http://www.jctjournals.com ISSN(ONLINE):2278 – 3814

Volume-13, Issue-02, February 2024
JOURNAL OF COMPUTING TECHNOLOGIES (JCT)
International Journal
Page Number: 01-05

# Machine Learning Based Plant Leaf Disease Recognition Using Different Algorithm: A Review

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***Abstract*— the capacity of machine learning algorithms to learn from data and provide accurate predictions has led to their extensive application in plant disease detection, which is the subject of this research. An essential and difficult area of study in agriculture is the early detection and diagnosis of plant diseases using photographs of their leaves using machine learning. This article provides an introduction of this topic. First, the paper defines plant leaf illnesses and their classifications. Then, it delves into the methods used to identify these diseases, including algorithms based on machine learning and image processing. Recent advances in the area, such as the use of deep learning and transfer learning architectures for the identification of plant leaf diseases, are also reviewed in the study.**

***Keywords*— Plant *Disease; Machine Learning; Feature Extraction; Plant Leaf Disease; and Fungi Bacteria.***

## I. INTRODUCTION

The living thing's natural condition is disrupted or altered, this is known as a disease. A disease is an abnormality in an organism's structure or function that is not immediately caused by external harm; it affects the whole organism or a specific component of it. The common understanding is that diseases are medical disorders characterized by a set of telltale symptoms [11]. The damaged tissues and symptoms of a disease are common ways to characterize it.

When an organism is sick, it usually acts out in ways that others may think are wrong. Therefore, in order to identify illness signs, one must be familiar with the normal state of an organism. However, it is not always easy to tell when someone is sick and when they are well [12].

Every one of the many plant diseases out there has the potential to wreak havoc on our economy, society, and environment. This is why it's crucial to detect plant illnesses as soon as possible, so farmers don't lose production or crop yields. Typically, Professionals in the field, like botanists and agricultural engineers, carry out these procedures, first by visual examination and subsequently in a controlled laboratory setting [17].

The conventional Procedures are often laborious and intricate. This is why the development of methods for automated illness detection using machine learning and image processing has gained momentum. People who don't know much about the plant they're growing can benefit from an automated system that can detect diseases by looking at the plants. Fungi, bacteria, viruses, and nematodes are only a few of the many plant disease types [15].

### *A. Fungi*

The most diverse class of plant diseases, may take many different shapes and sizes. Typically, their bodies are formed like wires, and they contain several cells [19]. The hyphen is threads with cell walls. Myceliums are formed when several threads come together. The fruiting bodies that a mycelium might develop as it grows may produce asexual or sexual spores. Identifying and diagnosing fungal issues involves analyzing the features of spores, fruit bodies, and mycelium. Without a biological host, certain fungi may live and multiply [20].

Fig.1. Fungi Disease in Plants

 

Some creatures can't survive outside of a host's immediate vicinity. In order to cause illnesses in plants, fungi either produce poisons that kill plant cells, invade and obstruct a plant's vascular system, decompose the roots, or insert structures similar to roots into plant cells Gains.

### *B. Bacteria*

The cells of bacteria, which are monocellular, are much simpler and smaller than those of plants. Lots of them are around the size of chloroplasts in plants. Infectious microbes may infect even healthy plants with the slugs that certain bacteria make, which in turn attract insects. Plant detritus or even seeds may provide a suitable environment for bacteria to thrive. Bacteria that produce poisons or enzymes that damage plant cell walls are the main causes of plant diseases. Crown bacteria are able to improve their living conditions and produce more of the substances they require for growth and reproduction by genetically engineering their host plant to make galls and amino acids.

Fig. 2 Bacteria on Plants Leaves

## II LITERATURE SURVEY

| Ref. No. | Techniques | Advantage | Disadvantage | Accuracy |
|---|---|---|---|---|
| Pragya Hari et. al[1] | Federated Deep Learning (FDL) for Plant Leaf Disease Detection | allows multiple local models to get trained with their region-based datasets | X | Accuracy of 95.7% |
| Prabhjot Kaur et.al [2] | Hybrid-Convolutional Support Machine | model can initially identify different plant leaf illnesses | X | Accuracy of 98.72 % |
| Saponaro,P.,et .al [3] | CNN (convolutional neural network) method | Frangi filter On real microscopy data, and found that the deep,CNN is totally automatic method not require any cluster | MCNN, require large time for training dataset. | F1 score of 77.3 %. |
| Jagadeesh D. Pujari et al.[4] | Principle component analysis (PCA) | As the level of decomposition increases, it lowers the classification percentage so to manage the classification percentage PCA is used. | Loss of information while compressing the data found to reduce the number of dimensions. | Using Mahalanobis distance classifier accuracy is 83.17% and using Probabilistic neural network classifier is 86.48%. |
| Jagadeesh D. Pujari et al.[5] | Neuro-Knn | Robust to noisy training data and effective if the training data is large. | Chan vase segmentation is used which was based on an active contour model, working process is slow for large image size and also not capable to segment nearest objects. | Using ANN classifier and Neuro-Knn classifier accuracies are 84.11% and 91.54% respectively. |
| D S Guru et al.[6] | Probabilistic neural network | It takes less time to train the system and it has good extension properties. | It requires large memory space and slow execution of the network. | Using first order statistical feature accuracy is 88.5933 % and using GLCM is 80.03%. |

