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Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques

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ABSTRACT

Plant diseases affect the growth of their respective species, therefore their early identification is veryimportant. Many Machine Learning (ML) models have been employed for the detection and classification of plant diseases but, after the advancements in a subset of ML, that is, Deep Learning (DL), this area of research appears to have great potential in terms of increased accuracy. Many developed/modified DL architectures are implemented along with several visualization techniques todetect and classify the symptoms of plant diseases. Moreover, several performance metrics are used for the evaluation of these architectures/techniques. This review provides a comprehensive explanation of DL models used to visualize various plant diseases. In addition, some research gaps are identified from which to obtain greater transparency for detecting diseases in plants, even beforetheir symptoms appear clearly.

Keywords : plant disease detection, classification of diseases, image processing, Deep learning,disease of plant leaf

I. INTRODUCTION

Plant disease is defined as the state of local or systemic abnormal physiological functioning of a plant, resulting from the continuous, prolonged 'irritation' caused by phytopathogenic organisms.pests and diseases pose a threat to food security because they can damage crops, thus reducing the availability and access to food, increasing the cost of food. Plant pests and diseases may also negatively affect the palatability of foods resulting in changes to the traditional food preferences of populations.

In general, pathogens that infect plants do not specialize in infecting people. You are not likely to catch a disease from working with diseased plants in your garden, but it is a potential risk (depending on the infection), and consideration should be taken.The most direct economic impact of a transboundary pest or disease is the loss or reduced efficiency of agricultural production - whether it be of crops or animals - which reduces farm income. The severity of the economic effect will depend on the specific circumstances.

Insects can vector or infect a plant with a pathogen when they feed on an infected host plant, and then move and feed on an uninfected plant. Pathogens can also spread through infected seeds, transplants, or

contaminated equipment, irrigation water, and humans.Plant diseases can affect plants by interfering with several processes such as the absorbance and translocation of water and nutrients, photosynthesis, flower and fruit development, plant growth and development and cell division and enlargement.

Plant diseases are caused by different micro-organisms such as viruses, bacteria and fungi. In addition, various soil-borne and above ground insect pests also affect crop production It causes the reduction of available resources for plants, which fail to produce enough biomass, seeds, and thus yield.Common methods for the diagnosis and detection of plant diseases include visual plant disease estimation by human raters, microscopic evaluation of morphology features to identify pathogens, as well as molecular, serological, and microbiological diagnostic techniques.

Inconsistency and delay in the identification of plant diseases cause a reduction in the quantity and quality of yield. Losses due to plant diseases or other pest accounts for 20 to 40% of global annual productivity. Studies have been carried out to assess the estimated loss caused by different diseases. Yield loss also contributes toward increased consumer prices and a drop in the earnings for crop producers. Accurate and timely identification of plant diseases is crucial for ensuring maximum yield and is beneficial for farmlands in remote areas.

The agricultural land mass is more than just being a feeding sourcing in today's world. Indian economy is highly dependent of agricultural productivity[9]. Therefore in field of agriculture, detection of disease in plants plays an important role.The existing method for plant disease detection is simply naked eye observation by experts through which identification and detection of plant diseases is done. For doing so, a large team of experts as well as continuous monitoring of plant is required, which costs very high when we do with large farms. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact to experts. Due to which consulting experts even cost high as well as time consuming too. In such conditions, the suggested technique proves to be beneficial in monitoring large fields of crops.

Plant disease identification by visual way is more laborious task and at the same time, less accurate and can be done only in limited areas[1][2]. Whereas if automatic detection technique is used itwill take less efforts, less time and become more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Image processing is used for measuring affected area of disease and to determine the difference in the color of the affected area.Deep learning techniques used to detect plant diseases are more accurate and less time consuming compared to the traditional image processing techniques. Researchers are facing major issues in the field of plant disease like unavailability of data set for each and every disease, background noise in captured images, sometimes texture property of plant leaf varies during the change of environment[4].

