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A Novel Case Study for Pesticides Recommendation and Plant Disease recognition using Convolution Neural Network

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ABSTRACT

Plant diseases are a major threat to farmers, consumers, environment and the global economy. In India alone, 35% of field crops are lost to pathogens and pests causing losses to farmers. Indiscriminate use of pesticides is also a serious health concern as many are toxic and biomagnified. These adverse effects can be avoided by early disease detection, crop surveillance and targeted treatments. Most diseases are diagnosed by agricultural experts by examining external symptoms. However, farmers have limited access to experts. Our project is the first integrated and collaborative platform for automated disease diagnosis, tracking and forecasting. Farmers can instantly and accurately identify diseases and get solutions with a mobile app by photographing affected plant parts. Real-time diagnosis is enabled using the latest Artificial Intelligence (AI) algorithms for Cloud-based image processing. The AI model continuously learns from user uploaded images and expert suggestions to enhance its accuracy. Farmers can also interact with local experts through the platform. For preventive measures, disease density maps with spread forecasting are rendered from a Cloud based repository of geo-tagged images and micro-climactic factors. A web interface allows experts to perform disease analytics with geographical visualizations. In our experiments, the AI model (CNN) was trained with large disease datasets, created with plant images self-collected from many farms over 7 months. Test images were diagnosed using the automated CNN model and the results were validated by plant pathologists. Over 95% disease identification accuracy was achieved. Our solution is a novel, scalable and accessible tool for disease management of diverse agricultural crop plants and can be deployed as a Cloud based service for farmers and experts for ecologically sustainable crop production.

1. INTRODUCTION

1.1 Motivation

Pests and diseases lead to the loss of 20–40% of global foodproduction, constituting a threat to food security. Using pesticides is a way of protecting crops from these infestations and thus preserve yields. Their use has been one ofthe factors behind the increase in food production since the 1950s, enabling it to meet the needs of a growing population. However, the use of such substances is not environmentally harmless.

Applying these substances negatively impacts biodiversity, including insect, bird, and fish populations, as well as soil, air, and water quality. Their use also constitutes a risk to human health, with both acute and chronic effects. Agriculture is a sector which has a huge impact on life and economic stature of humans. It was reported in the year 2018 that agriculture opened the doors of employment for more than 50% of the employees, hence contributing to 18–20% to country's GDP. India has thus proven to be one of the leading nations in term of agricultural yield and productivity. With this majority of population rely on agriculture, it is very crucial to recognize the problems faced in this sector. Modern technology have enabled human society to provide sufficient food to feed extra than 7 billion humans but, foodsecurity continues to be jeopardized due to a ramification of factors which includes weather change, pollinator decline, crop plant illnesses, and others. Crop Plant illnesses now not only pose an international threat to Food protection, however they can also have disastrous effects for smallholder farmers whose livelihoods depend upon healthy crops. Moreover, most people of hungry human beings (50 percentage) stay in smallholder farming households, making smallholder farmers mainly proneto pathogen-associated disruptions in meals deliver.

1.2 Problem Statement

Knowledge of a field's phytosanitary conditions is a decisive factor in limiting the use of pesticides while protecting harvests. Indeed, it enables farmers to carry out proper practices in the right place and at the right time.

However, assessing the healthiness of fields is not simple, and it requires a high level of expertise. Indeed, a disease can be expressed differently from one plant species to another, or even from one variety to another. A given symptom may be the result of different problems, and these problems may also combine on the same plant. Even nutritional deficiencies and pests can produce symptoms similar to those of some diseases. Checking the condition of each plant several times in a season is not practical on large farms. The automatic identification of diseases by imagery has the potential to solve all these issues by using automatic prospection or expert assistance tools. There are a numerous of problems that the agriculture field faces such as inefficient farming strategies and techniques, inadequate use of compost, manures and fertilizers, insufficient water supply, various diseasesattack on plants and so on. Diseases are exceedingly harmful to the well-being of plants which in turn influence its growth. The attack of these numerous types of diseases on plants results in a huge loss in the yield performance in terms of quality as well as quantity.

