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Recognition of Image-Based Plant Leaf Diseases Using Deep Learning Classification Models

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ABSTRACT

Plant diseases are spread by a variety of pests, weeds, and pathogens and may have a devastating effect on agriculture, if not handled in a timely manner. Farmers face umpteen challenges from a proper water supply, untimely rain, storage facilities, and several plant diseases. Crops disease is the primary threat and it causes enormous loss to farmers in terms of production and finance. Identifying the disease from several hectares of agricultural land is a very difficult practice even with the presence of modern technology. Accurate and rapid illness prediction for early illness treatment to crops minimizes economical loss to the individual and further proves to be productive for healthy crops. Many studies use modern deep learning approaches to improve the accuracy and performance of object detection and identification systems. The suggested method notifies farmers of different agricultural illnesses, prompting them to take further essential precautions before the disease spreads to the whole agricultural field. The primary objective of this study is to detect the illnesses as soon as they begin to spread on the leaves of the plants. Super-Resolution Convolutional Neural Network (SRCNN) and Bicubic models are employed in the system to identify healthy and diseased leaves with an accuracy of 99.175 % and 99.156 % respectively.

INTRODUCTION

Agriculture is one of the most important economic activities of the Indian subcontinent and two-third population is 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. To overcome this problem, a variety of pesticides, fertilizers, and research-based remedies are used nowadays. Agriculture is getting attention in every five-year plan and preference is given for the development of agriculture in India.

The agricultural field needs more up-gradation due to changes in weather and economic conditions in the country. The crops in the fields should be healthy to get more productive results. Technical and proper research-based methods are required to monitor the crops regularly. Crop disease is one of the reasons for decreasing the quantity and quality of crops in the fields. The use of toxic pathogens, extreme change in climate conditions, and poor disease control are one of the factors of poor food production. Large numbers of pesticides are available to control the diseases of crops in agriculture and to increase the production of crops in the fields. Identifying the current disease of the crops and finding the appropriate pesticide to control the diseases is a task that requires the advice of experts in the field of agriculture that makes this task very consuming and expensive. Accurate and timely identification of diseases of crops 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 some kind of 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 (Bangotra 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. Various researchers have conducted studies in this field by using traditional machine learning algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest algorithm, K-Means method, and Convolutional Neural Network.

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 appear 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 *Helminthosporium 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 fastidiosa*. 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 actually 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 particular 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 a number of 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).

MATERIALS AND METHODS

In this proposed system, a dataset of 54,343 images of different plant species was taken that involves diseased plants or healthy plants images of various fruits and vegetable crops. The dataset was split into three sets: training set, validation set, and testing set. Training is done by using the pre-trained model Inception V3 by fine-tuning the last layers of the 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 with softmax as an 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 overfitting between the batch normalization and different layers, 30% dropouts were used to reduce the internal covariate shift and this actually helps the model to avoid getting stuck in the local optimum. The evaluation metric named Multi-Class Log Loss was also used in the model with some data generators for training data and testing data. These generators help to load the required amount of data directly from the source folders with the batch sizes as per need of the detection and help to convert the batches into training data and training models. To do a fair comparison between the results of all experiments, an attempt has been made to normalize hyper-parameters across all the experimentations and research.

Pre-processing and Training the Model: Pre-processing is the foremost step that is performed on the images. In this step, the database is pre-processed such as reshaping of an image, resizing of an image, and conversion of an image into an array form (Fig. 1). Pre-processing is also done on the test images in the same way. A database consists of 54,343 images of different plant species and out of all the images any image can be used as a test image. The database is used to train the dataset using the Inception V3 model and it further helps to identify the test image and the disease of the test image. After the training of the model, the software can find the diseases in the plants that were already stored in the database. After the completion of training and pre-processing, the evaluation is done between the 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. There are many ways to generate the database as either to store all images or to collect the images from different sources and make own database for processing. The Kaggle Plant Village Dataset database was used in the present study. At first, the data was labeled and cleaned for prior image processing. For image processing, images with good resolution and angles were selected to ensure a high accuracy algorithm detection system. After the selection of all the images from the database, in-depth knowledge was gained for different plants and their diseases. Different types of plant diseases with their symptoms were studied in this processing system. After the deep and detailed study, image segregation was done to label the images and the following steps were performed:

1. The input test image was acquired and pre-processing was done accordingly. After pre-processing, the image was converted into an array form for evaluation.
2. Then the dataset was segregated and pre-processing has been done.
3. After pre-processing, training of dataset has been done by using Inception V3 model and further classification has been completed.
4. In the next step, a comparison of the test and trained model was done and the final results have been obtained as per system inputs.
5. In the last step, the software displayed, whether the plant is diseased or healthy.

