

Early Pest Detection in Greenhouse Crops

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ABSTRACT: *The techniques of machine vision and digital image Processing are extensively applied to agricultural science and it have great perspective especially in the plant protection field, which ultimately leads to crops management. The paper proposes a software prototype system for early pest detection on the infected crops in greenhouse. Images of the infected leaf are captured by a camera with pan tilt and zoom and processed using image processing techniques to detect presence of pests. SVM classifier is used for classification. SVM classifier helps to detect the pests and in the classification of pest based on their features. Results show more precision in identifying the presence of pest at early stage.*

Keywords: Early pest detection, feature extraction, image processing, pests, SVM (Support Vector Machine).

I. INTRODUCTION

In our country India larger portion of the population depends on agriculture. However, the cultivation of crops for optimum yield and quality produce is highly essential. A lot of research has been done on greenhouse agro systems and more generally on protected crops to control pests and diseases by biological means instead of pesticides. Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure and with increased profit, which has received importance in recent time. A strong demand now exists in many countries for non-chemical control methods for pests or diseases. In fact, in production conditions, greenhouse staff periodically observes plants and search for pests. This manual method is very time consuming. With the recent advancement in image processing techniques, it is possible to develop an autonomous system for disease classification of crops.

There are different crops which are cultivated under greenhouse e.g. Rose, Cucumber, Tomato, gerbera, Capsicum etc. Whiteflies, Thrips, aphids are the most common pests which attach on greenhouse crops. White flies, thrips and aphids are very small in size. Normally the size of adult whitefly is 1/12 inch in length. The female of whitefly is sap-sucking pest may lay 150 eggs at the rate of 25 per day. The entire life cycle of whiteflies is 21-36 days. Thrips are tiny, slender pest about 1/25-inch long in length. They range in colour from light brown to black. Thripes grows on flower plants and fruit plants. Aphids are very small in size. Aphids are soft-bodied, sluggish pests. They form cluster in colonies on the leaves of the host plants. Their life span is about 20- to 30-days.

The only way to stop the effect of these pests is pesticides. But excess use of the pesticides is very harmful to the crops, soil, air, water resources and the animals which came in contact with the pesticides. Pesticide residues have also been found in rain and groundwater. The use of pesticides decreases the general biodiversity in the soil. Excess of pesticides results in reduced nitrogen fixation and thus reduced crop yields. Animals may be poisoned by pesticides.

Early detection of pest or the initial presence of pests is a key-point for crop management. Improved crop protection strategies to prevent such damage and loss can increase production and make a substantial contribution to food security. In this paper, we focus on early pest detection. This implies to regular observation the plants. Images are acquired using cameras. Then the acquired image has to be processed to interpret the image contents by image processing methods. The focus of this paper is on the interpretation of image for pest detection.

II. LITERATURE REVIEW

In this section we will discuss some methods which are presently used for the early detection of pests in greenhouse crops along with their advantages and disadvantages. The methods are explained below with their features and drawbacks.

2.1 Method which use Static images.

The method of using static images is given by Paul Boissard, Sabine Moisan. In this method the image acquisition is done with the scanner. The next step is to perform image processing technique to detect the pests. The method has good accuracy and results but the biggest disadvantage of this method is to use scanner for image acquisition. Also the time required to generate the results is in hours. When we scan the image there may be a chance that the pests may fly away or there may be a chance of blurring of the image. Also there is a chance of improper scanning which leads the false information.

2.2 Method which use Sticky Traps.

The method of using sticky traps is given by Vincent Martin, Sabine Moisan Bruno Paris, and Olivier Nicolas. In this method the sticky traps are used to detect the pests. Sticky material which is on the sticky traps attracts the pests due to their properties. But to reach the sticky traps, the development of the pest must be completed i.e. the pest must fly but at that stage the damage is already done to the crops.

The drawback of these methods can be overcome by using pan tilt camera with zoom. The camera is continuously moving and used to capture the image so there is no problem flying away of pests and there is no false information. Also there is no need to reach the sticky trap.

