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Plant Disease Classification Using Machine Learning

Anjali Gupta[1] and Sandeep Rana[2]

[1]Scholar in Computer Science, JP Institute of Engineering & Technology, Meerut

[2] Department of Computer Science, JP Institute of Engineering & Technology, Meerut

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ABSTRACT

Plant diseases are widespread by a variety of pests, weeds and pathogens and can have devastating effects on agriculture if not treated in time. Farmers face a myriad of challenges due to adequate water supply, premature rain, storage facilities, and diseases of multiple crops. Plant diseases are a major threat to farmers with enormous production and economic loss. Identifying disease on a few hectares of farmland can be a daunting task, even in the presence of moderntechnology. Accurate and rapid disease prediction for early crop disease treatment has proven to be productive for healthy crops as well, minimizing personal financial loss. Many studies use modern deep learning approaches to improve the accuracy and performance of object detection and identification systems. Crop diseases are a constant challenge for smallholders, threatening income and food security. The proliferation of smartphones and recent revolutions in computer vision models has created a method of image classification in agriculture. Convolutional neural networks (CNNs) are considered the cutting edge of image recognition and offer the possibility of making timely and clear diagnoses. Thisarticle examines the performance of a pre-trained ResNet 34 model in the detection of plant diseases. The developed model can be used as a web application to detect seven plant diseases from healthy leaf tissue. A dataset containing images of 8,685 leaves. Captured in a controlled environment and established for model training and validation. Verification results show that the proposed method can achieve an accuracy of 97.2% and an F1 score of over 96.5%. It demonstrates the technical feasibility of CNN in plant disease classification and points the way to AI solutions for smallholders.

Introduction

Agriculture is one of the most important economic activities of the Indian subcontinent and two third populations are directly involved in farming and related occupations. Agriculture has long been considered India`s backbone, dating back to the Indus Valley civilization. To earn income, mankind established their residence land according to agricultural facilities and favorable conditions. Agriculture is important in most developing countries because it provides jobs and contributes a significant portion to GDP (Pradhan 2007). Bacterial growth and diseases are a primary threat for the crops and affect the agricultural cycles and patterns too. A variety of pesticides, fertilizers, and research-based therapies are used today to overcome this problem. Attention is paid to agriculture every five-year plan, and India's agricultural development is prioritized. Due to changes in domestic weather and economic conditions, the agricultural sector needs further improvement. For more productive results, the plants in the field must be healthy. Regular cultural monitoring requires technical and appropriate research-based methods. Plant diseases are one of the reasons for the decline in crop quantity and quality. The use of toxic pathogens, extreme climate change, and inadequate disease control are some of the factors behind inadequate food production. Numerous pesticides are available to control crop diseases in agriculture and increase crop production. Identifying the current disease of the crop and finding the right pesticides to control the disease is a task that requires the advice of agricultural experts, and this task is very tedious and costly. Accurate and timely detection of crop diseases is one of the reasons for successful agriculture. It is also very important to spend less time and money to identify the hazardous diseases on crops. These diseases on plants and crops can be pre identified with initial tracks and spots developed on leaves and fruits. Many farmers use their knowledge or seek assistance from other professionals to spot crop diseases with their naked eyes. Due to the similarities in symptoms of crops, this method raised the possibility of human error and faulty illness diagnosis. This type of disease diagnosis mistake leads to the overuse of pesticides and fertilizers that contains heavy metals, which reduces crop yield and even pollutes the environment through deposition in various areas, resulting in radiological and chemical exposures to humans, flora, and fauna (Bangura et al. 2019, 2021, Pandit et al. 2020, Mehra et al. 2015). Nowadays, server based, and mobile based technologies are used to identify the diseases of crops accurately (Sladojevic et al. 2016, Huang et al. 2014). Modern approaches like Machine Learning and Deep Neural networks are used to increase the accuracy of results in finding diseases of crops. There is a need for a Machine Learning Vision system to identify the disease from the image of crop and to suggest the pesticide as a solution to control the disease.

Tele:

E-mail address:anjaligupta098@gmail.com

Plant Diseases

1. Apple Scab: Apple scab is a serious disease of apple that attacks both fruits and leaves. Olive green spots or pale-yellow spots appear on the upper surface of the leaves. Dark and velvet spots appear on the lower surface of the leaves. Apple with this scab disease is not fit for eating. This disease reduces the quality and size of fruits. Apple scab can cause total failure of crops without control measures.

2. Black Rot: Black rot is a disease that is caused by bacteria that can infect crops. It is very difficult to control this disease by the growers. Generally, the loss of crops happens in hot and humid weather conditions. These diseases are generally found in apples and Grapes. Disease symptoms appear as yellow and dead tissues at the edge of the leaves in older plants. The spot-on leaves get larger and infect other plants and fruit bunch very rapidly.

