 from the blue organization) is regarded as the yield as a result of normal pooling and is referred to as the yield. It is necessary to adjust the final result of averaging to the closest whole number if it is a division.

1.3 Non-Linear Layer

The ReLU layer is responsible for updating the capacity y=max (x, 0). At the moment, the information and yield sizes of this layer are equal in size. This activity contributes to the development of the nonlinear features of the decision capacity, as well as the general organization. Neither the various fields of the convolution layer nor the convolution layer as a whole are affected by this. When compared to the other non-direct abilities used in CNNs (e.g., Sigmoid, exaggerated digression, and total of exaggerated digression), the important advantage of a ReLU is that the organisation trains significantly more rapidly. Figure 3.5 illustrates how ReLU may be of assistance in various situations. The exchange work was mapped throughout the length of the bolt. Everything that is good (positive characteristics 15, 20, 35, 18, 25, 100, 20, 25, 101, 75, 18, 23) is kept, and everything that is bad (negative qualities - 10, - 110, - 15, - 10) is transformed to a value of zero.

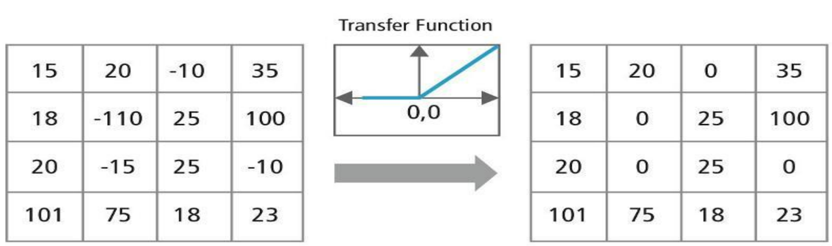


Figure 4. Representation of ReLU Functionality

1.4 Fully Connected Layer

The last levels of a CNN are often comprised of layers that are completely connected with one another. In terms of numbers, these layers are a summation of the weighting of the previous layer of highlights. This demonstrates the precise mixture of fixes required to determine a certain goal yield outcome. The count of every component of each yield inclusion is increased if there should be an occurrence of a wholly related layer because all of the components of an apparent plurality of highlights from the previous layer are used in the count of every component from the previous layer.

Figure 1.5 illustrates the entirely related layer L in further detail. Layer L-1 features two highlights, each of which is 2x2 pixels in size. It is made up of four parts. Every component in the primary element in the (L-1) layer is enlarged with two arrangements of loads and then summed to produce the element in (L-1). Layer L comprises two highlights, each of which consists of a single component.

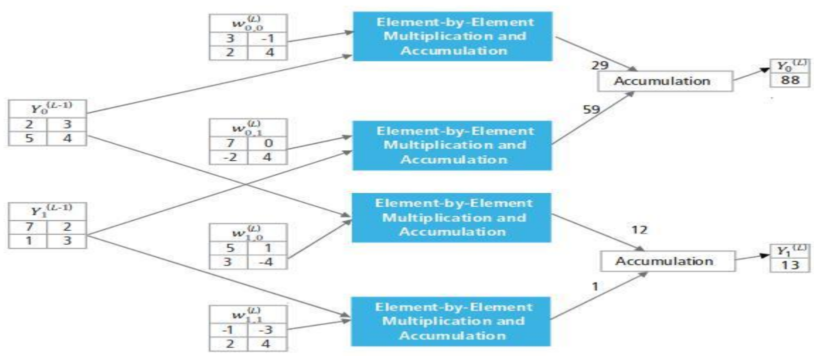


Figure 5. Processing of Fully Connected Layer

2. LITERATURE REVIEW

In 2016 Srdjan Sladojevic *et al.* [1] used deep convolution network approach for leaf disease recognition using classification method. Researcher proves that climate change can alter stage and pathogen development rate. The trained deep neural network to differentiate surrounding of leaves. To highlight region of interest all images are cropped manually by making square around the leaves. Author applied augmented process to increase dataset. Augmentation includes rotations, transformation and affine transformation. This paper presented caffe as a deep CNN framework.

In 2016 Feng Qin *et al*. [2] extracted numbers of texture, shape and colour features after the lesion segmentation by these methods for alfalfa leaf diseases. After selection of the features, disease classification models were built using three supervised learning methods, including the support vector machine, K-nearest neighbor method and random forest. A comparison of the recognition results of the models was conducted. The results showed that when the features were selected, the support vector machine model was built with some important features separated from a bunch of futures was the optimal model. For support vector machine model, the recognition accuracies of the training set is almost 97% and for the testing set it was 98%.

