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Tomato Plant Disease Detection using Image Processing

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Abstract: Agriculture is the major sector in India. About 58% of the rural livelihood influenced by in agriculture. Out of which tomato is one of the common food crops in India. Due to which detection of disease on tomato plant becomes important because less susceptibility. The plants productivity gets affected if proper care is not taken. Image processing is one of upbringing technology which is helping to resolve such issues with various algorithms and techniques. Most of the diseases of tomato plant detected at initial stages as they affects leaves first. By detecting the diseases at initial stage on leaves will surely avoid impending loss. In this paper four key diseases are identified using image segmentation and Multi-class SVM algorithm. For parting of damaged area on leaves image segmentation is used and for classification of accurate disease Multi-class SVM algorithm is used. In last stage symptoms and treatment to detected diseases recommended user.

Keywords: Tomato; Plant disease; Image segmentation; Multi-class SVM.

I. INTRODUCTION

Tomato is one of the most caring food crops of India. This plant grown in 0.458 M ha area with 7.277 M mt production and 15.9 mt/ha productivity. The tomato crop is cultivated in all the seasons but typically during winter and summer seasons. The crop cannot resist severe frost. It nurtures well under an average monthly temperature range of 21°-23°C but commercially it may be grown at temperatures ranging from 18°C to 27°C. Temperature and light intensity affect the pigmentation, fruit-sets and nutritive value of the fruits. Due to all these environments plant become very susceptible to diseases caused by fungi, bacteria, and viruses. Detection of plant disease is essential research topic. Most of the plant diseases are triggered by fungi, bacteria, and viruses. Morphological changes in leaves are the primary stage of Fungi. Bacteria are considered more embryonic than fungi in addition they generally have simpler life cycles and can be identified by morphological changes in the leaves.

(a) (b) (c) (d)

Fig. 1: Samples of tomato plant diseases; (a) Early Blight; (b) Septoria Leaf Spot; (c) Bacterial Spot (d) Iron Chlirosis

Figure 1 shows four common diseases on tomato plant. The most common method used by farmers for detection of is by naked eyes, which required experience which totally depends on knowledge of their ancestors. Other method is to refer experts which is followed by only 1% of farmers due to its higher cost. Another economical options is discussed in this paper that is using image processing.

All the diseases have common characteristics that they changes some morphological characteristics such as color or shape. These changes can be extracted through image segmentation and classification of different disease through Multi-class SVM algorithm.

II. RELATED WORK

There are many methods and algorithms that are being implemented on different plants for different diseases. Three steps that are followed by many of the authors.

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I. Image Preprocessing: At initial stage raw image is taken as input and smoothen through various techniques like thresholding [8], grey scale conversion [7], RGB to HIS [2], various filters like median filter[9], CIBAL color model [9] to remove noise and many more image smoothing techniques.
II. Image segmentation: the disease affected area is segmented from the leaf. For segmentation various methods are used such as k-nearest neighbor method [1], triangle threshold method and simple threshold methods [8].
III. Disease classification: For disease classification numerous algorithms are available. SVM is the most commonly used algorithm [1] [20], followed by Artificial Neural Network [5] [18], genetic programming [16] [17] [19], Histogram matching method is also used with edge detection [7].

One of the major drawback that found in SVM that it deals with binary system and can classify only 2 inputs. Histogram matching methods gives result with poor accuracy.

III.PROPOSED METHODOLOGY

Digital camera or mobiles with better resolution are used to take images of leaves of different diseases, these images are used in identifying the affected area in leafs. Various image-processing techniques are applied on them, to process raw images, to get useful image for further processing and analysis.

Algorithm written below illustrated the step by step approach for the proposed Image segmentation and disease classification processes:
1. The first step is Image acquisition, step that requires capturing an image with the help of a digital camera or mobile with better resolution.
2. Image is smoothen using Kurtosis and skewness filters.
3. Perform the image segmentation using inverse difference method to part diseases affected area from the leaf. After this stage two images are available, one with the only diseases and one with disease extracted image.
4. On this segmented image feature extraction is performed. Segmentation is the methodology in which texture and color of an image are considered, to get the unique features from the image.

Over the outdated gray-scale representation, in the visible light spectrum, an additional feature is available for image characteristic. There are three key mathematical processes in the color co-occurrence method. First is the conversion of the RGB image of a leave into HIS color space an additional feature image. After completion of this process, to generate color co-occurrence matrix, every pixel map is used, which results into three color co-occurrence matrices, one for each of H, S, I. Features called as texture features, which include Energy, Entropy, correlation and homogeneity as given in equations (1),(2),(3),(4).

