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Symptom based automated detection of citrus diseases using color histogram and textural descriptors

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ABSTRACT

This paper presents a technique to detect and classify major citrus diseases of economic importance. Kinnow mandarin being 80% of Pakistan citrus industry was the main focus of study. Due to a little variation in symptoms of different plant diseases, the diagnosis requires the expert's opinion in diseases detection. The inappropriate diagnosis may lead to tremendous amount of economical loss for farmers in terms of inputs like pesticides. For many decades, computers have been used to provide automatic solutions instead of a manual diagnosis of plant diseases which is costly and error prone. The proposed method applied ΔE color difference algorithm to separate the disease affected area, further, color histogram and textural features were used to classify diseases. Our method out performed and achieved overall 99.9% accuracy and similar sensitivity with 0.99 area under the curve. Moreover, the combination of color and texture features was used for experiments and achieves similar results, as compared to individual channels. Principle components analysis was applied for the features set dimension reduction and these reduced features were also tested using state of the art classifiers.

1. Introduction

Agriculture has been now considered much more than just feeding the ever-growing population of the world. Agriculture is the backbone of our economy as it not only provides food but raw materials for industry. Plants are not only the source food but also important as a source of energy-rich compounds, vitamins, minerals, specifically the importance of citrus in the agriculture and world is exhibited by its large-scale production and wide-reaching provision. It is referred as key genus to the family of *Rutaceae* for agriculture. Numerous kinds of citrus are well-thought-out to be inherent to both tropical and sub-tropical areas of Asia and Malaya archipelago. It positions carefully potential value and is elevated in more than 52 countries of the world (Javaid et al., 2006).

Citrus plants are prone to diseases such as Citrus canker (Qin et al., 2009), Gummosis, Citrus greening (Gre) (Hocquellet et al., 1999), anthracnose (Ant) (Almada-Ruiz et al., 2003), and downy (Dow) (Deng et al., 1997). To control these diseases, a large number of chemicals or fungicides are used on the citrus crop, which results in both economic loss and environmental pollution.

In this context, proper diseases diagnosis in a timely and accurate manner is of the uttermost importance. If these diseases are not properly diagnosed and controlled, it will adversely affect citrus production in coming years. The management of recurrent crops requires close monitoring to tackle diseases that can affect crop production significantly and successively after harvest life.

The major citrus diseases can be observed and classified by experts on basis of their symptoms. But this requires continuous monitoring and manual observation which could be error prone and costly. Therefore, in underdeveloped countries, where most farmers are uneducated, have to pay for such cost in addition to other expenses (e.g. fertilizer and pesticides). Moreover, farmers are unaware of non-native diseases (Pujari and Yakkundimath, 2013).

One solution to this problem is to use computer-aided techniques to identify and classify these diseases. Computer aided diagnosis systems (CADx) make the task of detection and classification of disease comparatively easy and less costly (Zhou et al., 2014). Researchers have developed different CADx for the diagnosis of different diseases found in crops.

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The CADx take red green and blue (RGB) images as input and classify these images into healthy and unhealthy. Then the unhealthy area is classified into different diseases. The segmentation of image is an important task, the input image I is segmented into N (normal) and D (diseased) sub-images as in Eq. (1). Moreover, features are extracted from the diseased part for the classification.

$$I_{input} = N + D \tag{1}$$

Citrus canker, gummosis, citrus greening, anthracnose and downy are serious diseases that could affect the yield of overall production in citrus plants. If these diseases can be early diagnosed, the right measures can be taken by the farmers to prevent the disease from spreading, at an immature state. The problem is the unavailability of experts in far-flung areas, and even if available, it becomes very costly for the farmer to hire some expert for a diagnosis job. Therefore, availability of such CADx that will replace the experts, or give a second opinion on the expert's decision and providing aid to maximizing the confidence level on the diagnosis of a specific disease.

