An Image Segmentation Technique -OEM for Plant Leaf Disease

Shanmuga Rajathi D, D. Maheswari

Abstract: Image segmentation plays a vital role in identifying plant leaf diseases. Hence it is considered as categorizing of a test image as set of non-continuous regions which are varied according to the features and its characteristics of the image along its properties in terms of homogeneous and computation on the grey level, texture and color component to provide easy image analysis. Familiar existing techniques for leaf disease segmentation use watershed method, thresholding and region based method. One applying these techniques, particular lesion represents a varied shape, texture and Color properties which makes the complex in the segmentation. In addition, these methods face several challenges such as inhomogeneous object detection and fragmentation. To combat those challenges, a segmentation model named as Object Evolution Mapping (OEM) has been proposed in this paper. It is developed for discretized representation of the inhomogeneous object based on the weight probability with specified limits.

The disease affected area is considered as object, as affected region may appear in varied shape and texture, the proposed model strongly correlate those changes through error correction process. Furthermore abstraction building has been carried out by the objective function on the matrix for the determine the correlation of the pixel based on the shape and texture interpretation on the image. It extracts the inhomogeneous objects accurately by traversing the horizontally and vertically. Finally changes between the object is computed accurately on the each positions as pipeline procedure. Experimental results show that proposed OEM model provides the good result in terms execution time and accuracy on comparing it with existing approaches

Key words: Plan Leaf Disease, Image Segmentation, Error Correction, Shape and Texture Analysis.

I. INTRODUCTION

Early recognition and prediction of plant leaf diseases is a primary aspect in the agriculture area. The background complexity of the image and its multiple affected symptoms regions are complex to detect by the image representing the plant disease. [1] Plant leaf disease prediction model developed in the last decade's leads to classification error. The inclusion of the multiple affected symptoms on particular regions will be identify the affected image boundaries, numerous characteristics [2] [5] of leaf lesion symptoms on the affected region, its large existence noise, changes in the condition of illumination and finally color variation among different category of symptoms. The lesion region has been differentiated in shape, [11] color and texture properties which make the detection process of the learning model to be difficult and it is later employed in the classification stage for effective discrimination. The classification error can be eliminated by initialing the process with image segmentation.[8] [13]

The familiar existing techniques used for image segmentation is thresholding method, [10] [7] region detection based methods, edge detection based methods, watershed based methods and finally clustering based methods. The partial differential equation has also been employed for identifying inhomogeneous object but it leads to fragmentation error. [14] Moreover, several challenges arise due to the shape of disease region, changes in color feature and texture feature and finally due to change of origin and scale. To handle these challenges, [6] new technique named as object evolution mapping has been proposed in this work based on the computational abstraction and correlation of the evolution objects of the pixel. [3]

The reminder of paper is organized into various sections which are as follows. The review of the literatures is discussed in the Section 2 which is followed by brief introduction and description of the proposed technique in the section 3. Experimental results and performance analysis on various performance metrics has been carried out in the section 4. Finally Section 5 concludes the work with future work.

II. LITERATURE REVIEW:

In this section, various image segmentation techniques employed to plant leaf disease image has been has been summarized on different constraints and characteristics.

A. Plant leaf disease image segmentation using genetic algorithm

In this model, genetic algorithms have been used for image segmentation as it belongs to category of evolutionary algorithms. The model generates partitions on the image. It has been considered for image segmentation with optimization.[12] However It is carried out based on the population. Population is considering as set of solutions which is computed based on the fitness function. The fitness function is estimated for each population (feature) on utilization of Euclidean distance between the pixels. Population of the image is initialized in each iteration. Genetic algorithm [9] generates population (partitions) for the input image based on the selection, cross over, Mutation and offspring process. Population generated is classified based on fitness vale into several classes.

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B. Plant leaf Disease image segmentation using Region based Growing method

The objective function employed for the segmentation examines neighbouring pixels for the input pixel and computes possibility of including the pixel neighbors to the specific region. [4] Input pixel selection is employed with some user criterion. The region grouping is carried out based on the several criteria's for region membership through iteration. [10] Regions are iterated until there is no change in features on continuous iterative stages. Finally it segments the similar pixel of the each iteration into regions.

III. PROPOSED MODEL

In this part, the architecture of the proposed model is defined in detail on several aspects

A. Image Pre-processing

The dataset contains most familiar issues such as noises in the images, brightness of the image and change of the illumination on various origins which has been eliminated using data pre-processing. The data pre-processing carried out using noise filtering, color differentiation and image normalization method in parallel. The difference on color with each pixel in the image to be partitioned has been improved on employing the color differentiation technique. Contrast of the image on changes in illumination level has been improved using image normalization process on the various ranges of values on pixel intensity values which is rarely meant as contrast stretching.

