Plant Health Monitoring with Photos based on Deep Learning

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***Abstract*—The quality and output of agricultural products can be affected by plant diseases. To safeguard the well-being of everyone on the planet, it is crucial to identify plant diseases as soon as possible. One of the most active research areas is autonomous plant disease detection. Large agricultural fields may be monitored with its help, and it aids in spotting disease signs when they appear on leaves. Finding plant diseases that cause reduced crop loss and, as a result, increase production efficiency is the major objective of this study. With the use of a Deep Learning (DL) approach, our suggested study can identify the first signs of plant diseases and classify them based on those signs. This approach attains a 90.0% accuracy in disease detection with a deep CNN technique. The model's performance as a warm-up or early advisory tool will be validated by this accuracy rate.**

***Index Terms*—Plant health monitoring, plant diseases, crop, crop products, deep learning, CNN**

I. Introduction

Finding plant diseases is one of the biggest issues the agriculture business has to deal with. In the past, knowledgeable individuals would identify diseases. It is exceedingly challenging for farmers to get in touch with professionals in remote towns. One of the main causes of plant diseases is climate change. In big farms, there is a significant loss in agricultural output if the illness is not identified at the appropriate time. Because they can't precisely view the farmer's issue at the service center, they occasionally advise farmers on plant diseases in the wrong way. The crop can be destroyed as a result of this.

Artificial intelligence (AI), deep learning (DL), and digital image processing (DIP) methods have all advanced significantly in recent years. It's critical to spot various plant diseases in their early stages in order to assist farmers. Therefore, it is essential to include these latest technology into contemporary approaches. The proliferation of plant diseases will result in a decrease in agricultural productivity. These diseases can harm plants, modify their structure, have an impact on the color and texture of the leaves, and even have an impact on the fruits, among other things. The characteristics of the diseases are quite similar. Therefore, it is very difficult for farmers to detect diseases in plants with their naked sight and they are unable to fully comprehend the severity of the condition, which might occasionally result in incorrect disease detection. Plant infections may be difficult to manage because of the less skilled or inexperienced farmers. Therefore, it is essential to create contemporary techniques that can help farmers spot ailments at an early stage and offer treatments for such diseases. For the recognition of diseases and various classifications of such diseases in plants, several researches [1], [2] have presented several machine learning methods, and image processing approaches. Machine learning algorithms are created for pattern extraction and image processing, which might lower the accuracy of a classification task. Deep learning algorithms are now mainly employed for pattern recognition since they have successfully identified various outlines. DL makes feature extraction automated. The DL delivers a high accuracy rate in the classification job and decreases error rate and computational time compared to other conventional machine learning methods. With the use of the CNN model, the primary goal of our work is to identify plant diseases and offer treatments for them.

The rest of the paper is followed by, Related work, then we introduce the deep learning algorithms, and then introduce the image processing for health monitoring, then the methodology with deep learning, then the implementation, result and discussion, then finally the conclusion.

II. Related Work

Finding plant diseases has mostly been done in the early stages using various machine learning approaches. The following stages are generally followed by all systems. Digital cameras are first used to capture the photographs. The photos are then preprocessed using several preprocessing methods. Then, the experts take the crucial elements out of those photos, and the classifier uses those features as inputs. Here, the method of image processing and feature extraction is what determines the classification accuracy. It takes a long time and is really difficult. Deep Convolutional neural networks (CNN) have recently demonstrated a considerable increase in picture segmentation and classification to improve classification accuracy in several domains, such as the categorization of digits and natural language. Because DL can utilize the picture directly, the computer vision community [16] accepted DL. The characteristics of the photos may be automatically learned by CNN using the datasets. It can be extracted and categorised more quickly with the same architecture.

This section discusses the most current developments in the use of CNN and deep learning architectures in agricultural applications. CNN uses photos of the leaves in [8] to identify diseases in cucumber leaves. Using CNN, they conducted their study and learned that two severe viral viruses are damaging the leaves: Melon Yellow Spot Virus (MYSV) and Zucchini Yellow Mosaic Virus (ZYMV). Their method has a 94.9% accuracy rate when using the Four-Fold Cross-Validation Strategy.

