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# Vision-based pest detection based on SVM classification method

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ABSTRACT

Automatic pest detection is a useful method for greenhouse monitoring against pest attacks. One of the more harmful pests that threaten strawberry greenhouses is thrips (Thysanoptera). Therefore, the main objective of this study is to detect of thrips on the crop canopy images using SVM classification method. A new image processing technique was utilized to detect parasites that may be found on strawberry plants. SVM method with difference kernel function was used for classification of parasites and detection of thrips. The ratio of major diameter to minor diameter as region index as well as Hue, Saturation and Intensify as color indexes were utilized to design the SVM structure. Also, mean square error (MSE), root of mean square error (RMSE), mean absolute error (MAE) and mean percent error (MPE) were used for evaluation of the classification. Results show that using SVM method with region index and intensify as color index make the best classification with mean percent error of less than 2.25%.



## 1. Introduction

Pest management in field and greenhouse conditions has been one of the main concerns for agricultural Scientifics and producers. Reductions in production loss and crop damages, which can severely affect marketable yields, enforce farmers to use different methods to control and protect fields against pest damages. In the present century, the use of pesticides has increased due to its initial low cost, easy accessibility, quick influence and the lack of knowledge on the part of growers, resulting in dangerous consequences.

Although the use of chemicals has a major influence on pest management, it has also had many side effects on human health, animals and environment. Therefore, agricultural Scientifics all around the world began working together to search for better methods of pest control than the use of chemical pesticides. They proposed integrated pest management (IPM), a program dating back to the late 1960s, as the best solution to reduce chemical usage. By the increasing concern of environment impacts as well as pest control costs, IPM has now become one of the most effective and accurate ways to pest manage in the orchard and greenhouse. This method is performed based on relying more on actual presence, or likelihood of presence, of insects in the site.

Monitoring of insect in orchards and greenhouse is most commonly accomplished with insect attractants and traps. Growers and IPM consultants regularly monitor the environment in orchards by manually counting the harmful pests on the traps, and apply control according to the pest situation in an orchard/greenhouse estimated by specific insect distribution and population observed (Wen and Guyer, 2012).

Using of traditional methods for Insect identification is a time-consuming work which requires expert knowledge for integrated pest management. With science progressing and creating new technologies such as machine vision systems, use of tools for increasing the work speed, precision and decreasing of human errors have been increased. Also, automated insect identification can be a significant contribution to producers who own large orchards and have limited pest scouting expertise.

Using of machine vision system that works based on image processing technique with different image segmentation methods has been one of the newest methods to identify insect especially in greenhouse. In this method the insect may be detected using its special characteristics (Khan et al., 2016; Yan et al., 2015; Wen et al., 2015; Wang et al., 2012; Qing et al., 2014; Wen and Guyer, 2012; Qing et al., 2012) or insect-induced effects and damages (Huang et al., 2013).

Color and shape are two parameters that have major roles in image processing technique. Hassan et al. (2014) used color-based and shape-based descriptors to automate the classification of insects. They proposed an automatic insect identification framework that can distinguish between grasshoppers and butterflies in colored images. Wen and Guyer (2012) conducted a study on image-based orchard insect automated identification and

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classification method with the aim of proposing a more robust automated method that can work suitably on field insect images considering the variant situation. Because of some small-sized insects, it won't be possible to gain accurate results use traditional image processing technique. To tackle this problem Li et al. (2015) decided to use multifractal analysis. In their research, multifractal analysis was adopted for segmentation of whitefly images based on the local singularity and global image characters with the help of regional minima selection strategy. According to different varieties of insects and their identification problems, alternative solutions were presented by researchers. Among them, Zayas and Flinn (1998) introduced a machine vision technique that used multivariate analysis to detect insects in crop background images. The extraction of small spots from biological images was first reported by Olivo-Marin (2002). Singh et al. (2009) reported on the use of near-infrared (NIR) hyperspectral imaging systems to detect wheat kernels damaged by insects. Some other related work were done by Gotsch and Braunschweig (1999), Koumpouros et al. (2004), Hanafi (2003), Li et al. (2009), Yao et al. (2013), Clement et al. (2015) and Ridgway et al. (2002).

