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# Plant Leaf Disease Detection Using Deep Learning and ML Techniques

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**ABSTRACT:** Economy contributes the most for the productivity of the agriculture. In agricultural field, the disease in plants is more common and the detection of disease in plants has become more feasible due to the above reason. These days's plant disease detection has acquired enlarging scrutiny in surveilling crops of large and various fields. Farmers undergo significant hassles in chop and changing from one disease administer principle to a different one. We can identify or spotting the tomato leaf diseases for detection for surveillance and monitoring experts is the standard approach for detection. The plants get seriously affected if the proper control hasn't been taken and this represents the quality of the pants the production of the plants will be affected. Detection of disease through some mechanized technique and methodology is efficient and constructive because it decreases an outsized toil of surveilling in the large cultivation. In the premature phase we can detect the symptoms of the plant diseases since their first appearance on their leaves of the plants. By using this paper we can identify the algorithm which is used for image segmentation and for automated classification used for the detection of diseases of leaves in the plants. It also covers distinct disease classification methods of working which is used for the detection of diseases in plants.

**KEYWORDS:** Plant diseases, machine learning, deep learning, CNN, ANN, SVM.

## I. INTRODUCTION

The automated identification of plant diseases based on plant leaves is a major landmark in the field of agriculture. Moreover, the early and timely identification of plant diseases positively impacts crop yield and quality. Due to the cultivation of a large number of crop products, even an agriculturist and pathologist may often fail to identify the diseases in plants by visualizing disease-affected leaves. However, in the rural areas of developing countries, visual observation is still the primary approach of disease identification. It also requires continuous monitoring by experts. In remote areas, farmers may need to travel far to consult an expert, which is time-consuming and expensive. Automated computational systems for the detection

and diagnosis of plant diseases assist farmers and agronomists with their high throughput and precision. In order to overcome the above problems, researchers have thought of several solutions. Various types of feature sets can be used in machine learning for the classification of plant diseases. Among these, the most popular feature sets are traditional handcrafted and deep-learning (DL)-based features. Pre-processing, such as image enhancement, color transformation, and segmentation, is a prerequisite before efficiently extracting features. After feature extraction, different classifiers can be used.

The occurrence of plant diseases has a negative impact on agricultural production. If plant diseases are not discovered in time, food insecurity will increase. Early detection is the basis for effective prevention and control of plant diseases, and they play a vital role in the management and decision making of agricultural production. In recent years, plant disease identification has been a crucial issue. Disease-infected plants usually show obvious marks or lesions on leaves, stems, flowers, or fruits. Generally, each disease or pest condition presents a unique visible pattern that can be used to uniquely diagnose abnormalities. Usually, the leaves of plants are the primary source for identifying plant diseases, and most of the symptoms of diseases may begin to appear on the leaves. In most cases, agricultural and forestry experts are used to identify on-site or farmers identify fruit tree diseases and pests based on experience. This method is not only subjective, but also time-consuming, laborious, and inefficient. Farmers with less experience may misjudgement and use drugs blindly during the identification process. Quality and output will also bring environmental pollution, which will cause unnecessary economic losses.

The problem of efficient plant disease protection is closely related to the problems of sustainable agriculture and climate change. Research results indicate that climate change can alter stages and rates of pathogen development; it can also modify host resistance, which leads to physiological changes of host-pathogen interactions. The situation is further complicated by the fact that, today, diseases are transferred globally more easily than ever before. New diseases can occur in places where they were previously unidentified and, inherently, where there is no local expertise to combat them.

Inexperienced pesticide usage can cause the development of long-term resistance of the pathogens, severely reducing the ability to fight back. Timely and accurate diagnosis of plant diseases is one of the pillars of precision agriculture. It is crucial to prevent unnecessary waste of financial and other resources, thus achieving healthier production, by addressing the long-term pathogen resistance development problem and mitigating the negative effects of climate change.

In this changing environment, appropriate and timely disease identification including early prevention has never been more important. There are several ways to detect plant pathologies. Some diseases do not have any visible symptoms, or the effect becomes noticeable too late to act, and in those situations, a sophisticated analysis is obligatory. However, most diseases generate some kind of manifestation in the visible spectrum, so the naked eye examination of a trained professional is the prime technique adopted in practice for plant disease detection. In order to achieve accurate plant disease diagnostics a plant pathologist should possess good observation skills so that one can identify characteristic symptoms. Variations in symptoms indicated by diseased plants may lead to an improper diagnosis since amateur gardeners and hobbyists could have more difficulties determining it than a professional plant pathologist.