B. Discretized Representation of objects

Discretized representation of the object is used to convert large number of pixel value into smaller counterparts based on the constraints such as maximum probability, contrast and inhomogeneity. It finds a function space with a reasonable finite number and it comprises a proper approximation. Discretization representation maximizes the interdependence between the pixel counterparts and it minimizes information loss. Each pixel membership value within a certain interval for a specific region may differ with a change of the discretization. The discretization can be achieved in following steps

- Interval boundaries have to be initialized to the pixels for corresponding initial discretization scheme.
- The new boundaries generation successively will results in the locally highest value of criterion.

❖ Probability Measure

It is considered as largest entry in the matrix based maximum difference of pixel intensity and it corresponds to the strongest response of region splitting. It reaches the maximum value in any specified matrices or the maximum in the overall matrix to select the counterpoint pixel using following function,

$$C_m = \max P_d[i,j]$$

❖ Difference moment

It is used to identify the evolution pixel in the image in order to partition it based on the distance conditions. The Difference Moment of the discrete pixel can be denoted as

$$DM_K = \sum\sum (i-j)^k P_d[i,j]$$

Contrast

Contrast is a calculation of the local pixel variations of the image. It is denoted by

$$C(L, D) = \sum\sum (i-j)^k \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} P_d[i,j]^n$$

Condition: If large amount of pixel variation in an image exist , it leads to greater changes due to P[i,j]'s on the concentrated away from the main diagonal and contrast will be high.

In home geneity

The Inhomegeneity is measure of variation of the pixel density on neighboring pixel on the co-occurrence matrix with the result of high and low P[i,j]'s

$$C_h = \sum\sum \frac{P[i,j]}{1+[i-j]}$$

- The range of gray levels in the cooccurrence matrix is small as P[i,j] tends to be least clustered on the axis of the main diagonal of the image.
- A heterogeneous image pixel will results in an even spread of P[i,j]'s on the axis of the main diagonals

C. Shape and texture analysis

Textures and shapes analysis of the image considers the important visual elements concerning the partitions and characterizing in an image. Shape analysis details the fundamental edges and boundary with high precision. Among the various analysis, Shape is the ensemble of all the geometrical information on the specified region of interest as the location and orientation of the object will be changing frequently. The figure 1 explains the architecture of the proposed image segmentation model for plant leaf disease.

Texture is characterized by the spatial distribution of intensity levels in a neighbourhood. Texture is a repeating pattern of local variations in image intensity. Texture cannot be defined for a point. Texture consists of texture primitives or texture elements, sometimes called texels. Texture segmentation is concerned with automatically determining the boundaries between various texture regions in an image

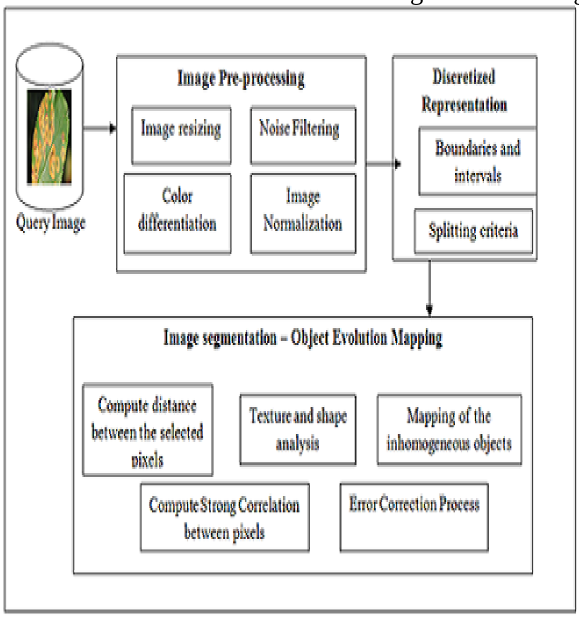

Figure 1: Architecture of the proposed image segmentation Technique

Texture analysis is mostly characterized by its pixel spatial distribution on various intensity levels of the pixel in a neighbourhood. Texture analysis evaluates the no of repeating pattern of the pixel on the image intensity. Texture analysis is considered for whole region as it does not specify the single region. Texture analysis carried out using either primitives or elements. Texture segmentation focused much on the boundaries as it automatically determines the varying texture regions in an image

- Texture analysis determines and describes the fine, coarse, grained and smooth properties of the pixel. Those features commonly refer the tone and structure of a texture.
- Tone refers to pixel intensity properties of the texel in each pixel while structure refers the spatial relationship between the portioned pixels.

