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LEAF DISEASE RECOGNITION USING SEGMENTATION WITH VISUAL FEATURE DESCRIPTOR

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Abstract

Agriculture has become the main sources of the income for many developed countries. The productivity in agriculture can be affected by various diseases present in the plant due to climatic conditions. The key step to improve the productivity of crops are to detect the disease at the preliminary stage. Automation becomes the best solution for this because it is more difficult to observe the disorders in plants parts. For that an image of affected plant leaf is acquired and segments the affected portion and to recognize the disease by using image processing and computer vision and machine learning techniques. The extracted features from the segmented portion are descripted using Global and Local Visual descriptors. Finally, we use the classifier to recognize the disease. Extracting a meaningful feature from an image is a central problem for a variety of computer vision problems like recognition, image retrieval, and classification. In this research, visual feature descriptor that best describe an image with respect to its visual property is explored. It is specifically focusing on recognizing tasks. The experimental results have proved that the combination of visual descriptors with various classifiers such as SVM and Ensemble Classifier produces high quality outcomes when compared to individual descriptors.

Keywords:

Duck Search Optimization based Image Segmentation, Grey Level Co-Occurrence Matrix, Scale-Invariant Feature Transform, Support Vector Machines, Ensemble Classifiers

1. INTRODUCTION

Economy of our nation highly depends on Agricultural productivity. Farmers of our nation are dealing with varieties of crops every year. If farmers fail to pay proper attention or lack of awareness about crops leads to harmful effects. Noticing the plant disorders at early stage is a major concern. It is highly complicated task to observe the disorders in plants physically. It necessitates huge volume of effort, more proficiency in the plant ailments, and also takes extreme processing time. Discovering the infections in the plant is the first step to prevent such harmful effects. It is very tough to observe plant infections physically. It necessitates a huge volume of effort, more proficiency in the plant ailments, and also takes extreme processing time. Discovery of weeds, categorization of fruits, ordering of grains, identification of food stuff, therapeutic herb recognition etc can be established by Computer Vision Systems (CVS) [13].

Photographic images of plants/food items/grains could be taken to extract the useful features that are really required for further analysis. Making use of digital cameras is a wise decision in this process. Appropriate discovery of infections in plant is not an easy task. More awareness on this domain is required to carry out this process. Usually, notable symptoms can be an indicator about diseases in plants. Such kind of symptoms will definitely help the researchers to take some timely decisions. The images of the infected plants play a major role in the areas of research, teaching, diagnostics, etc.

Experts involved in the process of plant disease identification usually adopt digital images [4] by means of accustomed tools during their analysis. Conventionally, this identification of plant diseases is carried out manually. Later on, it was clearly understood that this manual process needs so much of money for proper discovery. This means, hiring an expert for is case is very expensive, and thus it has become evident to identify these symptoms in an automatic way. That is to carry out disease discovery in plants without even minimum level intervention of humans. If this automatic process is initiated, huge amount of loss can be avoided and productivity can be very well improved. This can pave a way for smart agriculture in future.

The major focus of the researchers is automatic detection of diseases in crops and thus they have made use of several techniques of image processing and artificial intelligence. Alternatively, smart robots [3] were also used by a group of experts. Web camera [21] is an important part of smart robot which helps to capture the images of plants and its leaves. These images are considered to effectively identify the ailments in herbs. Also, this approach has some difficulties, for example, if the captured image compromises on clarity, the result will be obviously inaccurate.

