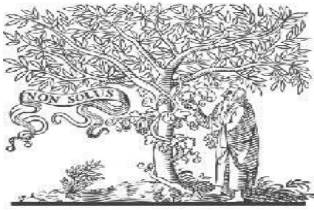


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10.48047/IJEMR/V12/ISSUE 08/57

Title **Disease Detection Of A Plant Leaf Using Image Processing And CNN With Preventive Measures**

Volume 12, ISSUE 08, Pages: 378-383

Paper Authors **Preethi Kulkarni, Dr.C.V.P.R Prasad**



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Disease Detection Of A Plant Leaf Using Image Processing And CNN With Preventive Measures

Preethi Kulkarni

Asst Professor, Department of CSE

Malla Reddy Engineering College for Women
UGC Autonomous

Dr.C.V.P.R Prasad

HOD, Department of CSE

Malla Reddy Engineering College for Women-
Women-UGC Autonomous

Abstract:

One of the biggest factors that increases agricultural productivity is the economic climate. Due to the aforesaid factor, plant disease is far more common in agricultural areas and is now much more likely to be discovered. These days, monitoring plants in vast and diverse locations has expanded the study of plant condition detection. Farmers experience a great deal of stress when switching from one disease management concept to another. It is possible to automatically identify and categorise illnesses of plant leaves using experimentally evaluated software application services. For novel development, artificial intelligence is used. Utilising machine learning to identify plant disease. Artificial intelligence can be used to start working right away or to give directions on how to complete a task. Understanding training materials and adapting them into forms that should be understandable by humans are the main goals of artificial intelligence. Therefore, we may apply device learning to identify plant diseases. It has aided in making wise decisions and forecasting the vast amount of information produced. The categorization is based on the colour of the leaves, the degree of damage to the fallen leaves, and the position of the dangerous plant falling leaves. Here, we looked at various machine learning algorithms for classifying various plant leaf states and finding those with the highest degree of accuracy.

Key words: *Machine learning, DNN, Color of leaves.*

I INTRODUCTION

Agriculture now serves much more purposes than just providing food for an ever-growing population. In fact, plants are now an essential source of energy and a key component in the solution to the global warming issue. Many diseases that affect plants have the potential to result in costly, societal, and environmental

losses that are harmful. In this situation, accurately and promptly detecting sickness is of miraculous importance.

Plant pathologies can be found using a variety of methods. Some diseases have no obvious symptoms at all, or they only show up when it is too late to take any action. In those circumstances, it is usually necessary to conduct

a sophisticated review, typically using a potent microscopic lens. In other circumstances, the signs can simply be found in regions of the electromagnetic spectrum that are invisible to humans. The employment of remote picking up techniques that examine multi and hyperspectral picture records is a common strategy in this situation. The ways that support this methodology frequently employ digital photo editing software to achieve their goals.

Parasites are a significant factor in the degradation of plant leaf crop quality and yield. The main reason for the decline in production of these goods is the lack of technical and scientific understanding to prevent pest disease. The goal of this project is to develop an autonomous computer vision system for the diagnosis of disease caused by pests in flat leaf plants. In this project, three different forms of attribute elimination are used to automatically detect illnesses using computer vision techniques. Images of diseased and also unaffected leaves are processed to remove the unhealthy area of the fallen leaf, textural descriptors using grey degree co-occurrence matrix (GLCM), and colour moments, creating a 21-D feature vector. By eliminating redundant characteristics and choosing relevant functions, a genetic formula-based attribute selection method creates a 14-D feature vector that reduces complexity. Support vector machines (SVM) and artificial neural networks (ANN) are both used for categorization. The suggested algorithm results

in category accuracy of 87.5% when using ANN and 92.5% when using SVM

The only method currently used to identify plant conditions is expert naked eye observation, which allows for both the identification and finding of plant ailments. When farms are enormous, it costs a lot to do this because it requires a large team of experts and ongoing specialist observation. Meanwhile, in some nations, farmers lack access to necessary resources or even know-how to contact professionals. Because of this, consulting with specialists is expensive and time-consuming. The suggested method seems to be helpful in inspecting large plant fields in such a condition. Additionally, automatic disease diagnosis is made simpler and less expensive by simply observing the symptoms on plant leaves. Additionally, it enables machine vision, which provides photo-based automated procedure control, evaluation, and robot support.

The visual approach of identifying a plant's state is more time-consuming, less accurate, and only practical in a few places. However, using an autonomous discovery technique will require fewer efforts, less time, and even more effectively. Some common plant illnesses include brownish and yellow spots, early and late scorch, as well as microbial, fungal, and viral ailments. The technique used to measure the diseased region and determine the difference in the affected area's shade is known as picture handling.