In 2016, Mohanty *et al.* [3] tested dataset of 54,306 images of disease and healthy plant leaves collected under controlled conditions, train a deep convolutional neural network to identify14 crops species and 26 diseases in 38 different categories in the Plant Village dataset using the AlexNet and GoogoLeNet networks, respectively, with a maximum identification rate of 99.35%.

In 2017 Toran Verma *et al*. [4] separated texture, colour, and wavelet attributes of the spots and stained part of segmented rice crop images after pre-processing of captured images. The image features has been applied to design linear vector quantization neural network model to identify leaf blast and brown spot disease. The model with hybrid features present better recognition efficiency as comparison to individual features used in neural network model. Here the observations says that Linear Vector Quantization neural network recognition model for rice leaf blast and brown spot recognition disease gives better presentation with hybrid statistical and signal features passed for training.

In 2017 Gittaly Dhingra *et al.* [5] describes application of agriculture using computer vision technology to recognize and classify disease of plant leaf. The paper deals with correlation between disease symptoms and impact on product yield. It also deals with increase the number of training data and testing to accomplish better accuracy.

In 2017 Mohammed Brahimi *et al.* [6] proposed deep learning method to create classifier for detection of disease. Also proposed the occlusion concept to localize the disease regions & help to understand the disease. Author uses datasets which is published in good fellow, Bengio etc, further research is need to reduce the computation & size of deep models for small machine like mobiles.

In 2017 Vijai Singh *et al.* [7] presented an algorithm for segmentation of plant leaf image. Author proposed image recognition and segmentation process. First, devices were used to capture image of different types and applied different segmentation method to process image. The author taken image of size m*n & every pixel has R, G, B components. Color co-occurrence method was used for feature extraction. Above experiments are done in MATLAB. Author demonstrates the results only for beans, leaf, lemon and banana leaf. Further research is needed for all types of leaves.

In 2018 A. Wajid *et al*. [8] carry out on the suitability and efficiency of different classification methods including Naïve Bayes, ANN, and decision tree. Comparisons are based on the output of these three algorithms, and it has been found that the technique of classification of the decision tree for orange conditions is more successful than ANN and naive based. In general, implementation of the Citrus fruit identification and classification algorithm comprises the following five consecutive steps, namely database, data augmentation, pre-processing of the dataset, feature extraction, Identification and classification.

In 2018, K. R. Aravind *et al.* [9] the grape leaves' characteristics were extracted using a transfer learning method by CNN and Alexnet. 4063 diseased leaves made up the dataset. In order to extract the features, the suggested CNN with Alexnet architecture included seven rectified linear unit ReLu, five convolution layers, three normalization layers, two drop out layers, and one softmax layer. To categorize the disorders, Multi-SVM was used with the extracted features. The accuracy of the suggested method was 99.23%.

In 2018, Banni *et al.* [10] carry out the infected area of citrus leaves and was segmented using the Bi-Level thresholding technique. Images of various citrus leaves taken from plants including grapefruit, lemon, and orange. The GLCM approach was used to extract the features, and the framed hidden markov model was then used to categorize the diseases. 236 samples of damaged citrus leaves make up the dataset. The accuracy of the approach was 85.71%, 84.21%, 82.50%, and 78% for canker, anthracnose, overwatering, and citrus greening, respectively.

In 2019 B. Doh *et al.* [11] carried an SVM with ANNs to increase the high classification speeds. The approach proposed will substantially engineer precise fruit disease identification and automatic classification. The paper explains four features that are shape, size, color, and texture. It is also noted that the outcome of the SVM classification changes as there is a change in the training and testing ratio.

In 2019, Andrushia *et al.* [12] adapted to find the best features from the built-in feature sets of grape leaves; the Artificial Bee Colony Optimization method was modified. The noises in the image were eliminated by the cellular automation filter. The grape leaves were used to extract the characteristics of colour, shape, and texture. The ABC algorithm uses the extracted features set as input to find the best features set. The disorders were then classified by the SVM classifier. The dataset from the plant village is used for testing. KNN classifier performance was contrasted with SVM performance. PSO and the genetic algorithm were used to compare how well the ABC feature selection approach performed. The experimental findings demonstrated that SVM with ABC feature selection produced an accuracy of 93.01%, which was better than other approaches.

In 2019 Y. Ashwani *et al.* [13] applied computer vision and identification for defects due to nutrient deficiencies in fruit. The pixels containing the defective regions and extracts the characteristics from them. Additionally, a support vector machine (SVM) classifier is employed to find the flaws and determine the stage of the problem. Fruits are divided into two groups throughout the classification process defective and non-defective. The defected sample image was further divided into three categories as the first, second, and final stages of fruit defect.

