IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

PLANT DISEASE DETECTION USING DEEPLEARNING(Potato Leaves)

A project to be submitted in partial ful llment of the requirementsfor the degree of

B.Tech in

Computer Science and Engineering

by

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Abstract

Identi cation of the plant diseases is the key to prevent the losses inthe yield and quantity of the agricultural product. The studies of the plant diseases mean the studies of visually observable patterns seen on the plant. Health monitoring and disease detection on plant is very critical for sustain-able agriculture.

It is very di cult to monitor the plant diseases manually. It requires tremen- dous amount of work, expertise in the plant diseases, and also require the excessive processing time.

Hence, image processing is used for the detection of plant diseases by cap- turing the images of the leaves and comparing it with the data sets. Thedata set consist of di erent plant in the image format. Apart from detection users are directed to an e-commerce website where di erent pesticides withits rate and usage directions are displayed.

This website can be e ciently used for comparing the MRP's of di erent pesticides and purchase the required one for the detected disease. This pa-per aims to support and help the green house farmers in an e cient way.

Keyword : : Plant disease detection, Tensor ow, Green house, Convo- lution neural network, Data model, image to byte code

0.1 INTRODUCTION

India is a cultivated country and about 70% of the Population depends onagriculture. Farmers have large range of diversity for selecting various suit- able crops and nding the suitable pesticides for plant. Hence, damage to the crops would lead to huge loss in productivity and would ultimately a ect the economy. Leaves being the most sensitive part of plants show disease symp-toms at the earliest. The crops need to be monitored against diseases fromthe very rst stage of their life-cycle to the time they are ready to be har- vested. Initially, the method used to monitor the plants from diseases wasthe traditional naked eye observation that is a time-consuming technique which requires experts to manually monitor the crop elds. In the recent years, a number of techniques have been applied to develop automatic andsemi-automatic plant disease detection systems and automatic detection of the diseases by just seeing the symptoms on the plant leaves makes it easier as well as cheaper. These systems have so far resulted to be fast, inexpensiveand more accurate than the traditional method of manual observation by farmers In most of the cases disease symptoms are seen on the leaves, stem and fruit. The plant leaf for the detection of disease is considered which shows the disease symptoms. There are many cases where farmers do nothave a fully compact knowledge about the crops and the disease that can get a ected to the crops. This paper can be e ectively used by farmers therebyincreasing the yield rather than visiting the expert and getting their advice.The main objective is not only to detect the disease using image processing technologies. It also directs the user directly to an e-commerce website wherethe user can purchase the medicine for the detected disease by comparing therates and use appropriately according to the directions given. Greenhousealso called a glasshouse, or, if with su cient heating, a hoth house, is a struc- ture with walls and roof made chie y of transparent material, such as glass,in which plants requiring regulated climatic conditions are grown. As green- house farming is gaining more importance now a day's, this paper helps the greenhouse farmers in an e ective way. Various techniques can be used toreview the plant disease detection and discuss in terms of various parameters.The paper is organized into the following sections. First section gives a brief introduction to the importance of plant disease detection. Second section discusses the existing work carried out recently in this area and also reviews the techniques used. Section three includes methodologies used in our paper.Lastly, fourth section concludes this paper along with future directions. [10]

0.2 Motivation:

Here are some key motivations:

i. Early Disease Detection

ii. Labor Intensity and Expertise

iii. accessibility and A ordability

iv. Economic Impact on Farmers

v. Technology Integration in Agriculture

India is an agricultural country, where most of the population depends onagricultural products. So the cultivation can be improved by technological support. Diseases may cause by pathogen in plant at any environmental condition. In most of the cases diseases are seen on the leaves of the plants, so the detection of disease plays an important role in successful cultivation ofcrops. There are lots of techniques to detect the di erent types of diseases in plants in its early stages. Conventional methods of plant disease detection in naked eye observation methods and it is non-e ective for large crops. Using digital image processing and machine learning the disease detection in plant is e cient, less time consuming and accurate. This technique saves time,e orts, labours and use of pesticides. Hope this approach will becomes a little contribution for agriculture elds.