Hulya Yalcin et al. [9] employed a CNN model to identify and categorize the phonological phases of the various plants. He trained and tested the model using photos of leaves. Several plants were classified according to their phonological stage using a pre-trained AlexNet architecture. The accuracy of this model was 87%. This model provides great accuracy when compared to other conventional machine learning algorithms.

The author of study [10] utilized the LeNet architecture to identify diseases in soybean plants. Three various kinds of pictures, including segmented, colorful, and grayscale images, were employed by the author. The colorful picture provides an accuracy of 99.32% after categorization. In contrast to segmented and grayscale pictures, it is quite easy to extract characteristics from colorful images. In study [12], the author employed AlexNet and VGG-16, two common architectures, to recognize the diseases affecting tomato leaves. To make the dataset larger, the author also used data augmentation. In his writing, the author applied transfer learning. The accuracy of these two models was 96% and 97.49%, respectively. The author of this research came to the conclusion that adding more photos directly affects how well the network model performs.

III. Deep Learning

A neural network with three or more layers is essentially what deep learning, a subset of machine learning and AI, is all about. These neural networks attempt to emulate the functioning of the human brain, but they are unable to match the brain's capacity for learning from a massive quantity of data. The accuracy of predictions made by a single-layer neural network may be improved and refined with the help of additional hidden layers. AI has a topic called machine learning that enables a system to learn from concepts and information without having to be explicitly programmed. To prepare for data aspects and patterns and enhance upcoming outcomes and judgements, it starts with observations, such as in-person encounters. In order to represent high-level abstractions in data, a variety of machine learning methods are combined to create deep learning [3]. Deep learning has several benefits, one of which is feature learning, or the automated extraction of characteristics from raw data. A key benefit of deep learning is feature learning, or the automated extraction of features from raw data. The composition of lower-level components results in the production of features from higher hierarchy levels [4]. Two common deep learning networks used in agriculture are the recurrent neural network (RNN) and the convolutional neural network (CNN).

A. *Convolutional Neural Network(CNN)*

Multiple convolutional layers, pooling layers, and fully linked layers make up a CNN, a deep learning method [5]. The animal visual cortex serves as the foundation for this multi-layer neural network [6]. CNNs are mostly utilized for handwritten character recognition and picture processing. CNNs have been utilized in various computer vision research for a variety of tasks, including image classification, object identification, picture segmentation, speech recognition, text and video processing, and medical image analysis. Convolutional, pooling, and fully linked layers are the traditional building blocks of a CNN architecture [7]. The architecture of CNNs is shown in Figure 1, and the layers are briefly described:

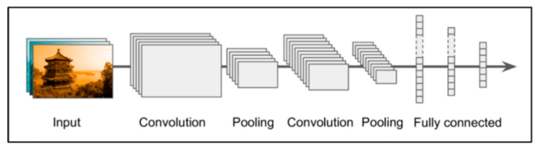

Fig. 1. A CNN Architecture [7]

1) Convolutional Layer: The most fundamental layer in a CNN is the convolutional layer. To create an activation map for the given image, the resulting pixel matrix for the supplied image or object is rotated or multiplied. The fundamental benefit of the activation map is that it stores all the distinctive features of a picture while reducing the quantity of data that has to be processed at once. Different picture variations are produced by using varying feature detector levels once the data is merged in a feature detector matrix. In order to obtain the least amount of error feasible in each layer, the complex model is additionally trained via backpropagation. The error set with the fewest mistakes determines the depth and padding [7]. The extraction of visual characteristics is done by the convolutional layer. Figure 2 shows the process of the convolution operation.

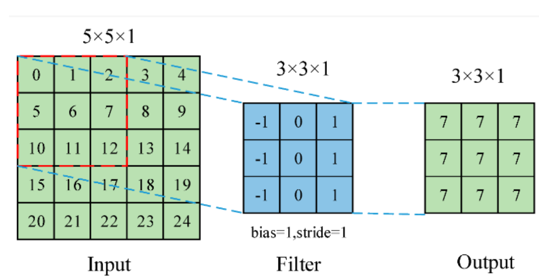

Fig. 2. A Convolution Operation Process [19]

