Analyzing Texture and Identifying the Disease of a Leaf using CNN

Dr. G. Umarani Shrikanth
Dept. of Computer Science
St. Peter's College of Engineering and Technology
Chennai, India

N.J.Jennifer
Dept. of Computer Science
St. Peter's College of Engineering and Technology
Chennai, India

M. Snega
Dept. of Computer Science
St. Peter's College of Engineering and Technology
Chennai, India

Vaishnavi Vijayan
Dept. of Computer Science
St. Peter's College of Engineering and Technology
Chennai, India

Abstract*—Plant disease is a major issue. Detection of Wetness and Dryness along with plant diseases, growth of leaf and color change is also essential. Detection of these isbenefited in monitoring large fields and also helps us detect disease symptoms once they appear on plant leaf. This process deals with four stages. Initially, for an input RGB image, color transformation structure in generated. Then, the pixels in green are masked and unfastened bysome specific threshold value followed by segmentation process. The texture data are reckoned for useful segments and drawn out feature are passed through classifier. This paper focus on the comprehensive survey various methods developed to solve the various diseases found on leaves.

Keywords: Scale-invariant feature transform; Convolution Neural Network; Rectified linear unit; Masking; Polling.

I. INTRODUCTION

Plant disease diagnosis is prime concern in the field of agriculture and it is main area of research. In Maharashtra there is loss 45% of cotton farm due to diseases on cotton plant. If misidentification takes place then this leads to loss of work, money and leads to major problem to crop. We are going to make system which can easily, accurately identifies the disease on plant. In this leaf image acquisition takes place then we proposed to proceed for image analysis part in which we are doing pre-processing of image, threshold of image using Mumford–Shah algorithm.

Scale-invariant feature transform algorithm extracts the feature. Using this result of SIFT feature the diseased and normal leaf is identified. In classification, using CNN process, the comparison of processed leaf image and database of different diseased leaf and normal leaf takes place. After this what type of disease is occur on plant is identified then what kind of precaution has to be takes on that plant. This system can reduce farmer's effort in identifying the disease on plant and taking precaution about pest and disease. In this paper the disease and wetness of leaf using image processing is studied.

II. LITERATURE SURVEY

The authors in [1] have proved that the image can be formed into networks. Using the process diffusion, the texture is layered. Image is carved as directed network and in further pixel isdetermined as a node. The directed network was the major contribution to this work which gave improved performance. The results surveyed showed that the method proposed was widely used in texture datasets. It also seemsto be a trust worthy method for plant species classification.

The image of textured surfaces was recognized by a texture representation introduced in [2]. During the stage of feature extraction, Harris and Laplacian regions were found, where those regions act as a texture component that has an elliptic shape and the pattern in distinctive appearance. In certain cases, where affine invariance is not required for recognizing the texture, the original elliptical shape is used.

The authors in [3] presented an efficient approach to gray scale that depends on local binary patterns. This was used for deleting the 'uniform' patterns for angular space quantization and spatial resolution. It was robust and simple in computation. The performance was increased by combining the binary texture with rotation invariance.

In this approach [4], a systematic filter selection method is proposed by reconstructing the image from sieved images based on the traits gained by exposing each filtered imagewith non-linear transformation measuring some quantity of energy around every pixel. A square-error clustering algorithm is also used to amalgamate segmented images by incorporating spatial adjacency information.

The authors in [5] proposed that the images which are blurred can be restored by a decomposition model using missed pixels. It was also assumed that the image underlying is the superposition of cartoon and texture component. An efficient numerical algorithm was introduced in additional by thesplitting version from an augmented Lagrangian method, in order to detect images. These methods which were developed recently not only gave the restored image but also an animated part was decomposed.

The authors in [6] stated that for Rotation, Scaling and Translation (RST) and invariant texture recognition, methods were introduced which are called as Bessel Fourier Moments (BFM) that have more zeros which were distributed evenly. It gave three testing sets of 16, 24 and 54 texture images. BFM also performs better in case of recognition and noise robustness in terms of RST texture.

In this approach [7], the edges of objects in an image are restored by using certain parametric and concepts providing more flexibility to curve design of the objects by interpolating their boundaries. Once the edges are restored using 2D texture. In additional to this, model parameters were also calculated by Yule-Walker method.