3. Bacterial Spot: Bacterial spot is a dangerous disease of plants found in warm and humid weather conditions. Bacterial spot occurs on pepper and tomatoes. Symptoms on the leaves appear as small yellow-green lesions which get deformed and twisted and change into the dark, water-soaked, and greasy lesions. This disease is due to bacteria that attack the vegetation, stems, and fruits of tomatoes and pepper. Once this is present on the plants it is very difficult to control the disease and these spot results in unmarketable fruits and vegetables.

4. Black Measles: Black measles occur in grapes and is also known as grapevine measles, esca, or Spanish measles. The term measles refers to artificial spots that appear on the grapes. The symptom on the leaves appears as a 'Tiger Stripe' pattern and it becomes more serious from year to year. During the season, the spot merges over the surface of the grapes and makes the grapes black. Spots on the berries can appear any time after the fruit set and before some days of the harvesting.

5. Cedar Apple Rust: Cedar apple rust is a fungal disease that occurs in apples. The infected leaves show yellow to orange round spots on the upper surface. As soon as the infection grows, the spots also appear on the lower surface of the leaves. This disease can affect the stems and fruits. When the disease of the fruits grows, then the lesions on the fruits may crack and appear brown in color.

6. Citrus Greening: Citrus greening is one of the dangerous plant diseases in the world. Once a plant is infected due to this disease then there is no cure. This disease is caused by one disease-infected insect- Asian Citrus Psyllid. This disease is mostly found in oranges. This disease shows the symptoms like yellowing of leaves, dieback of twigs, and decline in vigor which leads to death of the entire plant. Common Rust: Common rust is one of the serious fungal diseases which attack the roses, corns, and tomatoes, etc. This disease occurs mostly in mild and moist conditions. Rust is actually spread by spores from infected to healthy plants. The spores are generally transferred by wind or water. This is the reason rust appears often after watering. Yellow or white spots appear as symptoms on the upper part of leaves. This results in leaf distortion and deformation.

7. Early Bight: Early blight disease is very common in potatoes and tomatoes which are caused by the fungus name Alternaria Solani. Firstly, its symptoms appeared on old leaves as small brown spots with a pattern of Bull's eye. When it spreads than its color changes to yellow. After the stem, fruit, and upper portion of the plant get infected and crops can be devastated. Early blight disease develops at moderate to warm temperatures.

8. Gray Leaf Spot: Gray leaf spot is a fungal disease that attacks the corn plants which is also known as maize. First, symptoms of this disease are noticed in the lower leaves. The region on the leaf begins as a small yellow dot spot. As time passes this yellow spot changes to brown color and then to a gray rectangular shape. This region appears as the shape of a matchstick which slowly results in the killing of leaves. The grayish color on the leaves appears due to the presence of fungal spores.

9. Late Blight: Late Blight is a disease that attacks potatoes and tomatoes. This disease is caused by the water mold of Phytophthora infestans. This disease mostly occurs in humid regions where the temperature is ranging between 4-29°C. The infected tomatoes and potatoes may get rot within two weeks. This disease spreads very quickly in fields and results in total crop destruction if they are not controlled.

10.Leaf Blight: Leaf Blight is a fungal disease that attacks grapes. This disease is caused by a fungus named Helminthophobia turcicum Pass. This disease occurs in humid conditions, and it shows symptoms with reddish-purple or tan spots, and it gets bigger on the leaves. The symptoms on the leaves first appear on older or lower leave but after then it spreads on the younger or upper leaves. This drastic disease gives a burnt appearance to the leaves.

11.Leaf Mold: Leaf mold is a disease that is found in tomatoes. This disease causes loss in tomatoes which are found in high tunnels or greenhouses due to humidity in those environments. This disease is caused by a fungus named Passalora fulva. The oldest leaves are infected first due to this disease.

12.Leaf Scorch: Leaf Scorch is a disease that attacks strawberries. It is a serious disease that is caused by the bacterium Xylella fastidious. The first symptom which can be noticed is the browning of leaves in the mid-summer. The symptoms get worse throughout the late summer and after then gets fall. As the disease progresses over the years, branches and trees decline slowly. The symptoms first appear on the lower branches and then on the upper leaves.

13.Leaf Spot: Leaf spot is a serious disease that is found in tomatoes. This disease is a fungal disease that is caused by bacteria. Leaf spots show symptoms with brown color, but spots can be tan or black depending on the type of fungus. Some Concentric rings or dark margins are also found around the dark spots. Leaf spot diseases weaken the shrub or trees by blocking the photosynthesis process.

14.Mosaic Virus: Mosaic Virus is a disease that attacks tomatoes. This disease affects the leaves which show symptoms with spots of yellow, white, light, and dark green color. After then leaves may be curled, malformed, and reduced in size. This virus can also infect pepper, pear, cherry, and potatoes. This may reduce the fruit's number and size. This can create yellowish rings on the leaves if leaves ripen in warm weather.