Advances in computer vision present an opportunity to expand and enhance the practice of precise plant protection and extend the market of computer vision applications in the field of precision agriculture. Various different approaches are currently used for detecting plant diseases and most common are artificial neural networks (ANNs) and Support Vector Machines (SVMs). They are combined with different methods of image pre-processing in favour of better feature extraction.

In machine learning and cognitive science, ANN is an information-processing paradigm that was inspired by the way biological nervous systems, such as the brain, process information. The brain is composed of a large number of highly interconnected neurons working together to solve specific problems. can also take on any value between 0 and 1. Also, the neuron has weights for each input and an overall bias.

## II. RELATED WORK

[1] Maniyath, S. R., P V, V., M, N., R, P., N, P. B., N, S., & Hebbar, R: Crop diseases are a noteworthy risk to sustenance security, however their quick distinguishing proof stays troublesome in numerous parts of the world because of the non-attendance of the important foundation. Emergence of accurate techniques in the field of leaf-based image classification has shown impressive results. This paper makes use of Random Forest in identifying between



healthy and diseased leaf from the data sets created. Our proposed paper includes various phases of implementation namely dataset creation, feature extraction, training the classifier and classification.. It's not moderate for them to go to agribusiness office and discover what the infection may be. Our principle objective is to distinguish the illness introduce in a plant by watching its morphology by picture handling and machine learning.

**Summary:** First for any image we need to convert RGB image into gray scale image. This is done just because Hu moments shape descriptor and Haralick features can be calculated over single channel only. Therefore, it is necessary to convert RGB to gray scale before computing Hu moments and Haralick features

[2] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E.: The timely identification and early prevention of crop diseases are essential for improving production. In this paper, deep convolutional-neural-network (CNN) models are implemented to identify and diagnose diseases in plants from their leaves, since CNNs have achieved impressive results in the field of machine vision. Standard CNN models require a large number of parameters and higher computation cost. In this paper, we replaced standard convolution with depth=separable convolution, which reduces the parameter number and computation cost. To evaluate the performance of the models, different parameters such as batch size, dropout, and different numbers of epochs were incorporated. The implemented models achieved a disease-classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively, which were greater than that of traditional handcrafted-feature-based approaches. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time.. The accuracy results in the identification of diseases showed that the deep CNN model is promising and can greatly impact the efficient identification of the diseases, and may have potential in the detection of diseases in real-time agricultural systems.

**Summary:** There are many developed methods in the detection 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

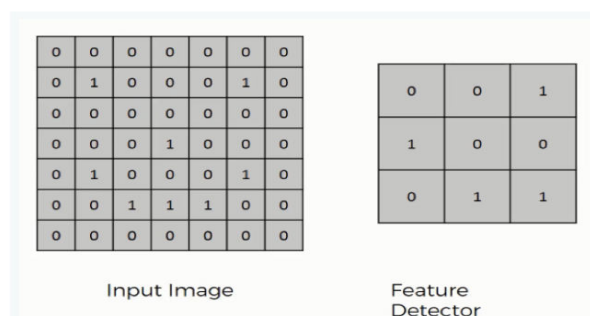
### III. METHODOLOGY

#### 1. Convolutional Neural Network

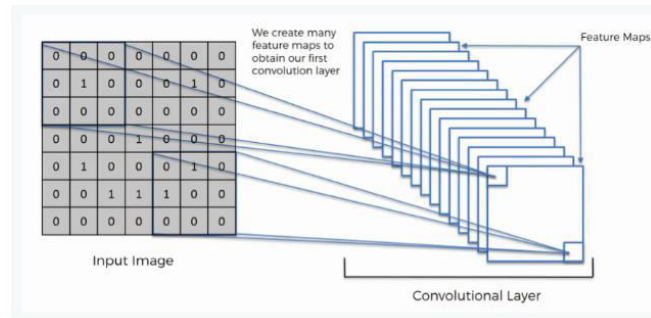
##### Step1: convolutional operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The Convolution Operation