Classification Models: To classify datasets, two models were used: SRCNN (Super-Resolution Convolutional Neural Network) Model and Bicubic Model.

- ***SRCNN (Super-Resolution Convolutional Neural Network) Model:*** In deep learning, generally Convolutional

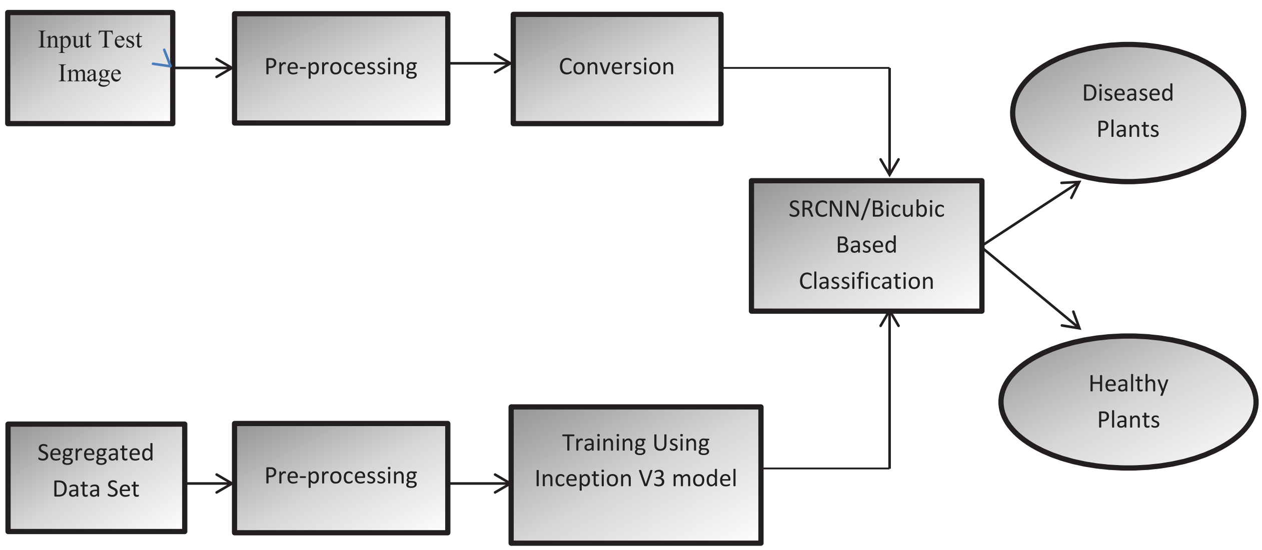

Fig. 1: Flowchart for plant disease detection.

Neural Network (CNN) is used for image classification. The objective of Super-Resolution (SR) is to recuperate high-resolution images from low-resolution images. The SRCNN network involves mainly four operations: pre-processing, feature extraction, non-linear mapping, and reconstruction.

1. *Pre-processing*: This step means upscaling of low-resolution to high-resolution images.
2. *Feature Extraction:* This step extracts the set of feature maps from the upscaled low-resolution image.
3. *Non-Linear Mapping:* Mapping of feature maps that represents low-resolution to high-resolution patches.
5. *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 (Fig. 2). This model is used to improve the quality of low-resolution images. With this approach of Super Resolution, a better quality of images can be obtained from even a small size of input images. The 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 that uses a polynomial technique for enlarging or sharpening digital images (Fig. 3). This algorithm (samples dimension: 4x4 and 16 samples at a time) upscale low-resolution images before going to the network. However, the computational cost increases with each pre-up sampling step. This algorithm is mainly used in computer editing software or by 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 the resampling of an image. There are two interpolation algorithms: Adaptive Interpolation and Non-Adaptive Interpolation.

