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Research Article

Detection of Disease in Banana Fruit using Gabor Based Binary Patterns with Convolution Recurrent Neural Network

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Abstract

Banana plant disease classification is an application which supports farmers by making easier to analyse, detect and control plant pathogens. In order to protect the crops with the feasible cost, banana crop infection symptoms need to be identified and treated at the initial stage. This can be analysed and bifurcated through the computer vision system which uses interpretation of information by image processing techniques. Banana, fruit of the genus Musa, of the family Musaceae, one of the most important fruit crops of the world. Determining banana's disease detection stages is becoming an essential requirement for standardizing the quality of commercial bananas. So this paper proposes the novel feature extraction technique in extracting the stages of disease detection of banana using Gabor based binary patterns with convolution recurrent neural network. The collection of fine-grained features of image on basis of mechanism which is driven by data also it provides the phases of disease affecting in banana fruit. For variation of symptoms which is resulted has been assisted for variations between subsequent groups of banana for disease affecting. The simulation results has been taken from banana image of 17,312 which shows various stages of disease growing in banana fruit which shows that the proposed neural network obtains enhanced accuracy on basis of computer vision for both classification in rough- and fine-grained for disease affecting stages of banana which cause severe impacts.

Keywords: *Banana plant disease, feature extraction, Gabor based binary patterns with convolution recurrent neural network, disease detection state.*

1. Introduction

One of the frequently consumed fruit worldwide is Banana. About 16% of fruit cultivation has the contribution on banana. In accordance with FAO (Food and Agriculture Organization of the United Nations), about 114 million of banana has been cultivated in 2014 throughout the world. Recently, higher cultivation of banana has been reported by china which ranks in second place. In china banana is highly tropical fruit that has been cultivated in region of 392,000 ha, cultivation of 11,791,900 tons in 2014 [1]. Consumers require the enhanced disease affecting stages of banana for accepting the fruit along with their quality [2]. For this detection of disease in banana fruit

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techniques on basis of computer-vision has been proposed in classifying the stages of disease on basis of their appearance and there many algorithm based on neural networks has been used [4]. The classification technique for disease detection offers automated as well as the tool which is non-destructive techniques which is highly optimized frequently. Moreover all those techniques are not frequently used since they have many disadvantages. Initially classification of fine-grained images of banana fruit is not concentrated highly, so the variations of disease affecting stages are not identified accurately.

Since the limitation for using the color of banana skin for detecting the disease along with the computer vision based system by them, it has been classified into 7 processes for detecting the disease [6]. Secondly the features have been attained by hand-crafts which resulted for outputs with limitation because of the difficulty features in designing manually. Thirdly the banana of minimal group has been avoided because of the banana skin effects modelling. Recent advantages in field of artificial intelligence, the deep learning techniques leads to application developments namely the issues related with computer vision in extracting the features, segmenting the image and their classification process. When compared with every neural network techniques, convolutional neural network (CNN) has been used widely and it obtains higher accuracy in classifying the image. Lately the models on basis of CNN for fine grained classification of image has been acquired extreme results in detecting the refined variations between the subsequent groups which also comprises the classification traffic, medical image classification, plant classification, and food classification [7].

The rest of this paper is organized as follows. In Section 2, we present the related works. Section 3 contains proposed technique discussion. In Section 4, we discuss the experimental results and in section 5 we provide our conclusion and vision for the future.

2. Related works

In existing works there are many techniques that rely on shape, size, color, and texture features in detecting the disease from banana fruit using classification. More than 94% of system has the capability in detecting the disease accurately by the 7 phases for disease detection in banana bunch. The 7 phases for detecting the disease are green banana, yellow marks on green banana, maximum green that yellow, maximum yellow that green, yellow along with green tip, fully yellow, brown flecked in yellow banana. Then their subsequent phases are done by statistical method which has been utilized in classification of banana fruit classes of under-mature, mature, and over-mature [8]. The accuracy of classification by this technique attains 3 classes of 99.1%. Disease detection in banana fruit relies upon the group of classification which involves pre-processing and segmentation techniques in obtaining the optimal accuracy. For application of computer vision the important part is segmentation. For medical imaging, fruit industry, face recognition, pedestrian detection frequently segmentation technique is used. In image compression, noise removing, segmentation and classification discrete wavelet transform (DWT) and wavelet packet transform (WPT) proved to be highly efficient [9]. Many domains make use of this segmentation technique. DWT and WPT have been represented and this can be utilized in 2D images for segmentation of surface as well as 3D images for segmentation of volume [10].

