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Deep Learning-Based Mango Leaf Detection by Pre-Processing and Segmentation Techniques

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Article History	***Abstract***
Received: 22 January 2020 Revised: 14 April 2020 Accepted: 19 May 2020	Different diseases afflict mango trees, and it can be quite challenging to see sickness with the naked eye.In contrast to the conventional system, the pre-processing and segmentation methods presented in this research for mango leaf disease detection use deep neural networks (DeNeuNet) to classify the segmented diseased part and make disease identification easier and more accurate.The goal of this project is to more effectively detect plant disease indicators using machine learning than a manual monitoring system. By using a classification technique to gather pictures of leaves that have various diseases affecting them, trained data are obtained in this case.A machine learning system is created to automatically upload and compare new photos of afflicted leaves with learned data in order to identify the symptoms of mangoes leaf diseases. Experimental results obtains by proposed technique is accuracy of 95.35%, precision of 90%, recall 88%, F-1 score 85%. Keywords: Mango trees, leaf diseases, DNN, pre-processing, segmentation, leaf diseases

1. Introduction:

Mango trees are a key source of fruits and are crucial for maintaining biodiversity. The majority of mango trees worldwide are affected by powdery mildew, which can kill up to 23% of untreated trees[1][2][3]. Anthranose is responsible with up to 39% of mango tree losses worldwide[4]. Technology innovation, particularly the development of image processing techniques, may make machine learning a viable MLD detection method [5]. In this study, a neural network for diagnosing mango leaf diseases is offered as an alternative to the conventional system for swiftly and accurately detecting diseases. Here in proposed technique, input image has been pre-processed the mango leaf using histogram pixel localization and noise removal using median filter, segment the image using region based edge normalization. The segmented image has been classified using DeNeuNet.

The organization of this document is as follows. Related work is discussed in Section 2, Methodology and design of the pre-processing and segmentation in Section 3, Result and discussion in Section 4, and Conclusion and future work in Section 5.

2. Related works:

The spread of plant or tree diseases is a major issue in the agricultural industries. The strategy to protect crops from severe loss is described by the author in [6] and involves thorough disease identification. An strategy that is described in [7] that is based on automated approaches that can identify damaged leaves utilising colour information of leaves is helpful in crop protection, especially in vast area farms.According to the researcher in [8], diagnosing is a process that is primarily visual, necessitates exact judgement, and also uses scientific methods. The accuracy of ANN classification performance is 80% higher.[9] offers research on various classification techniques that can be applied to the classification of plant leaf diseases. The support vector machine analysis presented in [10] is a very promising AI technique that can be used widely to address classification issues.

3. System Model:

This section discuss the proposed pre-processing and segmentation with classification of mango leaf disease segmentation and diseased part classification. From the below figure-1, initially the dataset has been pre-processed for noise removal, filtering and image resizing. Then the pre-processed image has been segmented using proposed region based edge normalization with classification of segmented image using DeNeuNet. By this the diseased part will be segmented and classified for prediction and determined through parametric measures like accuracy, precision, recall, F-1 score.

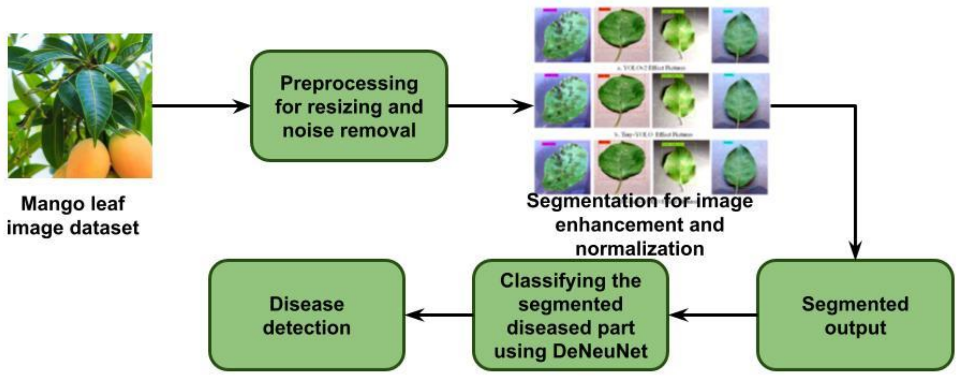

Figure-1 Overall proposed architecture

3.1 Dataset Description:

To train and test the developed model, open-access standard PlantVillage dataset consisting of 54,305 diseased and healthy leaf images of 38 classes from 14 species captured under laboratory conditions is used. The model was evaluated using three sets, namely 80–20 (where 80% were involved in training and 20% in testing), 70–30 (70% were involved in training and 30% in testing), and 60–40 (60% were involved in training and 40% in testing).