However all done studies have been benefits in the insect identification. The major aim of this study is to present a new system for real-time controlling of strawberry greenhouse environment, automatic detection the thrips and its position to protect of the product. In this work a mobile agricultural robot moved along the track, the photography was performed at the certain distances and online analysis for the detection of the pests from flower surface images in situ is proposed, then the result is shown as real time. Therefore, this study presents a new application of image processing powered by support vector machine (SVM) for the detection of the insect from the crop surface images in situ and other pests such as whitefly, housefly and ant that exist in strawberry greenhouse generally.

## 2. Material and methods

### 2.1. Samples and image acquisition

All images were obtained from a strawberry greenhouse at the Faculty of Agricultural Engineering, Tarbiat Modares University, Islamic Republic of Iran, Tehran (Fig. 1(a)). A mobile agricultural robot that controlled by a LabVIEW program was used in the experiments (Fig. 1(b)). While the robot moved along the pots row and it displaced the computer vision system in a horizontal direction. A digital camera (Canon EOS M, 18 MP, CMOS, Japan)) was mounted on the end effector of the robot arm to capture the flower images. Because the taken pictures were not compared together (unlike to fruit drying), the external lighting changes have no significant effect on the detection algorithm performance. In addition, the images were taken under a good natural light. Therefore, the photography was performed under natural light without any extra light source. Images were captured at 80 cm distances (as the photography cover through all the rows) and then processed using an image processing algorithm. Algorithm, which was developed in MATLAB R2010a, processed the taken image by removing the background and detecting any thrips using SVM classification.

### 2.2. Image processing

For improving the correct rate of thrips detection and the computational speed, the non-flower regions of captured images are considered as background and removed by applying the gamma operator. The gamma operator, $\gamma$, enhances the contrast of the brighter regions, which is defined as (Gonzalez and Woods, 1992):

$$S = cr^{\gamma} \quad (1)$$

where S and r represent converted gray scale and the original image, respectively. Therefore $0 \le S \le 1$, $0 \le r \le 1$. Since the gray scale of the original image was not suitable as input of the gamma operator, before applying the gamma operator, the layers of the captured images (Fig. 2) original by the agricultural robot in RGB color space were investigated. Each sample pixel is a 3-dimension feature vector in R, G, and B channels. The Red, Green and Blue

**Fig. 2.** Original RGB image.

(a) (b)

**Fig. 1.** View of the greenhouse (a) and the mobile agricultural robot (b).

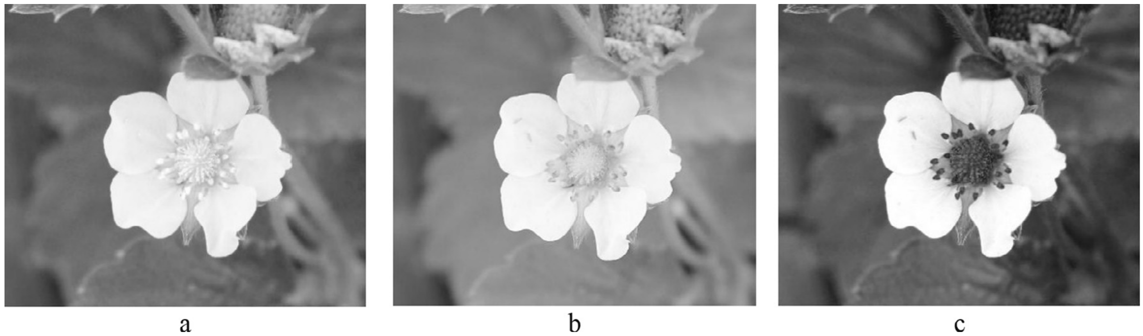


**Fig. 3.** Layers of Red (a), Green (b) and Blue (c) of the Original image. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