In 2019, I. Ojelabi et al., [14] describe the colour, geometric, and texture elements of a citrus fruit, image were extracted and reduced using PCA, and a diseased zone was described using the K-means clustering technique. Based on the retrieved features, SVM was used to categorize the diseases. 190 samples of infected citrus fruit were included in the collection. Performance of the proposed approach was contrasted with that of the KNN classifier. The SVM classifier's accuracy was 95%, which was 6% better than the KNN classifier's accuracy.

In 2020 Kukreja and Dhiman *et al.* [15] suggested a robust CNN algorithm for identifying and providing an effective approach for identifying apparent citrus fruit problems. The suggested method is compared to a dense model that does not employ data augmentation or pre-processing methods. The suggested model has an accuracy rate of 89.1%. The findings reveal that data augmentation and preprocessing strategies have yielded good results in estimating citrus crop damage.

In 2020 H. Singh, R. Rani *et al.* [16] suggested the Support Vector Machine, Linear Discriminant Analysis, K-Nearest Neighbors, and Multi-Layer Perceptron approaches were utilized to detect citrus leaf diseases. The k-means clustering method was used to segment diseased areas of leaves, and color and texture characteristics were collected. To choose the most relevant characteristics, the ANOVA F-test is used. Finally, the pathogens were identified using the methods described above. A total of 236 diseased citrus leaves were included in the study. The use of a combination of colour and texture characteristics improved precision. For colour and texture characteristics, the precision of LDA, MLP, KNN, and SVM was 84.32 percent, 81.36 percent, 77.12 percent, and 80.93 percent, respectively.

In 2021 Khanramaki *et al.* [17] proposed a smart technique, convolutional neural networks, to detect three citrus pests citrus Leaf miner, Sooty Mold, and Pulvinaria. To put the theory to the test, 1774 images of citrus leaves were used. Suggested method CNN accuracy was evaluated in an experimental study, 10-fold cross validation was used based on the results of the experiments with an accuracy of 99.04 percent outperformed other competing CNN algorithms.

In 2021 Sharifah Farhana *et al.* [18] proposed a model consists of two main stages first proposing the potential target diseased areas using a region proposal network and second classification of the most likely target area to the corresponding disease class using a classifier. The proposed model delivers 94.37% accuracy in detection and an average precision of 95.8%. The findings demonstrate that the proposed model identifies and distinguishes between the three different citrus diseases, namely citrus black spot, citrus bacterial canker and Huanglongbing.

3. PROPOSED METHODOLOGY

Deep architectures are derived from the conventional neural networks. Different from the other popular machine learning methods that have shallow structures, deep networks typically have more layers and parameters, and thus they have the potential to represent more complex inputs. A deep network consists of multiple layers of hidden units to extract features of given inputs. A non-linear activation function is applied to each hidden unit to generate the output. The activation functions add non-linearity to the model so that the deep neural networks are able to model complex non-linear relationships. The hidden units are connected with all or part of the units in the preceding layer and feed the outputs forward to the next layer. Among the stacked structure of many hidden layers, the deep neural network is able to learn multiple levels of feature representations that correspond to different levels of abstraction. Analysis of the weights in each layer shows that the earlier layers can extract the lower level patterns from the inputs, and the latter layers tend to learn high-level features by combining the lower level patterns with such structures, the deep neural networks are able to extract complex representations.

Feature extraction and classification techniques are the two popular data processing methods in machine learning. Choosing the appropriate machine learning algorithm is a difficult task as its performance depends on several determinants like the type of problem, type of data, the quantity of data, etc. Making the right choice of algorithm is essential for getting precise classification results. Traditional machine learning techniques have got some limitations. The limitations of the conventional learning methods include glitches such as high computational cost and inability to extract optimal features from raw data. These shortcomings decrease the overall productiveness when dealing with real-time signals. Deep learning techniques can overcome these limitations as it blends both the feature extraction and classification methods in a single model. This improves the overall classification performance and reduces the computational time. In order to get the finest outcomes, we have employed the idea of deep learning in the proposed work.

3.1 Description & Workflow

- In first step we need to create an image data store and save the images in different sub-folders by disease name.
- In the next step, the data will be divided into training and testing groups. Testing is essential to obtain accuracy.
- In the next step we will use pre trained model and modify network according to our data. In our case we have 609 images with 5 different classes.
- In the next step it is to define training parameters, like what will be initial learning rate, maximum number of epochs and batch size etc.
- Additionally we will train our model and optimize hyper parameters if it is necessary.
- When the model is trained we will test the model on testing dataset to check its accuracy.

