Classification of Diseases in Banana Leaves using Diagonal Path Value Pattern

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Abstract: The classification of diseases in Banana leaves is emerging as the latest research area using machine learning and deep learning techniques in agricultural image processing. A lot of banana plants are wiped out, due to diseases such as Banana Bunchy Top Virus (BBTV), Banana Bacterial Wilt (BBW) and Banana Black Sigatoka (BBS). But there is not much research work done in identifying these diseases. In the proposed method, texture features are extracted using the proposed Diagonal Path Value Pattern (DPVP). The proposed texture feature descriptors provide codes taking into account of elements in diagonal directions.Then, Pulse Coupled Convolution Neural Network (PCCNN) is utilized for classifying banana leaf diseases. The experimental results with standard datasets prove that the proposed method performs better than the existing techniques. Classification results are validated by agriculture biologists. (Abstract)

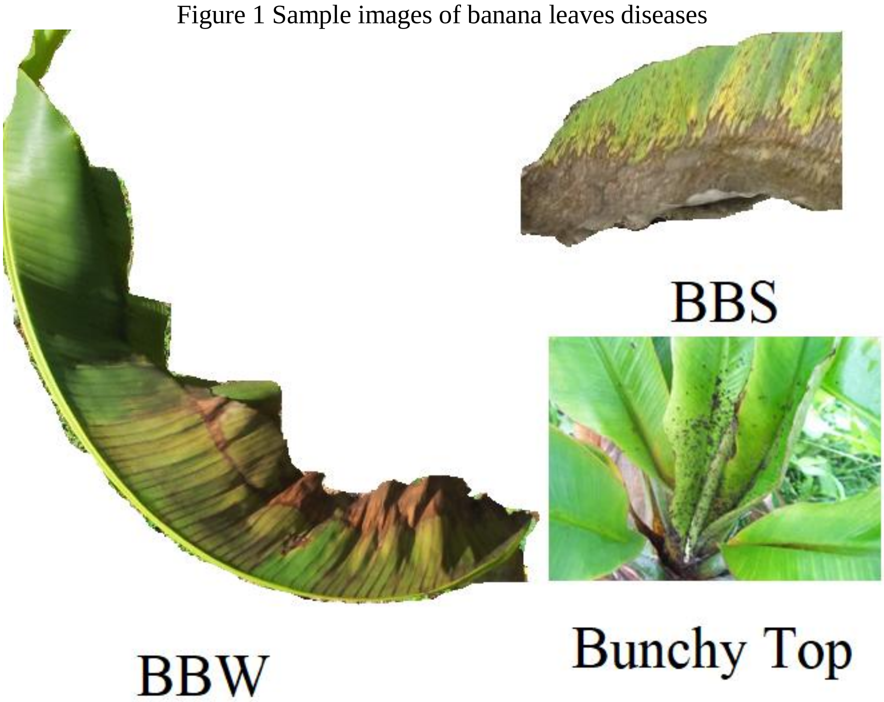
IndexTerms—Banana, classification, Pulse Coupled Convolution, Diagonal Path Value Pattern.(keywords)

I. INTRODUCTION

A lot of banana leaf diseases have been accounted. Among them, Banana Bunchy Top Virus (BBTV), Banana Bacterial Wilt (BBW) and Banana Black Sigatoka (BBS are the most widespread diseases. Sigakota disease is caused by a fungus, which is an airborne disease. Black sigakota is common in lowlands while yellow sigakota is common in highlands. Black sigakota and yellow sigakota are characterised by the appearance of small streaks which then enlarge into brown streaks. The streaks then enlarge and combine to form black patches which then turn to be a disease symptom as spots in banana leaves. Banana Bunchy Top Virus (BBTV) disease show bunchy leaves on the top of banana plant. Diseased plant leaves will be narrow and erected upright and will stop producing fruits. Removal of diseased leaves from plants will help to minimize infection in plantation. Diseases in plantation spoil the banana plants and their growth. Figure 1 shows some differences between diseased leaves.

The difficulty of classifying diseases is a tedious one. Farmers wait for the disease symptoms to be seen so as to recognize that the crops are diseased. However, since the plantation is large and clumsy, it becomes tedious to discover it at an early stage. Therefore, this study intends at early disease classification. The indications are able to be seen in the male bud, stem, leaves, and fruit. The disease commences with any leaf and makes them to turn brown, yellow, and later it wilts. Young diseased plants become underdeveloped and may not make any fruits. Therefore, there is a need for an automated system to classify banana leaf diseases.