Energy: Energy also means angular second moment or uniformity. The more homogeneous the image is, the larger the value. When energy levels are nearer to 1, more the image believed to be a constant image.

$$\text{Energy} = \sum_{i=1}^{Ng} . \sum_{j=1}^{Ng} . P_d(i,j) \ldots\ldots\ldots (1)$$

Entropy: Entropy is a measure of randomness of intensity image.

$$\text{Entropy} = \sum_{i=1}^{Ng} . \sum_{j=1}^{Ng} . \text{Pd}(i,j). \log(\text{Pd}(i,j)) \ldots\ldots (2)$$

Correlation: This feature measures how correlated a pixel is to its neighborhood. It is the measure of gray tone linear dependencies in the image. Feature values range from -1 to 1, these extremes indicating perfect negative and positive correlation respectively. µi and µj are the means σi and σj and are the standard deviations of Pd(i) and Pd(j), respectively. If the image has horizontal textures the correlation in the direction of 0 ° degree is often larger than those in other directions. It can be calculated as

$$\text{Correlation} = \frac{\sum_{i=1}^{Ng} . \sum_{j=1}^{Ng} . \ (1 - \mu i)}{\sigma i . \sigma j} \ldots\ldots\ldots\ldots (3)$$

Homogeneity: Homogeneity measures the similarity of pixels. A diagonal gray level co-occurrence matrix gives homogeneity of 1. It becomes large if local textures only have minimal changes.

$$\text{Homogeneity} = \sum_{i=1}^{Ng} . \sum_{j=1}^{Ng} . \frac{\text{Pd}(i,j)}{1+|i-j|} \ldots\ldots\ldots\ldots (4)$$

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TABLE 1 EXTRACTED FEATURE DATASET FOR TOMATO DISEASES USED IN DISEASE CLASSIFICATION

Disease name	Energy	Entropy	Correlation	Homogeneity
Early Blight	0.45	3.53	0.977	0.9746
	0.5592	3.0096	0.9225	0.9207
	0.3618	4.5526	0.8886	0.9215
	0.3938	4.0277	0.9745	0.9347
	0.4822	3.106	0.9019	0.9313
Septoria leaf spot	0.5472	2.6786	0.9017	0.9237
	0.6427	2.6788	0.8535	0.962
	0.5502	2.6686	0.9019	0.9257
Bacterial Spot	0.4864	3.4299	0.9824	0.9905
	0.7467	2.318	0.8604	0.9594
	0.486	3.43	0.9814	0.9805
	0.4884	3.4199	0.9764	0.9925
Iron chlorosis	0.5768	2.6576	0.8751	0.9639
	0.5786	2.6756	0.8571	0.9631
	0.5771	2.6578	0.8753	0.9641

5. Classification of disease: In this stage of classification, feature dataset is prepared shown in table 1. Which is an extraction of the co-occurrence features for the leaves with the analogous feature values are stored in the feature dataset. Minimum 80 sample images per disease and chosen to extract features. Variety of Extracted feature values per disease are shown in Table 1. This is the training dataset for multy-class SVM algorithm.

Then Support vector machine classifiers used for classification. Support Vector Machines only classify data into two classes. The most common technique in practice has build one-versus-rest classifiers and to select the class which classifies the test data with highest margin. Another strategy is to build a set of one-versus-one classifiers, and to choose the class that is selected by the most classifiers. As the training data set for each classifier is much reduced to binary, it encompasses building classifiers, the time for training classifiers actually decrease. However, this is unsophisticated approaches to solving multiclass problems. A better alternative to this problem is the construction of multiclass SVMs, where we build a two-class classifier over a feature vector $\Phi(\vec{x}, y)$ derived from the pair consisting of the input features and the class of the datum. At test time, the classifier chooses the class $y = \arg.\max_{y'} \vec{\omega}^T \Phi(\vec{x}, y')$. The margin during training is the gap between this value for the correct class and for the nearest other class, and so the quadratic program formulation will require this condition to be true.

$$\forall_i \forall_y \neq y_i \quad \vec{\omega}^T \Phi(\vec{x_i}, y_i) - \vec{\omega}^T \Phi(\vec{x_i}, y) \geq 1 - \xi_i$$

This broad method can be prolonged to give a multiclass design of various kinds of linear classifier

