Webology (ISSN: 1735-188X)
Volume 17, Number 4, 2020

Image-Based Maize Disease Detection: A Survey

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Abstract

Maize (corn, Zea mays) is an important crop. It has a variety of uses. It has the potential to change the world and make it more sustainable. But it suffers from many diseases that destroy over 20% of the production. Therefore, to protect and increase its yield, a fast, accurate and efficient disease detection system is needed. This paper presents a thorough survey of various stresses faced by the maize crop, various techniques and methodologies used for detection of these stresses and the future possible course of the field. A stepwise comprehensive survey of existing techniques is presented. The survey concluded that the field is still in an early stage and a lot of work needs to be done.

Keywords: Plant Disease Detection, Computer Vision, Pattern Recognition, Maize Diseases, Maize Nutrient Deficiencies

1 INTRODUCTION

Maize (corn), called the 'Queen of Cereals' is a very significant cereal crop in the world. Its worldwide production reached 1,400 MMT (million metric tons) in 2016-17. The global demand for maize is increasing at a Compound Annual Growth Rate (CAGR) of 15%, whereas the increase in maize production is 11% [1]. The main reason for this is the crop loss due to stresses like diseases, deficiencies, weeds and incorrect use of fertilizers and pesticides. Every year, over 20% of the crop production is lost due to these stresses [2].

The crop loss due to stresses can be prevented and its yield can be boosted by early identification of the stress and the use of appropriate remedy to it. Here, an image-based maize disease detection system assists the farmer in prompt and accurate identification of maize crop stresses. The system facilitates the farmer to know about the condition of the plant (the disease it is suffering from) and its remedy by uploading the plant's picture in it. The system also guides the farmer about the remedy like the quantity and periodicity of the pesticide or fertilizer to be used on the affected crop.

A basic maize disease detection system consists of five steps:

Step 1: Input: an image of diseased maize leaf is fed to the system as input.

Step 2: Pre-processing: the input image is processed; the noise and unwanted distortions are removed. Further, the features of the image are enhanced.

Step 3: Segmentation: the leaf is extracted from the image and the background is removed. Further, the disease lesions are extracted from the image.

Step 4: Feature extraction and selection: from the segmented image, various useful features are extracted to be further used for classification.

Step 5: Classification: this is the final step of the system as per the literature. In this step, the images are classified based on pre-recorded features. The final output is the name of the disease from which the plant is suffering.

2 IMAGE-BASED MAIZE DISEASE DETECTION SYSTEM

Image classification is a very important task and can be put to use in cases like crop disease detection. This section presents a detailed description of all these approaches put into use for image-based maize disease detection. These approaches are generalized in five main stages: the dataset, pre-processing, segmentation, feature extraction, and classification. Further, the pros and cons of each approach are discussed. A flowchart illustrating this process is displayed in Figure 1.