2) Pooling Layer: It is a critical step that seeks to further reduce the size of the activation map while simultaneously retaining just the fundamental characteristics and decreasing the remarkable invariance. The model's learnable feature count is subsequently decreased, which helps to alleviate the overfitting problem. In order to recognize the provided item, a CNN must pool all the distinct dimensions of the image. This is possible even if the object's shape is distorted or at an odd angle. There are several methods for doing pooling, including maximum pooling, average pooling, stochastic pooling, and spatial pyramid. Max pooling is the approach most frequently employed [7]. Figure 3 shows the process of the pooling operation

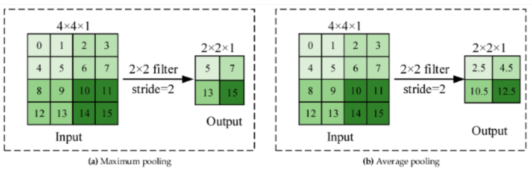

Fig. 3. A Pooling Operation Process [19]

3) Fully Connected Layer: The neural network is fed in this last layer. The matrix is typically flattened before being sent to the neurons. After this, data are challenging to follow because of several hidden layers with variable weights for each neuron's output. Here, all data computation and reasoning take place [7].

B. Recurrent Neural Network (RNN)

The neural sequence model known as an RNN excels at critical tasks including language modeling, speech recognition, and machine translation [17]. RNNs, as opposed to conventional neural networks, utilize the sequential information of the network; this feature is crucial in many applications where the underlying structure of the data sequence provides significant information. For instance, you need to comprehend the context before you can grasp a word in a phrase. The input layer x, hidden (state) layer s, and output layer y make up an RNN, which may be thought of as a short-term memory unit [6]. An RNN's general construction is shown in Figure 4. A RNN architecture called long short-term memory (LSTM) was developed to model temporal sequences and their long-term associations with more accuracy than standard RNNs [18]. The LSTM architecture is shown in Figure 5.

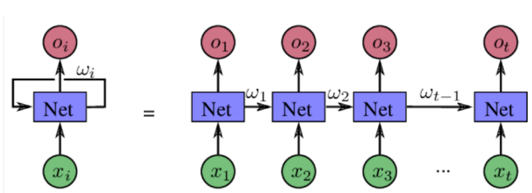

Fig. 4. A Generic Structure of RNN [6]

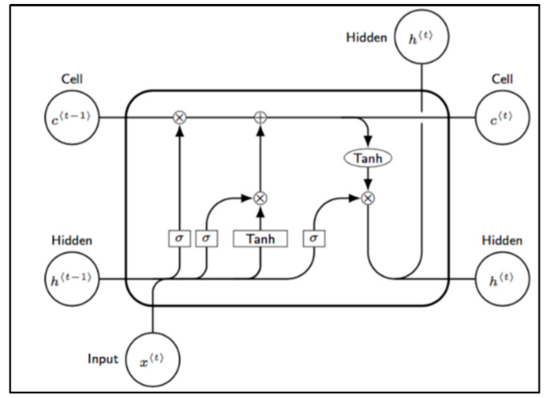

Fig. 5. A LSTM Architecture [18]

IV. Plant Health Monitoring With Photo Based

Techniques for image processing can be used to find plant diseases. Disease signs are often visible on the fruit, stem, and leaves. The plant leaf is taken into consideration for disease identification as it exhibits disease signs. This study provides an introduction to the image processing method used to find plant diseases. The fundamental procedures for plant disease classifications and detection utilizing image processing are displayed in figure 6.

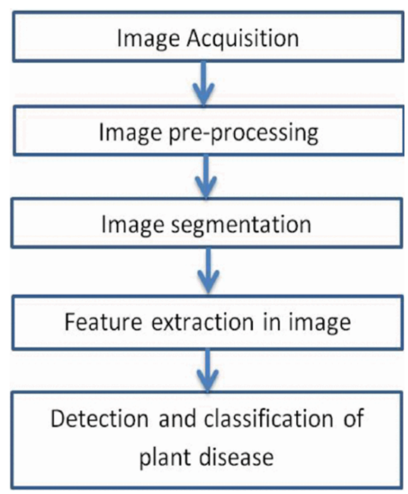

Fig. 6. Plant Disease Detection and Classification using photos/image processing [2]

A. Image Acquisition

The camera is used to take pictures of the plant leaf. Red, Green, and Blue, or RGB, is the format for this picture. A device-independent colour space transformation is then performed to the colour transformation structure, which was first generated for the RGB leaf picture [2].