3.2 Pre-processing of input training image:

According to the histogram physics, it is clear that every bar on the equalized histogram is of the equivalent height. That is shown by eq. (1)

$$p_s(s)ds = p_r(r)dr \tag{1}$$

When s=T(r) is a operation that maximizes gradually with their time interval along with their operation of inverse as r $=T^1$ (s) is a monotonic operation. Based on (1), $p_s(s)$ is assumed as in eq. (2),

$$p_s(s) = \left[p_r(r)\frac{1}{ds/dr}\right]\text{r} \; = \text{T1(s)} = p_r(r)\frac{1}{p_r(r)} = 1 \qquad (2)$$

The algorithm for normalization of conventional histogram: By the circumstances of discrete, the correlation among i (the value of gray scale in input image pixel) along with fi (the value of gray scale for the image which is enhanced) is shown in eq. (3)

$$f_i = (m-1)T(r) = (m-1)\sum_{k=0}^{i}\frac{q_k}{Q} \qquad (3)$$

when image is with various grayscale levels has been represented as n, then their rate of probability for i^{th}gray scale level is pi, then their level of grayscale of entropy has been given eq. (4)

$$e(i) = -p_i \log p_i \qquad (4)$$

Entropy of entire image is given eq. (5)

$$E = \sum_{i=0}^{n-1} e(i) = -\sum_{i=0}^{n-1} p_i \log p_i \qquad (5)$$

The entropy can be attained their maximum level only when $p_0 = p_{12} = \cdots . = p_{n-1} = \frac{1}{n}$. When the image has equal distribution of histogram has been attained through the maximum entropy of the image.

3.3 Segmentation of diseased part using region based edge normalization:

In the dataset, for each input leaf, edge map is created. This approach aims to find the positions of eminent slice edge which is used in segmentation. For specified pixel position $p = (x_p, y_p)$, a circular neighborhood with radius $r\epsilon$ ℕ is mentioned in eq. (6), (7), (8):

$$R_r(p) = \{q\epsilon\, \mathbb{Z} | 0 \leq (x_q - x_p)^2 + (y_q - y_p)^2 \leq r^2\} \qquad (6)$$

$$c(p) = \sum_{q\in R_r(p)} b(p,q) \qquad (7)$$

With

$$b(p,q) = \begin{Bmatrix} 1, |g(p) - g(q)| \leq \sigma \\ 0, otherwise \end{Bmatrix} \qquad (8)$$

3.4 Deep neural network classifying the diseased leaf:

We create the forward and backward propagation computation techniques, which are essential steps in the inference and training processes, based on the DeNeuNet representation. The weight matrix of a DeNeuNet fully linked layer is typically assumed to be a m by n block matrix, or W Rm n. Then, eq. (9) can be used to describe the value of any entry wij of W.

$$w_{ij} = \begin{cases} qk_{l\times p+c} & if\ (c+k_l) \quad modp \equiv d \\ otherwise \end{cases} \qquad (9)$$

Below figure 3shows mango leaf disease classification using DeNeuNet.

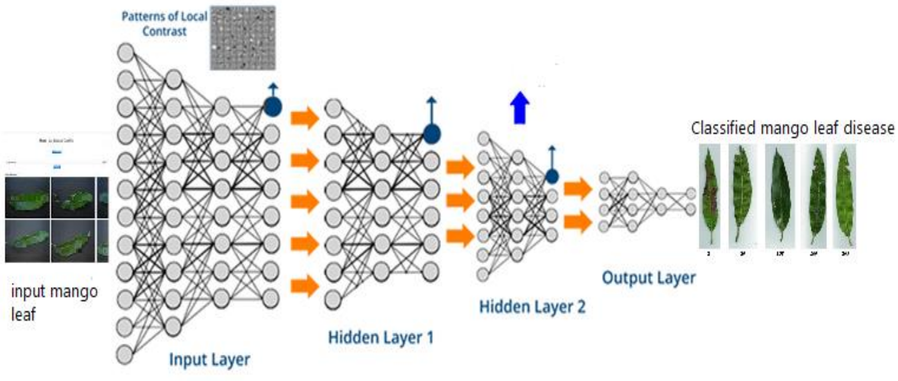

Figure 3- Mango leaf disease Detection using DeNeuNet

4. Performance analysis:

Parameters considered to determine the performance are accuracy, precision, recall and F1-score per epoch. The proposed pre-processing and segmentation is implemented in Python tool and the system configurations are: PC with Ubuntu, 4GB RAM, and Intel i3 processor.The parametric comparison of mango leaf disease detection has been shown between proposed and existing technique. The parameters calculated are accuracy, precision, recall and F-1 score.