0.3 Project Objectives

There are four objectives of the proposed methodology:

i. To develop a prototype for a plant disease detection system.

ii. To apply image processing techniques to identify the disease pattern

iii. Use machine learning algorithms to predict disease.

iv. Use transfer learning techniques to predict disease. [16]

0.4 Literature Review

Sardogan, M., et al. in 2018 presented a model with a combination of convolu- tional neural networks (CNN) along with learning vector quantization(LVQ) for the identi cation and categorization of diseases of tomato plant leaves. The presented framework was implemented on the data size of 500 images with the four categories of diseases considered for tomato plant leaves. The convolutional neural network is utilized for the extraction of vital attributes from the images as well as for the classi cation.
[15]

Wallelign, S., et al. in 2018 discussed the viability of convolutional neuralnetwork architecture for the classi cation of various plant diseases with theaid of leaf images. The mentioned framework is implemented by utilizingthe LeNet, one of the popular CNN architecture, for disease classi cationin the aspect of soybean plants. The soybean plant leaf images of 12,763 samples are obtained from the standard database called PlantVillage. Thementioned framework able to achieve an accuracy of 99.% indicating theviability of CNN with plant disease classi cation utilizing the leaf images. [13]

Sladojevic, S., et al. in 2016 concerned the generation of the new-age model for the identi cation of various diseases of 13 plant diseases out of the healthier plant leaf images. The deep learning architecture called Ca e was utilized for training the data. The results were obtained from the mentioned framework with a precision of 91percent to 98percent.

Fuentes, A., et al. in 2017 proposed a framework and can be applied intwo stages. At rst, the meta architectures of Faster R-CNN, R-FCN, and SSD will be combined to form a single meta-architecture. Lastly, certain methodologies such as VGG16, VGG-19, and ResNet-50 will be attachedto extract the features from more depth and these models' e ciency was estimated. When compared to many other models, the proposed frameworke ciency is better.
[8]

Arivazhagan, S. and Ligi, S. V. in 2018 proposed a framework basedon automated deep learning for the recognition and classi cation of various diseases in mango plants. The dataset utilized for this framework consists of 1200 images which include both diseased and healthy leaves of mango. The accuracy obtained from the proposed framework is 96.67%.
[3]

Oppenheim D. and Shani G. in 2017 proposed a framework based on con-volutional neural network architecture for the recognition and classi cation of various diseases in potato plants. The dataset 6 utilized for this frameworkconsists of 2465 potato images.

Barbedo, J. G. A. in 2018 investigated and identi ed the pros and cons through various factors that a ect the model and e ciency of deep learning neural networks which are used for the recognition as well as the classi cationof various plant diseases. The investigation carried out on the literature as well as the experiments carried out with the image database consists of 50000images of various plant

diseases.
[4]

Brahimi, M., et al. in 2017 proposed a framework based on a convolu-tional neural network for the detection and classi cation of various diseasesin the tomato crop. The dataset utilized for this framework consists of 14,828tomato leaf images with almost nine diseases from the plant village imagedatabase. The proposed framework able to achieve an accuracy of 99.18% [5]

Shrivastava, V. K., et al. in 2019 focused on the detection and classi - cation of various diseases in the rice plants using a framework with the aidof CNN architecture along with SVM. The framework was implemented on the dataset consists of 619 rice plant leaf images with all four categories of diseases. The accuracies are evaluated for various proportions of training andtesting datasets and the maximum accuracy achieved is 91.37%.
[18]

Ozguven, M. M. and Adem, K. in 2019 updated an existing faster region-based CNN architecture by varying the parameters for the identi cation of disease-a ected regions in the case of sugar beet. The dataset consists of155 sugar beet images and an accuracy rate of 95.48% achieved using the proposed framework.
[14]

Uguz, S. and Uysal, N. in 2020 considered a comparison of a transfer learn- ing scenario with CNN architectures such as VGG-16 and VGG-19 along withproposed CNN architectures in case of Olive plant diseases. The framework implemented on the dataset consists of 3400 Olive plant leaf images. In this framework, a data augmentation methodology was implemented for improv-ing the size of the dataset. Before data augmentation, the accuracy attained about 88% and after data augmentation, the accuracy attained about 95%.[1]