3.2 Image Acquisition:

In this paper datasets of plant disease containing lemon disease is collected from the Mendeley data repository for the detection and classification of plant diseases by applying deep learning models. We have trained the model with 70% data and tested the model for 30% data of the total dataset.

3.3 Image Pre-Processing:

Image processing technology is widely used in agricultural pre-processing with the goal of refining input data that contains undesirable features and improving certain image attributes that are useful for execution. The captured images of lemon leaves were initially pre-processed, and image rescaling was performed, resulting in the creation of new versions of the images. Improving the image is necessary to improve clarity, remove unwanted flickering, improve contrast, and find more information. Images used to train the models are preprocessed using various preprocessing techniques to provide the model with consistent and uniform data for training and validating the collection of images.

3.4 Data augmentation:

A common technique for increasing the size of a dataset is data augmentation. Image transformations are used to increase the number of images in the dataset and reduce over fitting by adding a few distorted images to the training data. Data augmentation is the most widely used method for dealing with the problem of insufficient training data for image classification tasks. The process of creating new images using various transformation techniques is known as data augmentation. It is a technique for creating a large number of trainable datasets from a small amount of data. This is done to give deep learning models more data. When a small number of samples are used for training, over fitting occurs. When working with image data, augmentation is the most effective way to avoid over fitting. Many of the techniques have been implemented by combining effects such as increasing contrasts, flipping, rotating in at different angles, and shifting vertically and horizontally.

3.5 Transfer learning using pretrained network

Training the network on your data set using the pretrained network as a starting point, transfer learning enables you to fine-tune deeper network layers. Instead of building and training a new network for fine-tuning, transfer learning is frequently quicker and simpler. The network has already learned a huge number of image properties, but when fine-tuned, it can learn features specific to your new data set. If you have a huge amount of data, transfer learning might not be quicker than starting from scratch.