The authors in [8] represented the texture images as histograms that involve the local characteristics as vocabulary which efficiently proved the classification of texture tasks. The performance was also calculated using visual vocabulary which has been done geometrically, based on Griffin and Lealholm characteristics. This method was further classified to deal with variants in scale. Here, the algorithm used was simple where it required no pre training step to study visual dictionary.

In this approach integrated surface stamps found on statistical descriptors was presented in [9]. The signature existing now is a variant to 3D geometric transformations which turned to be a limitation for several applications. Multi-Fractal Spectrum (MFS), a texture signature is involved that includes view-point changes and non-rigid deformation as well as estimation changes of a texture surface. This is mainly done in order to view a better histogram with greater robustness. This was done with low dimension and hence the texture is classified.

This practice based on complex network theory was developed in [10]. The authors designed novel texture analysis to investigate how efficiency a texture of the depiction can be appeared, distinguished and inspected in caseof a complex network. The outcome manifested the approach, higher in robustness and presented excellent texture discrimination by using rung quantification to formulate a texture descriptor set.

Authors in [11] specified the variation in texture scrutiny formed on gravitational replica that specifies pap-smear cell images. Here the complexity descriptor and fractal dimensions are utilized to distillate signatures from gravitational fall down. In addition to this the performance of the process is enumerated and juxtaposed to LBP based elucidation to demonstrate texture analysis.

The authors in [12] explained Google page rank upon a directed configuration model. The dissemination of the rack of a selected node inserts a defied random variable that is a linear combination of exogamic result to fastened point where the real-valued vector is fixed.

The approach represented by authors in [13] assessed certain scientific areas in contributing to a new theoretical approach in the real world problems. Here, the problem on the basis of complex networks is emphasized and also represented by classifying diversities of phenomena and hence the impact of complex network field is clearly indicated.

[14] Local binary patterns are assumed to be the best computational, efficient and high-performance patterns especially in terms of texture features, in spite of its sensitivity to image noise. In order to overcome the demerits a novel descriptor called the Median Robust Extended LBP (MRELBP) is introduced for texture analysis. After a comprehensive evaluation, it was resulted that MRELBP gave increased performance. It is proved to be highly sturdy to Gaussian noise, Gaussian obscure and stochastic pixel corruption.

S.No	Author	Objective
1.	Wesley Nunes Gonçalves, Etal.	Directed networks provide better performance.
2.	Svetlana Lazebnik, Etal.	Performance is evaluated by comparing the texture with other well-known texture operators.
3.	T. Ojala, Etal.	Performance was increased by combining the binary texture with rotation invariance.
4.	A. K. Jain, Etal.	Square-error clustering algorithm is used to integrate the segmented images.
5.	A. M. Atto, Etal.	Efficient splitting version from an augmented Lagrangian method to detect images.
6.	C.-M. Pun, Etal.	BFM performs better in recognition and noise robustness in terms of RST texture.
7.	D. Vaishali, Etal.	Edges of objects are restored by certain parametric and geometric concepts providing more flexibility to curve design of the objects by interpolating their boundaries.
8.	M. Varma, Etal.	Texture images are efficiently represented as histograms that involve vocabulary and its performance using visual vocabulary is calculated.
9.	Y. Xu, Etal.	MFS texture signature is mainly done in order to view a better histogram with greater

		robustness.
10.	A. R. Backes, Etal.	Excellent texture discrimination by using degree measurements to compose a texture descriptor set.
11.	J. J. de Mesquita Sá, Etal.	Performance is enumerated and juxtaposed to LBP based elucidation to demonstrate texture analysis.
12.	N. Chen, Etal.	Issuing the grade of eccentrically chosen node from the graph that converges a finite random variable R*
13.	L. da F. Costa, Etal.	The impact of complex network field is clearly indicated.
14.	Li Liu, Etal.	MRELBP gave high performance, robust to grey scale variations with low computational cost.