| | | | | |
|---|---|---|---|---|
| H. Al-Hiary et al.[7] | K-means clustering | By using otsu's method in segmentation phase makes computing faster and produce results more accurate. | Color co-occurrence method used for feature extraction is not reliable to large databases. | Accuracy of detection is 83% and classification is 94%. |
| Dheeb Al Bashish et al.[8] | Neural network classifier | More efficient. | Slow in processing. | Neural network classifier can successfully detect and classify with precision of 93%. |
| Huang KY et al[9] | Back propagation neural network and GLCM feature extraction | Very easy to implement and able to form difficult nonlinear mapping. | It is difficult to find the required number of neurons and layers, Learning process is | Effectively detected and classified to an accuracy of 89.6% while without classifying the disease |

## III. DATA SETS

There are different disease data sets taken for performing proposed work such as Alternaria Alternata, Anthracnose, Bacterial Blight, Leaf Spot and healthy leaf.

### *A. Alternaria Alternata disease data set*

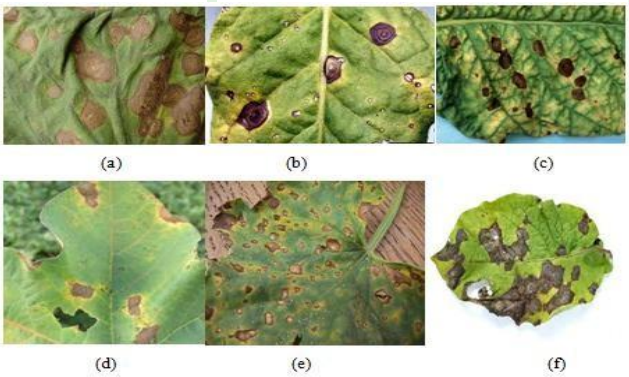

Fig. 3 Shows the Alternaria Alternata Disease Data Set

Graphics from the Alternaria alternata illness dataset are shown in figure 3. Six pictures of this condition are shown in the figure above. Also included in the data set for processing are twenty more photos shot in a similar manner. Three pictures of this condition are shown in figure 4, which is up there. Also included in the data set for processing are twenty more photos shot in a similar manner.

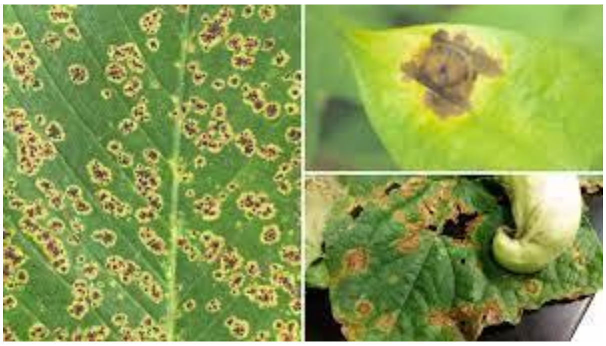
Fig. 4 Shows The Anthracnose Disease Data Set

In warm and humid regions, many plant species are susceptible to anthracnose, a class of fungal diseases that often infects young shoots and leaves. Tiny, submerged, saucer-shaped fruiting structures called Acervuli are spore producers in anthracnose fungus, often Colletotrichum or Gloeosporium.

### *B. Bacterial Blight*

Images from the bacterial blight disease data set are shown in figure 5, which is located below. There are only five pictures of this sickness in the figure. The same goes for the additional 20 photos added to the dataset for processing; the exact amount of photos may be adjusted according to needs. Bacteria are very simple, single-celled creatures, much smaller than plant cells. Some of them are as big as chloroplasts found in plants.