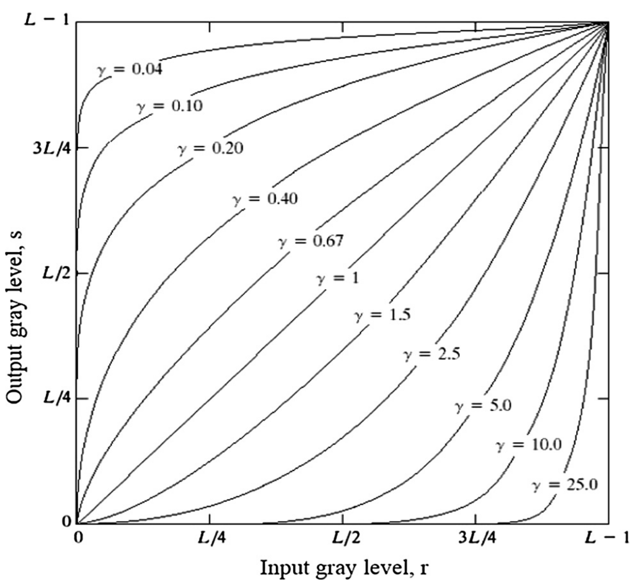


**Fig. 4.** Plots of the equation $\boldsymbol{S} = \boldsymbol{c}\boldsymbol{r}^{\gamma}$ for various values of $\gamma$ (c = 1 in all cases).

**Fig. 5.** Gamma-power transfer function.

layers of the RGB color space image are shown in Fig. 3. It was clear that the contrast between the background and the target in B-layer is more than the other layers (Fig. 4).

### 2.3. Features extraction

The resulting image after applying the gamma operator is shown in Fig. 5. Histogram equalization and contrast stretching was used to remove any remaining background. If the intensify of a sample pixel is less than a suitable threshold we set, the sample pixel is considered as a background and removed, whereas pixels with intensity higher than the threshold are identified as the target pixels. The threshold value for segmentation of the target pixels is obtained from the image histogram plot using automatic Otsu method (Otsu, 1979) (Fig. 6).

Opening and closing operations are the basic operations of morphological image processing, which are widely used for noise removing in image processing (Li et al., 2015). Minute noises remain on the binary image obtained after segmentation calculation. Opening and closing operations with the disk-shaped structuring element were utilized to remove them. Filling operation is other basic operation of morphological image processing, which is used in filling image regions and holes. As supplementary stage to remove background, holes created inside the target were filled using the filling operation.

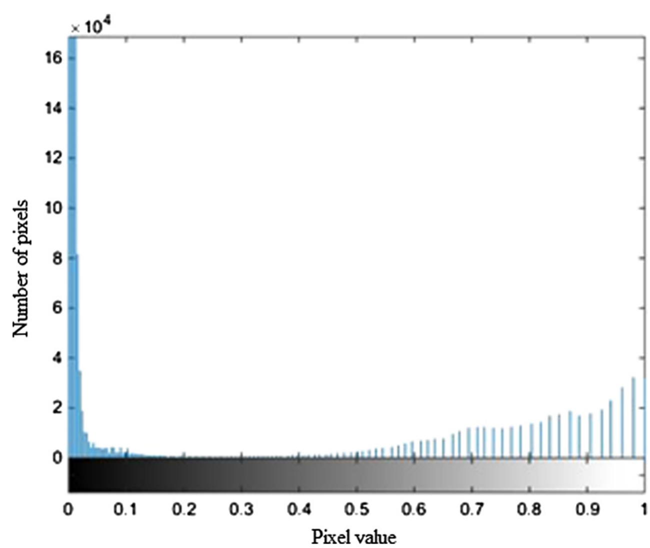


**Fig. 6.** image histogram plot.

Finally, value of the sample pixel on the binary image was applied for a given image obtained by the agricultural robot, if the value of the sample pixel on the binary image is 0, the sample pixel is identified as background and removed, whereas pixels with values equal to 1 were identified as the target pixels.