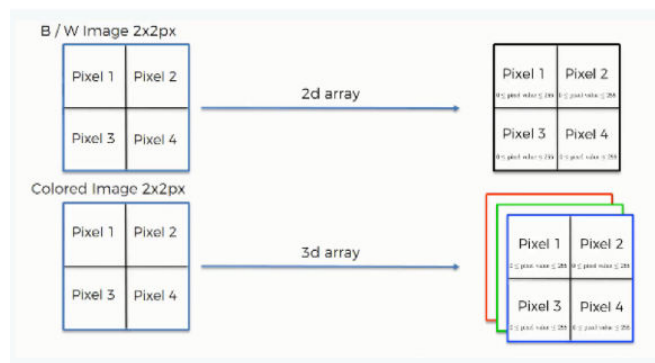


### Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or ReLU. We will cover ReLU layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.

#### Convolutional Neural Networks Scan Images



### Step 2: Conv2D

Keras Conv2D is 2D Convolution Layer; this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.

Kernel: In image processing kernel is a convolution matrix or masks which can be used for blurring, sharpening, embossing, edge detection, and more by doing a convolution between a kernel and an image

### Step 3: Flattening

This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

### Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

### Summary

In the end, we'll wrap everything up and give a quick recap of the concept covered in the section. If you feel like it will do you any benefit (and it probably will), you should check out the extra tutorial in which Softmax and Cross-Entropy are covered. It's not mandatory for the course, but you will likely come across these concepts when working with Convolutional Neural Networks and it will do you a lot of good to be familiar with them.



#### IV. EXPERIMENTAL RESULTS

Here in our project we train our datasets using some algorithms like CNN, SVM and ANN .

**HOME:**In our project, we are classifying the presence of Plant Leaf Diseases Classification, with the help of deep learning and machine learning.

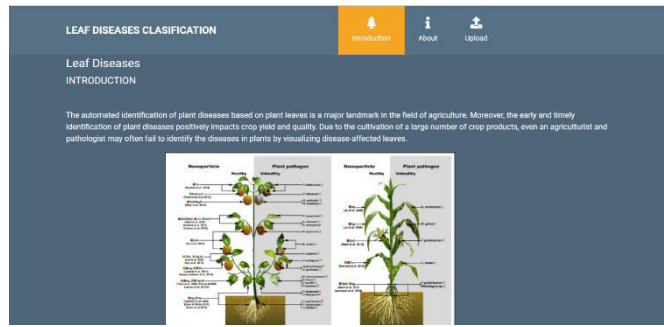


Fig1: Home

**About Project:** Here the user will get a breif idea about the project

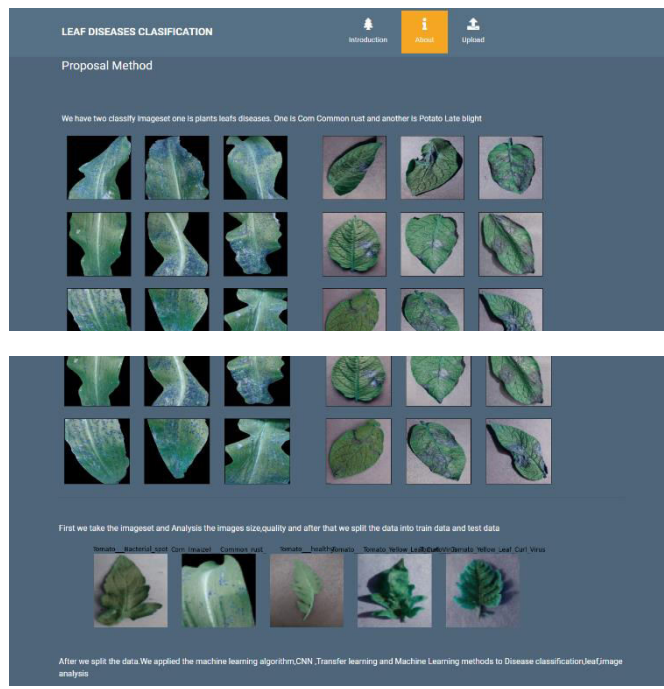
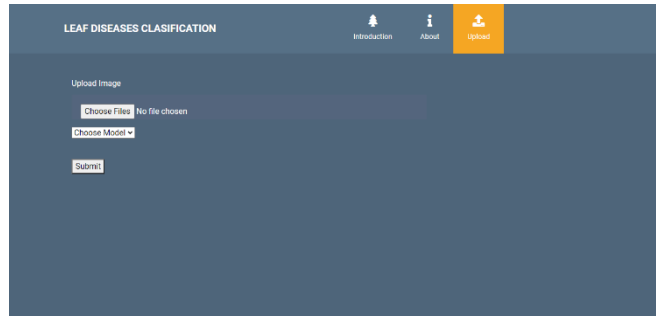