15.Northern Leaf Blight: Northern leaf blight is a disease that affects the corn leaves. This disease is caused by the fungus Setosphaeriaturcica. Symptoms generally appear on lower leaves with gray-green color and then turn to pale or tan color. Dark gray spores are produced under moist conditions, and it gives regions a dirty gray appearance. Spores are generally transferred by wind or by the splashing of water.

16.**Powdery Mildew**: Powdery Mildew is a fungal disease that affects a variety of plants, and it reduces the quality and quantity of fruits and flowers. When the fungus takes over on one of your plants then the spores make a layer of mildew on the top of leaves. The spores are then transferred to other plants by the wind. This disease can slow down the growth of plants and reduces the quality of crops.

17.Spider Mites: Spider mite is a disease that eats plants, and they look like tiny spiders. Most of the spider mites get active in dry and hot conditions. Because of the feeding of spider mites, white to yellow spots appear on the upper surfaces of leaves. The eggs also stick on the leaves' undersides. As the disease infiltration, the color of leaves appears as bronze and then becomes stiff.

18.Target Spot: Target spot is a disease that attacks the tomato leaves. Initially small, dark-brown spots appear on the upper parts of older leaves, and then eventually its size increases and makes concentric rings. This disease is spread by air-borne spores. This is a fungal disease and affects many other crops like pepper, papaya or cucumber, etc.

19.Yellow Leaf Curl Virus: Tomato yellow leaf curl disease is caused by the yellow leaf curl virus. The leaves which are infected are curled inward or upwards. The infected plants reduced the flowers and fruits in large numbers. This disease is not seed-borne but is spread by whiteflies. This disease is generally found in tropical and sub-tropical regions which cause economic loss.

Background and Related Work

Badage (2018) elaborated that disease in plants is caused by insects and various pests. Plant diseases decrease the productivity of crops. Farmers face a lot of problems and losses due to these various crop diseases. The system is proposed by the author who tells about crop diseases and actions to control them. This proposed system is divided into two phases: the first phase includes training of the datasets of crop diseases and the second phase includes the identification of crop diseases by using Canny's edge detection algorithm (Badage 2018).

Maniyath et al. (2018) proposed some techniques on the leaf-based image classification to find out the results and plant diseases. Random Forest algorithm was used to identify healthy and diseased leaves from the leaf-based image dataset. Various steps have been implemented like the collection of the dataset, feature extraction method, and training of dataset and classification approach. The machine learning approach gives a clear picture of training the dataset and classification of images.

Sladojevic et al. (2016) argued that Convolution Neural Network achieved more accurate results in the leaf image classification to identify plant or crop diseases. This new approach of training the dataset is a quick and easy method of implementation. This proposed model could find out thirteen different types of plant diseases by identifying the surroundings or edges of leaves. This proposed method showed the experimental results with an average precision of 96.3% (Sladojevic et al. 2016).

Saleem et al. (2019) analyzed that early identification of plants diseases is very prominent for healthy crops and plants. Many machine learning algorithms were used for the detection and identification of plant diseases but the subset of machine learning i.e., deep learning techniques showed more accurate results as compared to other machine learning algorithms. Various deep learning techniques were combined with other visualization techniques to identify the symptoms and diseases of plants. Performance metrics were used to evaluate the deep learning techniques (Saleem et al. 2019).

Sarangdhar & Pawar (2017) analyzed the attack of diseases that decrease the production of cotton crops. In this study, a vector machine algorithm was used to identify five different types of cotton leaf diseases. An android app will be used by the farmers where diseases after identification will be informed with their remedies. This android app also identifies the soil type with its moisture and humidity. This system has been made with sensors and raspberry pi that makes the system more effective. The accuracy achieved with this proposed system is 83.26 %.

Huang et al. (2014) proposed new spectral indices that are used to identify the different diseases on wheat crops. Optimized spectral indices were obtained by the combination of a single band and the difference of wavelength between two different bands. RELIEF-F algorithm has been used by an author to identify the wavelengths from the leaf spectral data. This algorithm is more effective as it can deal with multiclass classification problems. This study indicates new spectral indices can easily detect diseases by using hyperspectral data.

Qin et al. (2003) analyzed the stresses of rising diseases for pest management in fields. The research was carried out on a rice field, and correlations between ground data and image data were made. The experiment results show that remote sensing imagery has a very important application and ground data shows an average accuracy of more than 70% for classification (Qin et al. 2003) we first examine the applicability of broadband high-spatial-resolution ADAR (airborne data acquisition and registration.