After detecting the flowers, every one of them was processed again to identify the pest. Now, the flowers were obtained as background and pests were obtained as target. This process was contains of applying the cropping and labeling operations, finding the region properties and removing the regions that their area were out of a predetermined range. After the processing, some white regions were remained that must be denoted that it is thrips or not.

The color image of the insects was determined by multiplying element to element of the binary image to the original image. Using RGB components to detect thrips was not successful. At the other hand, transformations of an RGB (Red, Green, Blue) color representation of an image to an equivalent HSI (Hue, Saturation, Intensity) color representation is common in researches. Therefore RGB components were separated from the resulting image and the Hue (H), Saturation(S) and Intensity (I) components were extracted. Eqs. (2)(5), were used to obtain Hue, Saturation and Intensity parameters of the image samples (Pujari et al., 2013).

$$H = \left\{ \begin{array}{cc} \theta & \text{if } B \leqslant G \\ 360 - \theta & \text{if } B > G \end{array} \right\} \tag{2}$$

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \right\} \tag{3}$$

$$S = 1 - \frac{3(\min(R,G,B))}{(R+G+B)} \tag{4}$$

$$I = \frac{(R+G+B)}{3} \tag{5}$$

### 2.4. Pest detection using support vector machines (SVM)

SVMs are currently among the best performers for a number of classification tasks ranging from text to genomic data. They can be applied to complex data types beyond feature vectors (e.g. graphs, sequences, and relational data) by designing kernel functions for such data. Support Vector Machines are a system for efficiently training linear learning machines in kernel-induced feature spaces, while respecting the insights of generalization theory and exploiting optimization theory. Some of the general kernels are given at below:

$P^{th}$ Degree polynomial:

$$K(x_i, x_j) = (x_i.x_j + 1)^p \tag{6}$$

Radial bases (RBF):

$$K(x_i, x_j) = e^{-\|\frac{x_i - x_j^2}{2\sigma^2}\|} \tag{7}$$

Multi-layers Perceptron (MLP):