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

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

RESULTS AND DISCUSSION

Dataset Description

In this study, a plant disease village dataset of 54,343 images have been taken which are fine-tuned using a well-known model Inception V3 after pre-processing, and the 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, Tomato, etc. The different sets of healthy and diseased plant images are used. The research

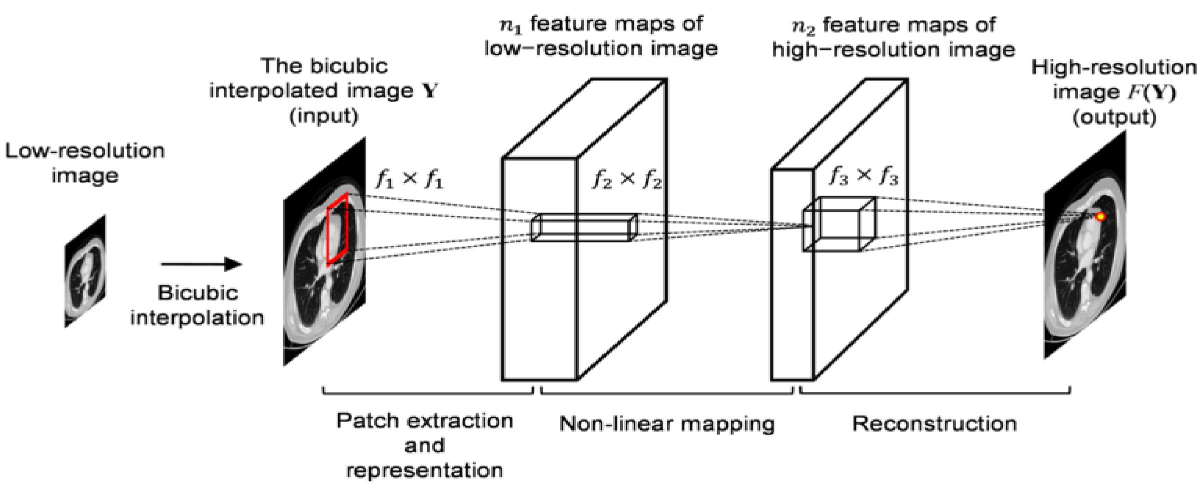

Fig. 2: SRCNN based classification model.

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	Gray 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

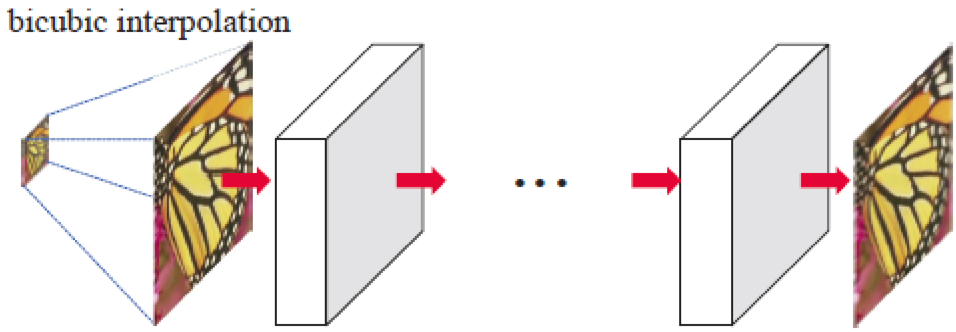

Fig. 3: Bicubic Interpolation based classification model.

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 the 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 the Inception V3 model and the dataset has been split into 70-30, 50-50, and 30-70. In the training phase, we train the classifiers and in the 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. Out of these classifiers, the SRCNN classifier shows better accuracy as compare to Bicubic (Table 3). The graphs of training and validation accuracy by epochs for the Bicubic and SRCNN model have been depicted in Fig. 4.