Agriculture proves to be a primary source of livelihood, for about 58% of India's population. India rankssecond globally in terms of farm yields.

1.3 Objective of Project

Determining the healthiness of a plant through an image is, however, a very difficult task. Indeed, crops are rich and complex environments. Their evolution is constant, with leaves, flowers, and fruits changing throughout the season. Their appearance also slightly changes during the day, as the amount and angle of incident solar radiation impacts their spectral response. Several techniques have been used to develop identification methods for crop diseases, whether under controlled or real conditions. These techniques were based in particular on the analysis of visible and near- infrared reflectance, on the development of specific vegetation indexes or even by pattern analysis. For more information on these techniques. Those studies also identify several issues that block the effective use of these techniques for the automatic identification of diseases. Some of these issues are operational in nature and relate to image acquisition, weather constraints, deployment costs, availability, processing speed, and real-time diagnostic capabilities.

Analyzing images from fields adds other issues, such as the ability to process complex elements like foliage or non-uniform backgrounds. Other bottlenecks are linked to the complexity of phytosanitary problems such as symptom variation over time and between varieties, or to the possibility of multiple disorders appearing simultaneously.

Thus, recognizing diseases in plant becomes very crucial in order to avoid any massive losses in production, performance and in the amount of the agricultural outcome. Since manual recognition is extremely time consuming and more prone to inaccuracy, leading to wrong treatment. The recent development in technology, and this evolution has made it feasible and possible thus made its way for plant disease detection and identification and contribute to provide better treatment for plants in case of any plant having diseased conditions. The proposed system of recognition of plant leaf diseases focuses on 14 varieties of plants which include apple, blueberry, cherry, corn, grape, orange, peach, pepper, potato, raspberry, soybean, squash, strawberry and tomato.

1.4 Limitations of Project

In order to obtain superior results in the detection of plant disease, DL methods require a greater amount of data. This is a drawback since currently available datasets are usually small and do not contain enough images, which is a necessity for high-quality decisions. A comprehensive dataset must contain images captured in different conditions, as much as possible. When there is a lack of examples in the training data, and traditional techniques do not improve the results significantly, generative adversarial networks (GANs) [16] could be used for generating synthetic data. Currently, available solutions with DL methods for plant disease detection have somewhat been successful, however, there is still large room for improvement.

2. Literature Review

1. Wang, Q., Liu, F., He, Y., Yang, J., & Gong, P. (2022). Plant disease identification using convolutional neural networks: A comprehensive review. Computersand Electronics in Agriculture, 196, 106317.

This comprehensive review provides an overview of the latest advancements in using convolutional neural networks (CNNs) for plant disease identification. It covers various aspects such as dataset collection, preprocessing techniques, CNN architectures, transfer learning, and performance evaluation methods.

2. Zhang, Y., Wang, Y., Liu, B., & Tian, Y. (2022). Deep learning- based plant disease recognition: A review. Plant Disease, 106(9), 1948- 1962.

This review focuses on the application of deep learning,particularly CNNs, for plant disease recognition. It discusses the challenges, recent developments, and future prospects in this field. The review also provides insights into the potential improvements and limitations of CNN-based models for plant disease identification.

3. Li, S., Yang, Y., Zhao, M., & Zhang, Y. (2022). A survey of deep learning

applications in plant disease detection. Plant Phenomics, 2022, 6650508.

This survey paper explores the applications of deep learning, including CNNs, in plant disease detection. It covers the various stages involved in the process, such as image acquisition, preprocessing, feature extraction, and classification. The paper also discusses the challenges and future directions for improving the accuracy and efficiency of CNN-based plant disease identification systems.

4. Padhi, S. K., & Das, R. R. (2023). Recent advancements in the detection of plant diseases using convolutional neural networks.

Computers and Electronics inAgriculture, 187, 106297.