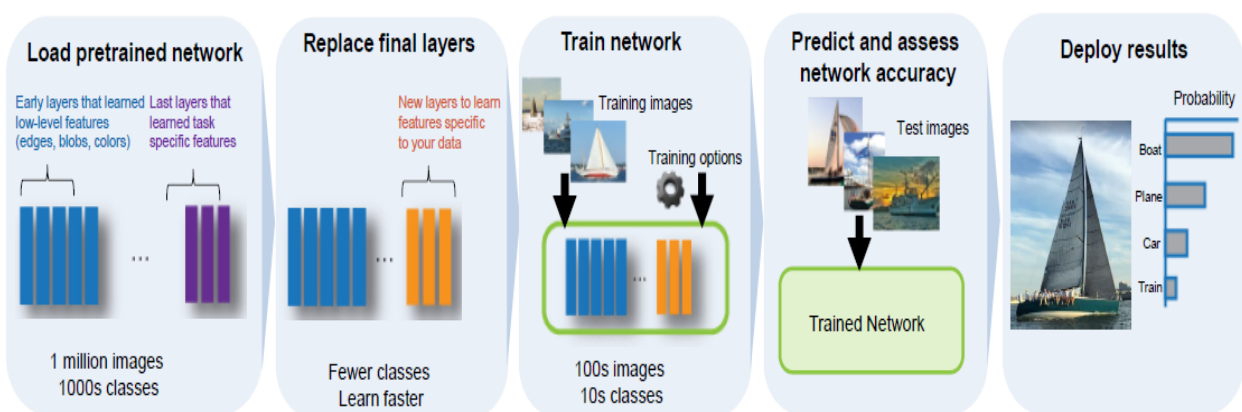


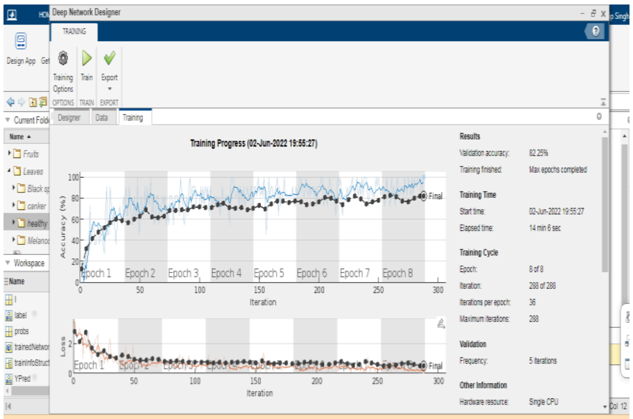
Figure 6. Transfer learning

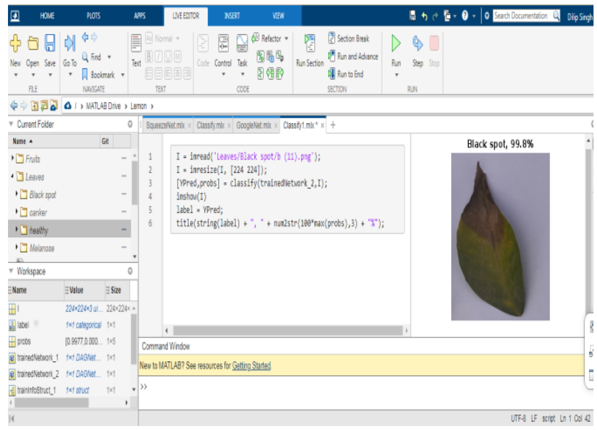
3.6 Train Network

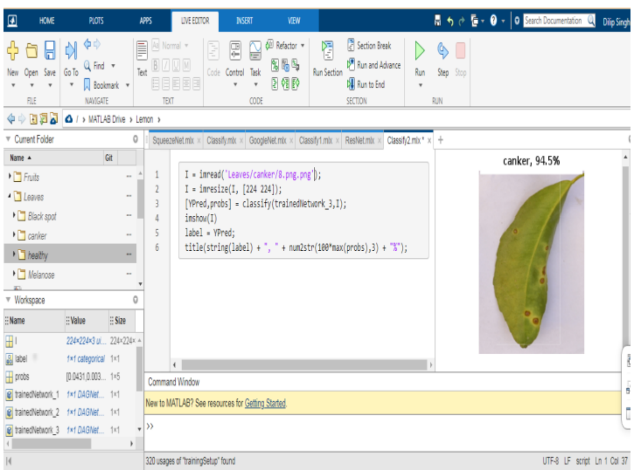
To choose the training options, Set the initial learn rate to a low value to slow down learning in transferred layers, and increase the learning rate factors for the 2-D convolutional layer to speed up learning in the new final layers while setting the starting learn rate to a low value to slow learning in transferred layers. To uniformly distribute the training data and guarantee that the full training set is used during each epoch, we set the Initial Learn Rate to 0.001, the Validation Frequency to 10, the MaxEpochs to 10, and the MiniBatchSize to 11.

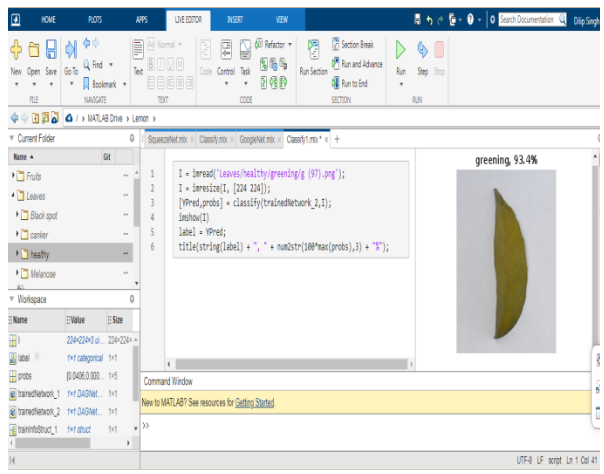
3.7 Classify Image using GoogleNet

GoogLeNet is a deep convolutional neural network with 22 layers. It is possible to load a pretrained version of the network that has been trained on ImageNet data sets. These networks have learned different feature representations for various images. Both pretrained networks have an image input size of 224 by 224. To learn a new task, we can use a pretrained image classification network that has already learned to extract powerful and informative features from natural images. It predicts the labels of the validation data using the trained network and computes the final validation accuracy. In this study, we evaluate the performance of GoogleNet networks in document image classification, and we find that an ImageNet pretrained GoogleNet achieves an accuracy of around 97.83%.