Figure 1 Sample images of banana leaves diseases



The proposed DDVP method with RGB (Red Green Blue) space provides efficient results. The proposed feature descriptor provides codes considering elements in diagonal directions. The resultant feature vector is then given as input to the Pulse Couple Convolutional Neural Network - PCCNN classifier to classify the diseased images. The efficiency of the proposed framework is demonstrated using real-time coral reef diseased images. To compensate the high computation cost produced by Convolutional Neural Network - CNN, Pulse Couple Convolutional Neural Network is proposed. The dimension reduction of image space is realized by PCCNN from multidimensional image space to low dimensional feature space. This approach can radically reduce the number of features for image classification.

II. Related work

There is not much research work reported in the literature for the classification of diseased images in banana leaves. Sharada et al [1] have applied deep learning with smartphone-assisted disease classification. Due to shortage of the required infrastructure, Crop diseases are a main risk to food safety. This method attained an accuracy of 99.35% in training. Godliver et al [7] have classified banana leaf diseased images using six classifiers, namely Nearest Neighbor, Random forest, Naive Bayes, support vector classifier, Decision tree, and and Extremely Randomized Trees. Banana leaf diseased image features are extracted using thresholding technique for the analysis of connected components and then the morphological features for each connected components. This technique has yielded an accuracy of 96%.Vipinadas et al [8] have classified banana leaf diseased image using Support Vector Machine (SVM) with Radial Basis Function, and features are analysed using Discrete Wavelet Transform (DWT). This method has also reported an accuracy of 95%. Jyoti et al [9] have explained survey paper on plant disease classification. Classification is performed using machine learning approach. Rajashree Patil et al [10] have prepared a survey on various techniques for detecting plant leaf and fruit diseases using Neural Network (NN). Aravindhan et al [11] have used YOLOv3 object detectorto extract a leaf from the input image. ResNet18 models are applied to analyze the extracted leaf. Transfer learning was used to train ResNet18 models. Sharada et al [12] have trained deep Convolutional Neural Network (CNN) for classifying 14crop species and 26diseases. Akila and Deepan [14] have applied deep-learning-based method to classify leaf diseases in various plants. Here, three detectors are used, namely Region-based Fully Convolutional Network (R-FCN),Single Shot Multibox Detector (SSD) and Faster Region-based Convolutional Neural Network(Faster R-CNN). Moreover, this technique effectively classified leaf in various complex scenarios. Muammer et al [15] have employed pre-trained deep models for feature extraction and also for fine-tuning. The resultant features which are obtained using deep feature extraction are then classified by Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Extreme Learning Machine (ELM).