Agarwal, M. et al. 2020 proposed a customized model based on CNN identi cation of disease of tomato leaves. Also, compared the proposed modelwith machine learning models and VGG-16. The proposed model attainedan accuracy of 98.4%, the KNN model attained an accuracy of 94.9%, and the VGG-16 model attained an accuracy of 93.5%. The tomato leaf images dataset utilized for this framework is extracted from the Plant village dataset [2]

Wang, J. et al. in 2018 considered a transfer learning scenario based on CNN architecture for detection and classi cation of diseases with the aid of leaf images of 2 crops such as cucumber and rice. The proposed framework was implemented on 2430 images of cucumber as well as rice with eight diseases extracted from the plant village dataset.
[22]

Toda, Y., and Okura, F. in 2019 reviewed the scenario of deep learning methodology impact the diagnosis of plant diseases utilizing the leaf images.CNN architecture works as a black box model for the diagnosis of diseasesof the plant. It is also discussed the various aspects of hyperparameters that a ect classifcation accuracy. So far the various models and research have been identi ed in terms of identi cation as well as the classi cation of various categorical diseases in the speci c plant using deep learning scenarios.Deep learning can also be utilized for the identi cation and classi cation of macro-nutrients in a speci c plant.
[20]

For instance, Tran, T. T. et al. in 2019 proposed a system based on a deep learning scenario providing a monitoring system that monitors across various stages from the seedling stage to the yielding stage to achieve an enhanced rate of yield. The proposed framework was implemented utilizing a dataset consists of 571 images include tomato leaf images and tomato fruit images of various stages of growth of the crop. The inception-ResNet v2 andautoencoder attained the accuracies of 87.27% and 79.09% respectively. Thisliterature work shows that the e ect of transfer learning on the detection and classi cation of plant diseases through leaf images.
[21]

According to Ehsan Kiani et.al, 2017 image segmentation done with the help of colors i.e. color image segmentation techniques helps to better un- derstand and solve the problem. One can rst nd out the three-color image components of an image which are Red, Green, and Blue components. The red and Green components help to identify the yellow components of the image which is usually marked as an infected part. Fuzzy logic is a good technique to solve a disease classi cation problem.
[11]

Vijai Singh et.al [2017] An advancement of genetic algorithm is proposedby the author named minimum distance algorithm to nd the infected plant part of the plant that is to perform image segmentation. After the image segmentation step the author has checked the accuracy of the algorithm with other classi cation algorithms like k mean clustering and SVM [19]

Konstantinos 2018 In this paper author has used a convolution neural network technique to identify various plant diseases. A detailed study has been done by the author. Images of various plant leaves are taken which includes both the infected leaves images and healthy leaves images and then the author has classi ed it in various classes and all CNN architectures gave more than 97% accuracy. The CNN architectures include AlexNet, AlexNe- tOWTBn, GoogLeNet, Overfeat, VGG [7]

Kamlesh Golhani et.al, 2018 In this paper author has done a detailed review of various deep learning algorithms along with their advantages and disadvantages also their optimization techniques. A comparison has also beenmade for these techniques about the related work [9]

Channamallikarjuna et.al, [2018]: In this paper, the author has explained in detail the algorithm proposed. The 1st step was image acquisition followed by image enhancement and then image segmentation. Color image segmen- tation was done with the help of the HSV technique. The tool made for testing plant disease was integrated with sensors that could also nd out the real-time atmospheric and climatic conditions which could a ect the plant disease. [12]

0.5 Methodology

The process of plant disease detection system basically involves four phases as shown in Fig.1 The rst phase involves acquisition of images either through digital camera and mobile phone or from web. The second phase segments the image into various numbers of clusters for which di erent techniques can be applied. Next phase contains feature extraction methods and the last phase is about the classi cation of diseases. [17]