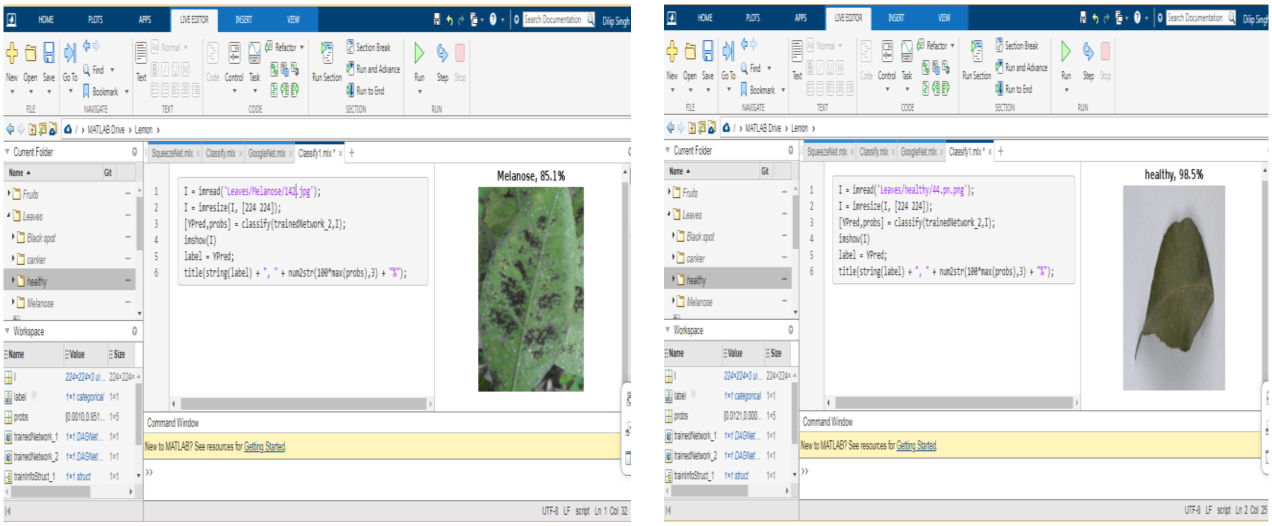
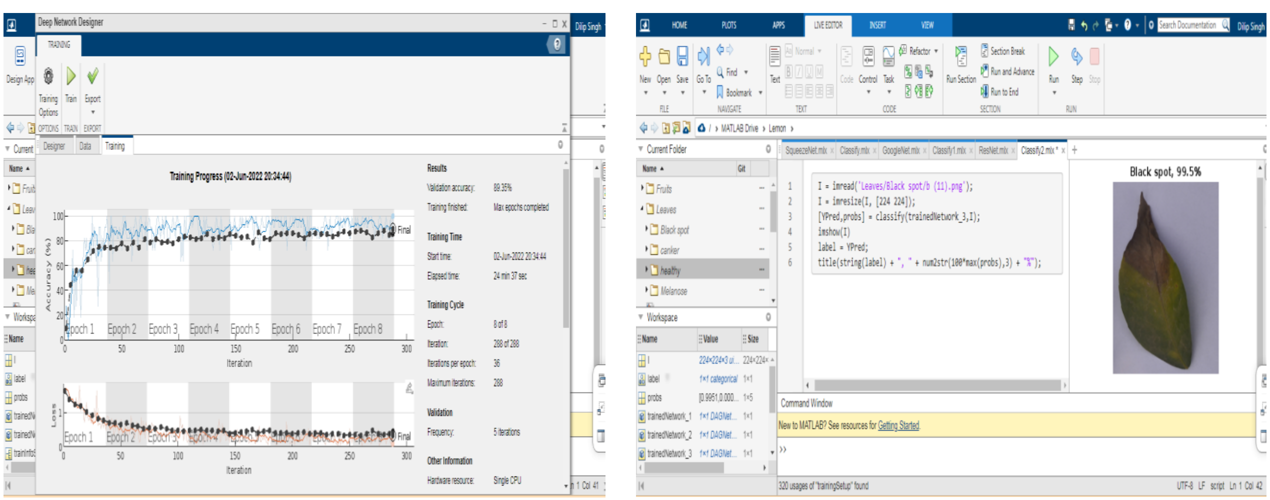


Figure 7. Testing result using GoogleNet

3.8 Classify Image using ResNet-50

ResNet is an abbreviation for Residual Network. ResNet-50 has many variants that use the same concept but have different numbers of layers. ResNet-50 is the name given to the variant that can work with 50 neural network layers. ResNet-50 is a deep convolutional neural network with 50 layers. It is possible to load a pretrained version of the network that has been trained on over a million images from the ImageNet database. Pretrained networks can classify images into over 1000 different object categories. As a result of this, the network has learned detailed feature representations for a wide range of images. The network accepts image input of 224 by 224 pixels. There are 50 layers in the network. The number of sequential convolutional or fully connected layers on a network is defined as its depth. There are 177 layers in ResNet-50. In this paper, we assess the performance of ResNet-50 networks in image classification, demonstrating that an ImageNet pretrained ResNet-50 achieves an accuracy of around 97.42%.