$$K(x_i, x_j) = \tanh(\beta x_i.x_j + \delta) \tag{8}$$

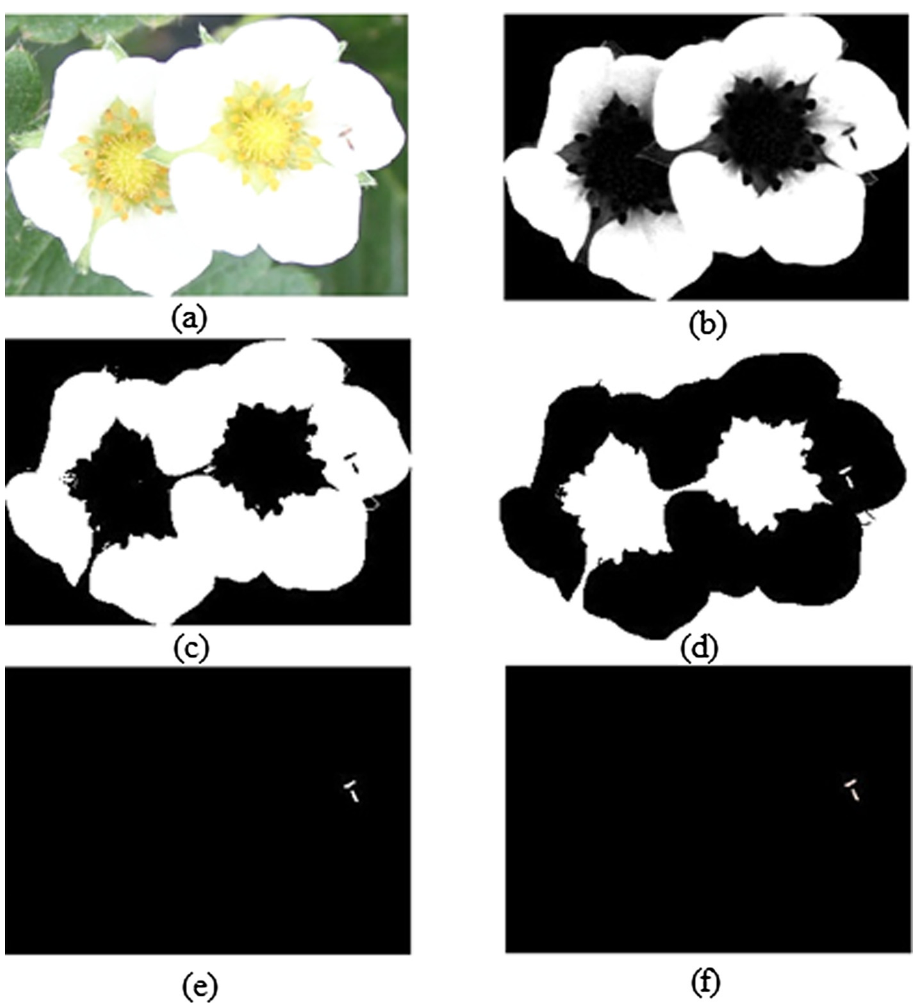


**Fig. 7.** Insect detection procedure. (a) Original image; (b) Result of gamma operator; (c) Converting to binary; (d) Reversing image; (e) Extraction pest; (f) Color pest image.

**Table 1**
Average values of indexes for various insects in captured images.

| | L/W | I | S | H |
|---|---|---|---|---|
| Larva | 3.34 | 163.04 | 0.30 | 0.85 |
| Adult | 4.30 | 77.79 | 0.38 | 0.49 |
| Whitefly | 1.69 | 203.75 | 0.04 | 2.03 |
| Housefly | 1.44 | 82.05 | 0.34 | 3.05 |
| Ant | 2.90 | 34.74 | 0.37 | 0.53 |

The objective function of the dual problem needs to be maximized. The dual problem is therefore:

$$W(\alpha) = \sum_i \alpha_i - \frac{1}{2}\sum_i \sum_j \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad i,j \in \{1,\ldots,n\} \tag{9}$$

Subjected to: $0 \leqslant \alpha_i \leqslant C, \quad \sum_i \alpha_i y_i = 0$

After solving, the matrix of $\alpha$ is found. Therefore the bias and y-classifier equations are described as follows.

$$b = \frac{1}{\|S\|}\sum_i \left[ y_i - \sum_j \alpha_j y_j k(x_j, x) \right] \tag{10}$$

$$y = Sign\left( \sum_i \alpha_i y_i k(x_i, x) + b \right) \tag{11}$$

where S denotes the non-zero values of $\alpha$ matrix while x is the input matrix. Therefore, the sign of the classifier equation determined the class of the input data.

The region index as $X_i$ and color index as $X_j$ were utilized to design and train the SVM structure. Due to various sizes of the flowers, the distance of the camera from the surface of them was changed. These changes altered the size of flowers and insects. Therefore, a region index was defined as the ratio of large diameter to small diameter to eliminate the effect of these changes. In addition, Hue, Saturation, and Intensity were used as the color index.