Instead the classifiers used on basis of learning and training needs the stage where the training takes place with intensity as well as their characteristics of features; therefore the maximum range in recognition has been acquired. Examples are the support vector machine [11] (SVM), the hidden

Markov model [12] (HMM), and the artificial neural network [13] (ANN). The classification techniques has been used for application for supervised methods which has been represented as laser light backscattering imaging (LLBI) with five laser diodes emitting at wavelengths 532, 660, 785, 830, and 1060 nm has been deployed in prediction standard features for banana fruit [14]. The attribute predictions are chlorophyll, elasticity, and soluble solids content (SSC). The accuracy standard classification of 92.5% and 95.5% was requested by the ANN model and the SVM design, correspondingly. In [15], the design of computer vision which extracts the texture feature using gray-level co-occurrence matrix (GLCM) has been proposed for training by ANN. The accuracy of 98.8% obtained in classifying banana by the model used. For supervised learning applications and classification the techniques namely SVMs, HMMs, and ANNs has been used. Moreover the techniques of deep learning have trained by unsupervised method for application of unsupervised learning. CNN is the type of deep learning of neural networks where it requires the wide application of classification in image. This technique has efficient system of visual design which obtains various stages of characteristics. The structure of CNN represents 17,312 images of banana which produces the accuracy for classification of 94.4% [17].

3. Research methodology

In this section, the feature extraction and classification of fine grained phases in detecting disease has been certain for images on basis of banana. The novel feature extraction technique Gabor based binary patterns with convolution recurrent neural network architecture designed in certain to extract features based on the appearance of banana. Here the CRNN architecture requires three input images where the similarity loss occurs. By integrating the enhancement in classification accuracy and triplet loss, this proposed technique has train the depiction of fine grained images efficiently in the procedure of detecting disease in banana. Architectural diagram for proposed system is given in fig 1.

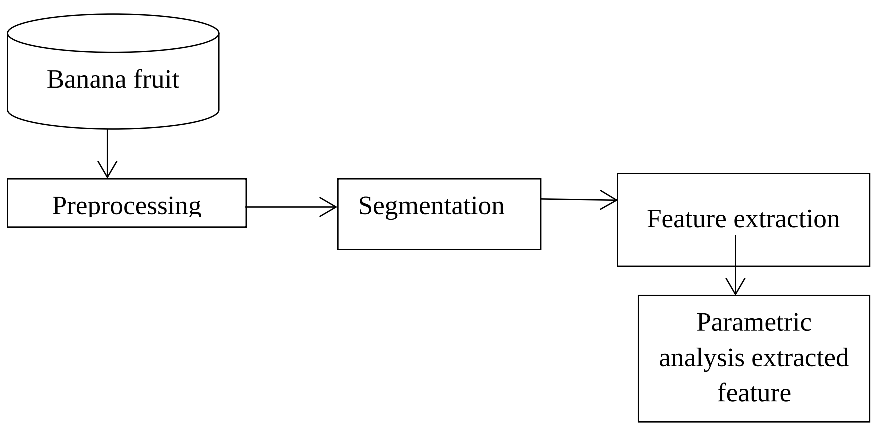

Fig. 1. Overall architecture of the Research methodology

From the below fig. 2 the dataset has been collected and initially the image has been trained. First the image has been preprocessed, here the image has been resized, cleaned and the noise is removed. Then this pre-processed image has been segmented based on the region for normalization. After the segmentation, the features of segmented image have been extracted using Gabor binary patterns where the image has been changed to frequency domain. Here the convolution recurrent neural network has been used for train the image and extract the disease affected area. After this the data accuracy has been calculated for the trained data and test image.