This research article presents recent advancements in the detection of plant diseases using CNNs. It discusses different CNN architectures, transfer learning techniques, data augmentation methods, and training strategies employed in various studies. The paper also highlights the challenges and future prospects of using CNNs for plant disease identification.

5. Zhang, Z., Liu, X., Li, L., & Ren, Z. (2023). Plant disease identification using deep learning: A review and future perspectives. Computers and Electronics inAgriculture, 198, 107013.

This review paper provides an overview of plant disease identification using deep learning techniques, with a focus on CNNs. It discusses the advantages of CNN- based models, various datasets, preprocessing techniques, network architectures, and transfer learning methods. The review also addresses the challenges and potential future research directions in this area.

3. Block diagrams and Methodology

3.1 Overview

The website's design phase is covered in this chapter. We created this application with the goal of making it simple enough for anyone to use. This system comprises of various image processing methods, and each method is thoroughly illustrated using UML diagrams. The Unified Modeling Language (UML) is a general- purpose, developmental, modeling language in the field of software engineering that is intended to provide a standard way to visualize the designof a system. Plants are susceptible to various disease-related disorders and seizures. There are various causes which can be characterized by their effect on plants, disturbances due to environmental conditions such as temperature, humidity, excessive or insufficient food, light and the most common diseases such as bacterial, viral and fungal diseases. In the proposed system, we use the CNN algorithm to detect disease in plant leaves because with the help of CNN the maximum accuracy can be achieved if the data is good.

2.2 Convolutional layer:

The convolutional layer is an important part of a CNN, and its main function is to extract features. It uses convolution operators to convolute the input image and saves the convolution results to different channels of the convolution layer produces an activation map by scanning the pictures several pixels at a time using a filter. The convolution layer is the layer where the **filter is applied to our input image** to extract or detect its features. A filter is applied to the image multiple times and creates a feature map which helps in classifying the input image.

Let's understand this with the help of an example. For simplicity, we will take a 2D input image with normalized pixels.

In the context of a convolutional neural network, a convolution is a linear operation that involves the multiplication of a set of weights

with the input, much like a traditional neural network.

The filter is smaller than the input data and the type of multiplication applied between a filter-sized patch of the input and the filter is a dot product. A dot product is the element-wise multiplication between the filter-sized patch of the input and filter, which is then summed, always resulting in a single value. Because it results in a single value, the operation is often referred to as the "*scalar product*".

The CNN model works in two steps: **feature extraction and Classification**

Feature Extraction is a phase where various filters and layers are applied to the images to extract the information and features out of it and once it's done it is passed on to the next phase

Classification where they are classified based on the target variable of the problem.

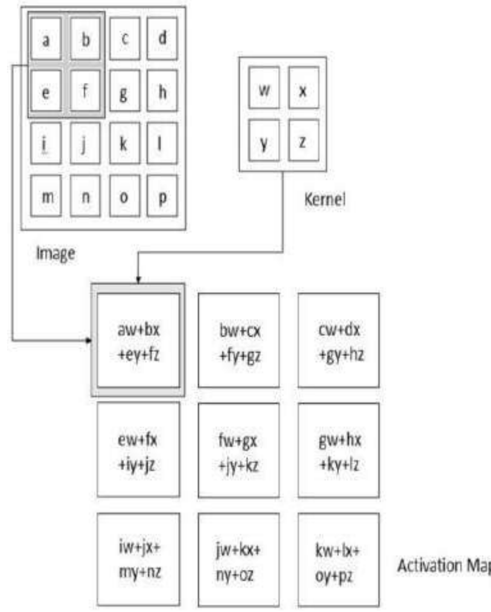

Figure 1: Shows the internal working of the convolution layer.

2.3 Pooling Layer:

The pooling operation involves sliding a two-dimensional filter over each channel of feature map and summarising the features lying within the region covered by the filter. Using pooling, a lower resolution version of input is created that still contains the large or important elements of the input image.