2. RELATED STUDY

There aren't many methods devoted just to the discovery problem because the data obtained by utilising photo processing techniques frequently enables not only finding the disease but also estimate its extent. There are two primary purposes for straightforward discovery:

- Partial classification: Instead of applying a full classification to any one of the possible illnesses, it may be more practical to perform a partial classification, in which prospective regions are classified as being the result of the illness of interest or not. This is useful when a disease needs to be identified among several potential pathologies. This is the situation with the methodology used by Abdullah et al. in 2007, which is described in Section 'Semantic networks'.

- Real-time tracking: in this scenario, the system continuously monitors the plants and issues an alarm system if the disease of concern is found in any one of the plants. Sena Jr. et al. (2003) and Story et al. (2010) documents fit this framework. The following provides additional definitions for both proposals.

linguistic networks

The method advocated by Abdullah et al. (2007) makes an effort to distinguish between a disease (corynespora) that affects rubber tree leaves and other illnesses. The method makes no use of division of any kind. Instead, a leaf image with a

lower resolution (15 15 pixels) is immediately evaluated using Principal Component Analysis on its RGB values. A Multilayer Perceptron (MLP) Neural Network with one hidden layer is then fed the first two primary components, and its output indicates whether the example is affected by the condition of interest or not.

Threshold

Sena Jr. et al.'s (2003) method uses digital images to distinguish between healthy and balanced maize plants and those damaged by loss armyworm. They divided the two primary steps of their formula into image processing and image analysis. The image is converted to grey scale during the picture processing stage, then it is thresholded and filtered to remove erroneous artefacts. The entire image is separated into 12 blocks during the image analysis stage. Blocks are removed if their leaf location makes up less than 5% of the total location. The number of related items that represent the unhealthy zones for each remaining block is tallied. If this number exceeds a threshold, which was determined to be ten by empirical analysis, the plant is assumed to be ill.

3 METHODOLOGY

The primary product demand for each country is agricultural goods. Plant disease outbreaks have an effect on the nation's agricultural production, manufacturing, and economic resources. This research describes a system that uses deep learning techniques to recognise and locate plant

leaf diseases. The images used were from the website (Plant Village dataset). As part of our work, we have chosen specific plant species, such as tomatoes, peppers, and potatoes, as they are the most prevalent worldwide and in Iraq in particular. This Data Establishment comprises 20636 images of both healthy and diseased plants. The convolutional semantic network (CNN), which is used to identify plant leaf diseases, was used in our proposed system. 15 classes were identified, including 12 courses for conditions of various plants that were detected, such as microorganisms, fungi, etc., as well as 3 courses for healthy leaves. This resulted in extremely accurate training and testing; we were able to achieve precision of (98.29%) for training and (98.029%) for screening for all used data sets.

4 RESULTS EXPLANATION

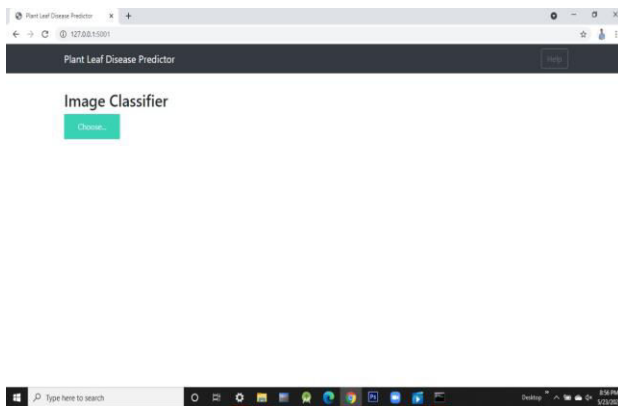


Fig.4.1. OUTPUT results.

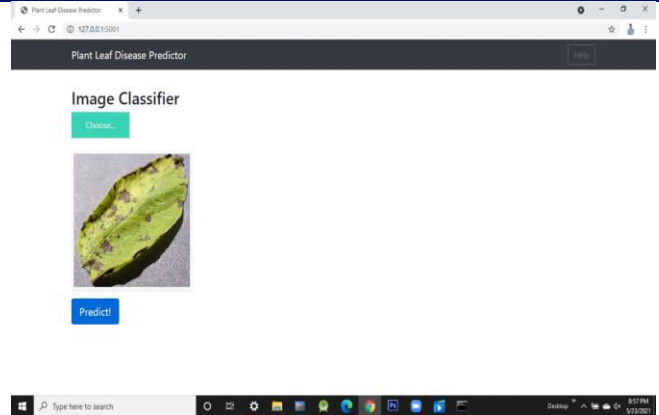


Fig.4.2. INPUT image.