III. PROPOSED METHOD

For this study, whiteflies are chosen because this pest requires early detection and treatment to prevent durable infection. Samples are collected by using the pan tilt camera with zoom in greenhouse as shown in Fig.2. Once the image is acquired the next step is to implement image processing technique in order to get the information about pest.

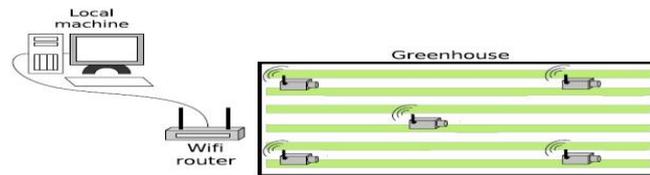


Figure 1: Overview of System

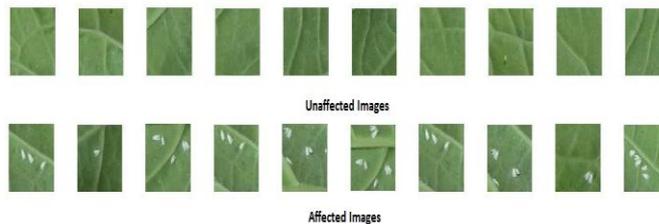


Figure 2: Database for the training of SVM

IV. METHODOLOGY

3.1.1 Image acquisition

Every image processing application always begins with image acquisition. The images are captured by using a pan tilt camera with 20X zoom maintaining equal illumination to the object. All the images should be saved in the same format such as JPEG, TIF, BMP, PNG etc. The camera is interfaced with the system which will take the image captured by the camera as an input.

3.1.2 Image pre-processing

Image pre-processing creates an enhanced image that is more useful or pleasing to a human observer. The image pre-processing steps used in the system are: 1) Conversion of RGB image to gray image 2) Resizing of the image 3) Filtering of the image.

3.1.2.1 Conversion of RGB to gray image.

In RGB color model, each colour appears in its primary spectral components of red, green, and blue. The colour of a pixel is made up of three components; red, green, and blue (RGB), described by their

corresponding intensities. RGB color image require large space to store. In image processing we have to process the three different channels. It consumes large time.

So we are going to convert the RGB image into gray scale image. The formula to covert RGB to gray is given below $I(x, y) = 0.2989*R + 0.5870*G + 0.1140*B$

The information retained by gray scale image is enough for our method so we convert RGB image to gray scale image for image processing.

3.1.2.2 Resizing of the image.

The acquired image is resized according to the requirement of the system. The different methods available for image resizing are Nearest-neighbor interpolation, bilinear, and bicubic. In Nearest-neighbor interpolation the output pixel is assigned the value of the pixel that the point falls within. No other pixels are considered. In bilinear interpolation the output pixel value is a weighted average of pixels in the nearest 2-by-2 neighborhood. In bicubic interpolation the output pixel value is a weighted average of pixels in the nearest 4-by-4 neighborhood. Here in our system we are using bicubic interpolation as it generates more accurate results than any other method.

3.1.2.3 Filtering of the image

Filtering in image processing is a process that cleans up appearances and allows for selective highlighting of specific information. A number of techniques are available and the best options can depend on the image and how it will be used. Both analog and digital image processing may require filtering to yield a usable and attractive end result.

There are different types of filters such as low pass filters, high pass filters, median filters etc. The low pass filters are smoothening filters where as the high pass filters are sharpening filters. Smoothening filters are used for smoothening of the edges. Sharpening filters are used for enhancing the edges in the image.

In our system we are using smoothening filter. The purpose of smoothing is to reduce noise and improve the visual quality of the image. Spatial filters are applied to both static and dynamic images, whereas temporal images are applied only to dynamic images. The simplest smoothening filter is average filter. It consists of a 3X3 matrix of 1 and it is divided by 9.

3.2.3 Feature Extraction

In feature extraction we are considering some properties of the image. There are different properties like region properties, gray covariance matrix properties. From that he properties like entropy, mean, standard deviation, contrast, energy, Correlation and eccentricity are extracted from the image. They are compared and based on that the support vector machine is trained and used to classify the images.