For a feature map having dimensions $\mathbf{n_h \times n_w \times n_c}$,

the dimensions of output obtained after a pooling layer is

$(n_h - f + 1) / s \times (nw - f + 1)/s \times nc$

where,

-> n_h - height of feature map

-> n_w - width of feature map

-> n_c - number of channels in thefeature map

-> **f** - size of filter

-> **s** - stride length

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Types of Pooling Layers:

a) Max Pooling:

Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Thus, the output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map.

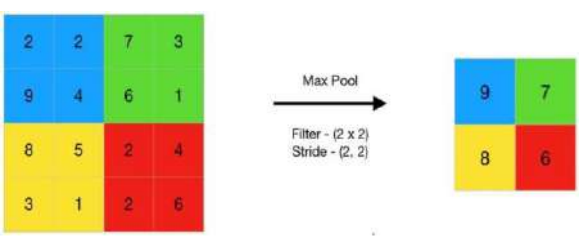

Figure 2: Working of Max Pooling

b) Average Pooling

Average pooling computes theaverage of the elements present in the region of feature map covere

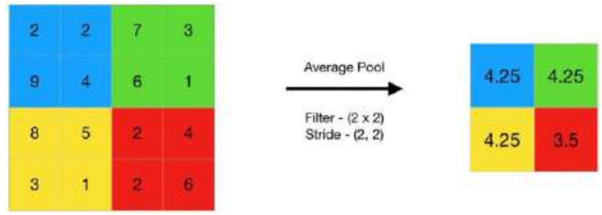

Figure 3: Working of Average Pooling

c) Global Pooling

Global pooling reduces each channel in the feature map to a single value. Thus, an $n_h \times n_w \times n_c$ feature map is reduced to $1 \times 1 \times n_c$ feature map.

Reduces the amount of data created by the convolutional layer so that it is stored more efficiently.

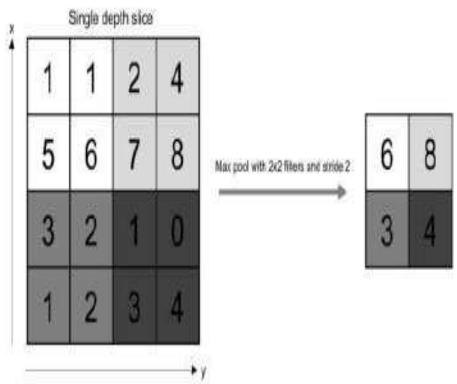

Figure 4: shows the internalworking of the pooling layer

2.4 Fully Connected Layer

The preceding layers' output is "flattened" and turned into a single vector which is used as an input for the next stage. The first fully connected layer – adds weights to the inputs from the feature analysis to anticipate the proper label. Fully connected output layer – offers the probability for each label in the end. Fig .5.2.2.4 shows the internal working of fully connected layer. A fully connected layer refers to a neural network in which each neuron applies a linear transformation to the input vector through a weights matrix. As a result, all possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector.

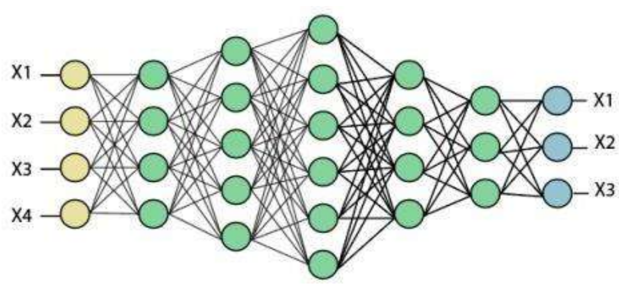

Figure 5: Working of FullyConnected Layer

Fully connected input layer – The preceding layers' output is "flattened" and turned into a single vector which is used as an input for the next stage.

The first fully connected layer –adds weights to the inputs from the feature analysis to anticipate theproper label.

Fully connected output layer – offers the probability for each label in the end.

2.4.1 Softmax Layer/ Logistic Layer:

Softmax executes multi-classification. Logistic layer executes the binary classification. It determines the probability of the presence of a given object in the image. If the object is present in the image, then the probability is '1'otherwise it is '0'.