B. Image Pre-Processing

Various pre-processing approaches are taken into consideration in order to reduce noise from images or other objects.

Picture clipping, or cropping, is the process of selecting the desired area of a leaf image. The smoothing filter is used for image smoothing. The purpose of image enhancement is to boost contrast, the RGB photos into the grey images utilizing equation(1) to convert colours.

$$\mathrm{f(x)} = 0.2989^{*}\mathrm{R} + 0.5870^{*}\mathrm{G} + 0.114^{*}\mathrm{B} - - - - - - - - \quad (1)$$

Then, histogram equalization, which distributes image intensities, is applied to improve the pictures of plant diseases. Intensity values are distributed using the cumulative distribution function [20].

C. Image Segmentation

Segmentation is the division of a picture into different parts with the same properties or similarities. Several techniques can be used for segmentation, including the otsu method, k-means clustering, and transforming the RGB picture into the HIS model.

D. Feature Extraction in Image

The identification of an item depends heavily on feature extraction. The use of feature extraction in image processing is widespread. The characteristics that may be employed in the identification of plant diseases include colour, texture, morphology, edges, and others. In their study [21], Monica Jhuria et al. take into account morphology, colour, and texture as features for illness identification. They discovered that morphological results outperform other characteristics. The term ”texture” refers to the image’s hardness, roughness, and colour distribution. Infected plant regions can be found using it as well.

1) Color Co-Occurrence Method: This technique uses both colour and texture to give a picture its own distinctive traits. To do so, the RGB picture is translated into the HSI format.

$$H = \begin{cases} Theta\ if B < G \\ 360 - Theta,\ B > G - - - - - \end{cases} \quad (2)$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] - -- \quad (3)$$

$$I = \frac{1}{3}(R+G+B) - - - - - - \quad (4)$$

The SGDM matrix is created for the texture statistics computation, and the feature is computed using the GLCM algorithm.

2) Leaf Color Extraction Using H and B Components: Before separating the colour from the background, the input picture is improved using the anisotropic diffusion approach to retain the information of the impacted pixels [22]. H and B components from the HIS and LAB colour spaces are taken into account to differentiate between the grape leaf and the non-grape leaf section. The use of a SOFM with a back propagation neural network enables the identification of disease leaf hues.

E. Detection and Classification

1) Using ANN: Following feature extraction, neural networks are used to classify the learning database photos. In an ANN, these feature vectors are regarded as neurons [21]. The neuron’s output is a function of the inputs’ weighted total. The back propagation method, Multiclass Support Vector Machines, and Modified SOM may all be employed.

2) Back Propagation: A recurrent network employs the BPNN algorithm. The neural network weights are fixed after they have been learned and may be used to compute output values for new query photos that are not already in the learning database.

V. Plant Health Monitoring With Photo Based on Deep Learning

This section describes the suggested methods for identifying plant diseases. Different image processing techniques using deep learning algorithms are applied to the picture of a leaf to categorize it as having a disease or not by taking into account that image. The framework, depicted in Fig. 1, consists of several steps to ensure accuracy in disease identification. The four steps that make up our system’s operation are listed below.

- For analytical purposes, the dataset named ”PlantVillage” is uploaded into the database.
- The database will be pre-processed after uploading, including picture resizing, rescaling, and array format conversion.
- A training set and a testing set are created from the dataset.
- a CNN model was built. The weights of CNN are changed in order to identify the disease using the training dataset as input properly.

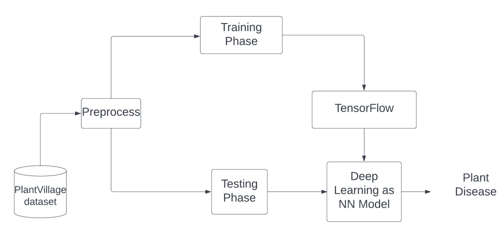

Fig. 7. Proposed System Overview [13]

A. Alexnet

The Rectified Linear Unit (ReLu), normalization layers, dense layer, and convolution layers will be used to form the Convolution Neural Network (CNN) model, which is pretrained AlexNet [13] and is depicted in Fig. 8. The picture is first resized to 227*227. Next, the first convolution layer receives the picture. 96 kernels of 11x11 pixels are applied in the first layer.