The texture can be categorized as

- Structural analysis: In this texture considered as intensity variation of the pixel on the arrangement of the color relationship.
- Statistical analysis: In this context, texture distribution is considered as a quantitative measure of the arrangement of intensities of the pixel on the various regions which sometimes called as feature vector.
- Modelling analysis: texture modelling techniques involve constructing models to specify textures.

Range function

Range function is the simplest texture operators which compute the range value of the pixel or its pixel difference of the contrast between maximum and minimum intensity values of the pixel in the specified regions with reference to its neighborhood. The range operator is used to convert the image into the brightest image for the texture analysis.

Variance Function

Variance function is used to measure the placement of primitives and illuminations on the sum of the squares intensity of the centroid pixel and its neighbors with respective to the intensity. Further difference is computed using color level co-occurrence matrix (CLCM) which contains geolocation information about the positions of pixels which has the similar color values.

Color level co-occurrence matrix

A Color level co-occurrence matrix is considered as two-dimensional matrix array which consists of P rows and Q columns to denote a various set of set of solutions with image values of the each pixel.

CLCM Pd[k,l] is considered as displacement vector

d_i= (du,dv) is intensity of pixel

Position of pixels separated by d having color levels

$$P_d\,[k,l] = n_{ij}$$

Where nij is considered as number of occurrences of the pixel values on the intensity (k,l) at distance d in the image taken for segmentation.

Co-occurrence matrix Pd has specified dimension x*y, where x is the number of Color levels in the image and y is no of the diagonals.

Algorithm: Normalized GLCM

Measure the similarity pairs of pixels.

- First pixel value is considered as i,
- Matching pair displaced from the first pixel is denoted as d with the value j.

The Computation for the pixel count = C_p which is considered on the ith row and jth column of the matrix Pd[i,j]

The value of Pd[i,j] is not symmetric on the pixel intensity,

If (pixel intensity is not symmetric)

Number of pixel pairs having Color levels [i,j] at first pixel will almost equal to the number of pixel pairs at specified interval having Color levels [j,i] at neighbour

The pixel elements of P d[i,j] can be normalised by dividing each pixel into various pixel pairs which is as follows

$$N_d[i,j] = \frac{P[,i,j]x(u,V)}{\sum\sum X(u,V)P[,i,j\}n}$$

The above the image normalization function contains the pixel value in the co-occurrence matrix between 0 and 1, and some cases it occurs in the probabilities. Color level co-occurrence matrices capture properties of a texture and shape analysis in addition for effective computation.

Algorithm: Object Evolution Mapping based Segmentation

- User criteria for the input pixel selection
- Compute the weight vector of the image
  - Choose any input pixel in the image vector
- Employ Euclidean distance to compute similarity of the input pixel and other pixel in the image
- Track the Image pixel produces the smallest distance with input pixel
  - Update the weight of the each image pixel on the matrix to the weight of the input pixel based on the object Evolution membership function
- W (S+1) = W (S)
  - Correlation is used to analysis the image linearity on the pixels. Correlation produces the high value if an image contains a considerable amount of linear structure in the pixel placement.

$$C_e^{=\,-} \sum\sum [ij\ln P_d[i,j]-\mu_i\,\mu_j$$

D. Error Correction Process

The process identifies erroneous regions in the proposed model by cross validating with min-cut segmentation. The min cit model deforms the mesh in the pixel by correcting its vertex coordinates of the matrix on employment of Laplace deformation based on local geometrical properties of the texture analysis. The Laplace interpolation minimizes the squared gradients on the summation.

The selection of the displacement vector is an important parameter to optimize the segmentation results. To obtain the error free surface, Dirichlet boundary conditions has to be applied in addition to Laplace interpolation using following equation

$$E\,(L_{ij}) = \sum\,(L_{ij} - L_{im})$$

Error correction process is used to locate the edges and boundaries of the image which t result on the intensity transitions of the pixel on the analysis.

IV. EXPERIMENTAL RESULTS

In this section, to compute the performance of proposed model the accuracy and robustness has been considered. The experimental studies have been conducted in ImageJ library in Java platform. Initially dataset has been described in detail which followed performance analysis.

A. Dataset description

Plant village dataset has been used as benchmark dataset for segmentation of the images. It consists of 54,306 images which contain both diseased leaves and healthy leaves of plant collected under different controlled conditions. The image resize process is applied to resize the images to 256 × 256 pixels. The distribution of the matrix will be large during the iteration of the pixel on the different intensities.