II. LITERATURE REVIEW

S.N	Title of the paper Year	Algorithm	Methodology	Result
1.	Plant leaf detection and disease recognition usingdeep learning	Deep learning convolutional neural network model.	Involves 3 key stages: acquisition of data, preprocessing of data and imageclassification	A 96.5% accuracy rate was achieved using 75 epochs during the training of the model. The model also achieved a maximum accuracy rate

	IEEE 2019			of 100% whentesting andom images of plant varieties and diseases.
2.	Disease detection on the leaves of the tomato plantsby using deep learning	One of the most used optimization algorithm is Stochastic Gradient Descent (SGD) algorithm. Briefly, SGD minimizes the loss through iterations by updating means according to gradient.	Deep learning is used to detect diseases from the leaves of the tomato plants. Two different deep learning network architectures AlexNet [9] and SqueezeNet [10] are trained and tested on the tomato images of the Plantvillage dataset. Both training and testing are done on the mobile supercomputer NvidiaJetson Tx1.	Accuracy results are the results from the Caffe tests.AlexNet performed slightlybetter than SqueezeNet. Accuracy on Test Set:AlexNet: 0.9565 SqueezeNet: 0.943
3.	Tomato Leaf Disease Detection Using Deep Learning Techniques ICCES 2020	A convolutional Neural Network algorithm used in this proposed method is a hierarchical feature extraction that maps the pixel values and evaluates the same withthe trained dataset image.	This has been implemented effectively using image processing technique, Feature extraction, segmentation and convolutional neuaral and the latest niche algorithms and usingthe open source programming language Python.	The proposed method is achieved an accuracy level of98%. The proposed method is used as a CNN algorithm for hierarchical feature extraction that map input image pixel intensities and compare the same with the trained dataset image.
4.	Sugarcane Disease Recognition using Deep Learning. IEEE 2019	This paper provides an idea of helping farmers with the aid of deep learning algorithm in detecting and classifying sugarcane diseases.	1. Image Dataset Acquisition 2. Pre-processing of Images 3. Feature Extraction 4. Classification	The highest recorded validation accuracy duringthe training was 95% with60 epochs. shows of detection and recognition of a sugarcane plant with 35.52% accuracy that it is infected with smut diseaseshow an accuracy rate of 98.98% infected with grassy shoot disease. infected with a yellow leaf

				disease on the right image..
5.	Plant Leaf Disease Classification Using Grid Search Based SVM. IEEE 2020	SVM is used as an algorithm to develop a plant disease identification and classification system.	[1] Image acquisition [2] Noise removal [3] Image segmentation [4] Feature extraction [5] Classification(SVM and grid search basedSVM) detection	The accuracy of SVM classifier was 80% and whenapplied with Grid Search hyper parameter tuning accuracy increased to 84%.

III. PROPOSED METHODOLOGY

Diseases in Plants are a major concern to the farmers these days. Many a times, the farmers are not sure which pesticide or insecticide is needed to treat a particular diseased plant because they are not sure of the type of disease. This results in spraying wrong pesticides, damaging the plants which affect the plant yield. To overcome with this problem, we have come up with a solution of developing a system that easily identifies some common diseases that occur in the plants.

Through image processing and Deep learning algorithms, we aim to classify diseases and generate a model that would provide an easy and accurate way of determining the plant disease through on click of an image of the affected plant leaf. This system is not only beneficial to the farmers in saving the crops, but also in saving money by buying only right kind of pesticides suitable to treat the particular disease. As the system does not involve any heavy machineries and electricity, the system proves to not only be a cost-effective solution, but also an environment-friendly one.