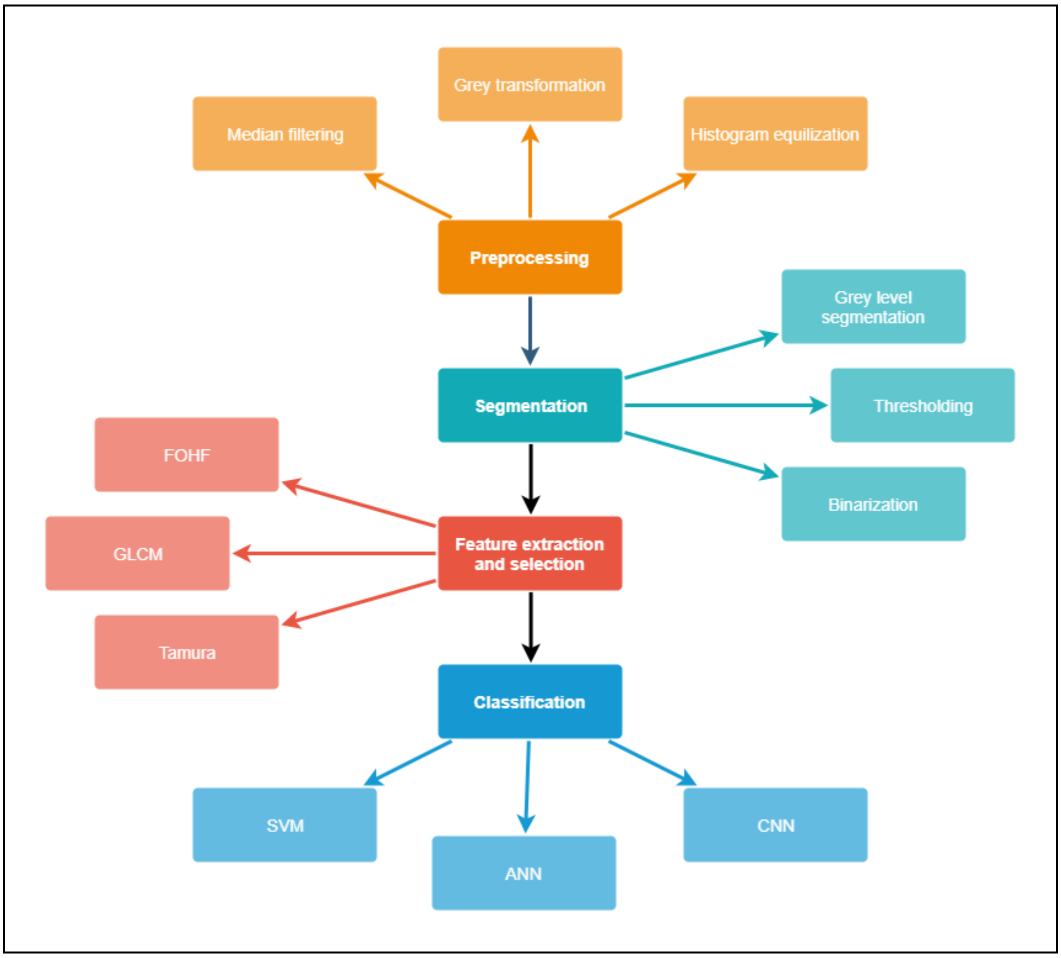


Figure 1: Overview of the image-based Maize disease detection process

2.1 Pre-processing

Pre-processing is used to enhance the quality of a digital image. In this, the digital image is modified and optimized according to the need of the proceeding stages. Mainly processes such as de-noising and normalization forms a part of this stage.

Median Filtering technique is a very compelling technique for eliminating salt-and-pepper noise but fails in preserving much of the image details when the noise density is high. The adaptive median filter is a type of the median filter which preserves the sharpness and detail in affected images by using median filtering for computing the image details of interest even at a low signal-to-noise ratio (SNR) [3].

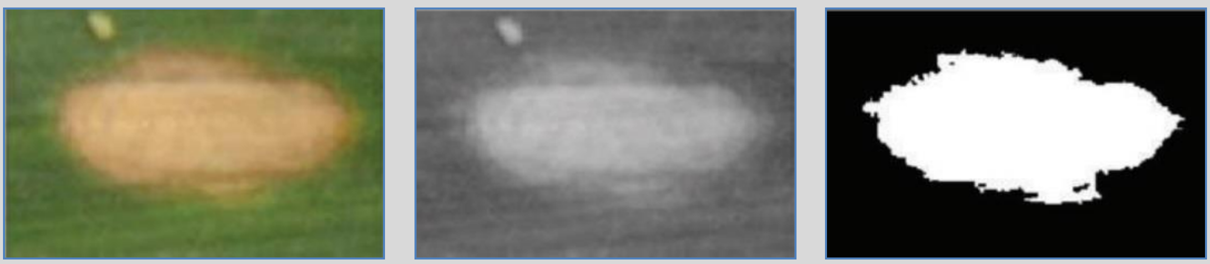
Grey transformation is used for improving leaf image quality [4]. Coupling it with histogram equalization proved to be quite effective, in irradiating the side effects caused by capturing images in direct sunlight; it also improved the precision of the segmentation stage [5]. Another histogram equalization method, namely contrast-limited adaptive histogram equalization (CLAHE) was used on images with varying contrast and non-uniform illumination conditions. For this, the RGB image was converted into L * A * B colour space, then CLAHE was applied to the L component, and the result was concatenated with the A and B components before converting the image back to the RGB colour space [6].