### 2.5. Model performance evaluation

Several statistical parameters were used for evaluation of the accuracy of the SVM. These parameters can help to determine which color index is suitable for the classification.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - \hat{Y}_i\right)^2 \tag{12}$$

$$RMSE = \sqrt{MSE} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{Y}_i - Y_i| \tag{14}$$

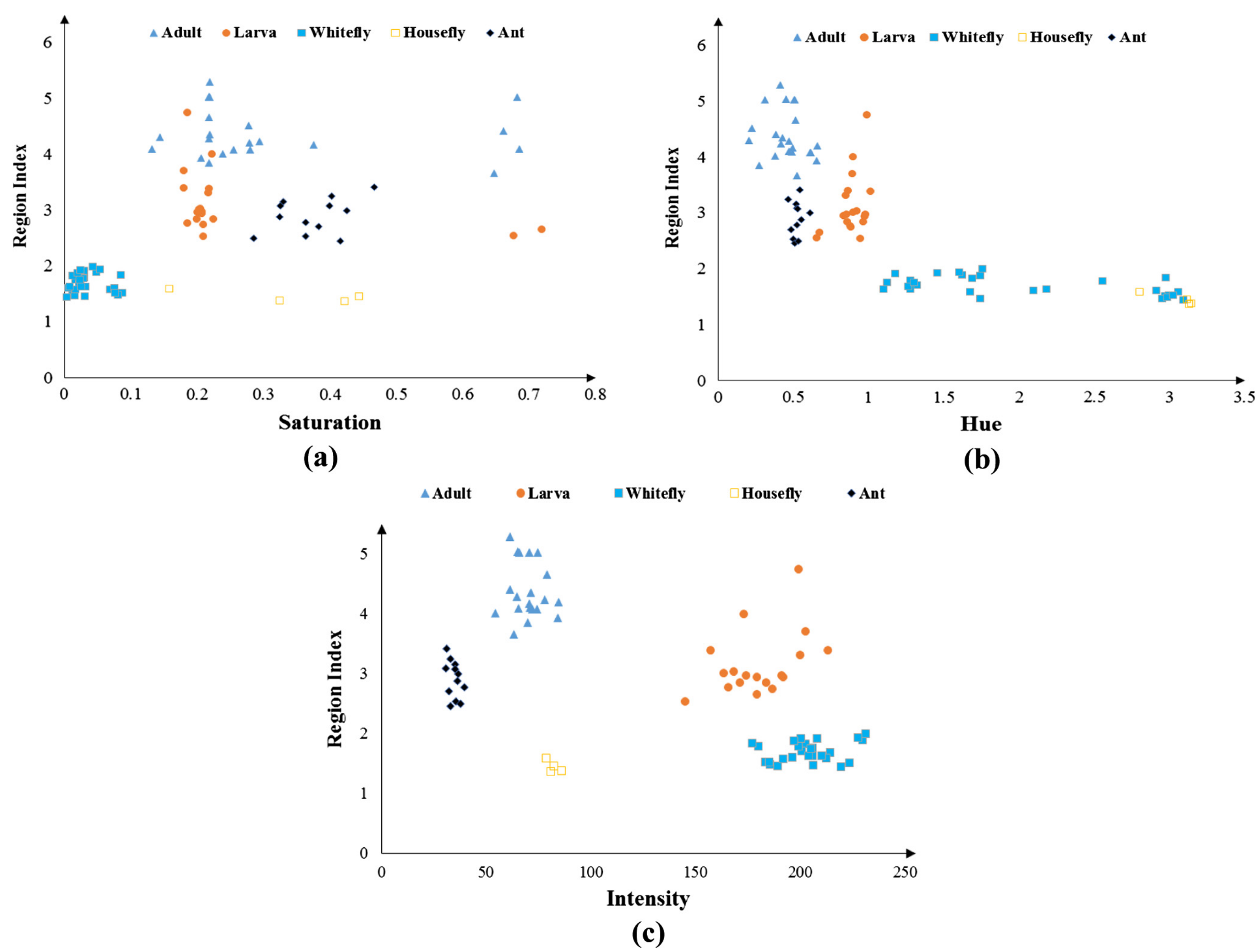


**Fig. 8.** Similar effects of the region and color index (a: Saturation b: Hue and c: Intensity) on pest detection. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$MPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\alpha_t - f_t}{\alpha_t} \quad (15)$$

where MSE: mean square error; RMSE: root mean square error; MAE: mean absolute error; MPE: mean percent error; $\hat{Y}$: actual class of the data; Y: predicted class of the data; $a_t$: the number of true classifications; $f_t$: the number of false classifications.