III. SYSTEM ARCHITECTURE

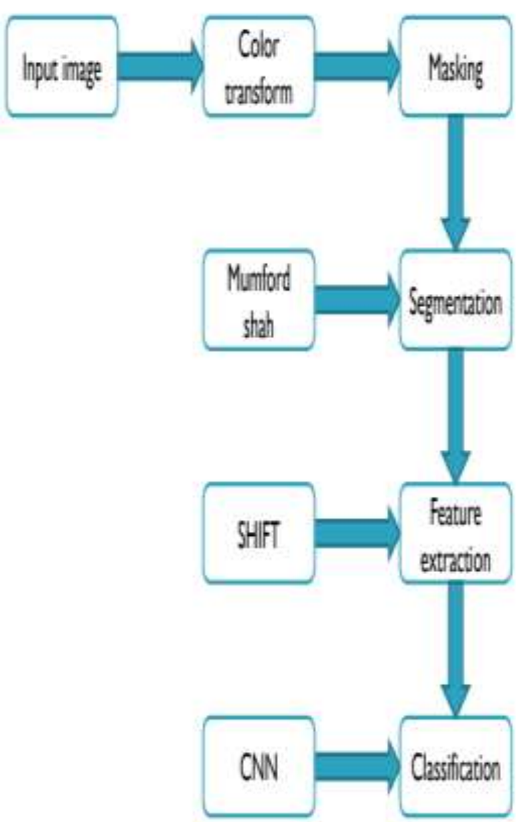

Fig.1 System Architecture

IV. PROCEDURE

1. Take the input in the form of image.
2. Transforms the input image into RGB and CMYK color spaces.
3. Then the image is converted into mask image.
4. Then mask image is segmented into sub regions.
5. The sub regions are modeled as a piece wise smooth function using Scale Invariant Feature Transform.
6. Create the network using Neural Network Tool Box.
7. Configure the network.
8. Finally the network is trained, validated and used.

V. RESULTS AND DISCUSSION

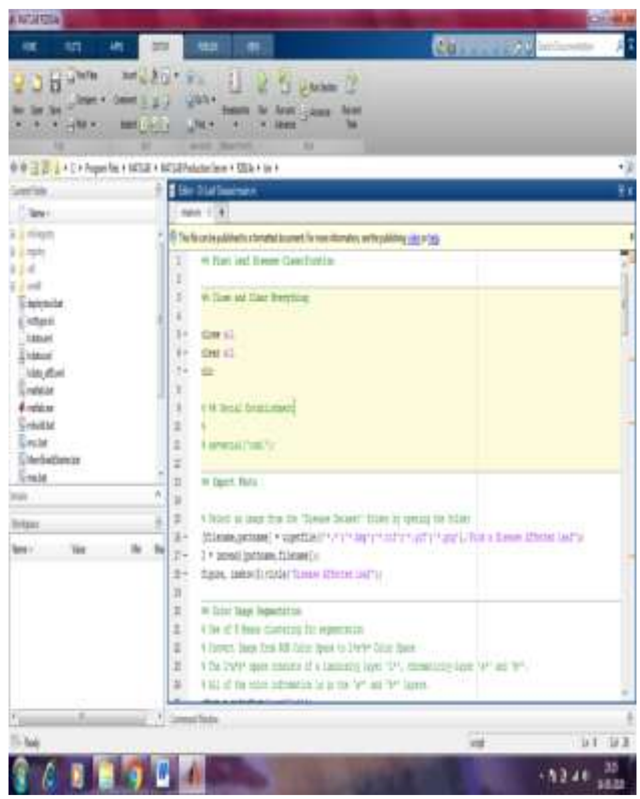

Fig.2 source program

To identify the leaf disease first we have to open the main.m file in MATLAB then run the code.