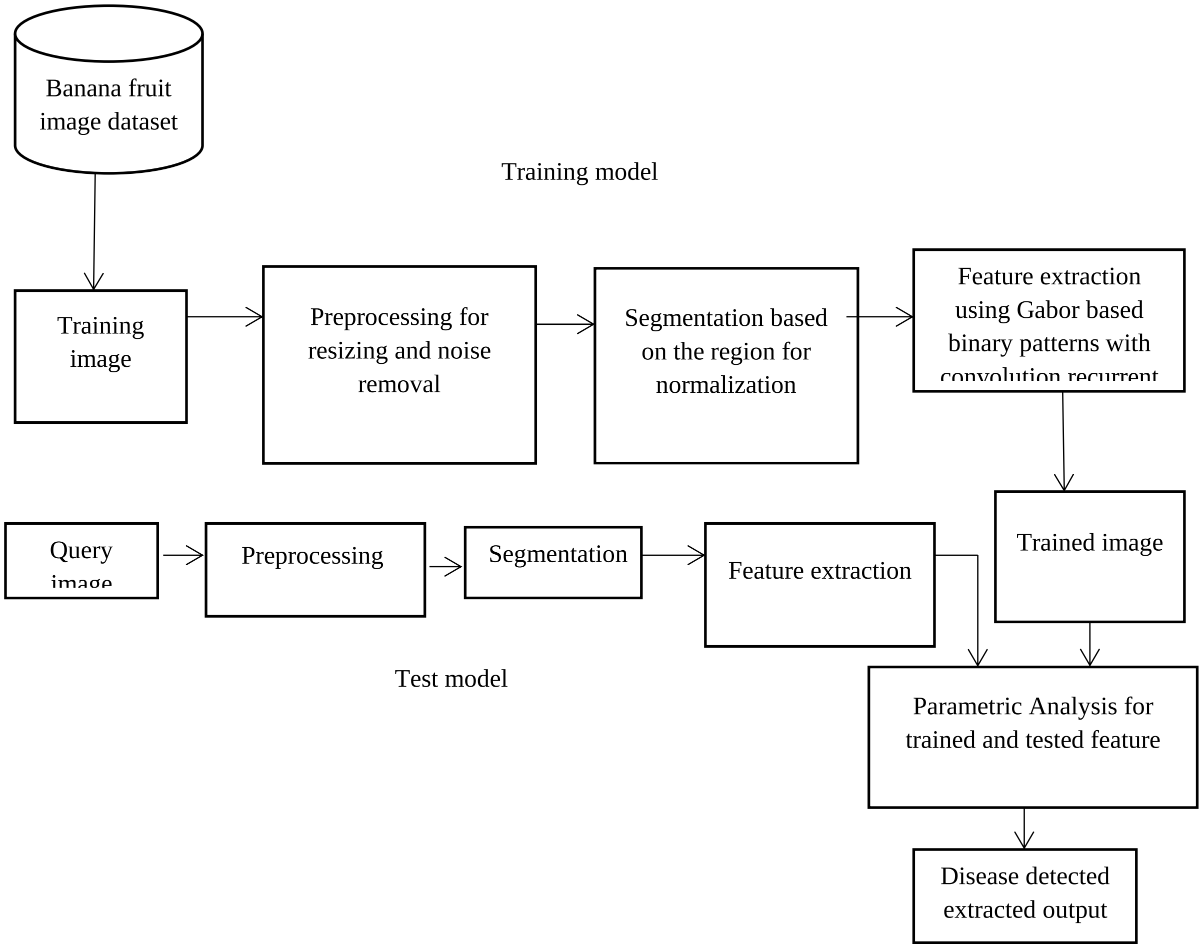

Fig. 2. Working Architecture of proposed methodology

Extraction of features from the segmented image

Here the segmented image has been extracted using the integrated method Gabor based binary patterns with convolution recurrent neural networks. The 2D Gabor wavelets can be defined as follows,

$$\psi_{v,\mu}(z) = \frac{\|k_{v,\mu}\|^2}{\sigma^2} e^{(-\|k_{v,\mu}\|\|z\|2\sigma^2} \left[e^{ik_{v,\mu^2}} - e^{\frac{-\sigma^2}{2}} \right] \qquad (1)$$

Where ν and μ define the scale and orientation of the Gabor wavelets, z = (x, y), denotes the norm operator, and the wave vector $k_{v,\mu} = ei\varphi$μ , where kν = kmax/λν and φμ is the alignment constant, λ is the positioning aspect among frequency domain in wavelets. Banana leaf image has been transformed by Gabor transformation has been acquired through convolution through the image by Gabor wavelets. The banana leaf image density has been assumed as f(x, y), then their convoluted Gabor wavelets has been given as f(x, y) and ψν,μ(x, y) is given as:

$$O_{v,\mu}(x,y) = f(x,y) * \psi_{v,\mu}(x,y) \quad (2)$$

The convolutional function is given by $*$. The entire image of banana leaf passes through the convolution slowly by their magnitudes that could differs. Gabor transform magnitudes depicted by the sequence of banana leaf characteristics has been indicated by variance of image extraction. Hence the magnitudes has been taken for extracting the features. Gabor feature of varied resolution has been attained through five various scales which is represented as $\nu \in \{0, 1,..., 4\}$ and eight orientations $\varphi\mu = \pi\mu/8$, $\mu = 0, 1,..., 7$ Gabor filters are used.

Convolution Recurrent Neural Networks

The neural network of CRNN comprises of five layers of convolution, one layer of recurrent and two layers of fully connected. In relation with initial five stages frequently used seven layer Alex-Net, the central stage has been studied using CNN layers and obtains visual patterns. To evaluation of spatial requirements among the visual patterns of central stage that is deployed using RNN layer. To collect the RNN results two fully connected layer has been used finally along with studying broad illustration of image. Subsequently softmax layer of N-way has been employed for image classification. The detail discussion of CRNN has been given below.