Rothe & Kshirsagar (2015) proposed a pattern recognition system to identify the different cotton plant diseases. This work was done on the images of cotton leaves taken from the fields. The contour model was used for the segmentation of images and training of the adaptive neuro-fuzzy inference method. The accuracy for the classification is approximately 85%. The diseases of cotton leaves were identified by using a back propagation neural network. Gulhane & Kolekar (2015) used Principal Component Analysis (PCA) and K-Nearest Neighbor (KNN) method to diagnose the diseases of cotton leaves in fields. In several cases, human assistance in identifying diseases may be incorrect. Machine learning models have been created to determine the accuracy of disease detection in cotton leaves plants. Implementation of PCA/KNN equipped with multi-variate techniques was used to analyze the statistical data. The PCA/KNN bases classifier showed a classification accuracy of 95% (Gulhane & Kolekar 2015).

Revathi et al. (2011) proposed a computing technology to help farmers all over the world to take care of the crops from various diseases. The author had proposed a method to diagnose the diseases of cotton plants by capturing the image using a mobile camera and then categorized the diseases using a neural network. The work is based on the image segmentation technique where RGB color feature image segmentation is used to identify the disease spots on cotton plants (Revathi et al. 2011).

Blessy & Joy Winnie Wise (2018) selected Convolutional Neural Network (CNN) technique to identify the disease spots on the plants. The image of the sample leaf was used as an input where green pixels from the image were marked in green color that represents the healthy part of the image. Further, this green area from the image was removed to calculate the rest of the infected area from the image. Following the extraction of characteristics from the affected areas, the CNN model is used to classify the diseases. After diagnosing the disease, detailed information about diseases was sent to the mobile of farmers with the solutions through

GSM device. Rastogi et al. (2015) studied the automatic detection of crop diseases based on the two phases used in the proposed system. In the first phase, pre-processing of leaf images, feature extraction, and classification using Artificial Neural Network (ANN) was done to recognize the leaves. In the second phase, K means-based segmentation was done to identify the defected areas, then feature extraction was done to find the defected portion and classification of the disease identified by using ANN. After the identification of diseases, grading was done based on the amount of disease present in the leaf.

Owomugisha et al. (2014) proposed machine learning techniques to identify bacterial diseases in banana plants. The computer vision technique was investigated to make an algorithm that is further divided into four phases. In the first phase, images of banana leaves were captured using a digital camera. In phase two, feature extraction techniques were used to send the data in phase three for classification. In phase three, different classifiers were used to identify the diseases. In the last phase, the performance of all the classifiers was compared based on Area under Curve (AUC) parameter for evaluation.

Tian et al. (2012) presented an SVM- based Multiple Classifier System to recognize the patterns of wheat leaf diseases. Encouraging results were obtained by using this proposed methodology to identify the diseases from wheat diseases. Three different types of SVM classifiers were used as color features, shape features, and texture features for training sets. Shi et al. (2015) proposed an automatic crop disease recognition method that takes the statistical features from leaf images and meteorological data and combines them. The Probabilistic Neural Network (PNN) method was used to identify the classification accuracy. Infected crop leaves images were captured by using a digital camera to extract the statistical features like color, shape, and texture by using the image processing method. PNN classifier accuracy rate was 90% which is more than the accuracy rate of other classifiers. Ashqar & Abu-Naser (2018) presented a deep learning technique to identify tomato leaves diseases using image-based recognition. Around 9000 images dataset of healthy and diseased tomato leaves were collected under controlled conditions. Training of deep convolutional neural network was done to identify the five diseases. The proposed method showed an accuracy of 99.84% that made this approach more feasible to diagnose the tomato leaves diseases in agriculture (Ashqar & Abu- Naser 2018).

Revathi & Hemalatha (2012) analyzed a comparative study of crop diseases using machine learning techniques in the field of agriculture. The algorithms like SVM machine learning algorithm, decision tree algorithm, and artificial neural network were used to represent the work. Data mining technique is one of the innovative techniques and used to predict various crop diseases. This study was based on the applicability of data mining techniques with a comparative analysis to find out the accuracy and other performance parameters for crop disease prediction (Revathi et al. 2011).

Sethy et al. (2018) developed a prototype to identify the diseases of rice crops using computational intelligence and machine learning techniques. Numerous diseases on the rice crops appear as a spot on the leaves and if diagnosis of the diseases has not been done on time, then it can cause great harm to rice crops. The pesticide-based treatment of crops can cause severe environmental pollution. In this proposed methodology, Fuzzy logic was introduced with a K- means algorithm to identify the degree of the sternness of disease on rice crops. This proposed methodology showed an accuracy of 86.35%.

Shruthi et al. (2019) presented a comparative analysis of various machine learning techniques to identify the best technique for crop disease detection. It was observed that Convolution Neural Network provides more accuracy to identify the diseases from crops (Shruthi et al. 2019).

Reza et al. (2016) framed a research methodology to detect jute plant diseases using image processing and machine learning techniques. The proposed methodology involves an android application that helps to capture the pictures of jute plant diseases and to send the pictures to the server to identify the jute plant diseases. The features were extracted from the captured image and extracted values were compared with the values stored in the database that helped to identify the leaf diseases. The classification of the diseases was done by using a multi-SVM classifier. After that, the final result was sent to the farmer within a fraction of seconds with the necessary solutions or control measures through the android application (Reza et al. 2017).