IV.RESULT

All the experimentation and paper related work is done in Matlab. Datasets are prepared with taking multiple images of each disease. Images are taken from different sources of camera, and at various locations near about radius of 100km, along with this images some standard images from different agricultural institutes are also used in preparing dataset.
The percentage accuracy is defined as the ratio of correctly recognized image samples to the total number of test image samples. The Percentage accuracy is given by Equation:

$$\text{Percentage Accuracy}\ (\%) = \frac{\text{Correctly Recognized Image Samples}}{\text{Total Number of Test Images Samples}} * 100$$

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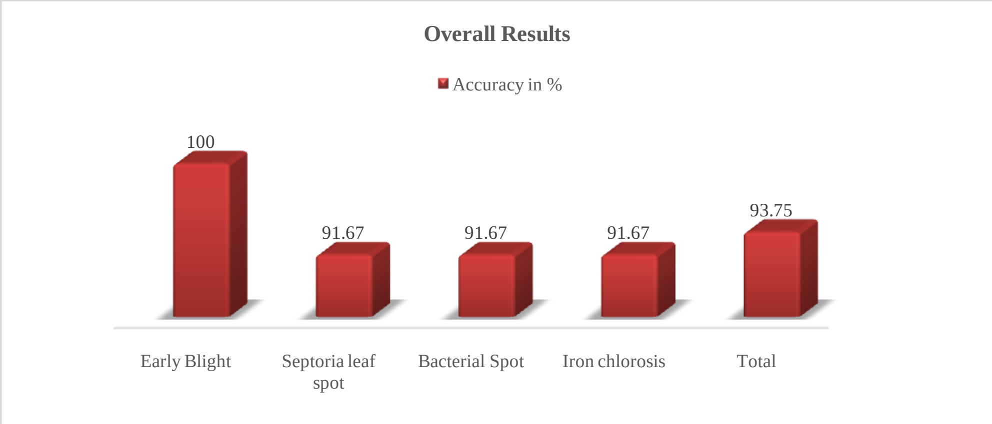

Fig. 2 Overall result

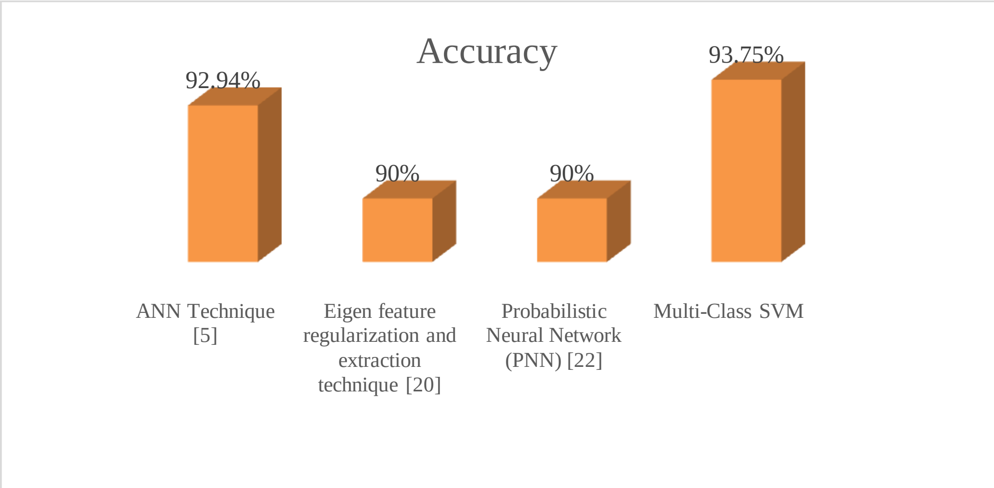

Fig.3 Comparison of Proposed technique with available techniques

V. CONCLUSION

For classification using Multi-class SVM model in MATLAB 15a is used. The Multi-class SVM model is trained with 80 images of one type of disease, totally algorithm is trained to detect four key diseases with 320 images. The remaining images are used for testing. Around 15% image samples are used for validation of the designed classifier model. With different parameters, the Multi-class SVM was trained. Once the training was complete, the test data for each class of leaves was tested.

The result shown in fig. 2 obtained using Multi-class SVM classifier for 4 different diseases. The proposed system result is compared with [5][20][22] in fig.3. The result reported better classification accuracies for all the disease and percentage accuracy is 93.75%.

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BIOGRAPHY

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