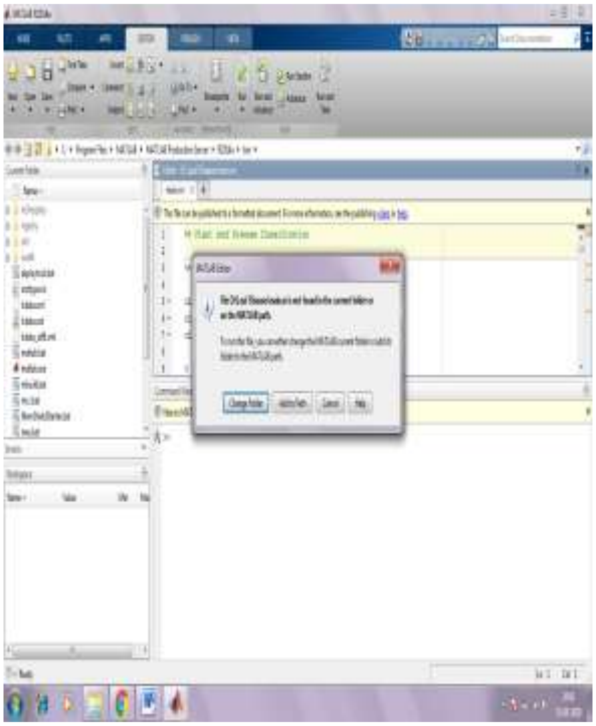

Fig.3 Choose the path

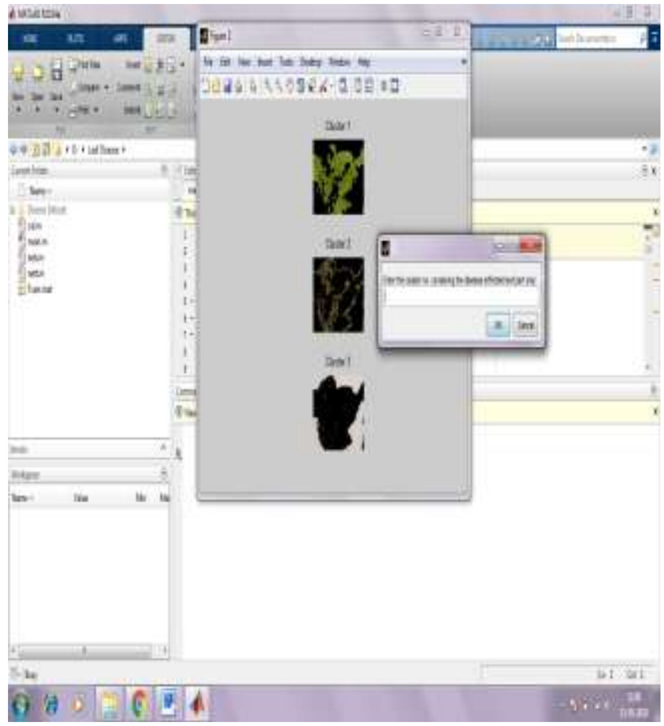

Fig.8 selecting the cluster

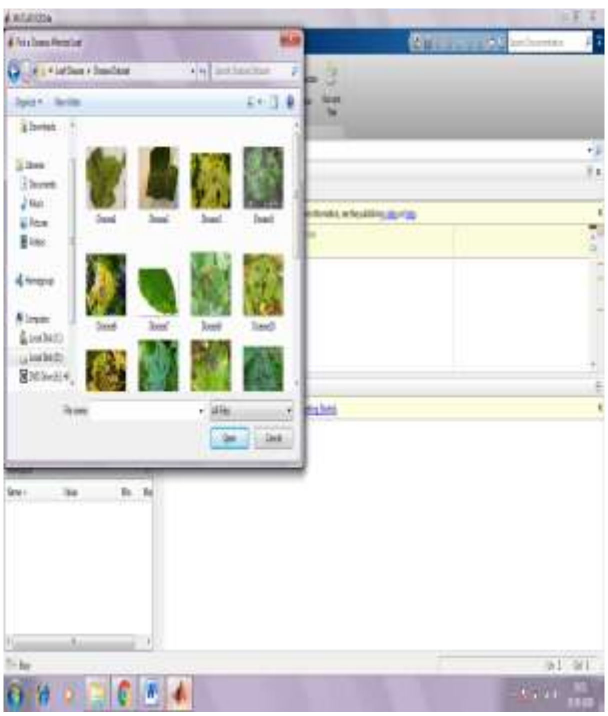

Fig.4 Select the image

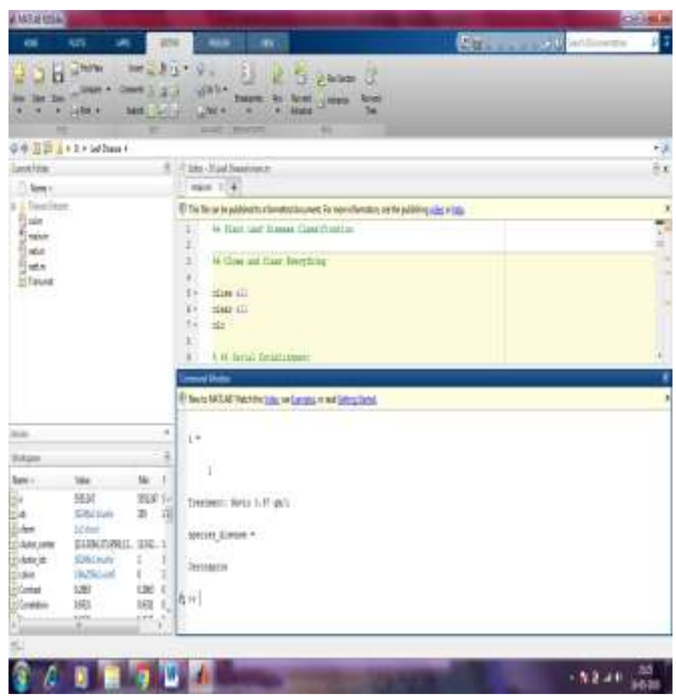

Fig.9 Output of the infected leaf

In figure 8 we have to select the appropriate cluster and figure 9 shows the treatment and species disease if the leaf is affected.

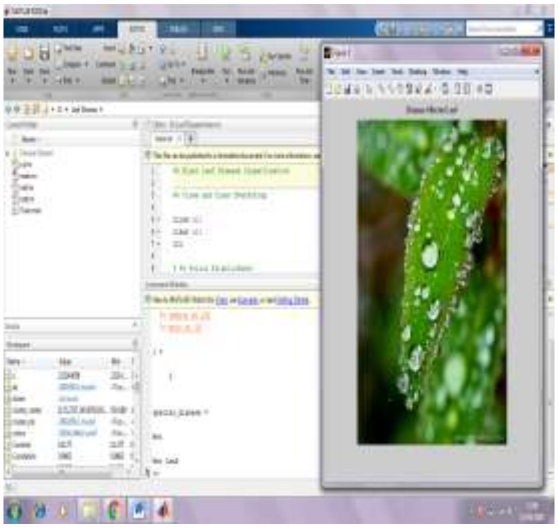

Fig.10 Output for wet leaf

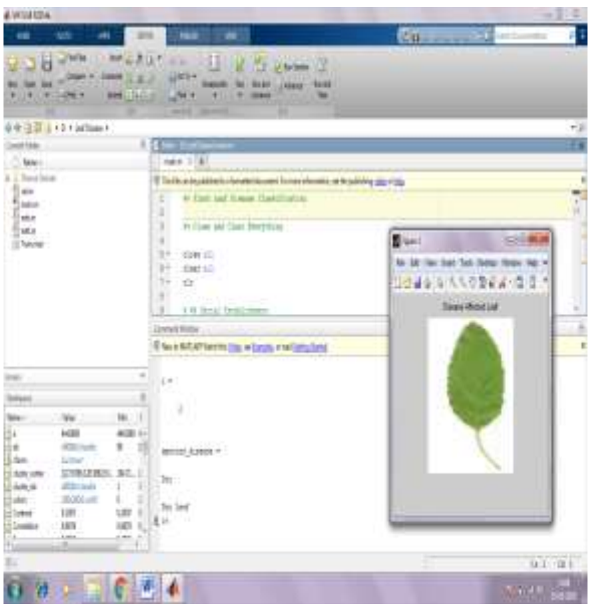

Fig.11 Output for dry leaf

VI. CONCLUSION

Image processing technique method is developed in order to make it useful for tomato plant disease detection. The vital purpose of this method is diseases identification based on less computational effort with four stages where the improved accuracy is gained by different image processing techniques such as image analysis, pre-processing, extracting features and categorizing. Here, the two essential characteristics are speed and accuracy.

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