2.2 Segmentation

Image segmentation is a process of extracting the Region of Interest (ROI) from the pre-processed image. Two main techniques used for segmentation are Edge-based Image Segmentation (EIS) and Region-based Image Segmentation (RIS). EBIS uses image discontinuities for segmenting the image whereas RBIS uses pixel homogeneities for segmentation.

Grey Level Segmentation and Thresholding is quite effective in segmenting the images having contrasting backgrounds. S. B. Patil et al. used the method on images captured in white background. Initially, the leaf was extracted by eliminating the white component from the image. Finally, the disease area of the leaf was extracted using triangle thresholding [7]. J. Luo et al in. segmented the disease lesions using a similar technique. The authors grey scaled (Figure 2(b)) the original image (Figure 2(a)) using equation 1. Then, the region-based SRG algorithm was used for finalizing the segmentation (Figure 2(c)) [8].

$$f\ (i, j) = 0.3R\ (i, j) + 0.59(i, j) + 0.11B\ (i, j) \qquad (1)$$



(a) (b) (c)

Figure 2: Segmentation used by J. Luo et al. [39]. (a) Original image, (b) Grey scaled Image and (c) segmented image after SRG.

Binarization is another useful tool for segmentation. It aims at getting two peaks in the histogram of the image. Using this information, the background elements are removed, while retaining the foreground ones. S. Kai et al first converted the RGB input image into YCbCr colour system using equations 2 to 4 and reduced the colour space to Cb-Cr to decrease brightness sensitivity of the segmentation algorithm. Finally, binarization was applied using equation 5.

$$Y = O.299*R + O.587*G + O.114*B \tag{2}$$

$$Cr = (R-Y) * O.713 + 128 \tag{3}$$

$$Cb = (B-Y) * O.564 + 128 \tag{4}$$

$$P (r, b) = \exp [-O.5 (x-m) TC - I(x-m)] \tag{5}$$

HSV Histogram Thresholding method for image segmentation uses the colour difference between the healthy and affected parts for segmentation of the deficient parts of the leaf [10]. Further, unsupervised learning approaches have proved effective in cluster analysis. K-means clustering classifies the given image into clusters by minimizing the objective function. This applied to disease detection, results in effective disease lesion cluster segmentation. Further, super-pixel segmentation i.e. pixel seeding was used to enhance the accuracy of k-means segmentation [11].

2.3 Feature extraction

Human vision identifies an object from its features, most prominently colour, texture and shape. The computer systems perceive these features based on the values of certain functions.

- Colour: moments and histograms.
- Texture: contrast, homogeneity, variance entropy, etc.
- Shape: Size, roundness, area, perimeter, eccentricity, etc.

In plant leaves, another vital feature is venation, which describes the pattern of the leaf veins.

First Order Histogram Features (FOHF): Features that are extracted based on individual pixel values, without taking into consideration the inter-pixel relationship are known as first order histogram features [12]. Commonly used features include: mean, variance, kurtosis, skewness, energy and entropy.

Grey Level Co-occurrence Matrix (GLCM) Features: The second order statistical texture features are extracted using spatial relationship of pixels of an image in GLCM. Commonly used features include Angular Second Moment (ASM), Contrast, Inverse Different Moment (IDM), Dissimilarity, Homogeneity and Correlation.

Tamura features: the features which are calculated based on human visual perception are known as Tamura features. They work best on homogeneous texture images but shows poor performance on generic images. Coarseness is a Tamura feature which was used by B. Jiang et al [13]. For this, firstly the average grey value (A_k) of each pixel was calculated as illustrated in equation 6. Secondly, the horizontally ($E_{k,h}$ (x, y)) and vertically ($E_{k,v}$ (x, y)) overlapped regions were calculated using equations 7 and 8 respectively. Next, at each pixel, the value of k was calculated to maximize the difference between ($E_{k,h}$ (x,y)) and ($E_{k,v}$ (x,y)) as $S_{best}(x,y) = 2^k$. Finally, the value of coarseness was calculated by averaging the value of S(x,y) over the entire image using equation 9. This feature is used in [13].