Proposed Research Methodology

In this project, a dataset of 54343 images of different plant species has been taken which involves diseases plants or healthy plants images of various fruits and vegetables crops. A dataset has been split into three sets- training set, validation set and testing set. Training is done by using pre-trained model Inception V3 by fine tuning the last layers of network. Four custom convolutional and max pooling layers have been added on the top of transfer learning architectures. At the last, two dense layers have been used with 64 neutrons and 2 neurons respectively. The last layer is used for classification and SoftMax is used as activation function. Training of the model has been done by 20 epochs or iterations by changing the various parameters like batch size, optimizer, pre- trained weights and learning rate. To reduce the over fitting between the batch normalization and different layers, we use 30% dropouts to reduce the internal covariate shift. This actually helps the model to avoid getting stuck in the local optimum. Here we have also used the evaluation metric named Multi Class Log Loss. Further we made some data generators for training data and testing data. These generators help us to load the required amount of data directly from the source folders with the batch sizes as per our need. This also helps to convert the batches into the training

Pre-processing and training the model: Pre- processing is the first step that is performed on the images. In this step, database is pre-processed such as reshaping of an image, resizing of an image and conversion of an image into an array form. Pre- processing is also done on the test images in the same way. A database consists of 54343 images of different plant species and out of all the images any image can be used as test image. The database which is trained is used to train the dataset using Inception V3 model. With this we can identify the test image and the disease of test image. After the training of model, the software can find the diseases in the plants which are available in database. After the completion of training and pre- processing, the evaluation is done between test and trained model to predict the disease.

Collection of Database: Acquiring valid database collection is the initial step of any image processing-based project. In some cases, we can get the proper database but, in some situations, where we are not able to get the proper database then we can collect the images from different sources and make our own database for processing. Our database has been collected from Kaggle Plant Village Dataset. First the data which you are using should be labeled and cleaned. For image processing, images with good resolution and angles are selected. After selection of all the images from database, in depth knowledge should be gained of different plants and their diseases. Different types of plant diseases with their symptoms are studied. After the deep and detail study, image segregation should be done to label the images and following steps to be performed:

1. Input test image should be acquired, and pre- processing should be done. After pre- processing the image should be converted into an array form for evaluation.
2. Then the dataset should be segregated, and pre-processing should be done.
3. After pre-processing, training of dataset should be done by using Inception V3 model. After then classification of images should be done
4. In the next step, comparison of test and trained model should be done. After then result should be displayed.
5. In the last step, software will display whether the plant is diseased or healthy plant.

Classification Models: In order to classify our dataset, we used two models: SRCNN (Super-Resolution Convolutional Neural Network) Model and Bicubic Model.

- ***SRCNN (Super-Resolution Convolutional Neural Network) Model:*** In deep learning, generally Convolutional Neural Network (CNN) is used for image classification. The objective of Super Resolution (SR) is to recuperate high-resolution image from low-resolution image. In SRCNN network is not deep. It involves mainly four operations: pre-processing, feature extraction, non-linear mapping and reconstruction.

a. *Pre-processing:* This step means upscaling of low-resolution to high-resolution image.

b. *Feature Extraction:* This step extracts the set of feature maps from the up-scaled low- resolution image.

c. *Non-Linear Mapping:* Mapping of feature maps which represents low-resolution to high-resolution patches.

d. *Reconstruction:* Produces or reconstructs the high-resolution image from high-resolution patches.

SRCNN is a deep convolutional neural network that is used for end-to-end mapping of low- resolution to high-resolution images. This model is used to improve the quality of low-resolution images. With this approach of Super Resolution, we can get better quality of larger images even if images are of small size. Performance of this network can be evaluated by using different parameters such as Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) Index

- ***Bicubic Interpolation Algorithm*:** Bicubic Interpolation Algorithm is a two-dimensional system which uses polynomial technique for enlarging or sharpening digital images. This algorithm upscale low-resolution image before going to the network. However, computational cost gets increased with pre-up sampling step. This algorithm is mainly used by computer editing software or editors for reconstructing and resampling the images. During interpolation of an image, the pixels get distorted from one grid to another grid. This is a very slow algorithm as it takes time to process during resampling of an image. Bicubic algorithm samples 4x4 or 16 samples at a time. There are two interpolation algorithms: Adaptive Interpolation and Non-Adaptive Interpolation.

a. *Adaptive Interpolation:* Adaptive Interpolation algorithm depends on what is introducing in the image. Adaptive algorithms are used in exclusive techniques which are used in various latest photos editing software like Adobe Photoshop and Photo zoom Pro.

b. *Non-Adaptive Interpolation:* Non- Adaptive Interpolation method treats all the pixels equally. Non-Adaptive algorithms involve various other algorithms like k-nearest neighbor, spline, Bicubic and bilinear.

