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# Performance Analysis of Mango Leaf Disease using Machine Learning Technique

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Abstract: Plants have developed an imperative source of energy and aimportant problem in solving the problem of global warming. However, plant diseases threaten the livelihoods of this important source. Convolutional Neural Networks (CNN) have shown excellent performance (more than humans) in recognizing problems and image classification problems. This paper describes the possibility of classifying plant diseases with leaf images taken by CNN in the natural situation. The model is designed based on the Le-Net architecture for organization of soybean plant diseases, including healthy leaf images taken from the plant village database. Performance evaluations on several popular benchmark datasets prove that our method is better than the latest technology. This article proposes a method to improve the classification performance of classes with few training examples

Keywords: CNN, KNN, Mango leaf disease, machine leaning

#### INTRODUCTION

I.

The great number of present plant species in world makes it cumbersome and time consuming to manually identify them, especially for non-professional stakeholders Such as land directors, foresters, agronomists and amateur gardeners. Therefore, automated plant identification tools should accelerate the development of plant species identification tasks. Even for experienced botanists, this identification tool can be useful. Plant documentation is created on thought of its organs, namely buds, leaves, fruits, stems, etc. In this article, we focus on leaf shape and shape-based leaf gratitude methods. To describe the shape of the blade, a specific method can be developed, or a general method for retrieving shape can be applied to the specific situation of the blade. Shape of the blade, a specific method can be developed, or a general method for retrieving shape can be applied to the specific situation of the blade. This article summarizes the participation of the ReVeS project in the Image CLEF 2012 Plant Identification project. To progress a blade recognition system on mobile devices, our method aims to tackle challenge of compound natural pictures rachieve teaching interaction with users. The method trusts on two-step model-driven subdivisionor evaluation of high-level functions that enable semantic interpretation and more general form functions. [1] [2] All these descriptors are combined in a chance forest organization algorithm and their implication is appraised. Our team ranks fourth in natural images and third in natural pictures, which is a very satisfactory presentation in relation to project goals. Today, the ability to identify plant species orappreciate their specificity has become a task available to most experts. Most flora books have difficulty for beginners with no theoretic background. However, mobile systems provide the ability to introduce such knowledge interactively at the user level. The mobile guide to plant species identification has already achieved great achievement on white background images. The goal of the ReVeSdevelopment is to build a system that helps users identify trees in the natural environment from photos of leaves in an instructiveorcooperative way. Retrieving the leaf contour is first step in understanding the image, and it is also an important step. In unsupervised complex natural images, this is a really challenging problem [5], where it is essential to absorb as much knowledge as probable to simplify task. Including prior knowledge of predictable conditions of the object we are looking for is a good way to condense risk of error. In case of mobile applications, however, it is regrettable that human users are not used to guide the automated process, otherwise the process is prone to unstable behavior. [6] [8]

On images with potential defects and using the idea of approximate leaf shape, color seems to be the most dependent information. Given the diversity caused by seasons, species, and light, it is impossible to establish an effective a priori color model for all leaves, but to quotation a color model from each image, we must first have a general understanding of location of the leaves. The problem that is easy to solve on a white background image (just thresholding a gray scale image is sufficient to determine the location of the leaf) becomes more difficult for natural pictures. This is where we need the help of the user to draw an area inside the magazine. In the case of a composite blade, the area must contain at least three components. We also rotated and cropped some photos so that they obviously only comprise a leaf of interest, with its nodes pointing roughly to top of image, which resembles to our mobile application frame. This is the only manual interference in gratitude procedure or is achieved only for photo images. [10] [11]



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#### II. RELATED WORK

The proposed approach is based on image processing and consists of four steps. In first step, we create a color conversion system for RGB image rendering, and then apply the conversion to any space independent of the device in the color conversion system. Next, in the second step, the K-art construction technique is used to divide the image at hand. In the third step, the features are calculated for the features defined in the section. Finally, in the fourth stage, the extracted material is transmitted to a pre-trained neural network. In the test phase, we use a leaf image. The results of the current experiments show that the way it is presented can greatly support the accurate and clear identification and identification of leaf disease. The reason for the missing classification may be the geometry depending on the morphological properties of the other blue leaves. For example, two blue "Langela" leaves are not known by the name "Amrapali". Upon examination, it was found that the geometric features were very close to these "Amrapali" leaves. Special work was taken to improve the skills of the blue species.