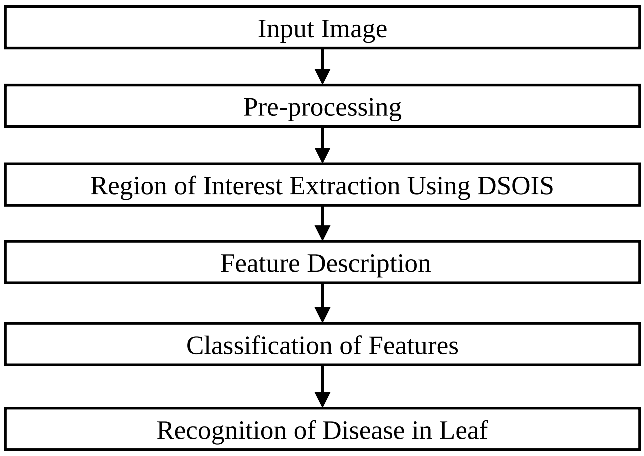

Fig.1. Overall architecture

Thus, it is essential to come up with an approach that is exclusively software based. By taking the images of plants, extraction of disease part and its recognition can be done with the help of automated methods. Disease in the plants is noticed by some abnormal patches or spots present in different parts of the plant such as stem, leaf, flower, fruit, root, etc. [6]. The leaf part of the plant highly influenced by the healthiness of the plants. So, appearance of leaf image is taken as a main source for recognition of disease in the plants.

Recognition of disease in images can be performed by various phases like Image segmentation, feature extraction and recognition of disease. Image Segmentation is the process of partitioning the digital image into different sub-sections. Feature extraction is process of simplifying the representation of the image into something meaningful one. Based on the representation, various diseases in the leaf image are recognized. Plant Leaf Image was taken by digital camera or mobile camera. Noise in the image can be removed by median filter, DWT filter, CNN technique, etc and then the image can be enhanced to highlight the image details. The region of interest is segmented from the plant leaf image. Next, appropriate feature is extracted from the image and the feature descriptor is formed. This descriptor is given to the Classifier for recognizing the disease present the image.

2. LITERATURE SURVEY

Many researches have been undergone to detect, classify and recognize the disease in plant with various parts utilizing image processing and machine learning techniques. Disease in Plant are happened by factors such as bacteria, virus, fungi, climatic conditions, etc. Many diseases have same symptoms. It is difficult to find the appropriate disease of the plant. This problem is solved by using various technologies like Image processing, computer vision, machine learning, deep learning techniques, etc. In this paper, feature extraction used for recognition of diseases is proposed. This section gives the survey of various feature extraction method used in plant disease recognition. Bakhsipour et al. [1] extract shape features by Fourier descriptors and Moment Invariance from the image for robotic weed detection. GLCM texture are used for retrieval of similar image from the database. Kulkarni et al. [2] proposed color feature, texture features with Gobor filter for early and accurately recognize the plant disease detection and gives 91% recognition rate with ANN.An image processing procedure is recommended for detection of Soybean infection [5] and its exactness.

Waghmare et al. [6] proposed a system for Grape plant disease detection and classification using opposite colour local binary pattern features from the leaf images and the automated decision supported system. Herdiyeni et al. [7] used LBP texture feature for classification of medicinal plants. Hlaing et al. [8] proposed a combination of statistical information extracted from texture and color features of the leaf image for tomato plant diseases classification using Scale Invariant Feature Transform (SIFT) for texture information and color information from the RGB channel. Mohan et al. [9] proposed disease recognition in paddy plant by using Scale Invariant Feature Transform (SIFT). Jana et al. [10] used GLCM feature with SIFT can be used for classifying the pepper plant disease. Color and Shape features are used by Joshi et al. [11] for rice leaf disease classification. Jun et al. [12] proposed SIFT features for sunflower leaf disease detection. Neumann et al. [14] proposed the first order and second order statistical features for beet plant disease classification.

Babu et al. [15] Proposed GLCM texture feature extraction method with K-means for image segmentation and KNN for classification of disease in leaf. This method gives 70 to 75% for different plant leaf inputs. Bashir et al. [16] used Color and texture features for Malus domestica plant disease detection with K-means clustering, Bayes classifier and principal component Analysis. Texture features are extracted by GLCM and LBP are proposed by Devi et al. [17] with K-means and SVM Classifier. Kumar et al. [18] used the combination of SIFT and SURF features are used for plant species identification. Sathwik et al. [19] used texture feature to identify and classify medicinal plants. Local statistical and Gray Level Co-occurrence Matrix (GLCM) features are extracted to differentiate the infected plant image and unindicted plant image by Sengar et al. [20]. Tigistu et al. [22] proposed texture features extracted by Gabor feature extraction method for flower disease detection system with artificial neural networks.