Results and Discussion

Dataset Description

In this study, Plant disease village dataset of 54343 images have been taken which are fine-tuned using a well-known model Inception V3 after pre-processing. This dataset has been taken from Kaggle Repository. This dataset involves the study of different plants like Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper bell, Potato, Raspberry, Soybean, Squash, Strawberry and Tomato. The different sets of healthy and diseased plant images are used. The research has been done on different diseases like apple scab, bacterial spot, black measles, black rot, cedar apple rust, citrus greening, common rust, early blight, gray leaf spot, late blight, leaf blight, leaf mold, leaf scorch, leaf spot, mosaic virus, northern leaf blight, powdery mildew, spider mites, target spot and yellow leaf curl virus. Table 1 describes the Plant Category, Healthy or Diseased image and number of images in each category.

Experimental Results

In each model data is divided into two sets- training set and testing set. Training has been done by using Inception V3 model and dataset has been split into 70- 30, 50-50 and 30-70. In training phase, we train the classifiers and in testing phase, testing is done to analyze the performance of the classifier. Results are demonstrated using different parameters like accuracy, loss, validation accuracy, validation loss and learning rate by epochs using two different classifiers SRCNN and Bicubic algorithm as shown in Table 2 below. Out of these classifiers, SRCNN classifier shows better accuracy as compared to Bicubic which is shown in Table 3.

Here, we plotted the graphs of training and validation accuracy by epochs for Bicubic and SRCNN model. Graph is shown in Figure 4.

Conclusion

Protection of crops in an agriculture field is not a simple and easy task. Thorough study and research are required to know about the crops and their likely weeds, pathogens and pests. The main objective of this research is to identify diseases in plants to increase the productivity of crops in fields. The system is developed for the benefits of farmers and agricultural sector. In our system, deep learning models are used for the detection of plant diseases using different leaf images to identify whether leaf is healthy or diseased. Our experimental results and comparison between two models SRCNN and Bicubic demonstrate which accuracy to recognize the correct disease in plants. Out of these two models, SRCNN gives the accuracy rate of 99.175. Diseases are not the specific problem in the agricultural sector, but crops are in good soil and getting nutritious food protects the plant from various pest attacks. The experimental result represents the effectiveness of our proposed system, and it can be widely used in agricultural sector for the help of farmers. We hope our proposed research will make an effective contribution in agriculture research field.