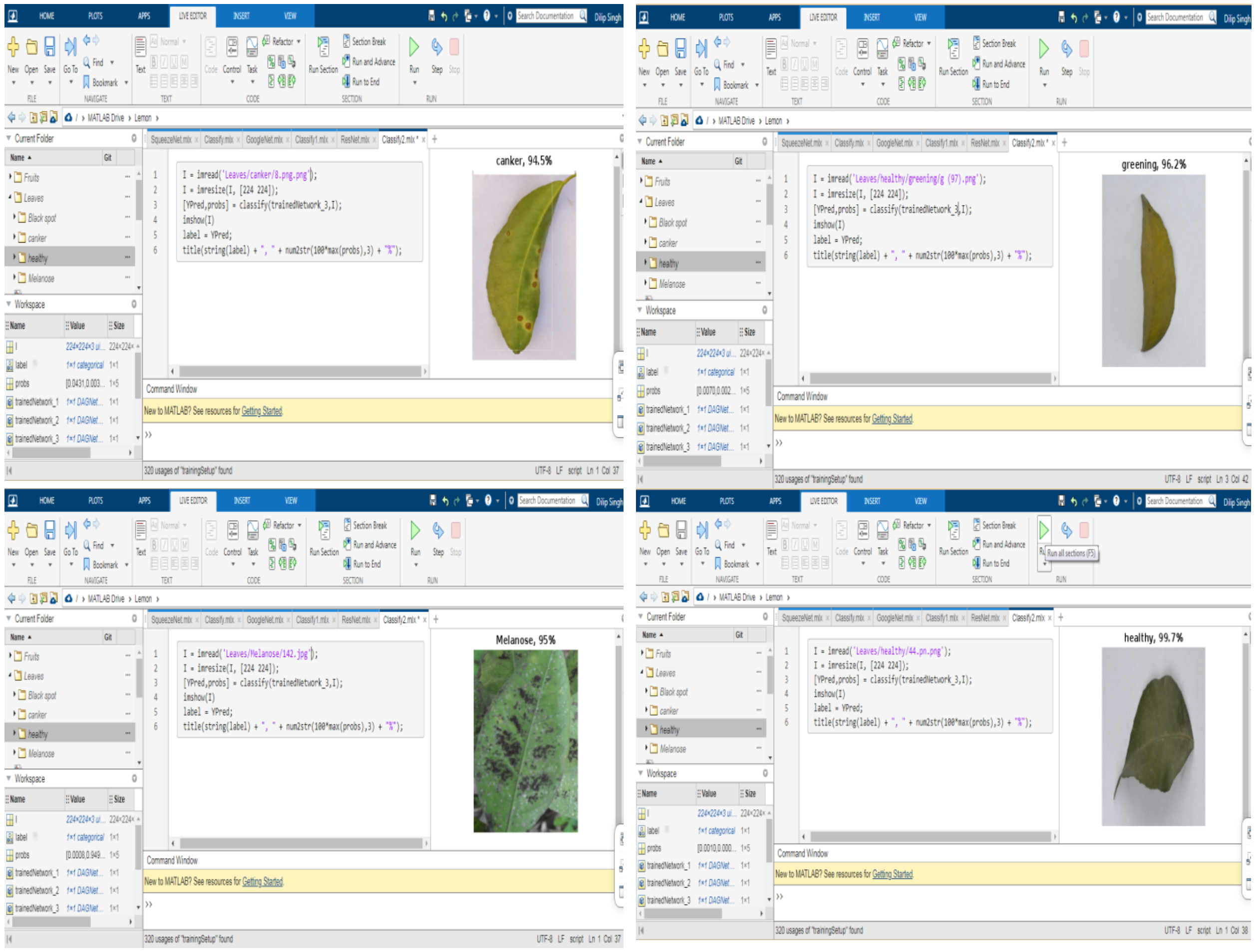


Figure 8. Testing result using ResNet-50

3.9 Classify Image using SqueezeNet

SqueezeNet is a deep convolutional neural network with 18 layers. It is possible to load a pretrained version of the network that has been trained on over a million images from the ImageNet database. Pretrained networks can classify images into over 1000 different object categories. As a result of this, the network has learned detailed feature representations for a wide range of images. The image input size for the network is 227 by 227 pixels. SqueezeNet networks outperform state-of-the-art convolutional neural networks in image classification tasks. We evaluate the performance of SqueezeNet networks in document image classification in this study, demonstrating that an ImageNet pretrained SqueezeNet achieves an accuracy of approximately 99.07% across 5 different classes on the lemon disease dataset.