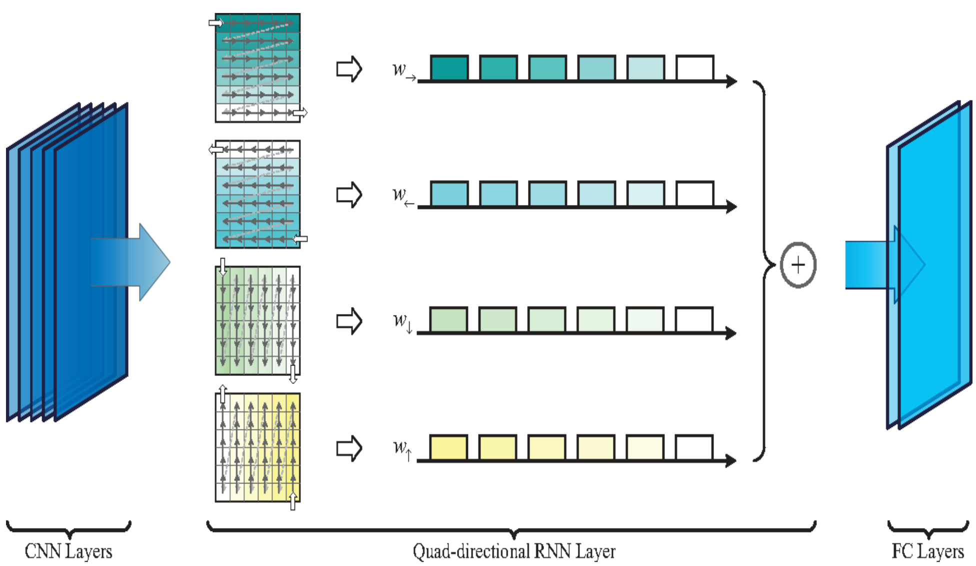

Fig. 3. CRNN architecture

As shown on the left part of fig. 3, we initially use layers of five convolutions in evaluating depiction of feature from the central layer of pixels from raw images. On basis of the output in visualization, maximum abstract and feasible patterns have been extracted when there are numerous convolution layers. When image net train the image, the fifth layer of convolution has been probably localize segments as well as the image objects. Hence these features of CNN has become highly appropriate in depicting the features of central stage, on basis of which they are similarly study the spatial requirements of highly suitable for using RNN, along with attaining optimal broad depiction of image through linking with the two layers which are fully connected. By back propagation, the broad depiction might be transformed in reverse for RNN which could enhance encoding due to requirements spatially also CNN get assistance from RNN for optimal learning of middle-level and low-level features.

The image training requires image which is resized initially by 256 × 256 pixels, where these are minimized through their mean value of pixel, on basis of where the ten sub-crops of size 227 * 227 (1 midpoint, 4 curves, as well as their parallel flips) has been obtained for training the data. The similar settings of filter in Alex-net have been required by CNN. The numbers of filter (sizes) were: 96 (11 * 11), 256 (5*5), 384 (3*3), 384 (3*3), also 256 (3*3). The stride is 2 and remaining is 1 in the layer initially. For the first, second and fifth layer they also has three layers of pooling correspondingly and each one of them has kernel size of 3 × 3 with max pooling as well as their strides will be 2. Hence the feature size for their response maps of layer five in CNN is given as 256×6×6 (channel number × width × height), and this will be input for RNN layer. But the output region in layer five of CNN is 6 × 6 regions; hence the RNN sequence length must be 36. The window size for scanning has been fixed as 6 (1 * 6 for one row or 6 * 1 for one column of regions) for RNN layer, as well as 6 RNN windows are present for every four sequences. Each region has been depicted as vector feature of 256 dimension (channel number of the fifth layer CNN). Therefore RNN matrix for weight and their size is given as Whh→, Wih→; Whh←, Wih← Whh↓ , Wih↓; Whh↑ , Wih↑ were all set to 256 * 256. The non-linear transformation fh, fg, and fo were all set to ReLU functions.

4. Performance analysis

Here the database in the collection of 17,312 images from various phases in disease affection of banana. 30 images in the dataset have been obtained from the farm as pre-historic data with previous disease affecting stage of banana. The effect of over fitting has been overcome by extending the original dataset using pre-processing techniques which comprises of translations (varying from 10 to 100 pixels with a gap of 10 pixels), vertical, and horizontal reflections. In this pre-processing the images has been resized into 256 × 256.