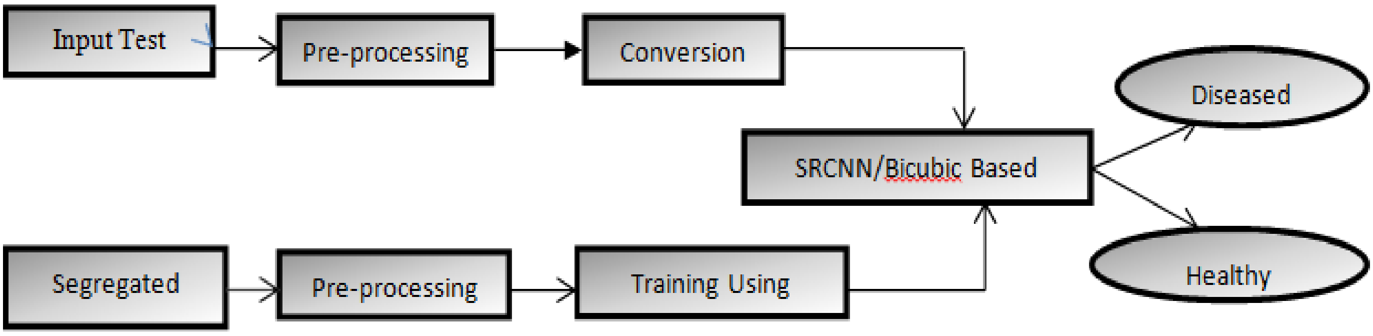

Figure 1. Flowchart for Plant disease detection

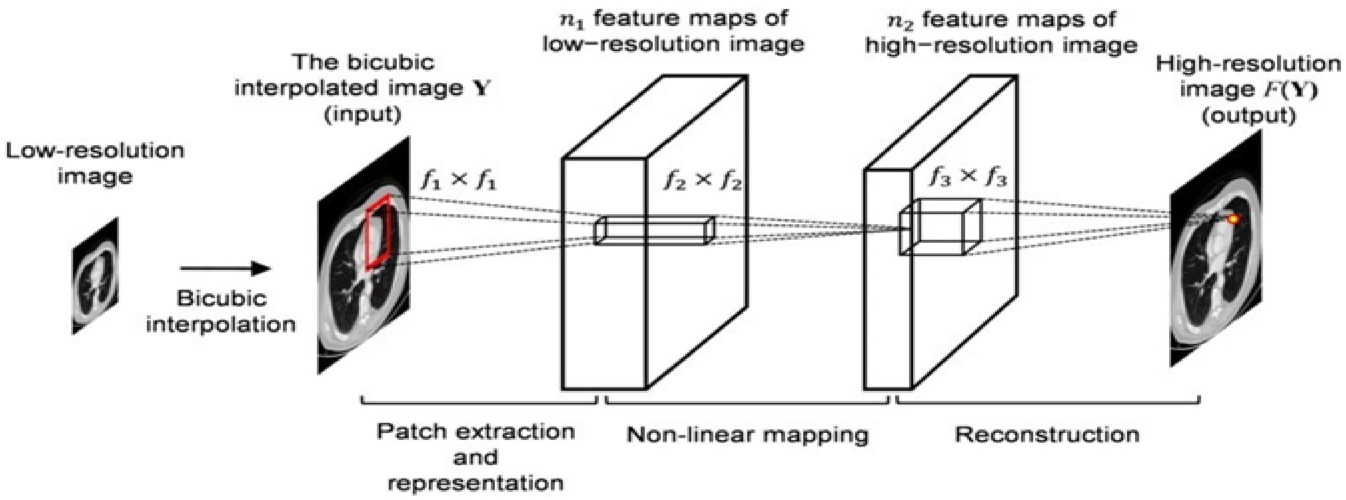

Figure- 2. SRCNN Based Classification Model

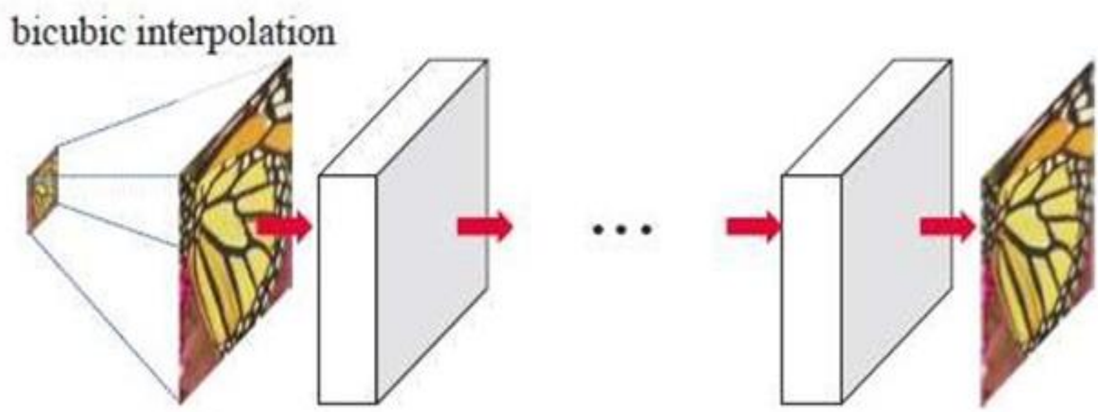

Figure 3. Bicubic Interpolation based Classification model

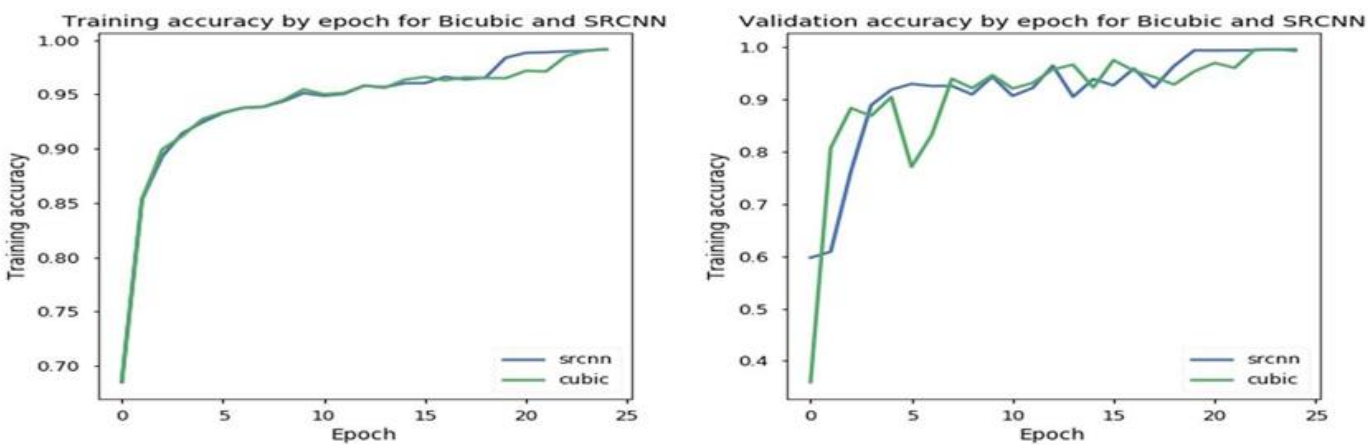

Figure 4. Graphs representing training and validation accuracy for models

Table 1. Dataset for image classification of leaf disease

Sr No.	Plant Category	Disease/ Healthy	Number of Original Images
1	Apple	Apple Scab	631
2	Apple	Black Rot	622
3	Apple	Cedar Apple Rust	276
4	Apple	Healthy	1646
5	Blueberry	Healthy	1503
6	Cherry	Healthy	855
7	Cherry	Powdery Mildew	1053
8	Corn	Common Rust	1193
9	Corn	Grey Leaf Spot	514
10	Corn	Healthy	1163
11	Corn	Northern Leaf Blight	986
12	Grape	Black Measles	1384
13	Grape	Black Rot	1181
14	Grape	Healthy	424
15	Grape	Leaf Blight	1077
16	Orange	Citrus Greening	5508
17	Peach	Bacterial Spot	2298
18	Peach	Healthy	361
19	Pepper Bell	Bacterial Spot	998
20	Pepper bell	Healthy	1479
21	Potato	Early Blight	1001
22	Potato	Healthy	153
23	Potato	Late Blight	1001
24	Raspberry	Healthy	372
25	Soybean	Healthy	5091
26	Squash	Powdery Mildew	1836
27	Strawberry	Healthy	457
28	Strawberry	Leaf Scorch	1110
29	Tomato	Bacterial Spot	2128
30	Tomato	Early Blight	1001
31	Tomato	Healthy	1592
32	Tomato	Late Blight	1910
33	Tomato	Leaf Mold	953
34	Tomato	Leaf Spot	1772
35	Tomato	Mosaic Virus	374
36	Tomato	Spider Mites	1677
37	Tomato	Target Spot	1405
38	Tomato	Yellow Leaf Curl Virus	5358
			53343

Table 2. Comparison of Bicubic vs. SRCNN Classifier

Bicubic Result by Epoch					
Epoch	Acc	loss	lr	val_acc	val_loss
0	0.68675	1.078107	0.001	0.359188	3.793237
1	0.853313	0.452098	0.001	0.807466	0.675127
2	0.899355	0.314722	0.001	0.883504	0.393525
3	0.911813	0.27287	0.001	0.868497	0.433363
4	0.927396	0.225642	0.001	0.904577	0.324232