In this article, we present a technique to classify diseases in images of citrus plants. The presented method classifies the images into the disease (P) and non-diseased (N) image, further classifies the images according to the disease. The system's aim is to identify, the presence of any symptom of diseases in citrus plant images. This is known as image level classification. After detection of a disease, the second task is the assignment of the class label to an image. This multi-class classification is referred as disease level classification. Our main contribution includes:

- We used ΔE method for the region of interest selection, which chooses the threshold on the basis of energy difference of the diseased area and matched with stored template.
- The Red Green Blue (RGB) histogram, Hue Saturation Value (HSV) histogram and Local Binary Patterns (LBP) are extracted from the diseased region which is segmented through the ΔE method. A hybrid feature's set is proposed by combining the RGB, HSV, and LBP descriptors. Furthermore, the dimensionality reduction is done using Principle Component Analysis (PCA). The comparison of classification results of the individual channel with combined channels is done to show which set of descriptors performs better.
- State of the art classifiers used to check the performance of RGB, HSV, individual channel, combined channel, LBP and hybrid features extraction methods.
- We found that the RGB has better performance than other descriptors, and LBP features are good descriptors for image level classification. Moreover, our results show that the Bagged tree classifier outperforms the other classifiers.

1.1. Related work

In the research, identifying and classifying citrus disease images by using image processing and machine learning techniques especially in the field of agriculture is a crucial job. The key question is the recognition of diseased regions in images, which may affect the performance and design of the classifying application. Various methods have been developed for the diagnosis of the plant diseases. Some of the good approaches targeting this diagnosis problem are discussed below.

In (Zhou et al., 2014) presented a method for continuous Cercospora Leaf Spot (CLS) qualification that focused on exploring a precise and robust algorithm for sugar beet in natural illumination. Similarly, a method of spectral vegetation indices was used for detection of CLS in sugar beet plants, using powdery mildew and sugar beet rust (Mahlein et al., 2013). Pre-symptomatic foliar disease sugar beet identification of disease was demonstrated in (Rumpf et al., 2010). The drawback of these methods is that it does not differentiate between plants diseases. A robust and simpler method based on TaqMan® Technology, which uses extraction for testing large numbers of aphid and banana samples was proposed (Chen and Hu, 2013). The hyperspectral imaging system is proposed in (Qin et al., 2009) as in (Mahlein et al., 2013) for detection of greasy spot, insect damage, melanoses, scab, and wind scar in Ruby Red grapefruits. All these methods employ different technologies to classify disease of various plants as compared to our proposed methodology.

The machine vision and image processing algorithms are used to segment leaf decay ailment in betel vine leaf, Otsu threshold was applied (Dey et al., 2016). (VijayaLakshmi and Mohan, 2016) provides a method in which input leaf images are processed with the help of cellular automate filter. An image processing approach to detect bacterial blight (Telya) in pomegranate fruitlet was proposed (Bhange and Hingoliwala, 2015). Anthracnose affected lesion from the normal area, segmentation techniques like K-means clustering, region growth, threshold and marker-controlled watershed were used in (Pujari et al., 2015) and Artificial Neural Network (ANN) is applied for classification. Similarly, Back Propagation Neural Network is used for identification of corn/weed conditions in the field at an early stage (Wu et al., 2009). Color co-occurrence matrix (CCM) is used as texture feature from edge response of images from HSI color space in (Pydipati et al., 2006). Imaging sensors are mounted on the (unmanned air vehicle) UAV in (Garcia-Ruiz et al., 2013) for obtaining full field map of citrus plants and to detect the region under the effect of diseases, SVM and linear discriminate analysis (LDA) are used.

A similar method for differentiating healthy plants from diseased plants was proposed in (Gandolfo et al., 2016). In (Zhang and Chaisattapagon, 1995) developed a system of weed detection using color filters for detection in Kansas wheat. A vision system was developed (Woebbecke et al., 1995) using color indices for weed detection under numerous circumstances such as soil, residue, and lightening. Work presented in (Guyer et al., 1993) proposed an algorithm that used statistics gathered from local maxima and minima to extract leaf/plant shape features. To increase disease control, escalate yield, and decrease pesticide in the orangery, a robotic disease detection is described (Schor et al., 2016). Similarly (Harrell et al., 1989) experimented a robotic manipulator in the harvesting of orange fruit. In (Bulanon and Kataoka, 2010) They proposed an automatic system for detecting apples ready to harvest, for the application of robotic fruit harvesting (Table 1).

In all above-given methods, some work only focuses on the detection of specific diseases, other focus on the quality and ripeness of fruits, our method first detects the disease and then assigns the class of disease according to its symptoms.

2. Proposed methodology

The proposed method uses computer vision techniques to classify images of leaves of citrus plants in normal and abnormal and further classify image in specific disease class. Fig. 1 shows a complete flow diagram of the proposed system. Our proposed method consists of following steps:

- Image preprocessing
- Image segmentation
- Feature extraction
- Classification