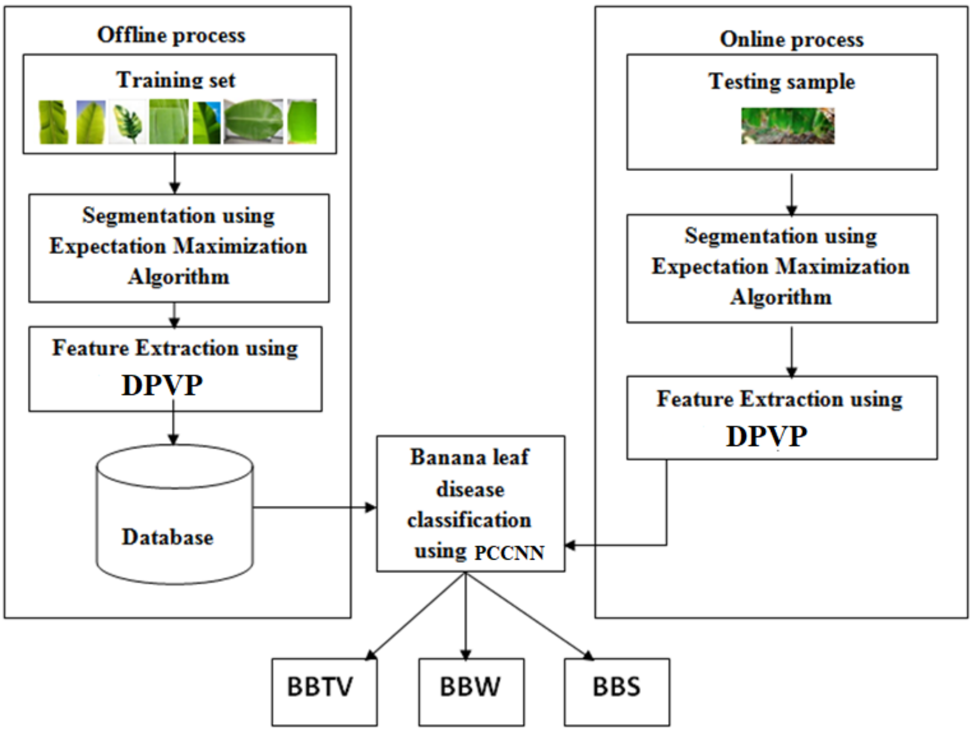


Figure 2 The proposed architecture

Konstantinos et al [16] have developed CNN models-based deep learning methodologies to present plant disease detection anddiagnosis. Marko et al [17] have proposed novel two-stage architecture of a Neural Network forplant disease classification. The two steps applied are state-of-the-art approach generative adversarial networks and conventional augmentation techniques. This method is mainlypaying attention on a real environment. This model has attained an accuracy of 93.67%.Rajeswari et al [18] have applied neural network technique with an imageprocessing technique to solve the issues of phyto- pathology. Here, the diseased features are extracted by applying Gray-Level Co-Occurrence Matrix - GLCM technique and the classification is performed using Artificial Neural Network (ANN). This model has attained an accuracy of 90%. Jihen et al [21] have applied a deep learning-based approach for banana leaf diseased image classification. LeNet architecture is used as a CNN network to classify banana leaf diseased image data sets. But this technique is not suitable for Bunchy Top diseases. Here, an experimental results show that while training is more and testing is less, they have obtained 93% of accuracy. Ani et al [30] have proposed an enhanced Gabor feature descriptor for classification. Ani et al [31] have proposed a novel deep learning technique called Heap Auto Encoders (HAEs). This proposed method can extract important features and reduce the exhausted use of handcrafted features.

III. PROPOSED METHOD

The proposed architecture of the banana leaves disease classification is depicted in Figure 2. The diseased banana leaf region has to be segmented from an image, and a set of points from the contour is extracted to represent the shape of the leaf. This makes the segmentation problem tough because banana leaf disease data set comprises leaf images with uniform pattern or diseased pattern.Expectation-Maximization (EM) algorithm is used for segmentation. In EM algorithm, each data point associates with a cluster with certain probability, and it belongs to the cluster with the highest probability in the final assignment [18].

Diagonal Path Value Pattern (DPVP)

Numerous feature descriptors are available in the literature for texture classification. Most of the feature descriptors make use of only the gray scale values of the pixel in an image. But the relationship between the diagonal path elements in three planes of an image is not considered.

$R_{i-1,j+1}$	$R_{i,j+1}$	$R_{i+1,j+1}$
$R_{i-1,j}$	$R_{i,j}$	$R_{i+1,j}$
$R_{i-1,j-1}$	$R_{i,j-1}$	$R_{i+1,j-1}$

(a) R-plane

$G_{i-1,j+1}$	$G_{i,j+1}$	$G_{i+1,j+1}$
$G_{i-1,j}$	$G_{i,j}$	$G_{i+1,j}$
$G_{i-1,j-1}$	$G_{i,j-1}$	$G_{i+1,j-1}$

(b) G-plane

$B_{i-1,j+1}$	$B_{i,j+1}$
$B_{i-1,j}$	$B_{i,j}$
$B_{i-1,j-1}$	$B_{i,j-1}$

(c) B-plane

Figure 3 RGB plane images

DPVP extracts features diagonally along four (〖45〗^0, 〖135〗^0 , 〖225〗^0 and 〖315〗^0) directions from three planes efficiently. The speciality of DPVP is that diagonal direction difference among pixel values in the three planes of the image are considered while reducing the bin size of histogram used in the classification stage. The steps in the proposed feature descriptor are summarized as follows:

In an image I, let R_(i,j), G_(i,j)and B_(i,j)be the centre pixels of a 3 ×3 local region termed as Block B_k, in each of the three planes as shown in Figure 3, where 1 ≥k≤N, N is the total number of 3 ×3 blocks in the image I. R_(i-1,j+1) , R_(i,j+1) , R_(i+1,j+1) , R_(i+1,j) , R_(i+1,j-1) , R_(i,j-1),R_(i-1,j-1) and R_(i-1,j) are the eight neighbors of the centre pixel R_(i,j) in the Red plane. G_(i-1,j+1) , G_(i,j+1) , G_(i+1,j+1) , G_(i+1,j) , G_(i+1,j-1) , G_(i,j-1),G_(i-1,j-1) and G_(i-1,j) are the eight neighbors of the centre pixel G_(i,j) in the Green Plane. B_(i-1,j+1) , B_(i,j+1) , B_(i+1,j+1) , B_(i+1,j) , B_(i+1,j-1) , B_(i,j-1),B_(i-1,j-1) and B_(i-1,j) are the eight neighbors of the centre pixelB_(i,j) in the Blue plane.