3. METHODOLOGY FOR PLANT DISEASE RECOGNITION

The plant disease recognition is a five-step process. It encompasses image acquisition, pre-processing, segmentation, feature extraction and classification.

3.1 IMAGE ACQUISITION

The digital images of leaves are captured with the help of a mobile camera or digital camera and that could be considered as an input for the identification system. The system has to recognize the infection in this input image.

3.2 IMAGE PRE-PROCESSING

Before extracting the relevant features from an image, it is evident to pre-process it. The phases in image pre-processing are- Image cropping, image transforming and image enrichment. Only the infected area of leaf is focussed and rest of the image is ignored in image cropping. Once the infected area is pointed, it could be transformed to grey stages. In this procedure the outliers are eradicated in the input image to improve its excellence

3.3 IMAGE SEGMENTATION

Image segmentation is the procedure of distributing a digital image into diverse blocks. The primary aim of segmentation is to develop and/or modify the illustration of an image into something which is more important and less challenging to scrutinize. Image segmentation helps to give a better granular understanding of an image by the creation of a pixel-wise mask for the objects. It is the process to categorize each pixel in the image so that it can be divided into different categories or segments. To categorize each pixel, pixel-level features are taken into account. Pixel-level features are color, texture and edge or shape information. Various image segmentation techniques can be used in literature. Generally, Image segmentation techniques are based on Thresholding, Clustering, Similarity based and Discontinuity based techniques. In this research, Image can be segmented by using Duck Search Optimization Image Segmentation Technique. This is the nature inspired algorithm and it is based on the food searching behaviour of Ducks. Once the input image has gone through all necessary pre-processing steps, it can be taken for segmentation.

To evaluate the explanations from ducks' searching behaviour, the sequence of steps is listed.

Step 1: Various sets if ducks are collectively termed as population. Ducks of every set is responsible to optimize their movement during food search process.

Step 2: The tallness of a duck is more significant factor to regulate the hunting spot

Step 3: In general, ducks travel as a gang and it won't travel beyond their local guide.

Step 4: Once the job is done, ducks would reach to the spot as a gang through a proper communication factor.

Step 5: When there is a scarcity in food for a certain group of ducks, it will migrate to some other spot.

Step 6: Finalize the optimal solution. Else, go to step 2.

Its pseudo code is given as below.

It consists of five stages such as Initializing the duck population, Evolution and Reproduction, Competitive exclusion, Computing robustness and Identification of optimal solution.

Here, D_{td} denotes tallest duck; D_{te1} and D_{te2} are two temporary ducks in duck group.

Step 1: Initialize $D_{td}= D_{te1}= D_{te2}= \Phi$;

Step 2: Set the greatest Duck D_{td} as D_{te1}.

Step 3: Randomly select D_{te1}, D_{te2} using random () function.

Step 4: Check robustness of $D_{te1}$and robustness D_{te2}.

Step 5: Set the Greatest Duck D_{td} as D_{te1} If robustness (D_{te1}) ≥ robustness (D_{te2}) else set $D_{td} = D_{te2}$;

Step 6: Go to step 3 while end condition is satisfied;