This section discusses the simulation results for banana fruit disease detection from the input dataset. Various outputs have been discussed below: initially the dataset folder has been generated where the different images for banana fruit are available for testing process. The indication of fruit disease has been identified with higher accuracy also trained properly and collected in the dataset. Those fruit images which affected by disease has been selected and given as input as shown in the fig. 4 for detection. Then this image has been resized to exact dimensions due to the uneven dimensions to pre-set dimension. This resized image has been transformed from RGB to grayscale level image as shown in the fig. 5 for fruit. Hence this image is enhanced and segmented based on region for normalization process as shown in the fig. 6 for fruit. The feature extraction is done using Gabor based binary patterns with CRNN as shown in the fig. 7 for fruit.

Fig. 4. Input Image **Fig. 5. Contrast Enhanced Image**

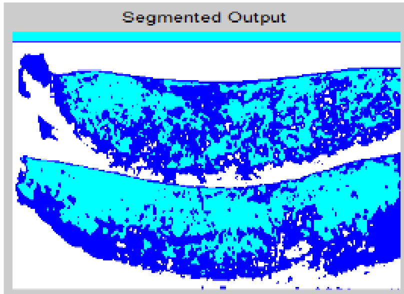

Fig. 6. Segmented Output Fig. 7. Feature Extraction of Diseased Fruit

Table 1 Comparison between Proposed and existing techniques

Parameters	KNN	CNN	DNN	PRO_CRNN
Precision	85	71	88	96
Recall	88	76	93	97
Accuracy	63	70	87	96
F1-score	89	73	93	97

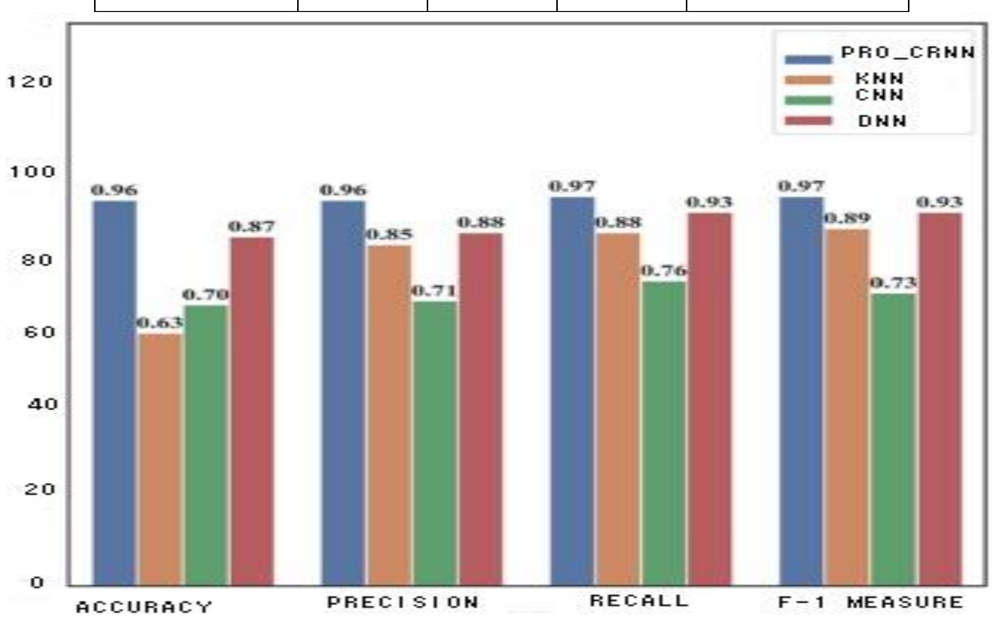

Fig. 8. Comparison of Existing technique with proposed for fruit disease detection

The above fig. 8 shows overall comparison for accuracy, precision, recall, F-1 score for proposed and existing techniques.

5. Conclusion

The detection of disease with enhanced accuracy by image processing techniques in identifying as well as classifies the images of banana plant. Manual system has been interchanged in detecting and classifying the disease of banana plant where the symptoms for consumption of time and the accuracy is low in comparison with proposed technique. Here the proposed technique extracts the diseased part of banana fruit dataset. The attained accuracy is higher when compare with the existing techniques. Therefore this proposed architecture ensures the farmers for smart cultivation. Moreover here the possible risk has been avoided and enhance the cultivation with equipped technique also prevent the cultivation of banana. The future work has been extended with real time implementation and evaluated with larger datasets along with the enhancement of various features of color and texture have been extracted in enhancing the accuracy of classification.

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