Baoyuan Liu et.al. The problem of large acceptance with thousands of categories presents a special challenge because as the number of categories increases, the implementation of the class requires more calculation. The model with the tag tree incorporates the classification and path of the tree, which increases the complexity of the logic. In this article, we will show you how to use the most accurate estimates to determine the dimensions of a brand tree. This new probabilistic learning technique can produce a small tree of identification with excellent accuracy.

In this work, we present a probabilistic measurement system to address the problem of large classification. Because the method we use is entirely based on what might be the most accurate and best possible, it can be applied to a wide variety of potential readers. Our experiments show that studying the signal tree in such a way can improve the accuracy of the recognition and speed compared to previous work. In this article, we present a revised probabilistic approach to studying horizontal tree tags. We have shown how learning to learn from tree symbols. As the results in Section 7 show, this method can improve the accuracy compared to the previous results. Proper diligence can correct the truth and success without repeating the tree. From a broader perspective, the design of a tree symbol in the probabilistic system provides a direct way to introduce more precise and accurate modeling models for the tree structure. Using this probabilistic thinking, all participants who can be considered probabilistic can be included in the tag tree. [13] [14]

#### III. PROPOSED SYSTEM

The main concept of this process is to develop an appropriate and effective method for diagnosing the disease and its symptoms and thus support the use of appropriate systems for early and cost effective solutions to this problem. Due to their higher performance in calculation and accuracy, computer vision and deep learning procedures have been popularized in the classification of various fungal diseases. For this process, therefore, an intricate neural network CNN is proposed to classify mango leaves infected with anthracnose fungal disease.



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- 1) Input Image: In the MATLAB workplace, greatest pictures are signified as two-dimensional arrays, where each component of matrix matches to aonly pixel in exhibited image. For sample, an image consisting of 200 rows or 300 columns with dots in dissimilar colors is saved as a 200 x 300 matrix. Some images (such as RGB) involve a three-dimensional matrix, where first hydroplane in third measurement signifies intensity of red pixels, second plane signifies the intensity of green pixels, or third plane represents the intensity of blue pixels.
- 2) Processing: Histogram Equalization: This technique frequently improves overall contrast for many pictures, specifically when available data in image is signified by close contrast values. With this modification, the intensity can be better circulated on histogram. This consents areas with lower local difference to succeed higher contrast. Histogram equalization is achieved by efficiently spreading the most frequent strength values. This technique is useful on pictures where the background and foreground are both light or dark. In particular, this technique can lead to better display of bone construction in X-rays and better details in overexposed or underexposed photos. The chief improvement of this method is that it is a fairly simple technique and a reversible operator. Supposedly, if histogram equalization purpose is known, inventive histogram can therefore be restored. The control is not calculation intensive. The difficulty of this method is that it is indistinguishable. It can growth difference of background noise while reducing the available signal.
- 3) Feature extraction (CNN): In deep learning Convolutional Neural Network (CNN or ConvNet) is a wireless network, often used to monitor paintings. CNN is a duplicate of the work of the multilayer perceptron. Multilayer perceptron often refers to a fully connected network, i.e., each neuron in a cell is connected to all neurons in the next layer. "Completely connected" to these systems is very offensive to the release of data. Representative control tools include setting the measurement of the value of the lost function. However, CNN is changing its approach to innovation: they take advantage of hierarchical models in data and use smaller or simpler modifications to integrate many other composite models. So, CNN is at the end in terms of connectivity or complexity. Based on the common wall structure and translational translation, they are also called artificial neural networks (SIANN). Conventional networks are inspired by biological processes [3] [4] [5] [6] because the interaction between neurons is similar to the regulation of the perception of large animals. A single cortical neuron responds only to stimuli in a limited field of view called the receptive field. The receptive fields in dissimilar neurons incompletely connection, so they cover the entire field of view. Compared to other image rating procedures, CNN uses moderately little treating. This means that network learns filters physically designed in traditional algorithms. This independence, which has nothing to do with prior knowledge and work in functional design, is the biggest advantage.
- 4) Classification: (KNN) In pattern appreciation, k-nearest neighbor algorithm (k-NN) is a non-parametric technique of organization or regression. [1] In both cases, input contains k closest exercise samples in the function area. The result depends on whether k-NN is used for organization or processing: In k-NN organization, the product is a member of the class. According to the many votes of a neighbor to an object, that object is a secret, or the object is designated as the largest common class among its neighbors (k is your good deed, often a small one). If k = 1, place the object in the next neighborhood class. By reducing k-NN, the value of the substance is produced. This weight is typical of the weight of the nearest neighbor. The k-NN is a type of learning-based or lazy study, so the work is only about average local, and all the calculations are fixed. The K-NN algorithm is the simplest algorithm for each learning mechanism. Whether in the organization or in return, useful techniques can be used to give value to helping the community, so that the neighbors can be close to the separated community. For sample, a communal weighting scheme is to give each neighbor a weight of 1 / d, where d is reserve to neighbor. Neighbors are obtained from a set of objects whose category (for k-NN classification) or object attribute values (for k-NN regression) are known. It can be considered as teaching set in algorithm, although no obvious training steps are required.