3.4 VISUAL FEATURE DESCRIPTOR FOR FEATURE EXTRACTION

It is an important step and the recognition procedure be determined by the set of features. Extracting appropriate features is essentially dimensionality lessening which is carried out to successfully denote the remarkable portions of unhealthy region in a compact form. Outline, shade and surface-based attributes signifies different leaf-based classification attributes. Color is one important aspect in finding healthy or unwell leaves. The shade of the contaminated area is different from healthy area. Likewise, the texture of the infected area he determines the nature of ailment and can be used as a major forecaster. The description of Visual features present in images, videos are called Visual Descriptors or Image Descriptors. Visual descriptors can be Local or Global. Local descriptors capture low-level properties of the Image, and global descriptors signify the overall spatial information of the Image. This work proposes on describe the features using the Combination of Local and Global feature extraction technique. Various statistical feature extracted in this research are Color moments, Histogram, GLCM. This feature is derived from the image globally. Edges, corners, blobs are somewhat unique to that specific image which are interesting areas of an image. These are popularly called key point features or interest points. Local statistical features are extracted using SIFT with GLCM using these interest points. This new approach improves the performance of recognition than the state of art approaches.

3.4.1 Local Descriptors:

Local Descriptors are shaped by calculating features from the pixel region on neighbouring the interest point of the Image. Interest points may also state as *key points*. Interest points may be considered as a set corners, edges or contours, and regions such as blobs. In this research, Interest points are used as local features. SIFT algorithm is used to extract image features.

- **SIFT:** Several features would be present for a single feature, stimulating facts on the object can be mined to offer an attribute depiction of the object. This portrayal can then be considered while attempting to discover the object in an input image encompassing additional objects. There are many concerns while mining these attributes and the ways to save them. SIFT image attributes offers a bunch of features of an object that are not influenced by several difficulties that occurred in former approaches, like object scaling and rotation.

However, permitting an object to be familiar in a higher input image, SIFT image attributes also let for objects in numerous images of the identical position, retrieved since dissimilar places inside the location, to be documented. SIFT attributes are highly robust to the impact of outliers in the input image.

SIFT image attribute generation, considers an image and converts it into a huge assembly of narrow attribute vectors. Every attribute vector is common to any scaling, rotation or transformation of the input image. To support the mining of these attributes the SIFT procedure relates a 4-phase screening approach:

- **Scale-Space Extreme Detection**: This phase of the filtering aims to recognizing the positions and scales that are distinguishable from diverse outlooks of the similar object. This can be proficiently attained by means of a scale space function. Additionally, it has been revealed with sensible conventions and it is essential to establish the Gaussian functions. The scale space is denoted by:

$$F(a,b,r) = GF(a,b,r)*L(a,b)$$

where,

* denotes convolution operator,

$GF(a,b,r)$ - variable-scale Gaussian

$L(a,b)$ - input image.

- **Key Point Localization:** This phase aims to eradicate additional facts from the list of key points by identifying those which has got minimum gap or improperly located. This is attained by estimating the Laplacian, where the significance for every key point is discovered in phase 1. The position of A, is

$$A=\frac{\delta^2 M^{-1}}{\delta N^2}\frac{\delta M}{\delta N}$$

When the function value at A is lower than a threshold value, then this point is omitted. This eliminates extrema with small difference.

- **Orientation Assignment:** This phase targets to allocate a steady alignment to the key points with the help of confined image properties. The key point descriptor can then be expressed in terms of this alignment, resulting in rotation invariance. The following is the approach used to discover an orientation:

Step 1: Utilize the key points scale to choose the Gaussian curved input image L

Step 2: Calculate gradient magnitude, m and Calculate orientation, θ

Step 3: Arrange a positioning histogram from gradient alignments of trial values

Step 4: Trace the maximum peak in the histogram.

Step 5: Utilize this highest point and additional limited peak below 80% of the elevation of this peak to generate a key point with that alignment

Step 6: Certain points will be allocated numerous alignments

Step 7: Fit a parabola to the 3 histogram values nearby to every highest to incorporate the peak's location

- **Key point Descriptor:** The local gradient data is considered for generation of key point descriptors. The ascent data is revolved to link the alignment of the key point and then prejudiced by a Gaussian through modification of 1.5 * key point ruler. This information is to generate a group of histograms above a window positioned on the key point. This naturally practices a group of 16 histograms, associated in a 4×4 grid, with 8 orientation cases. This leads to an attribute vector that contains 128 features.