These kernels identify various picture edges. The picture is then passed on to the second convolution layer, where 256 kernels of size 5*5 are used. The max-pooling layer then uses 3*3 pooling with each kernel function to minimize the picture size. Until the input size reaches 3*3 with 256 kernels, this will be repeated. Finally, 4096 neurons were used to build the two completely linked layers. The connections between each neuron are extensive. According to the classes in our dataset, the final layer's 1000 classes are broken down into 38 classes. After all convolution and the last two fully linked layers, a non-linear, non-saturating activation function called ReLu is used. The speed is increased. To address the overfitting, the dropout is added to the network. The dropout will enhance network performance during the testing phase [14]. In order to improve the speed, performance, and stability of the neural network, batch normalization is employed in this model.

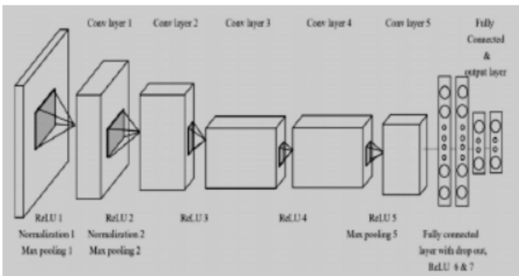

Fig. 8. Alexnet Architecture [13]

Layer	Feature Map	Size	Kernel Size	Stride	Activation
Convolution	96	55 × 55 × 96	11 × 11	4	relu
Pool/Max	96	27 × 27 × 96	3 × 3	2	relu
Convolution	256	27 × 27 × 256	5 × 5	1	relu
Pool/Max	256	13 × 13 × 256	3 × 3	2	relu
Convolution	384	13 × 13 × 384	3 × 3	1	relu
Convolution	384	13 × 13 × 384	3 × 3	1	relu
Convolution	256	13 × 13 × 256	3 × 3	1	relu
Pool/Max	256	6 × 6 × 256	3 × 3	2	relu
FC1	-	4096	-	-	relu
FC2	-	4096	-	-	relu
FC3	-	1000	-	-	Softmax

Fig. 9. CNN based Model, Alexnet Parameters [13]

VI. Dataset Discussion

In this work, the Plant Village Dataset from SP Mohanty's GitHub repository [15] is utilized. This collection comprises photos of common plant illnesses and 54323 photographs of plant leaves over 38 distinct categories, as demonstrated in Figure 11.

Since coloured photos provide more accuracy than grayscale photographs, all of the images utilized in this study are coloured images. All of the photos were taken from various perspectives and under various circumstances. Several of the photographs are shown in figure 10 below.

The training and testing sets are created by randomly dividing the total dataset. The model is trained using the training set. These sets are typically divided into portions of 20% to 80%, 40% to 60%, 60% to 40%, 80% to 20%, etc. The training dataset can be expanded to include additional photos to provide the most accurate results. Figure 11 shows that in this study, 80% of the dataset was used to train the model and 20% for testing.

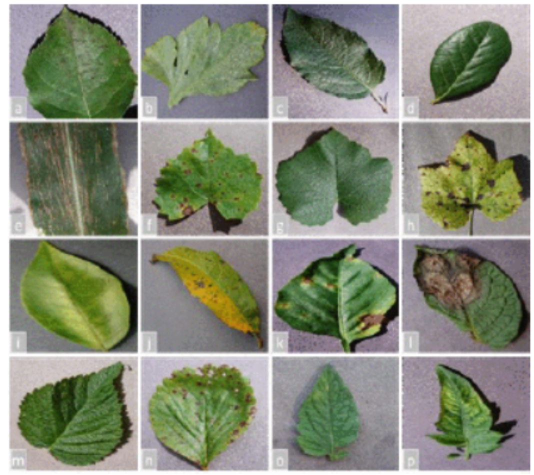

Fig. 10. A) apple scab, b) squash powdery mildew, c) apple healthy, d) blueberry healthy, e) corn (maize) cercospora leaf spot gray leaf spot, f) grape black rot, g) grape healthy, h) grape leaf blight, i) orange huanglongbing (citrus greening), j) peach bacterial spot, k) bell pepper bacterial spot, l) potato late blight, m)raspberryhealthy, n) strawberry leaf scorch, o) tomato leaf mold, p) tomato mosaic virus [15]

VII. Implementation

The whole procedure, including data collection, preprocessing, feature extraction, and model creation, is described in length in this section. Utilizing metrics for performance evaluation, the model will be verified.