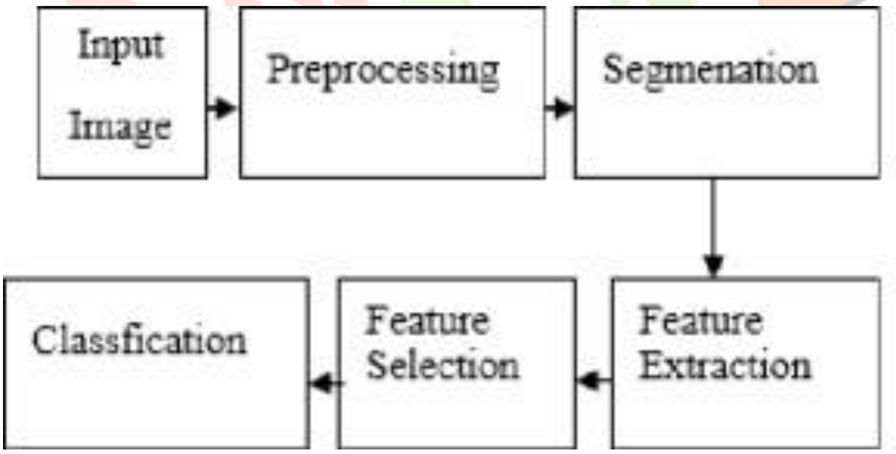


Fig.1 phases of plant disease detection process

0.5.1 Image Acquisition:

In this phase, images of plant leaves are gathered using digital media like camera, mobile phones etc. with desired resolution and size. The images can also be taken from web.
The formation of database of images is completely dependent on the application system developer. The image database is responsible for bettere ciency of the classi er in the last phase of the detection system.

0.5.2 Image Segmentation

This phase aims at simplifying the representation of an image such that itbecomes more meaningful and easier to Analyze.
As the premise of feature extraction, this phase is also the fundamentalapproach of image processing.
There are various methods using which images can be segmented such ask-means clustering, Otsu's algorithm and thresholding etc. The k-meansclustering classi es objects or pixels based on a set of features into K number of classes. The classi cation is done by minimizing the sum of squares of distances between the objects and their corresponding clusters

0.5.3 Feature Extraction

Hence, in this step the features from this area of interest need to be extracted. These features are needed to determine the meaning of a sample image.
Features can be based on colour, shape, and texture. Recently, most of theresearchers are intending to use texture features for detection of plant diseases. There are various methods of feature extraction ithat ican ibe iemployed ifor ideveloping ithe system such as gray-level co-occurrence matrix (GLCM), color cooccurrence method, spatial greylevel dependence matrix, and histogram based feature extraction. The GLCM method is a statistical method for texture classi cation.

0.5.4 Classi cation

The classi cation phase implies to determine if the input image is healthy or diseased. If the image is found to be diseased, some existing works havefurther classi ed it into a number of diseases. For classi cation, a softwareroutine is required to be written in MATLAB, also referred to as classi er.
A number of classi ers have been used in the past few years by researcherssuch as k-nearest neighbour (KNN), support vector machines (SVM),
arti cial neural network(ANN), back propagation neural network (BPNN),
Na ve Bayes and Decision tree classi ers. The most commonly used classi er is found to be SVM.
Every classi er has its advantages anddisadvantages, SVM is simple to use and robust technique.

0.6 Overview Of Plant Disease

Plant diseases are generally caused by infectious agents such as fungi, bacteria, and viruses. Signs of plant disease are observable evidence of infection and symptoms are the visible e ects of these kinds of disease. Fungal infections cause signs like visible spores, mildew, or mold and thebasic symptoms are like leaf spot and yellowing.
Fungal diseases are plant infections caused by fungi. Fungi can be single or multicellular, but either way infect plants by stealing nutrients and breaking down tissue. Fungal diseases are the most common infection in plants. There are some characteristic symptoms, or observable e ects of the disease, in plants.
Fungi infections can be recognized by symptoms like spots on plant leaves, yellowing of leaves, and birdseye spots on berries. With some fungal diseases, the organism itself can actually be viewed on the leaves appear asa growth and as a mold

Fig 2 Leaf a ected by fungal infection

These may a malformations on stems or the underside of leaves. These direct observations of the disease-causing organism are called signs ofinfection Bacteria are single-celled, prokaryotic organisms. Bacteria are
everywhere and many can be bene cial, but some can cause disease both inhumans and plants. The signs of bacteria are often harder to detect than fungi, since bacteria are microscopic. Upon cutting an infected stem, a milky white substance may appear, called bacterial ooze. This is one sign of a bacterial infection. Other signs include water-soaked lesions, which are wet spots on leaves thatooze bacteria.
Eventually, as the disease progresses, the lesions enlarge and form reddish-brown spots on the leaves. A common symptom of bacterial infection is leaf spots or fruit spots. Unlike fungal spots, these are oftencontained by veins on the leaf.