3.4.2 Global Descriptors:

A Global Descriptor is a generic description of the whole Im age. Global features include contour representations, shape representations, color and texture features. In this work, Statistical Information about the entire image is used as a Global Descriptor. This information is derived from Color, Histogram and texture of the image. In the image processing, function of spatial variation of the brightness intensity of the pixels is defined as Texture. A very important role for texture analysis is played in a variety of computer vision cases, including object recognition, surface defect detection, pattern recognition, and medical image analysis. Since now many approaches have been proposed to describe texture images accurately. Feature extracted from Texture are classified into four categories: statistical methods, structural, model-based and transform-based methods. Gray Level Co-occurrence matrix (GLCM), Gabor Filter Response, and Local Binary Pattern etc are used to extract texture features. Statistical properties of the spatial distribution of grey levels are used as texture descriptors that can be derived by GLCM methods.

- **Gray Level Co-occurrence Matrix-GLCM:** Surface is more significant portion for sickness identification as it signifies more evidence associated to the unhealthy region. Here 10 surface attributes are mined from Gray-Level Co-occurrence Matrix (GLCM) of gray scale leaf image. The shade evidence is previously prearranged by means of color instants. The GLCM is considered over gray scale input image for which the boundary is resampled into 8 gray-levels. It estimates how often a pixel with a gray-level is positioned together to a pixel with the value *j*. The elements (*x*,*y*) of the GLCM matrix of 8×8 denotes the quantity of intervals that pixel with value *i* happened nearby to a pixel with value *j*.

For an image with 8 different gray-level concentrations, the GLCM *G* of measurement 8×8 is definite over *m*×*n* image *I*, with an equalizer parameter (Δ*a*, Δ*b*) formula in Eq.(1) terms it.

$$G\Delta a,\Delta a(x,y)=\sum_{a=1}^{m}\sum_{b=1}^{n}\begin{cases}1 & if\ l(a,b)=x\,\&\,l(a+\Delta a,b+\Delta b)=y\\0 & otherwise\end{cases} \quad (1)$$

where

x, *y* indicates the values of pixels

a, *b* denotes the positions in the matrix l of an image

Δ*a*, Δ*b* are offset values that denotes the spatial relation of the matrix

l(*a*,*b*) denotes pixel values at position (*a*,*b*)

Features extracted from GLCM are angular second moment, contrast, and correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, and difference entropy. In this research GLCM features have been computed between pixel distances.

- **Moments:** Moments are quantitative measures related to the distribution of information present in the data. The Probability distributions are categorized by a number of unique moment's. The color of an image was interpreted as a probability distribution. So, the moments can be used to gather the information from it. In RGB images, all the three components are detached and the first three low order color moments values of each component are computed. The three-color moments are mean, standard deviation and Skewness.
- **Histogram Features:** Next, the feature extracted from the image is based on histogram analysis and it is based on first order statistics. Histogram of an image is formed by counting number of pixels of each color and it represents intensity concentration on all parts of the image. In this work, no. of pixels of each intensity is derived from gray scale version of the original image and the feature vector is formed
- **Recognition:** Classifying images is an essential job that tries to realize and consider a complete image. The objective is to categorize an input image by fixing it with an explicit label. Normally, recognition of input images refers to images in which only one object is considered and is investigated. In addition, object discovery includes both categorization and localization jobs and is utilized to evaluate additional accurate cases in which several objects may occur in an image. The SVM and Ensemble Classifiers are adopted in this paper for effective recognition of infected images of plants.

3.5 SUPPORT VECTOR MACHINE

Numerous modern studies have stated that the SVM is highly proficient of bringing notable outcomes in terms of classification accurateness when compared to traditional classification procedures. It is a dual categorizer based on supervised learning that provides healthier performance than other classifiers. SVM categorizes among dual classes by building a hyper plane in large attribute space that can be utilized for categorization. Hyper plane can be signified by $v.x+t=0$, v is load vector; t is bias or threshold.