For a Block B_(K,) 〖R〗_θ, B_θ, G_θ, 〖RG〗_θ, 〖RB〗_θ, 〖GR〗_θ, 〖GB〗_θ, 〖BR〗_θ and 〖BG〗_θare constructed as shown in Eq.(1) to Eq. (9) from the neighbors of the centre pixel in three planes along the directions θ= 〖<45〗^°, 〖135〗^°, 〖225〗^° and 〖315〗^°>.

$$R_{B_k,\theta}[m] = R_{i,j} - R_{i+u,j+v} \quad (1)$$
$$G_{B_k,\theta}[m] = G_{i,j} - G_{i+u,j+v} \quad (2)$$
$$B_{B_k,\theta}[m] = B_{i,j} - B_{i+u,j+v} \quad (3)$$
$$RG_{B_k,\theta}[m] = R_{i,j} - G_{i+u,j+v} \quad (4)$$
$$RB_{B_k,\theta}[m] = R_{i,j} - B_{i+u,j+v} \quad (5)$$
$$BR_{B_k,\theta}[m] = B_{i,j} - R_{i+u,j+v} \quad (6)$$
$$BG_{B_k,\theta}[m] = B_{i,j} - G_{i+u,j+v} \quad (7)$$
$$GR_{B_k,\theta}[m] = G_{i,j} - R_{i+u,j+v} \quad (8)$$
$$GB_{B_k,\theta}[m] = G_{i,j} - B_{i+u,j+v} \quad (9)$$

where 'B_k' is of size 3 × 3,
1 ≥ m ≤4,
1 ≥k≤N and
(u, v) = {█(u=1 ,v=1, ifθ = 〖45〗^°@u= -1, v= 1,ifθ= 〖135〗^°@u=-1,v=-1,ifθ= 〖225〗^°@u=1 ,v=-1,ifθ= 〖315〗^°)┤

Pulse Coupled Convolution Neural Network (PCCNN)

PCCNN is an organically motivated neural network. It is diverse from usual techniques, namely Back-Propagation models and Self Organizing Maps. The basic form was proposed by Eckhorn to describe the experimentally observed synchronous activity. PCCNN comprised with one layer and two dimensional neural networks with lateral connection of weights.

IV. RESULTS AND DISCUSSION

Data set

To analyze the performance of the proposed technique, a collection of experiments are performed using Scotnelson, Godliver, Plant village project and real dataset of banana diseases which are obtained from avillage are represented in Table 1. Scotnelson's data set [23] consist of 1350 images. Among them 702 images are healthy leaves, 123 images consist of Bunchy top diseases, 312 images consist of BBW disease and remaining 213 images consist of BBS disease. Godliver data set [24] consist of 865 images. Among them 437 images are healthy leaves, 212 images consisting of BBW disease and remaining 216 images consist of BBS disease. Plant village project data set [25] has totally 3700 images. Among them 1643 images are healthy leaves, 1817 images consisting of BBW disease and remaining 240 images consist of BBS disease.

All these images in the data set are of various orientation poses, different sizes, illumination and diverse backgrounds. MATLAB 2019a is used for implementation,. System requirements used for execution are Windows 10, 8 GB Ram and Intel x86-64 processor.

Here, the deeplearning4j 4 as an open source deep learning library is also employed. This supports theuse of GPUs to make the execution of the deep learning algorithms faster. The primary goal of this work is to provide the predictive performance for any type of real time banana diseases. The proposed work is evaluated using F-measure, for quantitative measurement.

Table 1 Feature Extraction Techniques with Overall Accuracy

Feature Extraction Techniques	Overall Accuracy	
	Scotnelson [9]	Godliver [10]
Proposed DPVP	99.29	98.63
Enhanced Gabor	98.12	97.43
Gabor	95.76	96.56
Log Gabor	96.6	96.73
SHIFT	85.99	89.43
SURF	84.43	88.9

V. CONCLUSION

Befor This paper has proposed Mean Direct Code Pattern (MDCP) and Diagonal Path Value Pattern (DPVP) for extracting features. Banana leaf disease is classified with good accuracy when compared to the other existing feature extraction approaches. Not only, accuracy, but the time complexity has been reduced compared to the existing feature descriptors. This proposed method has good feasibility, high efficiency and provides results with high robustness. It is presented that an experimental accuracy of 98.8% may be considered as a good estimate when compared to other descriptors. 3% more accuracy is attained, when compared to the existing methods.

VI. FUTURE WORK

In future, other diseases on banana plant predominant on various parts of the plant namely stem, etc will also be considered.

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