Fig 3 Leaf a ected by bacteria

Viruses are infectious particles that are too small to be detected by a lightmicroscope. They invade host cells and hijack host machinery to force the host to make millions of copies of the virus. Viral diseases don't show any signs in plants since viruses themselves
cannot be seen even with a light microscope. However, there are symptomsthat the trained eye can observe. A mosaic leaf pattern, yellowed, or
crinkled leaves are all characteristic of viral infection. This classic patternof discoloration is where

many plant viruses get their name, such as the tobacco mosaic virus. Also, decreased plant growth is also commonly seenin viral infections.

Fig 4 Leaf a ected by virus

se are our observation on how to classify the various plant diseaseand how to be cautious about that. [6]

0.7 Proposed System

Proposed system have an end-to-end application . Proposed system opted to develop an Android application that detects plant diseases. It has the algorithms and models to recognize species and diseases in the crop leaves by using Convolutional Neural Network. Proposed system use Colab to editsource code.

A dataset of 4,348 images of diseased and healthy potato leaves collectedunder controlled conditions Plant Village dataset. This datasets are classi ed into 3 types, Early blight ,Late blight, Healthy.

Data generators that will read pictures in our source folders, convert them to ` oat32` tensors, and feed them (with their labels) to our network is set up. As data that goes into neural networks should usually be normalized insome way to make it more amenable to processing by the network. In our case, we will pre-process our images by normalizing the pixel values to be inthe `[0, 1]` range (originally all values are in the `[0, 255]` range). We will need to make sure the input data is resized to 224x224 pixels or 299x299 pixels as required by the networks.

0.8 Results And Discussion

In the provided code, the model's performance is evaluated primarily usingtwo metrics: accuracy and loss. These metrics are commonly used to assessthe performance of classi cation models, including image classi cation models.
Accuracy: It measures the proportion of correctly classi ed samples out ofthe total number of samples. In the context of image classi cation, accuracy indicates the percentage of images that the model correctly classi es into their respective categories.
Loss: The loss function (speci cally, Sparse Categorical Crossentropy in this case) measures the discrepancy between the predicted output of the model and the actual labels. It quanti es how well the model is performingduring training. The goal during training is to minimize this loss function. These metrics are computed during both training and validation phases.
Monitoring them over epochs provides insights into how well the model is learning and whether it's over tting or under tting. By plotting these metrics over time (epochs), you can observe the training progress and makeadjustments to the model architecture or training process if necessary.

