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Classification of Agricultural Pests Using Statistical And Color Feature Extraction And Support Vector Machine

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Abstract— Beetles and bugs are most common harmful pests that affect plants easily and can damage entire plant. Most of the beetles and bugs bruise the front surface of leaves to lay eggs so and some of the bugs feed on the extract of leaves. So, the leaves get damaged often and it is essential to detect pest affected leaves as early as possible to take further precautions. In this paper, an automated approach based on digital image processing and machine learning is used to classify three vulnerable pests - blue mint beetle, white mealy bug and red lily beetle from affected leaf images. Image pre-processing methods like noise removal and contrast enhancement followed by color space transformation and k-means clustering is used to segment affected parts of leaves, after that both texture and color features are extracted from segmented leaves and based on extracted features support vector machine classification method is used to classify the pests.

Keywords—Bugs, Beetles, Machine learning, k-means clustering, Feature Extraction, Support Vector Machine

I. Introduction

Plants are severely damaged by bugs and beetles in many stages of its life and when they are attacked it is difficult to save the plants in certain cases. So constant monitoring is required to increase the field yield and also sustain the quality of the plant and plant products. In warmer areas bugs and beetles not only affect the gardens but also the agricultural fields causing huge damage in trees and plants. The loss due to the same is in billions. There are several insects that are considered as serious threat for the agricultural field which cause huge loss to the people who are benefitted directly or indirectly from harvesting that particular crop. Rather than investing huge amount of money on killing the pests or re-growth of the crops it is better to detect the bugs whenever they attack the crop. There are several preventive measures that can be applied to kill these insects easily if identified properly. Using control measures without proper identification is pure waste and cause damage in plants as well. In this paper three insects are considered which are true threat for cultivation of several plants, i.e. a)blue mint leaf beetle b) red lily beetle and c)white mealy bug.

In this paper a method has been proposed to classify the insects stated above. It has been observed that the maximum bugs are of solid colour and their texture are quiet similar. So this method can be used to classify several other bugs as well. In the proposed method image processing with machine learning has been used to classify three vulnerable pests i.e. blue mint beetle, white mealy bug and red lily beetle shown in Figure 1.

(a) (b) (c)

Figure1. (a) Blue mint beetle, (b) Red lily beetle , (c) white mealy bug

Both male and female blue mint beetle feed on foliage and flowers of milkweed plants. They cause severe damage in plants by consuming large amount of leaf tissue.Red lily beetles are found mostly in warm climates in environment where humidity is high. The adults feed on foliage of lilies, fritillaries and other members of the family Liliaceae and lay eggs there as well. White mealy bugsare mostly found on greenhouse plants and feed with long mouthparts by extracting sap out of tissue of plants. They mainly damage plants like citrus, sugarcane, grapes, pineapple etc.

In the proposed method, at first the image is preprocessed. Then colourspace transformation is done to identify the proper segment [1] of the affected area and also once again the changed colourspace is used to identify the colour and texture features of the images. Finally the set of features are used to train support vector machine classifier [2] which can be used later to identify the pest that has affected the leaf with high accuracy.

The rest of the paper is organized as follows. Section II describes related works that has been performed in this field in recent years, section III elaboratesproposed methodology Experimental results are summarized in section IV. Finally, the conclusion is given in section V.

II. RELATED WORK

In recent years, quite a number of methods have been used to automate pest detection in leaves. [1] has proposed a method that identifies pests using k-means clustering algorithm and objects has been identified by proper use of voronoi cells .[2] has introduced a method based on local descriptors (SIFT, DSIFT, SURF, PHOW) and classified the pests using SVM and HOG (histogram oriented graph).[3] has proposed a method to identify proper features like Mean, Eccentricity, Standard deviation, Euler number etc. as features to train the SVM classifier and has performed a hierarchical classification which first classifies affected and unaffected leaves and in the next level classifies pests that has been affected the leaves.[4] has proposed a system that identify pest in tomato with morphological filtering and classification methods.[5] has used an advanced mechanism to identify pests early in plants.Foreground extraction has been done using saliency map based segmentation,then features are extracted and stored in a database and then neural network has been used to classify the pests.[6] has used technique to segment the cluster using blob like algorithm and SVM is used as classifier.