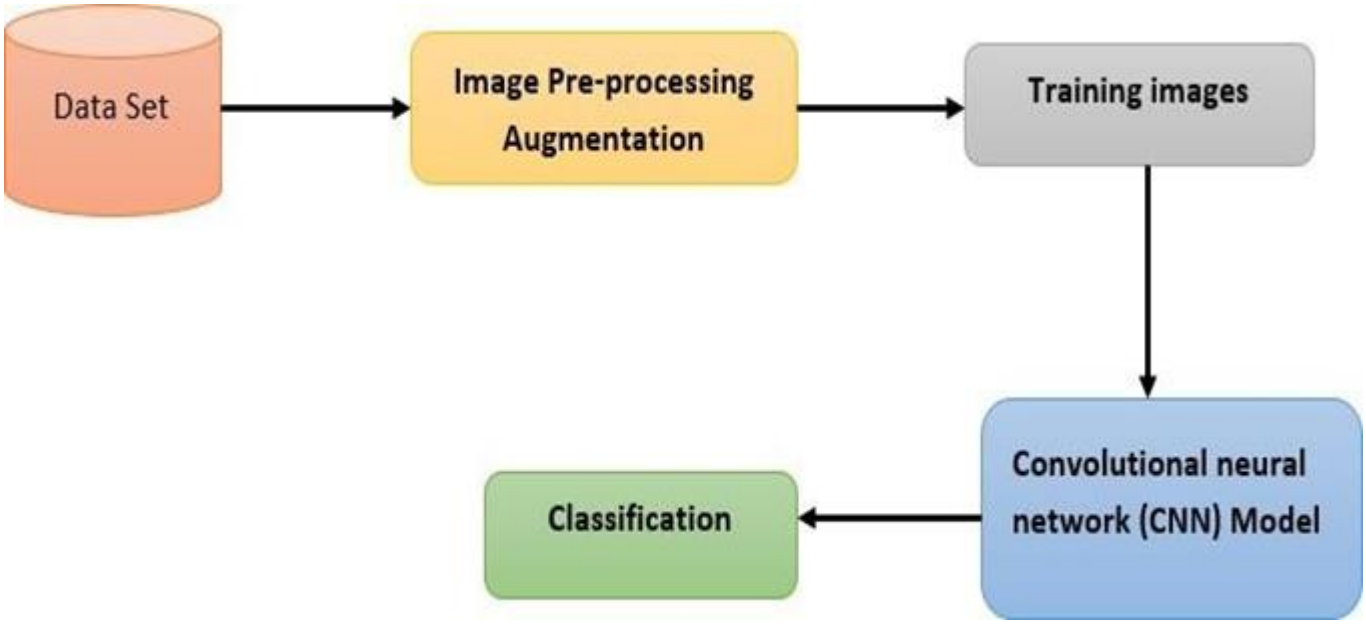

Fig 3.1: Flowchart diagram

Image Database: The next point in the project is creation of the image database with all the images that would be used for training and testing. The construction of an image database is clearly dependent on the application. The image database in the proposed approach consists of 28 different classes of image samples. The image database itself is responsible for the better efficiency of the classifier as it is that which decides the algorithm.

Image Pre-processing: Image pre-processing is the name for operations on images at the lowest level of abstraction whose aim is an improvement of the image data that suppress undesired distortions or enhances some image features important for further processing and analysis task. It does not increase image information content. Its methods use the considerable redundancy in images. Neighbouring pixels corresponding to one real object have the same or similar brightness value. If a distorted pixel can be picked out from the image, it can be restored as an average value of neighbouring pixels. In the proposed approach image pre- processing methods are applied to the captured image which are stored in image database.

Augmentation: Image augmentation is a technique of altering the existing data to create some more data for the model training process. In other words, it is the process of artificially expanding the available dataset for training a deep learning model.