A. Dataset Collection

The Plant Village Dataset used in this study was downloaded from SP Mohanty's GitHub repository. Large datasets are required for DL in order to prevent overfitting. This data collection includes both healthy and damaged plant leaves from various species. This collection of data is unprocessed at this time. Preprocessing of the dataset is necessary.

B. Dataset Preprocessing

Prior to transmitting any training or testing pictures to the network, they should all be processed. This project, which is represented in Fig. 7, makes use of the TensorFlow library. This library has a transform module that carries out the usual preprocessing transformations, such normalization. It is best to resize our data to the input size of the network before applying it to the model. The dataset should next be converted to a tensor data type, which requires converting a NumPy array with a range of 0 to 255 to a float tensor with a range of 0 to 1. The dataset is normalized before the mean and standard deviation are computed. Finally, apply these transformations to each image in the collection. The dataset is also subjected to data augmentation to expand it and somewhat distort the photos. This data augmentation lessens overfitting during the training phase.

S. No	Name	Total Images No.	Training Images No.	Testing Images No.
1.	Apple Scab	630	504	126
2.	Apple Black Rot	621	497	424
3.	Apple Cedar Rust	275	220	55
4.	Apple healthy	1645	1316	329
5.	Blueberry healthy	1502	1201	301
6.	Cherry healthy	854	683	171
7.	Cherry Powdery Mildew	1052	842	210
8.	Corn Gray Leaf Spot	513	410	103
9.	Corn Common Rust	1192	954	238
10.	Corn healthy	1162	930	232
11.	Corn Northern Leaf Blight	985	788	197
12.	Grape Black Rot	1180	944	236
13.	Grape Black Measles (Esca)	1383	1106	277
14.	Grape Healthy	423	338	85
15.	Grape Leaf Blight	1076	861	215
16.	Orange Huanglongbing	5507	4406	1101
17.	Peach Bacterial Spot	2297	1838	459
18.	Peach healthy	360	288	72
19.	Bell Pepper Bacterial Spot	997	798	199
20.	Bell Pepper healthy	1478	1182	296
21.	Potato Early Blight, Alternaria solani	1000	800	200
22.	Potato healthy	152	122	30
23.	Potato Late Blight, Phytophthora infestans	1000	800	200
24.	Raspberry healthy	371	297	74
25.	Soybean healthy	5090	4072	1018
26.	Squash Powdery Mildew, Erysiphe cichoracearum	1835	1468	367
27.	Strawberry Healthy	456	365	91
28.	Strawberry Leaf Scorch, Diplocarpon earlianum	1109	887	222
29.	Tomato Bacterial Spot	2127	1702	425
30.	Tomato Early Blight	1000	800	200
31.	Tomato Late Blight	1591	1273	318
32.	Tomato Leaf Mold	1909	1527	382
33.	Tomato Septoria Leaf Spot, Septoria lycopersici	952	762	190
34.	Tomato Two Spotted Spider Mite	1771	1417	354
35.	Tomato Target Spot	1676	1341	335
36.	Tomato Mosaic Virus	1404	1123	281
37.	Tomato Yellow Leaf Curl Virus	373	298	75
38.	Tomato healthy	5375	4300	1075

Fig. 11. Plant Village Dataset Details [15]

C. Model Building

In this study, feature extraction and classification are both carried out using pre-trained AlexNet. The big dataset named ImageNet, which comprises 14 million photos, has previously been used to train AlexNet in this case. Section V provides a description of how AlexNet was created and operates.