III. METHODOLOGY

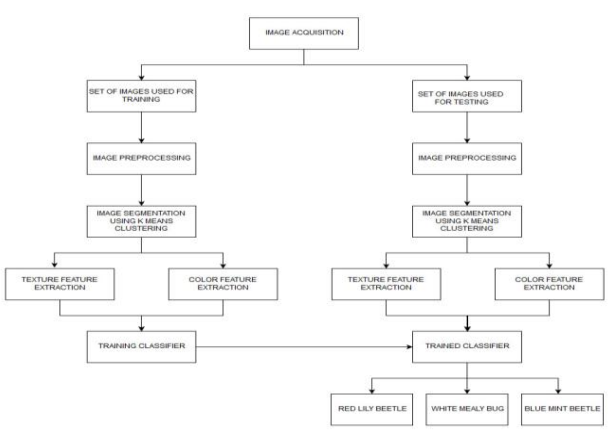
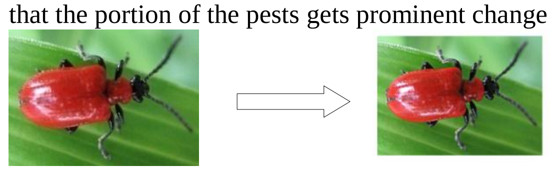


Figure2. Block diagram of the proposed system

The block diagram of proposed method is shown in Figure 2. The steps are elaborated in subsequent subsections.

A. Preprocessing

Pre-processing removes disease independent variations from the input image, enhances some image features and curbs unwanted distortions, thus making it suitable for further processing tasks like feature extraction and classification. The raw input images are normalized in the range [0,1] and resized,so that all of the images have same size which helps to identify the relative proportionate of measurement. [2] Then, noise removal is done using 2-D Gaussian filter. Contrast is also enhancedusing unsharp masking method so that the portion of the pests gets prominent change in texture.



(a) (b)

Figure3. (a) Normalized and resized leaf image with pest, (b)Pre-processed image after noise removal

B. Colour space convertion and segmentation

Once the pre-processing is done, the affected portion of leaf image is found using image segmentation. In this method the colour space is transformed into L*a*b colourspace [1]. Then segmentation is done using k–means clustering [8, 11]. Here twoclusters are sufficient to identify the pest affected segment shown in Figure 4.

(a) (b)

Figure 4. (a) Cluster containing affected portion, (b) Cluster containing unaffected portion

It can be observed from Figure 5, in L*a*b colour space the green components has low value of ‘a’ axis. On the other hand, L has high value for white and ‘a’ has high value for red [3]. On the other hand green portion has lower values for b. So, only portions with less value of b will be considered as leaves and others are considered as affected portions. Thus the unaffected cluster is separated and affected cluster is selected for feature extraction.

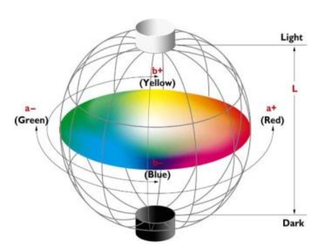


Figure 5. L*a* b* color space

C. Feature extraction

The target of feature extraction is to decrease the original data by measuring some properties i.e. features that can distinguish one input object from another object. Image texture refers to the appearance, organization and structure of the parts of an object within the image[3].

In this paper, colour space of the segmented image is changed to HSV in order to obtain three channels. Among them, one channel contains luminance information and other two channels contain information on chrominance. Texture features are then extracted from the Value (V) channel that is the luminance or intensity of the image samples. Gray Level Co-occurrence Matrix (GLCM) is used for texture feature extraction purpose [7]. GLCM signifies the spatial relationship between each intensity tone by calculating changes between grey levels i and j at a particular distance d and at a particular angle θ [10]. After defining d and θ, pixel pairs separated by d, calculated across the direction defined by θ, are analyzed. After that, the number of pixel pairs that possess a given distribution of grey-level values is counted. After obtaining GLCM of the segmented leaf image sample, d = 1 and θ = 0^o are used for extracting following features from the matrix:

Entropy: $-\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\log\big(P(i,j)\big)$ (1)

Contrast: $\sum_{n=0}^{Ng-1} |i-j|^2 \left\{\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\right\}$ (2)

Dissimilarity: $\sum_{n=0}^{Ng-1} |i-j| \left\{\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\right\}$ (3)

Correlation: $\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} \frac{ijP(i,j)-\mu x\mu y}{\sigma_x\sigma_y}$ (4)

Variance: $\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}(i-\mu)^2 P(i,j)$ (5)

Energy: $\sum_i \sum_j \big(P(i,j)\big)^2$ (6)

Inverse Difference Moment: $\sum_i \sum_j \frac{1}{1+(i-j)^2} P(i,j)$ (7)

Sum Average: $\sum_{i=2}^{2Ng} iP_{x+y}(i)$ (8)

Sum Entropy: $-\sum_{i=2}^{2Ng} P_{x+y}(i)\log\{P_{x+y}(i)\}$ (9)

Sum Variance: $\sum_{i=2}^{2Ng}\left(i-\left[\sum_{i=2}^{2Ng} iP_{x+y}(i)\right]\right)^2$ (10)