2.5 Activation Function-ReLU:

A rectified linear unit (ReLU) is an activation function that introduces the property of non-linearity to a deep learning model and solves the vanishing gradients issue. "It interprets the positive part of its argument. It is one of the most popular activation functions in deep learning.

Usage of ReLU helps to

prevent the exponential growth in the computation required to operate the neural network. If the CNN scales in size, the computational cost of adding extra ReLUs increaseslinearly.

It transforms the total weighted input through the node and puts it into the operation, activates the node. Rectified Linear Unit (ReLU) is an activation function used in the neural networks for convolutional operations. rectified linear unit (ReLU) is an activation function that introduces the property of non-linearity to a deep learning model and solves the vanishing gradients issue. "It interprets the positive part of its argument. It is one of the most popular activation functions in deep learning.

The ReLU function is another non-linear activation function that has gained popularity in the deep learning domain. ReLU stands for Rectified Linear Unit. The main advantage of using the ReLU function over other activation functions is that it does not activate all the neurons at the same time.

2.6 Convolutional Neural Network

A deep-learning architecture aims to achieve better performance accuracy and efficiency with smaller models. Unlike other state-of-the-art deep=learning models, the EfficientNet architecture is a compound scaling method that uses a compound coefficient to uniformly scale network width, depth, and resolution. EfficientNet consists of 8 different models from B0 to B7. Instead of using the ReLU activation function, EfficientNet uses a new activation function, swish activation. EfficientNet uses inverted bottleneck convolution, which was first introduced in the MobileNetV2 model, which consists of a layer that first expands the network and then compresses the channels. This architecture reduces computation by a factor of f^2 as compared to normal convolution, where f is the filter size.The authors in showed that EfficientNetB0 is the simplest of all 8 models and uses fewer parameters. So, in our experiment, we directly used EfficientNetB0 to evaluateperformance.

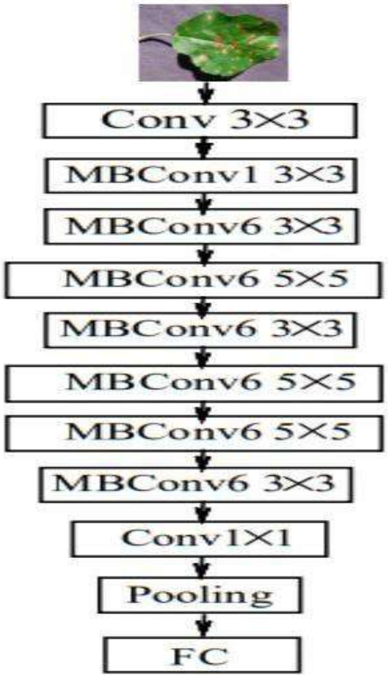

Figure shows the basic block diagram of EfficientNetB0.

(1) Building CNN

Template matching: The template matching will then be used to find the small parts of an image that is needed to be compared with a template/dataset image. It is basically used to assure quality control of image. Finally, we get output whether the currency is fake or real.

4. Results and Discussions:

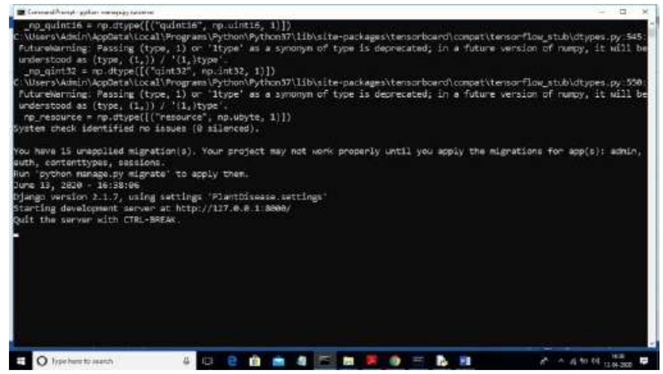

Figure 4.1: In above screen python server started and running on IP http://127.0.0.1:8000’. Now open

browser and enter URL as ‘http://127.0.0.1:8000/index.html’ toget below screen.