CONCLUSION

Protection of crops in an agriculture field is a very tedious task and still, there is a need for a qualitative study to know about the crops and their likely weeds, pathogens, and pests. The present methodology identifies diseases in plants to increase the productivity of crops in fields. The system is developed for the benefit of farmers and the agricultural sector. In this system, deep learning models were used for the detection of plant diseases using different leaf images to identify whether the leaf is healthy or diseased. The outcome

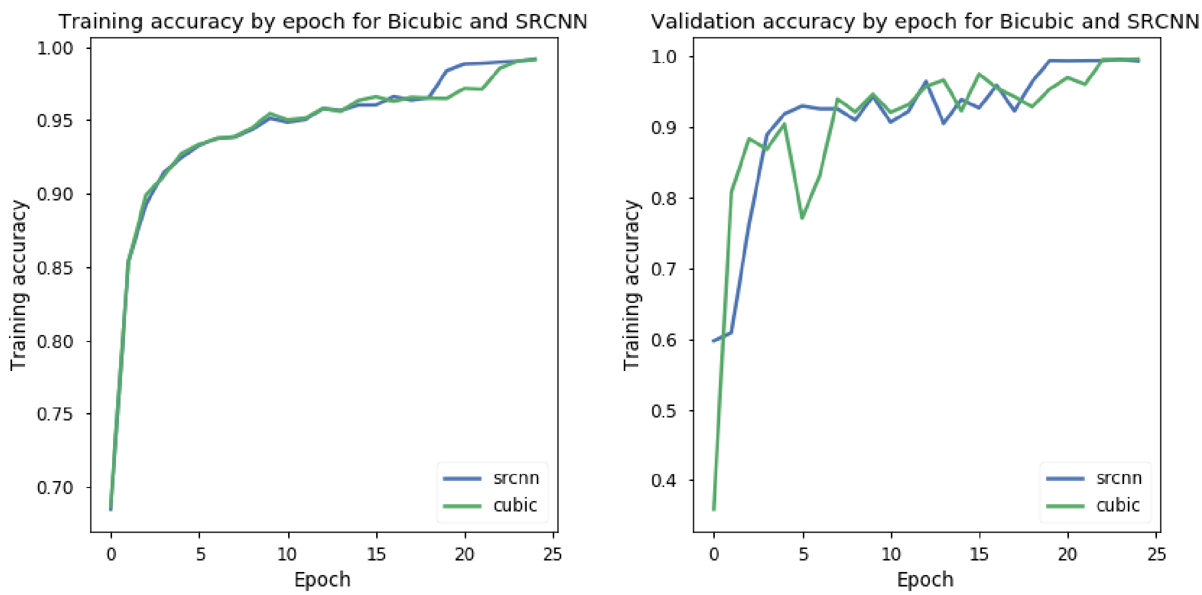

Fig. 4: Graphs representing training and validation accuracy for models.

Table 2: Comparison of bicubicvs 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
21	0.971209	0.087371	0.001	0.96048	0.147692
22	0.985438	0.04471	0.0002	0.99556	0.016243
23	0.990236	0.030135	0.0002	0.995373	0.013251
24	0.991563	0.024861	0.0002	0.996248	0.013701

SRCNN Result by Epoch

Epoch	acc	loss	lr	val_acc	val_loss
0	0.685	1.076052	0.001	0.597313	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
21	0.988859	0.034741	0.0002	0.993934	0.018891
22	0.989688	0.031454	0.0002	0.994122	0.019938
23	0.990299	0.029428	0.0002	0.995998	0.012489
24	0.99175	0.025347	0.0002	0.993184	0.02261

Table 3: Shows the comparison report with other models.

Model Proposed	Classification Accuracy
Bicubic	99.156
SRCNN	99.175

of experimental results and comparison between two models SRCNN and Bicubic demonstrates the accuracy to recognize the correct disease in plants. Out of these two models, SRCNN gives an accuracy rate of 99.175 % in recognizing plant diseases. Diseases are not the specific problem in the agricultural sector but crops growing in good soil and getting nutritious food protect the plant from various pest attacks. The experimental result represents the effectiveness of our proposed system and it can be widely used in the agricultural sector for the help of farmers.

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