Difference Variance: $\sum_{i=2}^{2Ng}\left(i-\left[\sum_{i=2}^{2Ng} iP_{x-y}(i)\right]\right)^2$ (11)

Difference Entropy: $-\sum_{i=0}^{Ng-1} i^2 P_{x-y}(i)\log\{P_{x-y}(i)\}$ (12)

Information measure of correlation 1: $\frac{HXY-HXY_1}{\max(HX,HY)}$ (13)

Information measure of correlation 2: $\sqrt{1-e^{-(HXY2-HXY)}}$ (14)

Cluster Prominence: $\sum_i \sum_j \big(i+j-\mu_y-\mu_x\big)^4 P(i,j)$ (15)

Cluster Shade: $\sum_i \sum_j \big(i+j-\mu_y-\mu_x\big)^3 P(i,j)$ (16)

Homogeneity: $\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} \frac{P(i,j)}{1+(i-j)^2}$ (17)

In all equations, P(i, j) is the (i, j)-th entry of the normalized GLCM, that is, P(i, j) $= \sum_{i,j} P(i,j) \,/\, ij\ P(i,j)$, where P(i, j) is the (i, j)-th entry of the computed GLCM; Ng is the total number of gray levels in the image; and μ_y, μ_x and σ_x, σ_y denote the mean and SDs of the row and column sums of the GLCM, respectively. The gray level sum distribution is given by: Px+y(k)=$\sum_{\substack{i=1 \\ i+j=k}}^{Ng} \sum_{j=1}^{Ng} P(i,j)$, k= 2, 3. . . 2Ng; it is related to the distribution of the sum of co-occurring pixels in the image. The gray level difference distribution is given by: Px-y(k)=$\sum_{\substack{i=1 \\ |i-j|=k}}^{Ng} \sum_{j=1}^{Ng} P(i,j)$, k= 0, 1, 2. . .,Ng-1; it is related to the distribution of the difference between co-occurring pixels in the image.

Hue (H) and Saturation (S) channels contain chrominance or colour information. H represents the wavelength of a colour and S represents the amount of white colour mixed with the monochromatic colour. Therefore, the mean and standard deviation of both H channel and S channel are taken as features of the image. Then, all these colour and texture features are fused into a single feature matrix [9, 10].

D. Classification

In any classification method, input data is divided into training and testing sets. Each training set instance contains one target value (i.e. the class labels) and several attribute which are basically the features[3, 5]. In this paper, Support Vector Machine (SVM) classifieris used for classification purpose. SVM is a supervised model of learning that separates a set of training samples into two different classes, (x_1, y_1), (x_2, y_2),…(x_n, y_n) where $x_i \in R^d$, the d-dimensional feature space, and $y_i \in$ {-1,+1}, the class label, with i=1..n. SVM computes the optimal hyper planes, which separates the classes, based on a kernel function (K). All samples, of which feature vector lies on one side of the hyper plane, belong to class -1 and the others are belong to class +1 [9].

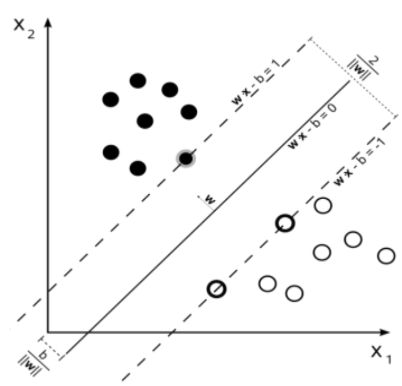


Figure6. Maximum-margin hyper plane and margins for a linear SVM trained with samples from two classes

In linear SVM, the training samples are linearly separable. A linear function of this form is shown below:

$$f(x) = w^T x + b \tag{18}$$

such that for each training sample x_i the function results $f(x_i) > 0$ for $y_i = +1$, and $f(x_i) < 0$ for $y_i = -1$. In other words, training patterns of two different classes are separated by the hyperplane $f(x) = w^T x + b = 0$, where w is the weight vector and normal to hyperplane, b threshold or bias and x_i is the data point. In Figure 6, linear SVM classification with a hyperplane that minimizes the separating margin between the two classes are indicated by data points by black and white circles. Support vectors are patterns of the training set that lie on the boundary hyperplane of the two classes.