Fig2: About Project



**Upload Image:**

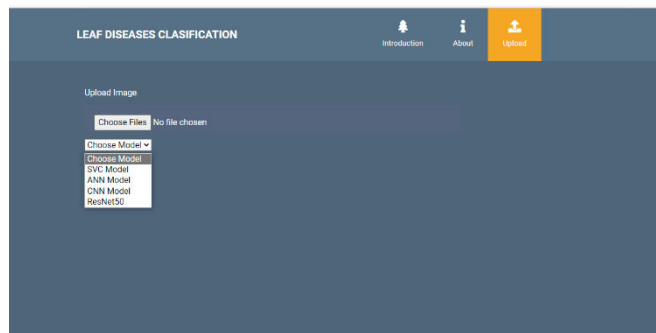
Here the images can be uploaded those which are to be classified.



**Fig3:** Image Uploading

**Model choosing:**

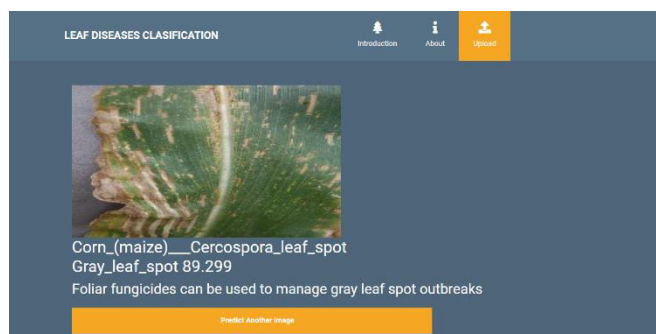
Here the model can be selected, by which the image is to be classified.



**Fig4:** Model choosing

**Classified output:**

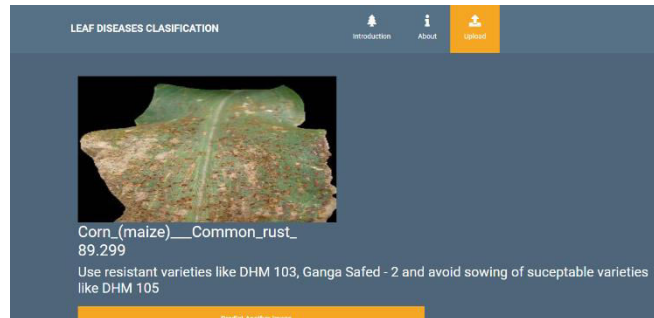
The uploaded image is classified as the Corn\_(maize)\_\_\_Cercospora\_leaf\_spot Gray\_leaf\_spot



**Fig5:** Classified output

**Classified output:**

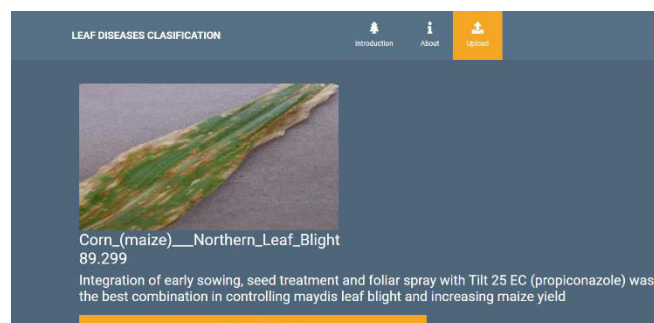
The uploaded image is classified as the Corn\_(maize)\_\_\_Common\_rust\_.



**Fig6:** Classified output

**Classified output:**

The uploaded image is classified as the Corn\_(maize)\_\_\_Northern\_Leaf\_Blight



## V. CONCLUSION

In this project we have successfully classified the images of Identification of Plant Leaf Diseases Classification, are either affected with the Plant Leaf diseases using the deep learning and machine learning. Here, we have considered the dataset of Plant Leaf Diseases Classification images which will be of different types and different plants (healthy or unhealthy) and trained using SVC, CNN, ANN along with some Resnet50 transfer learning method. After the training we have tested by uploading the image and classified it.

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