## 3. Results and discussion

Example segmentation results for insect detection are shown in Fig. 7. In this figure, the background removed image, binary image, inversed binary image, binary insect image and color insect image are shown as well. Since the flowers are brighter than the strawberry leaves, enhancing the contrast of brighter regions using exponential operator helped to remove the background. By choosing the suitable point (0.3) in the image histogram plot, the binary image was obtained. The binary image was inversed because the insect was the target. Next, labeling of the image resulted to two separate white regions. With determining a suitable threshold, the wider region was removed. Finally, the original image was adapted with binary insect image to create insect color image (Fig. 7(f)).

In addition to thrips other insects such as Whitefly, Housefly and Ant may be exist in the strawberry greenhouse. Therefore, the remaining regions in the processed images are not necessarily thrips. On the other hand, the shape and color of the thrips changed during phyletic from larva to adult. Table 1 was shown average region and color indexes of them. In this work, more comparison were compared between thrips and other insects. Therefore, the data were divided into 2 groups, first target group and another parasite group. For better perception, the graph of the region index was drawn against color indexes in Fig. 8. It seems, detection of the thrips using intensity color index is better than other indexes.

Near 100 sample images were captured, 80% were used to train and 20% were used to test. Fig. 9 shows the results of SVM classification using RBF kernel function. Where, L/W as $x_i$ and Hue, Saturation or I (in Fig. 9(a), (b) and (c), respectively) as $x_j$ were used as the inputs of the SVM classification. In Fig. 9(a), it is clear that the support vector distance from classification line is very low. This means that a few changes in the size or color of the target/parasite pest will increase the error of classification. According to Fig. 9(b), the results are more acceptable but still the probability of risk is high and in critical condition this classification may conduct with high error. In Fig. 9(c), it is visible that intensity color index has been able to make an acceptable difference between target and