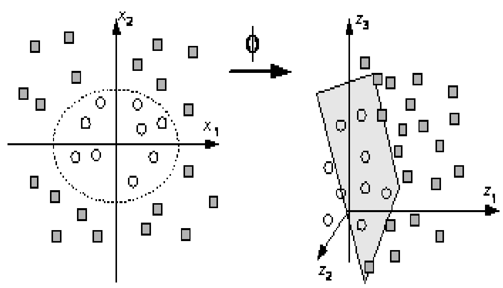


Figure7. Non-linear SVM classification

If the data of the classes are non-separable, then non-linear SVM classifier is used. Here, a nonlinear operator is used to map the input pattern x into a higher dimensional space H as shown in Figure 7.
The nonlinear SVM classifier is defined as,

$$f(x) = w^T \phi(x) + b \tag{19}$$

The transformation from non-linear to linear separating hyperplane in higher dimensional feature space is obtained by taking help of kernel functions. A kernel function on two samples, represented as feature vectors in some input space, is defined as k(xi, xj) = ϕ(xi)T ϕ(xj), ϕ is the feature vector. Most commonly used kernels are:

Linear kernel: $k(x_i, x_j) = x_i^T x_j$ (20)

Polynomial Kernel: $k(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma>0$ (21)

RBF Kernel: $k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \sigma>0$ (22)

σ, γ, r and d are all kernel parameters.

In general, when number of observed samples or patterns is larger than number of features, RBF kernel generally gives better performancethan other kernel functions [12]. Proper selection of kernel parameters is an important issue in order to gain very high accuracy of classification. In this paper, RBF kernel is used for training the SVM classifier.Though SVM was originally designed for binary classification, the proposed method requires multiclass classification since three classes of leaf diseases are considered. In the proposed method, one-against-all method is used for multiclass classification [13].

IV. RESULTS AND DISCUSSION

All the image pre-processing, segmentation, feature extraction and SVM classification techniques in our proposed method are simulated in MATLAB version R2016a and run on a Intel(R) Core(TM) i3-4005U CPU with 4 GB memory. Total 73pest affected leaf images has been considered. Among them 29 images are of blue mint beetle,24 images are of red lily beetle and 20 images are of white mealy bug. All of these images are pre-processed and once the pre-processing is done, train set and test set is separated from the above images. 6images of blue mint beetle, 5 images of red lily beetle and 5 images of white mealy bug are used for training set. Rest of the images are used for test cases.

After pre-processing and segmentation steps, 17 texture features and 4 colour features are extracted from these samples and a 16 X 21 feature matrix is formed as described in section II and this feature matrix is fed into SVM classifier for training purpose. Rest images are used for test cases. A 57X21 feature matrix is formed as test matrix.

Performance of the classifier are tested and evaluated by
Accuracy (ACC)= (TP + TN) / (TP + TN + FP +FN)
Sensitivity (SEN) = TP / (TP + FN)
Specificity (SPE) = TN / (TN + FP)
Precision (PRE) = TP/ (TP + FP)
These parameters can be defined by using the following basic terms-
True positives (TP): It is the number of positive images that are correctly labelled by the classifier.
True negatives (TN): It is the number of negative images that are correctly labelled by the classifier.
False positives (FP): It is the number of negative images that are incorrectly labelled as positive.
False negatives (FN): It is the number of positive images that are incorrectly labelled as negative.

Table 1. Confusion Matrix

	Blue mint beetle	Red lily beetle	White mealy bug	FN
Red lily beetle	18	0	1	1
Blue mint beetle	2	19	2	4
White mealy bug	0	2	13	2
FP	2	2	3	7

Table 1 shows the confusion matrix for classification of the insects. From the data of table1 it can be said that 18 blue mint beetle has been identified properly and 1 blue mint has been false diagnosed as white mealy bug. Similar analysis can be done for all of the bugs and beetles.

Table 2. Performance of SVM classifier (using RBF kernel) for 57 test samples of affected leaf image consisting of 23 images of blue mint beetle, 19 images of red lily beetle and 15 images of white mealy bug

	TP	TN	FP	FN	PRE	SEN	SPE	ACC
Red lily beetle	18	32	2	1	90	94.73	94	94
Blue mint beetle	19	31	2	4	90	82	93	89
White mealy bug	13	37	3	2	81	86	92	90
Red lily beetle	18	32	2	1	90	94.73	94	94

From Table 2 the values of TP,TN,FP,FN (in %) has been obtained and hence all of the measurements of performance evaluation parameters have been done accordingly.

V. Conclusion and Future Scope

Three harmful pests are classified with high accuracy in this paper.Manual intervention is totally eliminated by developing a new logic to automatically identify the segment containing pest as explained in Methodology section. For classification purpose, multiclass SVM classifier is used which is much efficient than other classifiers in terms of computational overhead. It can be concluded that the proposed method can be helpful for agricultural improvement to increase field yield by saving trees from early damage and loss. The experiment has been done on only leaves of plants. Though these bugs affect fruits and stems of plants as well.Further experiment can be done on images of those portions .Similar process can be used to identify several other objects as well like disease in plants, several objects in medical images.

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