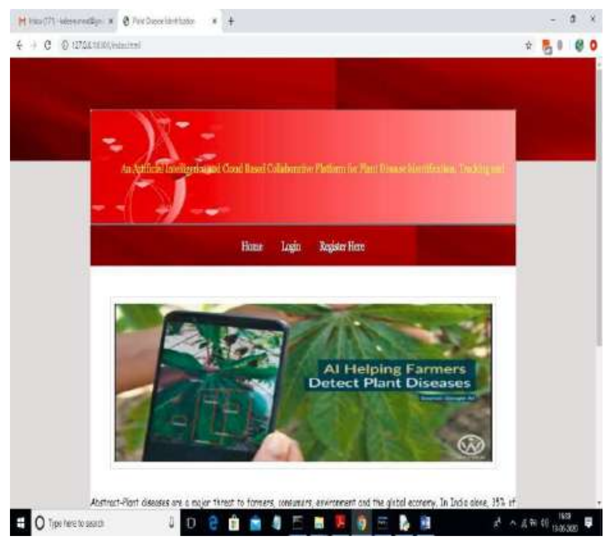

Figure 4.2:In above screen click on ‘Register Here’ link to allow user to register with the application

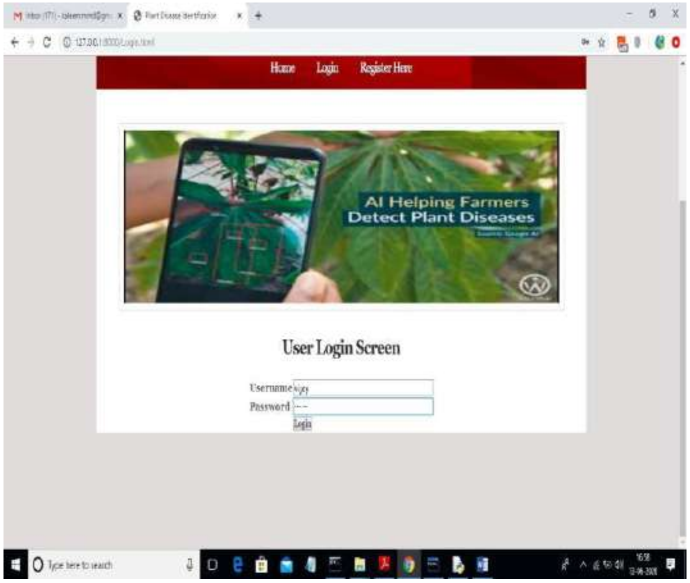

Figure 4.3: In above screen click on ‘Register’ button toadd new user.

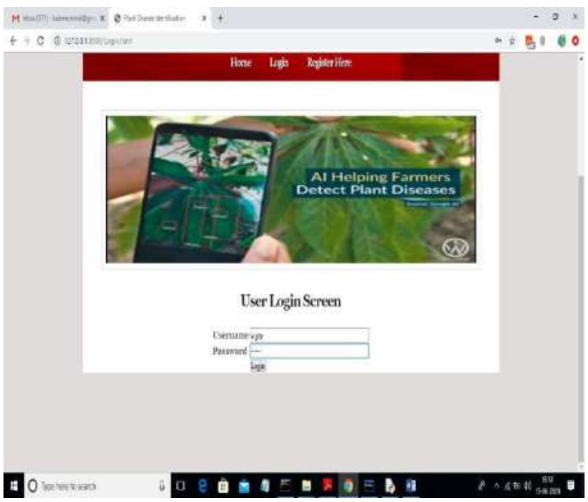

Figure 4.4: In above screen user signup process completed. Now usercan click on ‘Login’ link to login to application