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{i=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j) \ / m \tag{6}$$

$$E_{k,h}(x,y) = |A_k(x + 2^{k-1}, y) - A_k(x - 2^{k-1}, y)| \tag{7}$$

$$E_{k,v}(x,y) = |A_k(x, y + 2^{k-1}) - A_k(x, y - 2^{k-1})| \tag{8}$$

$$f_{coarseness} = \sum_{x,y=0}^{x = x_{max}, y = y_{max}} S_{best}(x,y) \tag{9}$$

K. R. Aravind et al. worked on a dataset of 2000 images divided into four classes. The researchers extracted a bag of location and order independent features. Starting with the extraction of Speeded up Robust Features (SURF), feature descriptors were estimated using wavelet technique. These features were clustered using the K-means clustering algorithm to create a visual vocabulary. Further a frequency histogram was constructed using nearest neighbour algorithm. Finally, the histogram is further used as the input to the classification algorithm [14].

2.4 Classification

The final stage of the Image-based Maize crop disease detection is classification. This stage takes a feature map as input and outputs a prediction, i.e., which maize diseases might be contained in the image in question. This is the most important stage. All the previous stages are helper stages for increasing the efficiency and accuracy of this stage. All the machine learning and recognition action happen in this stage. Many approaches have been used by researchers for image classification of maize disease images; traditional ones include SVM, ANN, BPNN and K-NN; whereas the newer deep learning approaches include CNNs.

Support Vector Machine (SVM) is a classifier which distinguishes between the data points, draws a suitable hyper-plane between them and classifies them into separate classes. N. Leena et al. coupled it separately with Genetic Algorithm (GA) and Symbiotic Organism Search (SOS) creating the fusion models SVM-GA and SVM-SOS respectively. The algorithms were applied on a dataset of 30 leaves achieving an average classification accuracy of 86%and 90% respectively [10].

Artificial Neural Networks (ANN) are specialized type of classifiers, that are inspired by biological neural networks, has multiple layers of functions and have multiple nodes or formulae for each layer. State-of-the-art performances can be achieved using neural networks. E. Alehegn used ANNs on self-captured dataset of 800 maize images comprising of 4 classes using 80-20 split, achieving overall classification accuracy of 94.4%[15].S. Kai et al. used Back Propagation Neural Networks (BPNN) on 10 maize images of corn leaf blight, sheath blight, southern leaf blight, yielding an overall accuracy of 98% [9].

Convolution Neural Networks (CNNs) are shift-invariant artificial neural networks. They increase the feature maps of an image and extract the most important ones automatically. This makes a CNN model structure very effective, as it is not just a list of features to be extracted; but instead, are the definitions of the machine which will itself extract important features. They extract small details in images and combine them to understand the bigger pattern in the image and ultimately understanding an image. Thus, are quite powerful in the domain of image recognition and classification. Many powerful CNN models have been proposed till date, many of which have been thoroughly experimented with and proved successful by researchers on image-based maize disease classification. K. P. Ferentinos [16] used AlexNet, VGG, GoogLeNet, Overfeat, and AlexNetOWTBn; S. P. Mohanty et al. [17] used AlexNet and GoogLeNet; E. C. Too et al. [18] used VGG net, ResNet, Inception V4 and DenseNet; and X. Zhang et al. [19] used GoogLeNet and Cifar10 DCNN models.

3 CONCLUSION AND FUTURE DIRECTION

A comprehensive survey of image-based maize leaf disease detection techniques using computer vision and machine learning is carried out. Various stages involved in the same are studied and techniques used at each stage are investigated. After thorough research, the following conclusions are drawn.

i. All the stages are necessary for effective maize disease detection.

ii. The pre-processing stage is overlooked by many researchers.

iii. The segmentation stage was well researched, and the k-means clustering has emerged as the most successful segmentation technique.

iv. In feature extraction stage, Tamura features have produced the best results.

v. The classification stage was previously dominated by SVM technique. But now, deep learning is taking a leap. But still, many promising DCNN models haven’t still been tested for detection of Maize diseases.

vi. The post-processing stage hasn’t been used at all by any researcher.

Further, the deep learning algorithms used for maize disease detection are still the general-purpose DCNN models. Therefore, specialized deep learning models need to be developed. Moreover, limited annotated datasets is a big challenge in the field. The state-of-the-art DCNN models has failed in real cultivation conditions due to lack of quality and quantity of the training data. A dataset should simulate the entire sample space. Therefore, larger annotated datasets need to be developed. Finally, the datasets may be augmented using Generative Adversarial Networks[20] to diversify the same.

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