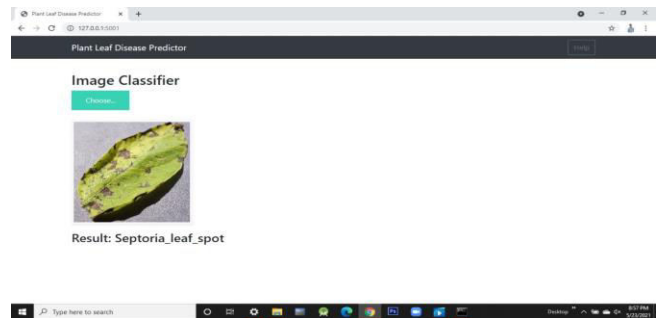


Fig.4.3. OUTPUT image.

```

_np.float32 = np.dtype([('float32', np.float32, 1)])
/home/user/.local/lib/python3.6/site-packages/tensorflow/python/framework/dtype
py:502: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is de
recated; in a future version of numpy, it will be understood as (type, (1,)) /
(1,)type'.
_np.resource = np.dtype([('resource', np.ubyte, 1)])
ARNING:tensorflow:From /home/user/.local/lib/python3.6/site-packages/tflearn/t
raining.py:119: UniformUnitScaling.__init__ (from tensorflow.python.ops.l
e_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.initializers.variance_scaling instead with distribution=uniform to get e
quivalent behavior.
ARNING:tensorflow:From /home/user/.local/lib/python3.6/site-packages/tflearn/o
perations.py:66: calling reduce_sum (from tensorflow.python.ops.math_ops) with k
ernel_dims is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.nn.reduce_sum instead
2017-10-17 19:59:00.426572: I tensorflow/core/platform/cpu_feature_guard.cc:137
Your CPU supports instructions that this TensorFlow binary was not compiled to
use: SSE4.1 SSE4.2 AVX

```

Fig.4.4. Track outputs.

Numerous environmental assaults and situations can harm plants. There are a number of variables that can be used to characterise how an environmental issue affects plants, including temperature, moisture, nutritional surplus or losses, light, and the most prevalent microbial,

infectious, and fungal diseases. The illnesses that affect both the plants and the leaves may cause changes in the fit, colour, and other physical characteristics of the falling leaves. Due to their similar patterns, the aforementioned alterations are difficult to distinguish, which makes it difficult to identify them. An early identification and treatment, however, can reduce the number of losses in the entire plant. In this paper, we discuss the use of cutting-edge detectors for the detection and classification of plant leaf diseases that affect a variety of plants, including Single Shot Multibox Detector (SSD), Region-based Fully Convolutional Networks (R-FCN), and Faster Region-Based Convolutional Neural Network (Faster R-CNN). The difficult aspect of our approach is not only to manage disease discovery, but also to recognise the infection state of the illness in fallen leaves and also attempt to offer assistance (i.e., the name of the appropriate organic plant foods) for those worried diseases.

CONCLUSION

The automatic plat leaf disease discovery system presented in this article makes use of various attributes, including location, GLCM, and colour minute. Hereditary formula is used to choose the drawn-out qualities, which results in reduced dimensionality and computing complexity. The k-means clustering formula, which provides more accuracy with less processing time, is used to segment data. Additionally, the proposed system compares SVM and CNN classifiers,

with CNN providing better condition detection precision (96.7%) than SVM (92.5%). After outlining every function, a hereditary method is used to select 14 suitable features. Two different types of classifiers are used to divide the images into the diseased (plat leaf blast, brown region) and non-diseased classes. demonstrates the private attribute finding accuracy using CNN and SVM classifiers. When classified with CNN and SVM, a 13-D GLCM feature that explains the image's grey level co-occurrence matrix has the highest detection accuracy (96.75%). With an execution time of 0.002287 seconds, the colour moment feature has an accuracy of 95.5% when classified with CNN and 87.25% when classified with SVM. The area attribute, which describes the morphology of the unhealthy part of the leaf, has an accuracy of 96.5% and 95.25% when classified with CNN and SVM, respectively. It demonstrates that for all the extended features, CNN provides significantly greater detection precision than SVM. The data also makes clear that location factors have a minimal impact on disease discovery.

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