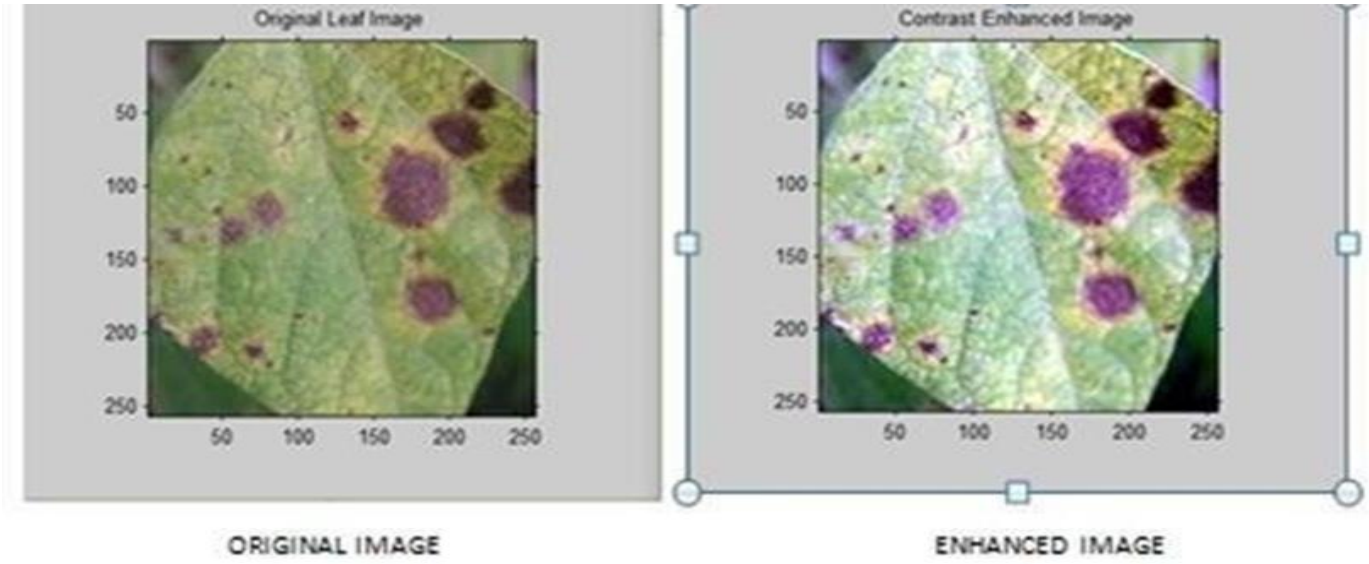

Figure.4.1 Enhanced Image

Classification: Classification is a process of categorizing a given set of data into different types of classes. Classification of image is done using CNN (Convolutional Neural Network).

IV. RESULTS

All the experiments are performed in Deep Learning(DL). For input data disease, samples of plant leaves Apple leaf, Apple rust leaf Bell_pepper leaf, Bell_pepper leaf spot, Corn Gray leaf spot, Corn leaf blight, Squash Powdery mildew leaf, Tomato Early blight leaf , Tomato leaf late blight, Tomato mold leaf and so on are considered.