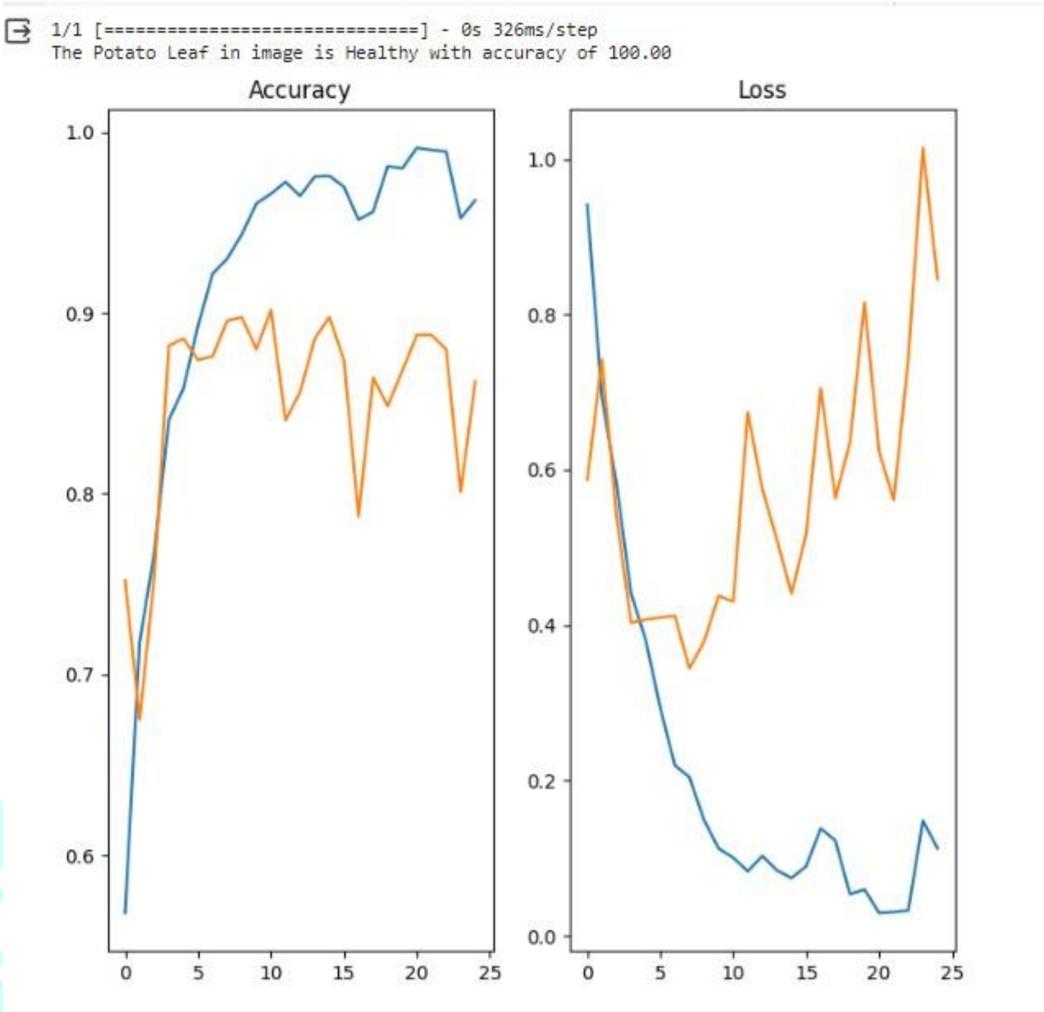


Fig 5 Perfomance

In the provided code, a Convolutional Neural Network (CNN) is used forimage classi cation. A CNN is a type of deep learning algorithm that is particularly e ective for tasks like image classi cation.

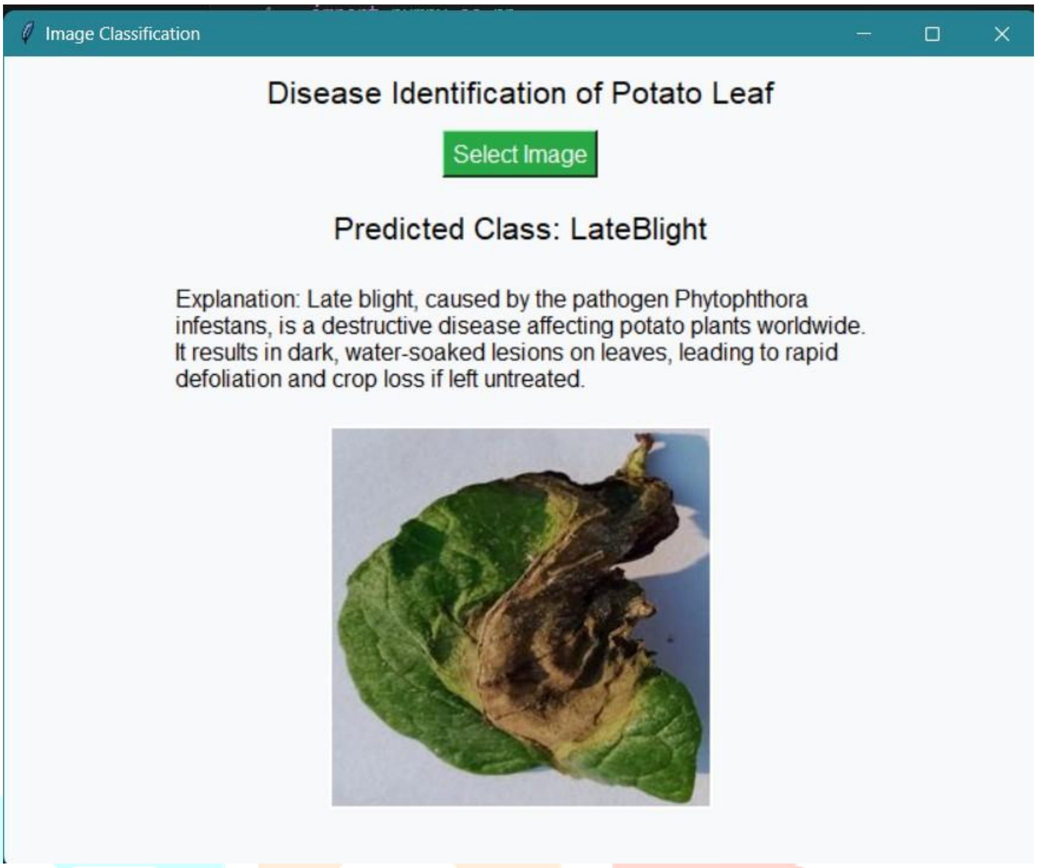
Here's a breakdown of the key components of the CNN used in the code:

Convolutional Layers: These layers apply a set of learnable lters to theinput image. These lters detect various features in the input image, such as edges, textures, or shapes. In the code, there are three convolutional layers with increasing numbers of lters (16, 32, and 64).

Pooling Layers: These layers downsample the output of the convolutionallayers, reducing the spatial dimensions of the feature maps while retaining the most important information. In the code, max-pooling layers are used after each convolutional layer. Flatten Layer: This layer attens the outputof the previous layer into a one-dimensional vector, which can then be fed into a fully connected neural network.

Fully Connected Layers: These layers process the attened feature vector and perform classi cation based on the features extracted by the convolutional layers. In the code, there are two fully connected layers withReLU activation functions, followed by a nal output layer with a softmaxactivation function for multi-class classi cation.

Dropout Layer: This layer helps prevent over tting by randomly settinga fraction of input units to zero during training, which temporarily removes them from the network. In the code, a dropout layer with a dropout rate of 0.2 is applied after the atten layer.



g 6 Disease prediction result

0.9 Conclusion

In conclusion, plant disease detection using image processing is a transformative and indispensable approach that holds immense potentialfor revolutionizing agriculture. Leveraging advanced techniques in image processing, such as pre-processing, background removal, and segmentation, provides a robust foundation for creating accurate and reliable plant diseasedetection systems. The following key points summarize the signi cance andimplications of employing image processing in plant disease detection:

Precision and Accuracy: - Image processing techniques enable precise identi cation and accurate classi cation of plant diseases. The applicationof these methods contributes to minimizing false positives and negatives, thereby enhancing the overall accuracy of detection.
Early Detection and Intervention: - Early detection is crucial in preventing the rapid spread of plant diseases. Image processing facilitatesthe identi cation of subtle symptoms and allows for timely intervention, enabling farmers to take proactive measures to mitigate crop losses.
E cient Data Utilization: - Techniques like image pre-processing andbackground removal ensure that machine learning models receive high-quality, standardized input. This e ciency in data utilization resultsin more e ective model training and improved generalization to real-world scenarios.
Quantitative Analysis: - Image processing enables quantitative analysisof disease severity, providing valuable insights into the extent of the infestation. This quantitative data aids in decision-making regarding the appropriate treatment and management strategies.
Automation and Scalability: - Automated plant disease detection systems, powered by image processing, o er scalability and e ciency inmonitoring large agricultural elds. This scalability is particularly benefecial for modern, technology-driven farming practices.

Precision Agriculture: - The integration of image processing into plantdisease detection aligns with the principles of precision agriculture. By precisely identifying and localizing diseases, farmers can optimize resource utilization, including water, fertilizers, and pesticides, leading to sustainableand environmentally friendly practices.

Technological Advancements: - Ongoing advancements in image processing algorithms and technologies, coupled with the increasing availability of high-quality imaging devices, contribute to the continuousimprovement of plant disease detection systems. This ensures the adaptability and relevance of these systems in dynamic agricultural landscapes.

0.10 Future Work

*The forecasting of disease diseases in early stage, so that appropriatemeasures can be taken to minimize the loss in crops

*Our project have shown pretty good accuracy, it can be implemented in real time mobile applications and web services, so that formers can identifydiseases simply by taking photo of suspected leaves of plants.

*Other than plant leaf disease identi cation, it can also be used for identi cation and classi cation of nutrients de ciency of plant leaves.

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