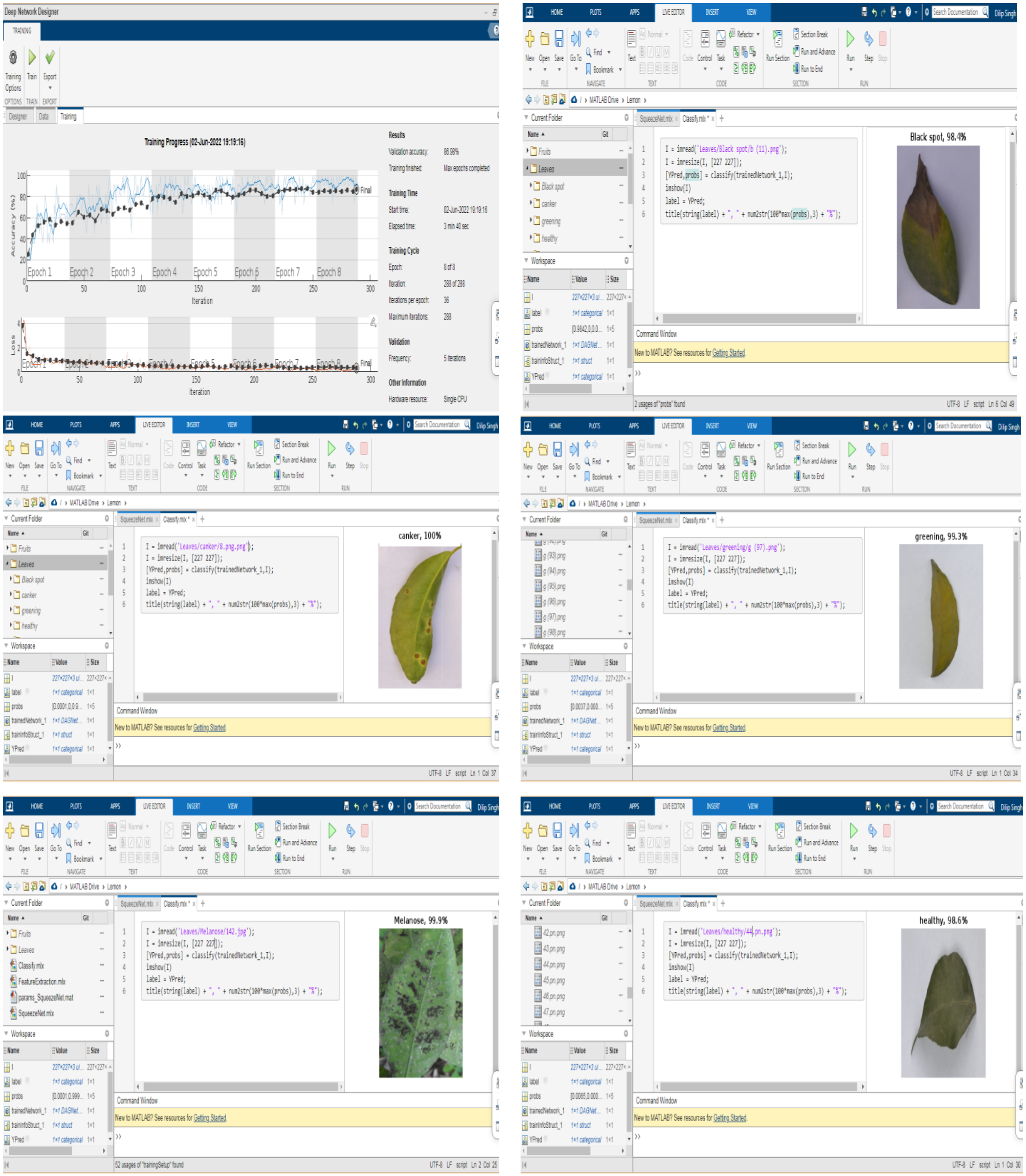


Figure 9. Testing result using SqueezeNet

4. RESULT

There are numerous methods for calculating classification accuracy on the ImageNet validation set, and they are used by different sources. Sometimes a group of multiple models is used, and each image is analyzed multiple times with multiple crops. But often the top-5 accuracy is quoted instead of the standard accuracy. Because of these distinctions, comparing the accuracy of different sources is frequently impossible. This section discusses the outcomes and findings of experiments conducted on various models. The accuracy of detecting lemon disease using the GoogleNet, ResNet-50 and SqueezeNet models is 97.83%, 97.42%, and 99.07% respectively. The SqueezeNet model outperforms GoogleNet and ResNet in predicting lemon disease.

5. CONCLUSION

When selecting a trained network to apply to your problem, different trained network characteristics must be considered. The most important characteristics of a network are its accuracy, speed, and size. Choosing a network is usually a result of balancing these factors. A good network is both accurate and fast. The most commonly used metric for assessing the accuracy of ImageNet-trained networks is classification accuracy on the ImageNet validation set. When applied to image data sets via transfer learning or feature extraction, networks that perform well on ImageNet are frequently accurate. Because the networks have learned to extract powerful and informative features from images, they can generalize to other similar data sets.

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