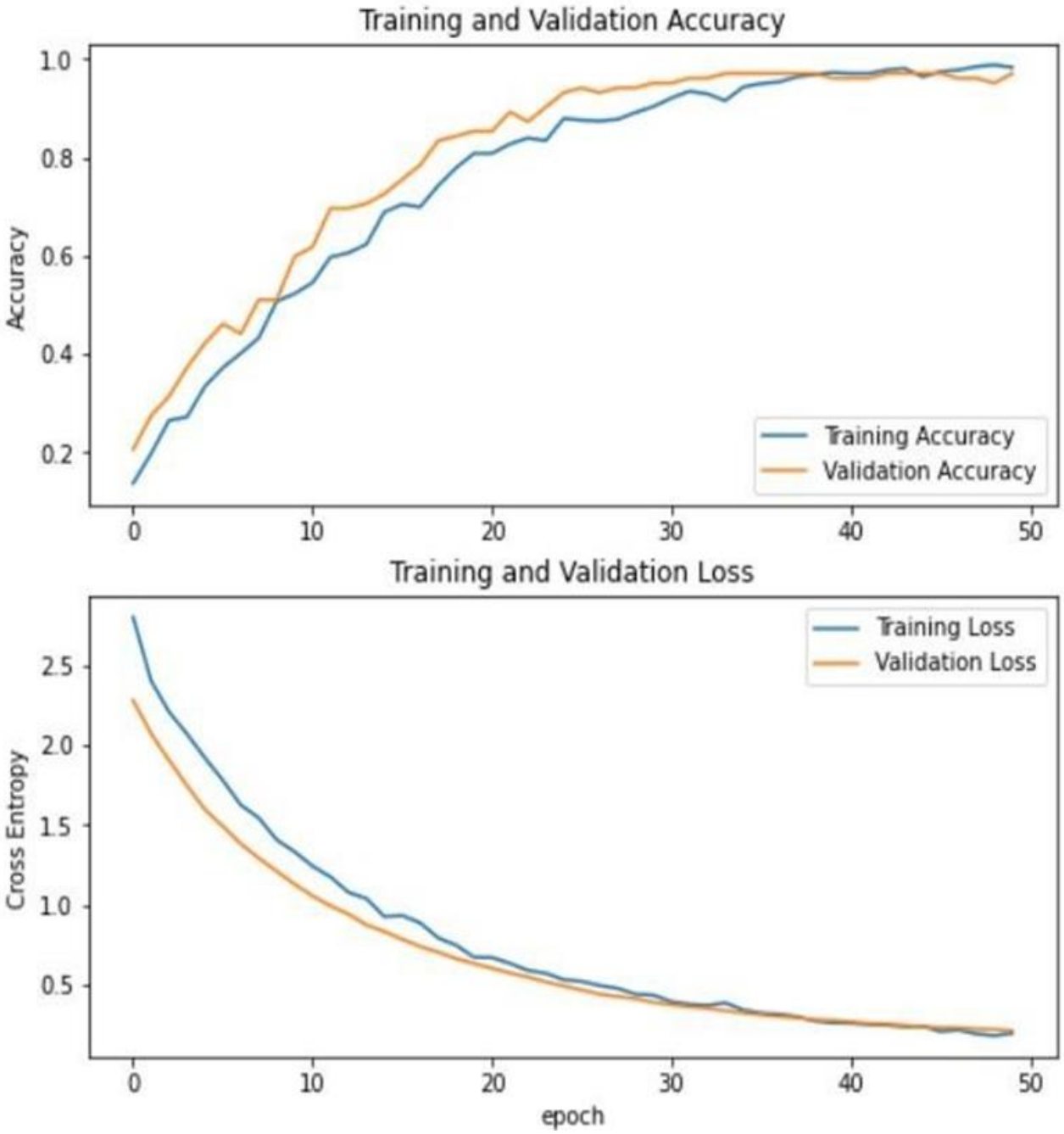

Figure 5.1: graph for epoch 50

Here in figure 5.1 for only 50 times training is happened for the dataset. In the figure 5.1 we can see that the line of training and validation are not a straight line so it says that the trained model is less accurate.