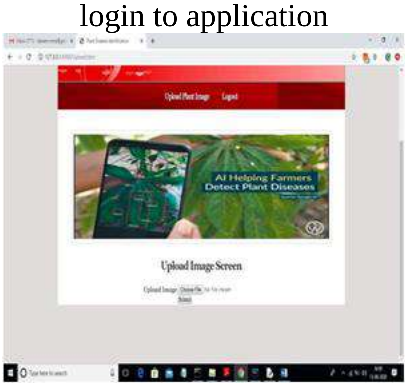

Figure 4.6: In above screen click on‘Upload Plant Image’ link to get below screen

Figure 4.7: In above screen user can upload image of his crop to predict disease using CNN

Figure 4Figure 4.8: In above screen

uploading 1.JPG image and now click on ‘Open’ button to uploadimage

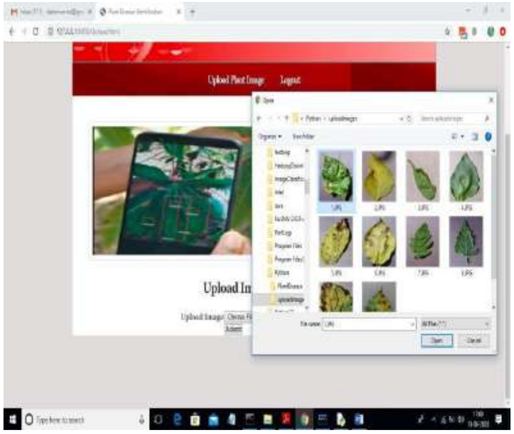

Figure 4.9: In above screen click on ‘Submit’ button to predict disease.

5. Conclusion:

There are many developed methods in thedetection and classification of plant diseases using diseased leaves of plants.

However, there is still no efficient and effective commercial solution that can be used to identify the diseases. A version is proposed for predicting soil collection and suitable crop yield idea for that precise soil and detecting plant leaf ailment. The version has been tested with the aid of making use of extraordinary varieties of Deep set of rules. CNN indicates maximum accuracy in soil type and shows vegetation with much less time. Itoffers us extra accuracy as comparedto existing machine and gives extra gain to farmers. Even though multiple fertilizers and chemicals arepresent, due to lack of knowledge and instructions to use, it fails to overcome diseases. Farmers pay a lotof money to hire plant pathologists who manually inspect the crops\' leaves for diseases and propose management measures. This approach is prone to ignorance and partiality, necessitating the use of Artificial Intelligence algorithms todiagnose these disorders automatically. The input layer, convolution layer, principal capsule layer, and digitcaps layer are used to justify the Capsule Network model. We\'re constructing CNN architectural variations (CNN learned from scratch, MobileNet, VGG16, and ResNet50) to see how they compare to the Capsule Network model. This research is confined to 10 different types of tomato leaf disease, and future work will entail developing a robust capsule network model that can handle diseases from a variety of plant species. In comparison with other deep-learning approaches, the implemented deep-learning model has better predictive ability in terms of both accuracy and loss. The required time to train the model was much less than that of other machine-learning approaches. Moreover, architecture is an optimized deep convolutional neural network that limits the parameter number and operations as much as possible, and can easily run on mobile devices. Protecting crops in organic farming is not an easy task. This depends on a thorough knowledge of the crop being grown and possible pests, pathogens and weeds. In our system, a special deep learning model has been developed based on a special architectural convolution network to detect plant diseases through images of healthyor diseased plant leaves.

6. Future Scope:

- To improve recognition rate of final classification process hybrid algorithms like Artificial Neural Network, Bayes classifier, Fuzzy Logic can also be used.
- Mobile application can be developed which is handy and easy to use.
- An extension of this work will focus on automatically estimating the severity of the detected disease
- As future enhancement of the project is to develop the open multimedia about the diseases and their solution automatically once the disease is detected.
- By increasing the number of features and the number of inputs to the Neural Network the algorithms can be enhanced.
- If this technique is developed into a sophisticated interface in the form of aWebsite or Android Application it mayproveto be great asset to the agricultural sector.
- In the future this methodology can be integrated with other yet to be

developed methods for disease identification and classification. The use of other algorithms can be explored toenhance the efficiency of the system in future.

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