B. Performance analysis

Across the experiment, a coloured version of the Plant Village dataset has been carried out. The accuracy of segmented images is evaluated and cross validated with corresponding ground truth images segmentation results in numerical form. The segmentation accuracy of the proposed method computed gives 98.79%. Table 1 represents the performance of the image segmentation methods for specified dataset

Table 1: Performance Evaluation of the Image Segmentation Technique

Technique	Accuracy	Execution Time
Object Evolution Mapping – Proposed	98.8	25.58ms
Region based Growing Method	96.6	35.56ms
Genetic Algorithm	95.8	41.27ms

○ **Accuracy**

Accuracy is expressed as changes in the volume of delineation and confidence interval (CI) to express the range of variation on the color pixel on the specified location. Confidence interval is the s a measure of the dispersion of the pixel weight of input pixel and neighbourhood pixel in the partition. In another words, accuracy is defined as percentage of similarity between the classified instances to the cluster.

$$\text{Confidence interval} = \sum(WC_v - WC_e)$$

Accuracy = 100- changes in (weight of instance 1 – weight of Instance 2)

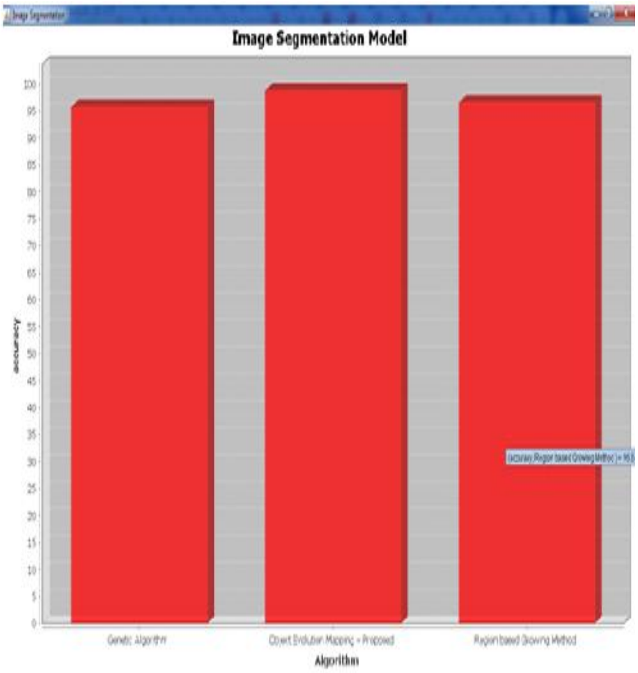

Figure 2: Evaluation of the Accuracy

The figure 2 indicates performance analysis of image segmentation technique in terms of the accuracy.

Execution Time

Execution time mentions to the viability of a segmentation method with respect to time required to complete segmentation on the iteration of the pixel.

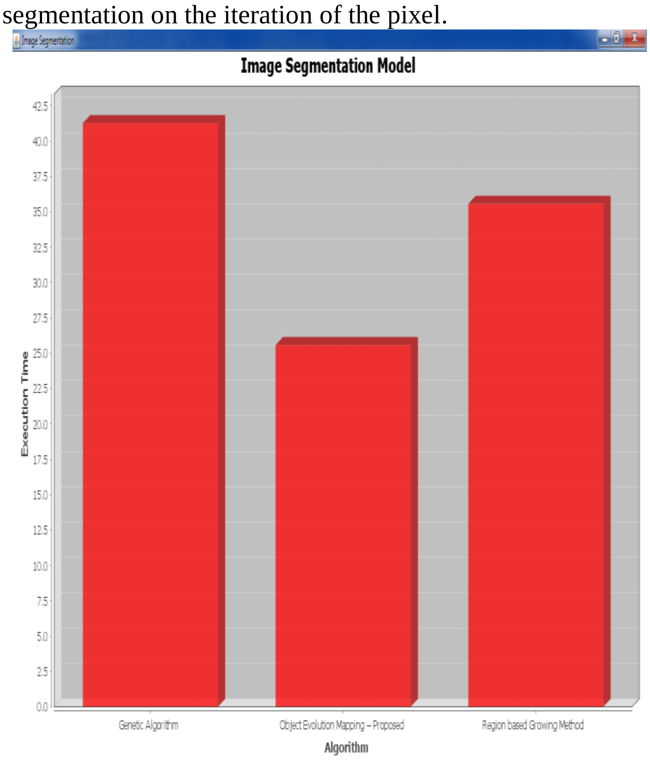

Figure 3: Evaluation of the Execution Time

The figure 3 represents the evaluation of the execution time for the image segmentation techniques.

V. CONCLUSION

The Object Evolution Mapping segmentation model has been designed and implemented to the plant leaf disease images.

The image segmentation process correlates the similar pixel and object growing pixel together. Weight of the pixel is computed for pixel in the matrix and it is iterated with Euclidean distance measure. The results indicate the superiority of the proposed model on segmentation of diseases region exhibiting the color, texture and shape evolution. The proposed model is also simple and flexible to extracting the variation and non homogeneity characteristics of the objects. The proposed model produces the high accuracy on the segmented objects instances.

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