3.6 ENSEMBLE CLASSIFIER

It is a mode of producing several fundamental classifiers from which a novel classifier is extracted. This accomplishes superior than any essential classifier. Such fundamental classifiers may vary in the procedure used, hyper parameters, illustration or the preparation set. The main aim of ensemble classifier is to minimize unfairness and variance. Random Forest is the mostly used ensemble method where a number of decision trees are used to predict outcomes. Some of the commonly used ensemble techniques are Bagging, Boosting and Stacking.

Algorithm for Plant disease Recognition using DSOIS with Visual descriptors

Input: Infected Color Leaf Image.

Output: Class of the Disease to recognize

Step 1: For each image I=1:N where N is the total number of Input Leaf Image

- **a.** Pre-process the image to improve quality by reducing noise present in the image.
- **b.** Segment the Image to find the Region of Interest (ROI).
- **c.** Find GLCM features from the ROI and describe it as Global Descriptor (GD)
- **d.** Find Sift features from the ROI and describe it as Local Descriptor (LD).
- **e.** Find the Interest point from the ROI.
- **f.** Calculate the features using Histogram of Gradients, GLCM and describe it as Proposed Descriptor (PD).

Step 2: End for

- **a.** Use these descriptors as input for Classifier Algorithms SVM and Ensemble Classifier.
- **b.** Evaluate the performance of the Descriptors using the classifier algorithms

4. RESULTS AND DISCUSSION

The dataset entails around 1,500 images of leaf samples which have been segmented into healthy and infected parts. Local and Global features are taken per Image from the binary version of Region of Interest segmentation from the input image and are stored in a vector.

For experimental purpose SVM and Ensemble classifier is used to recognize the disease in a plant from duck search optimization-based image segmentation techniques with proposed descriptor. By comparing the descriptor with Global GLCM and Local SIFT features, the accuracy of the classification is more in Proposed Descriptor.

The performance of the proposed descriptor is evaluated by Accuracy, Precision and Recall.

Accuracy is computed by using number of correctly recognized disease to total number of samples.

$$Accuracy=(N_{True\ positives}+N_{True\ negatives})/N_{Total\ samples} \quad (2)$$

where,

$N_{True\_positives}$ is total number of True Positives

$N_{True\_negatives}$ is total number of True Negatives and

$N_{Total\_samples}$ is total number of Samples.

The Fig.2 shows the recognition accuracy of plant disease detection and it shows proposed Descriptor gives better recognition rate as compared to Local and Global descriptors respectively.

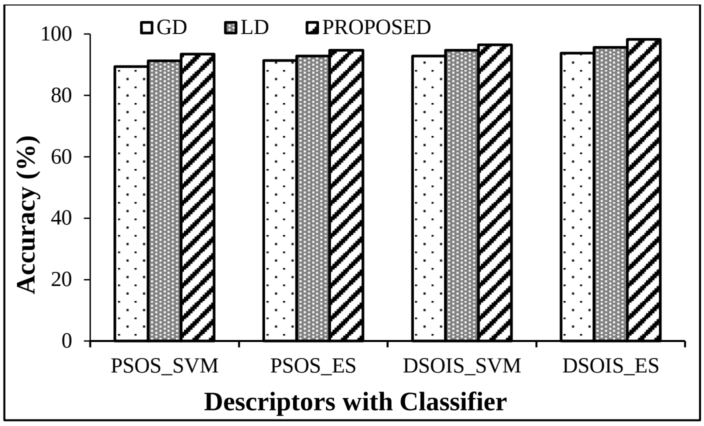

Fig.2. Accuracy

5. CONCLUSION

The problem of plant disease identification is addressed in this paper which is a major concern of farmers right now. From the studies, it is evident that identification and detection of such diseases cannot be handled manually. So, various image processing techniques such as image segmentation and feature description algorithms are discussed in this regard. Experimental results have shown that the proposed descriptors produce promising results when compared to Local and Global Descriptors respectively with classifiers techniques.

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