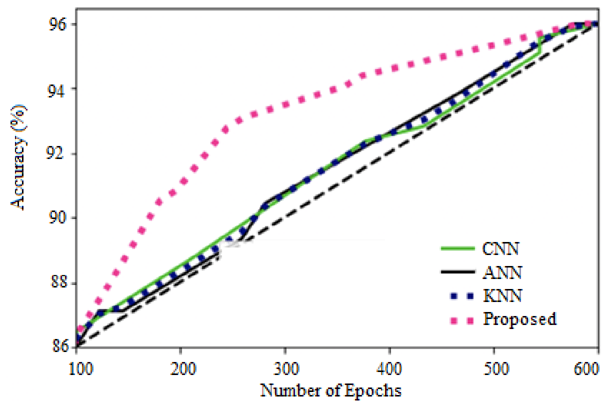

Figure-4 Analysis of accuracy for existing and proposed technique

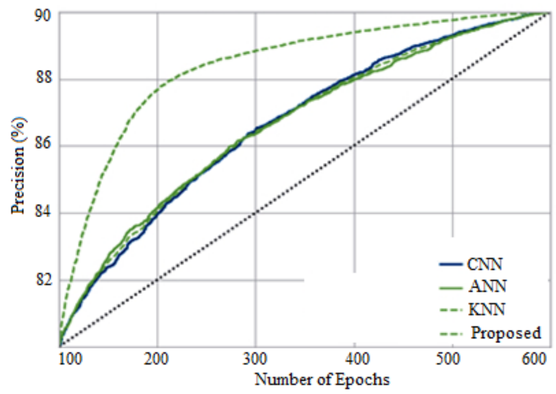

Figure-5 Analysis of Precision for existing and proposed technique

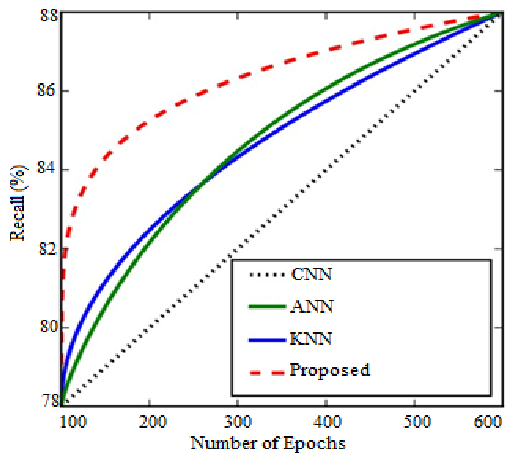

Figure-6 Analysis of Recall for existing and proposed technique

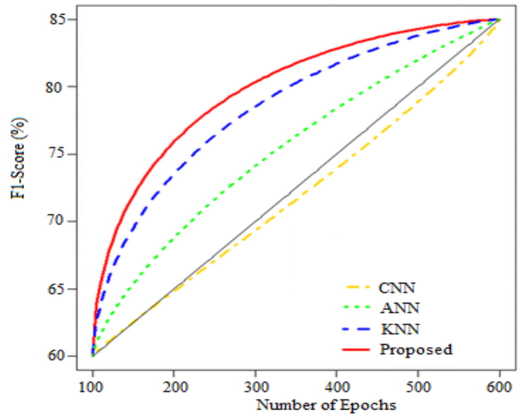

Figure-7 Analysis of F-1 Score for existing and proposed technique

Above figure 4,5,6 and 7 shows the parametric comparative analysis of accuracy, precision and recall between existing and proposed technique. The accuracy achieved by proposed technique is accuracy of 95.35%, precision of 90%, recall 88%, F-1 score 85%.On comparison with proposed technique and existing technique the obtained output achieved optimal accuracy in detection of mango leaf disease. For both pre-processing and segmentation with classification of DeNeuNetby which the mango leaf disease is identified.

5. Conclusion:

This work proposed a mango leaf disease identification by pre-processing and segmentation with classification of diseased leaf part using DeNeuNet.Here in proposed technique, input image has been pre-processed the mango leaf using histogram pixel localization and noise removal using median filter, segment the image using region based edge normalization. The segmented image has been classified utilizing DNN.The experimental results obtains by proposed technique is accuracy of 95.35%, precision of 90%, recall 88%, F-1 score 85%.Future study will compare the underlying properties of textures first, and then look at colour attributes to increase recognition accuracy.

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