Fig 2 Input GUI Window



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Fig 3 Input Dataset GUI window

Input Leaf Image			Accuracy = Sensitivity =	nput Image ast Enhancement
Row = 601	Histogram Equalization for -	Static Text	Specificity =	nage Resize
Col = 320	R G B Train Features	Static Text		CNN
1 2 1 2 3 4		Classified As	Percentage of Disease Area in the Leaf	lassification Ierformance
			Percent	of disease area

Fig 4 Histogram Equalization GUI Window

Main_GUI				– 🗆 X
Input Leaf Image		Resized Image	Accuracy =	
			Sensitivity =	Input Image Contrast Enhancement
Row = 601	Histogram Equalization for -	Row = 256	specificity =	image Resize
Col = 320 Feature Extraction	Train Features	Col = 256		CIN
1 2 1 2 3 4	1 2 1 2 3 4	Classified As	Percentage of Disease Area in the Leaf	Classification Performance

Fig 5 Resized GUI Window



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Fig 6 Feature Extracted GUI Window



Fig 7 Train Features GUI Window



Fig 8 Classified Result GUI Window



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Fig 9 percentage of disease area in the leaf Graph

- A. Performance Analysis
- *1)* True positive (TP) = number of cases correctly identified as patient.
- 2) False positive (FP) = number of cases incorrectly identified as patient.
- 3) True negative (TN) = number of cases correctly identified as healthy.
- 4) False negative (FN) = number of cases incorrectly identified as healthy.

Accuracy: The validity of test lies in the ability to distinguish between patients and healthy cases. To calculate truth of the test, we need to analyze true conversion rate for real negatives in all evaluation cases. People talk about mathematics

Accuracy = (TP+TN) / (TP+TN+FP+FN);

Sensitivity: The sympathy of study lies in its ability to accurately control the patient's condition. To make an estimate, we need to count the number of patients who actually acted. Mathematically speaking, it can be said:

Sensitivity = (TP) / (TP + FN)

Specificity: The test is unique in that it can accurately identify health problems. To evaluate this, we need to calculate the most effective combination of healthy cases. To be precise, it can be said:

Specificity = (TN) / (TN + FP)



Fig.0 Performance graph

### **IV CONCLUSION**

The central method of the scheme is to identify infections on various plants in agriculture, where swiftnessor accuracy are most important properties of syndromerecognition. Therefore, the expansion of this work will attention on development of innovative algorithms for rapid orpreciserecognition of leaf diseases. After studying all the above technologies orprocedures, we can arrange that we can detect plant diseases using different methods. Each has advantages and disadvantages. Therefore, existing research has opportunities for improvement. Image processing is a technology that helps recoverstanding research or can quickly and accurately achieve the results of plant diseases. Diagnosis of plant diseases plays an important role in the control of disease control to recover quality or quantity of products. Logic disease is very beneficial because it condenses the control of large farms. The leaves are a source of nourishment for the plant, so it is important to diagnose leaf infections as quickly as possible. This work includes a machine-based learning method that can instantly detect leaf disease in blue varieties



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