5	0.933563	0.206778	0.001	0.771073	0.849628
6	0.937688	0.195976	0.001	0.831978	0.864499
7	0.93885	0.188665	0.001	0.93972	0.185791
8	0.944938	0.166638	0.001	0.921461	0.267373
9	0.954747	0.139192	0.001	0.946598	0.169225
10	0.95025	0.148785	0.001	0.92096	0.29281
11	0.951493	0.149138	0.001	0.931528	0.23313
12	0.958125	0.130086	0.001	0.957604	0.129822
13	0.956125	0.131764	0.001	0.966483	0.120217
14	0.963573	0.11314	0.001	0.922961	0.291764
15	0.966125	0.108081	0.001	0.975175	0.074392
16	0.963009	0.112118	0.001	0.955103	0.145883
17	0.96575	0.10554	0.001	0.943034	0.19108
18	0.965137	0.105917	0.001	0.928589	0.264863
19	0.964938	0.110921	0.001	0.953789	0.142576
20	0.97175	0.089099	0.001	0.96986	0.093184

SRCNN Result by Epoch					
Epoch	acc	loss	lr	val_acc	val_loss
0	0.685	1.076052	0.001	0.59713	1.825342
1	0.853563	0.456332	0.001	0.608867	1.734919
2	0.892846	0.326332	0.001	0.762569	0.936293
3	0.914438	0.266576	0.001	0.889007	0.34634
4	0.924454	0.234888	0.001	0.918772	0.274175
5	0.932875	0.209391	0.001	0.929777	0.229069
6	0.937688	0.196275	0.001	0.925775	0.234507
7	0.938537	0.189037	0.001	0.925775	0.282873
8	0.943688	0.173809	0.001	0.909642	0.28659
9	0.951368	0.151127	0.001	0.943534	0.188381
10	0.94875	0.15574	0.001	0.906891	0.306541
11	0.950491	0.154059	0.001	0.922149	0.271082
12	0.958	0.129596	0.001	0.96467	0.110303
13	0.95675	0.131862	0.001	0.90514	0.346343
14	0.960381	0.120436	0.001	0.939032	0.210869
15	0.960438	0.126139	0.001	0.926963	0.260596
16	0.966201	0.103237	0.001	0.959042	0.139745
17	0.963875	0.110578	0.001	0.922836	0.268867
18	0.96545	0.108457	0.001	0.964107	0.109852
19	0.983813	0.046763	0.0002	0.993997	0.018768
20	0.988375	0.036806	0.0002	0.993684	0.017171

Table 3 Shows the comparison report with other models

Model Proposed	Classification Accuracy
Bicubic	99.145
SRCNN	99.165

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