D. Feature Extraction

Each of the network's convolutional layers serves as a feature extractor. The AlexNet model is divided into a stage for feature extraction and another for classification. Convolutional layers make up the feature extractor, while fully linked layers make up the classifier. The crucial characteristics are extracted from the input by the convolutional layer. Edges, lines, and corners are low-level features that are extracted by the first convolution layer. Higher-level layers get higher-level characteristics out of the data.

The SGD, base learning rate, momentum, and batch size hyperparameters are employed in the AlexNet architecture. This hyperparameter represents the network's hierarchical structure and training process.

To get around the vanishing gradient constraint, this design uses the SGD algorithm as a solver type. This algorithm's primary goal is to raise the objective function. It is crucial to choose the right learning rate value since the learning rate indicates the step size utilized to complete training more quickly. It may start diverging if the value is huge, while it takes longer to converge if the value is too little. The SGD method updates the weights and biases using momentum. The batch size designates how many samples will be delivered to the network at once.

E. Classification

The model is prepared to classify any unlabeled plant photos once the training procedure is complete. The model receives an image as input, compares it to photos used for training and testing, and outputs both the plant name and the disease name.

Hyperparameters	AlexNet
Solver type	SGD
Base Learning Rate	0.001
Momentum	0.9
Batch Size	20

Fig. 12. Hyperparameters used for training experiment [14]

VIII. Result and Discussion

This study emphasizes how critical it is now to recognize plant diseases. In this study, a convolution neural network model is built, and the learning rate of the model is set to 0.001 using AlexNet. The momentum 0.9 is updated in comparison to the weights and biases after using the Stochastic Gradient Descent (SGD).

10 epochs were used, and the batch size was set at 20. A 20% sample of the photos from the Plant Village dataset were used to evaluate the model's precision. 20% of the photos in each class were chosen at random for testing. The testing dataset provides an accuracy of above 90.0%. This indicates that 90 out of 100 input photos were successfully categorized. Below are graphs produced by the model during training and validation that display accuracy and loss. Accuracy increases along with increasing the training dataset and epoch. The model provides the best accuracy of 90.0% at the Tenth epoch.

Figure 13 and Figure 14 show the loss and accuracy of the training, respectively. The Matplotlib function has been used to plot the graphs for accuracy and loss for the training and validation of our model.

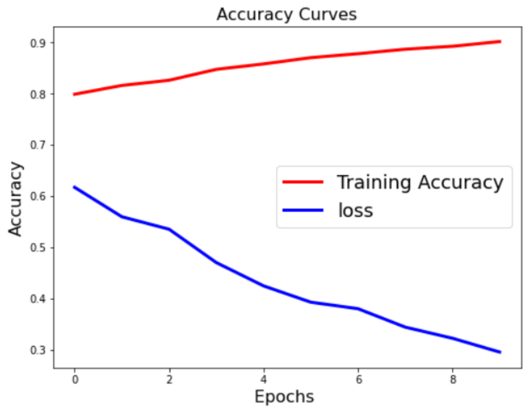

Fig. 13. Epoch vs Accuracy Graph[matplotlib]

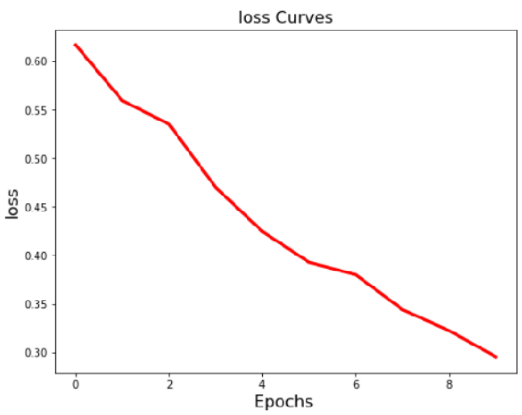

Fig. 14. Epoch vs Loss Graph[Matplotlib]

IX. Conclusion

One of the most significant areas of any world economy is agriculture. It is crucial to foresee crop diseases if you want to see your country's economy grow. Using a CNN model, the suggested technique classifies the various plant diseases included in the Plant Village dataset. The AlexNet architecture will classify the numerous plant diseases into 38 different distinct classes. Additionally, our suggested approach provides a decent way to anticipate and monitor plant diseases and can aid in their early detection. Future study on our suggested system's varied learning rates is conceivable.

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