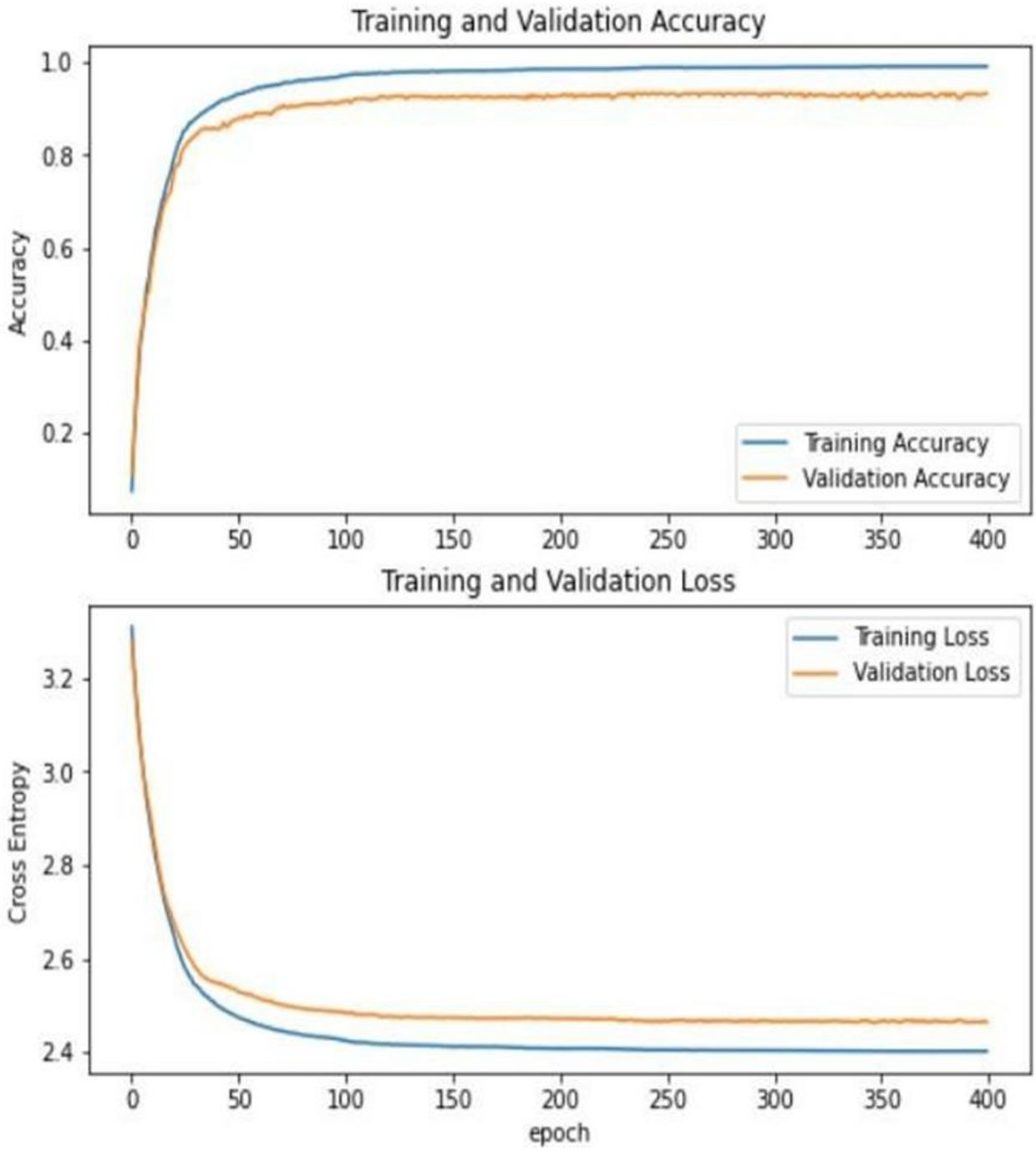

Figure 5.2 graph for epoch 400

Here in figure 5.2 for only 400 times training is happened for the dataset. In the figure 5.2 we can see that the line of training and validation are straight line so it says that the trained model is of more accurate than the first one.

The model was trained using images of disease leaves. The model could classify with approximate 90 percent accuracy. By comparing figure 5.1,5.2 we can say that accuracy can be increased when trained withmore number of epochs.

V. CONCLUSION

The objective of this project is to recognize abnormalities that occur on plants in their greenhouses or natural environment. The image captured is usually taken with a plain background to eliminate occlusion. The algorithm was contrasted with other machine learning models for accuracy. Using CNN classifier, the model was trained using images of disease leaves. The model could classify with approximate 90 percent accuracy. The accuracy can be increased when trained with vast number of images.

VI. REFERENCES

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