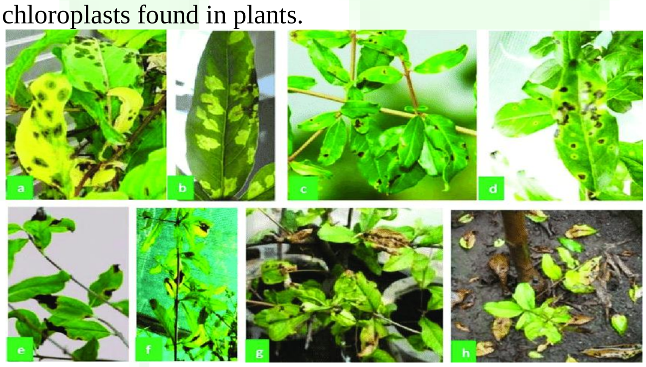
Fig. 5 Shows the Bacterial Blight Diseases Data Set

### *C. Cercospora Leaf Spot*

Figure 6 displays a limited selection of five photos from the dataset pertaining to bacterial blight illness. In a similar vein, an additional 20 photos are captured inside the dataset for the purpose of analysis.

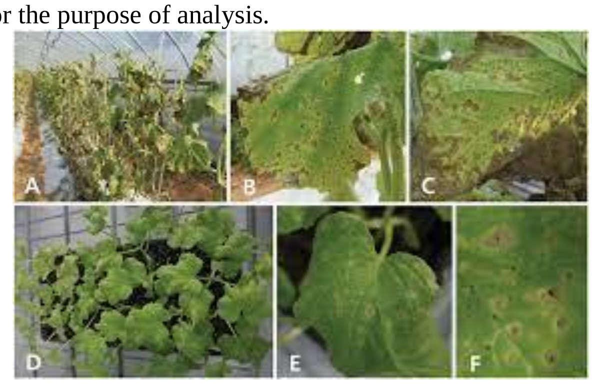

Fig. 6 Shows the Cercospora Leaf Spot Disease Data Set

 

The photos may be increased or decreased according to the necessity. Bacteria are unicellular creatures that exhibit much reduced size and complexity compared to plant cells. Several are about the dimensions of a plant chloroplast.

### *D. Healthy Leaves*

Figure 7 displays a dataset of photos depicting healthy leaves devoid of any diseases. The graphic below displays a mere five photographs of disease-free leaves. In a similar vein, an additional 20 photos are captured inside the dataset for the purpose of analysis


Fig. 7 Shows the Healthy Leaf without any disease data set

## IV. OUTCOME ANALYSIS PARMETER

The last non-destructive methodology involves the use of sensing techniques in the context of plant diseases. This is the location where data is acquired without the need for physical presence at the plant during observation. In this methodology, hyper-spectral and multispectral methods are used for the purpose of remote sensing. The hyper-spectral technique facilitates the attainment of increased spectral and spatial resolution. The use of multispectral remote sensing enables the assessment of disease severity.

### *A. Result Parameters*

This suggested study focuses on several disease classifications in plant disease detection, including multiple outcome criteria. Hence, the primary objective of the proposed study is to accurately identify illnesses. The subsequent outcome parameter pertains to the impacted region or affected area resulting from illnesses, whereas the last parameter pertains to accuracy.

#### *Accuracy*

The identified portion of a plant as a pathological condition is carefully assessed. The precision of calculating the affected area is contingent upon the occurrence of genuine positive and true negative results. A true positive refers to a properly estimated effected area. A true negative refers to a plant leaf that is properly recognized as not being affected.

#### *Precision*

In the domain of information retrieval, precision and recall are operationally defined as the quantity of retrieved documents, such as the list of documents generated by a web search engine in response to a query, and the quantity of relevant documents, such as the comprehensive list of all documents available on the internet that pertain to a specific topic. This concept is closely related to the concept of relevance.

#### *Recall*

The concept of recall in the field of information retrieval refers to the proportion of relevant documents that are effectively retrieved. In the context of a text search conducted on a collection of documents, recall may be defined as the ratio of correctly identified results to the total number of results that were expected to be returned.

### *B. Classification*

The primary objective of the proposed study is the use of machine learning methods to perform plant disease detection and classification. This is achieved via the application of image processing and soft computing methodologies.

### *C. Affected Region (Area)*

The section of the plant's leaf that is impacted is often referred to as the affected area.

## V. CONCLUSION

This survey study examines several machine learning methodologies used in the detection of plant diseases via the analysis of leaf photos. Plants are susceptible to many illnesses that disrupt their regular development. The survey included the use of both handcrafted- feature-based and deep learning-based approaches for illness detection. The performance was evaluated by comparing the pre-processing and segmentation approaches used, the features utilized for illness classification, and the datasets included in each respective publication. Based on the examination of illness identification using shape- and texture-based characteristics, it can be inferred that the utilization of pre-processing and segmentation procedures significantly contributes to enhancing accuracy. The Support Vector Machine (SVM) was the predominant classification approach used for illness detection.

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