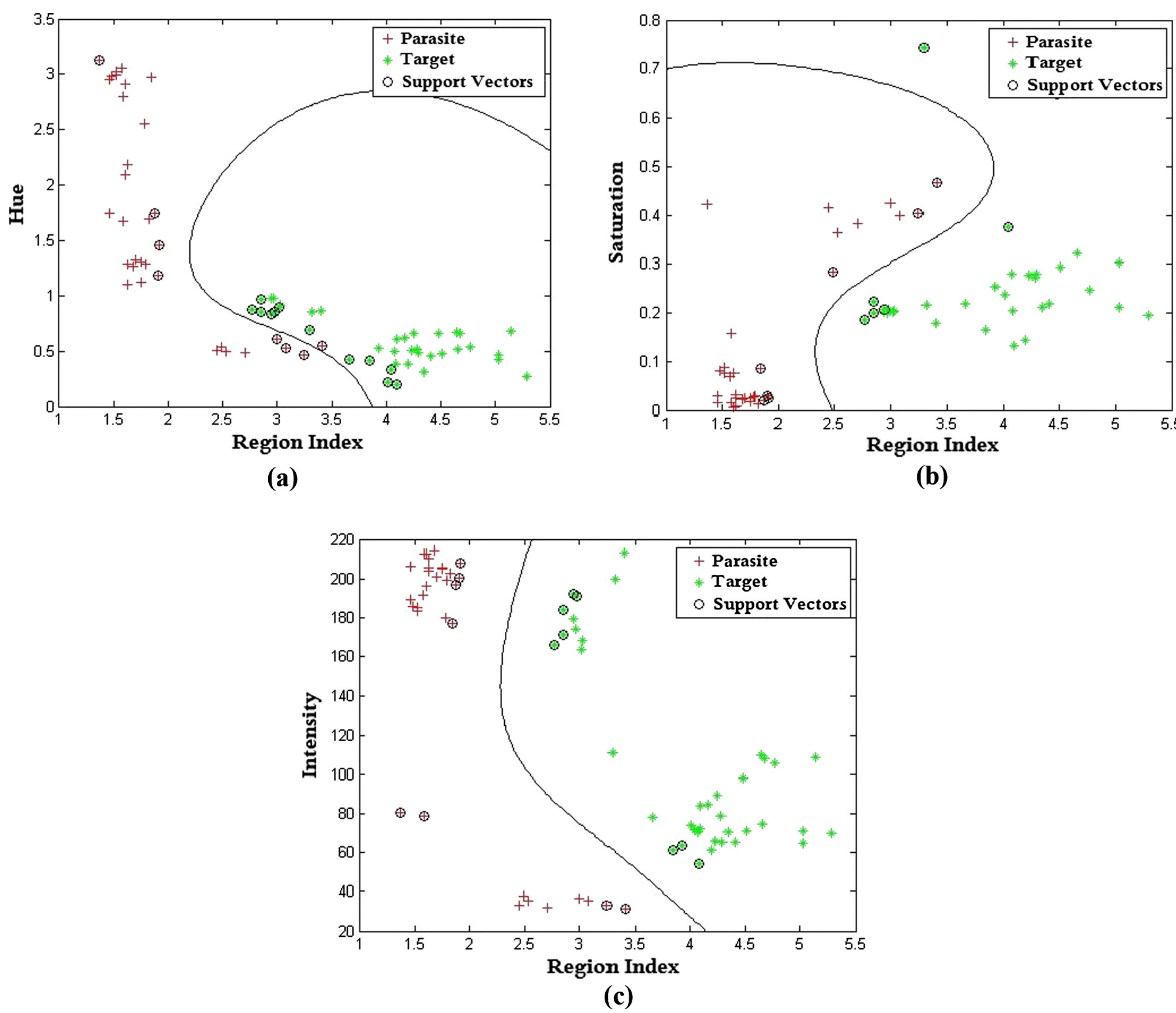


**Fig. 9.** the graphical results of SVM classification (a: Saturation b: Hue and c: Intensity).

**Table 2**
the statistical results of SVM classification.

| | H | | | S | | | I | | |
|---|---|---|---|---|---|---|---|---|---|
| | Train | Test | All Data | Train | Test | All Data | Train | Test | All Data |
| MSE | 0.278 | 1.412 | 0.494 | 0.222 | 1.177 | 0.404 | 0.000 | 0.471 | 0.090 |
| RMSE | 0.527 | 1.188 | 0.703 | 0.471 | 1.085 | 0.636 | 0.000 | 0.686 | 0.300 |
| MAE | 0.139 | 0.706 | 0.247 | 0.111 | 0.588 | 0.202 | 0.000 | 0.235 | 0.045 |
| MPE | 6.94 | 35.29 | **12.36** | 5.56 | 29.41 | **10.11** | 0.00 | 11.77 | **2.25** |

parasite. In this classification, even if the critical condition happened, probability of the error will be low.

The statistical results related to the above discussion are shown in Table 2 (in all L/W was obtained as region index). However, all used statistical parameters can describe the result of SVM classification but it seems MPE parameter is better. Based on MPE values, the percent error of Hue and saturation parameters is not acceptable for classification because more than 10% of the prediction will be wrong. While, classification based on intensify color index resulted to reduce error lower than 3%.

## 4. Conclusion

It was shown that the developed image processing procedure is capable of identifying parasites in the greenhouse environment. Also, the parasites can be classified using the SVM classification method and the target parasite can be detected. In this study, incorporation of the image processing technique with SVM method and choice of suitable region and color index was successful in detecting the target (thrips) with an error less than 2.5%.

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