Support Vector Machines (SVM's) are a relatively new learning method used for binary classification. The basic idea is to find a hyper plane which separates the d-dimensional data perfectly into its two classes. However, since example data is often not linearly separable, SVM's introduce the notion of a "kernel induced feature space" which casts the data into a higher dimensional space where the data is separable. Typically, casting into such a space would cause problems computationally, and with over fitting. The key insight used in SVM's is that the higher-dimensional space doesn't need to be dealt with directly (as it turns out, only the formula for the dot-product in that space is needed), which eliminates the above concerns. Furthermore, the VC-dimension (a measure of a system's likelihood to perform well on unseen data) of SVM's can be explicitly calculated, unlike other learning methods like neural networks, for which there is no measure. Overall, SVM's are intuitive, theoretically well- founded, and have shown to be practically successful. SVM's have also been extended to solve regression tasks (where the system is trained to output a numerical value, rather than "yes/no" classification).

The meaning of the properties which are stated above is given in following table

Mean	Returns the mean values of the elements along different dimensions of an array
Standard deviation	computes the standard deviation of the values in matrix or array
Eccentricity	Scalar that specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment.) This property is supported only for 2-D input label matrices
Euler Number	Scalar that specifies the number of objects in the region minus the number of holes in those objects. This property is supported only for 2-D input label matrices. regionprops uses 8-connectivity to compute the Euler Number measurement. To learn more about connectivity, see Pixel Connectivity.
Filled Area	Scalar specifying the number of on pixels in Filled Image.
Solidity	Scalar specifying the proportion of the pixels in the convex hull that are also in the region. Computed as Area/Convex Area. This property is supported only for 2-D input label matrices.
Gray Co-occurrence matrix	It creates a gray-level co-occurrence matrix (GLCM) from image I. graycomatrix creates the GLCM by calculating how often a pixel with gray-level (grayscale intensity) value i occurs horizontally adjacent to a pixel with the value j. (You can specify other pixel spatial relationships using the 'Offsets' parameter -- see Parameters.) Each element (i,j) in glcm specifies the number of times that the pixel with value i occurred horizontally adjacent to a pixel with value j.
Contrast	Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. It is computed by formula $\sum_{i,j} i - j ^2 p(i, j)$
Energy	Returns the sum of squared elements in the GLCM. It is computed by formula $\sum_{i,j} p(i, j)^2$

Table 1: Definition of different Parameters

3.2.4 Disease classification and grading

The disease classification is done by the support Vector machine classifier. The two categories are formed such as affected leaf and unaffected leaf. Based on this the data provided to train the support vector machine. From above table we can clearly see that there is a variation in standard deviation and contrast. So we will consider the standard deviation and contrast for training the support vector machine.

3.2.5 Detection

The input image is given to the support vector machine. As the support vector machine is trained with the data collected from our data base which we have collected. The features of the input image are extracted and given as a input to the support vector machine, Based on the comparison with the parameters of database support vector machine generates the output.

V. FLOWCHART

The flow chart for the propose system is given in fig.3. The flowchart gives the complete idea about the system.

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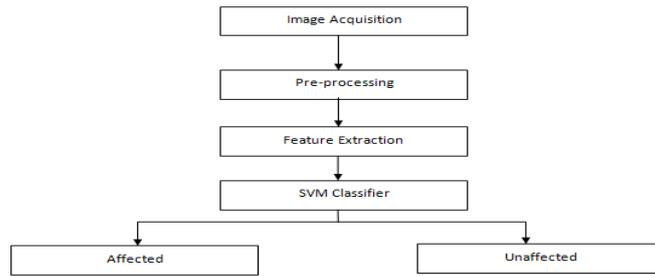


Figure 3: Flowchart of the system

VI. RESULTS

The results obtained by performing the operations are shown below. The different parameters which are calculated for given data base are shown in table 2. The graph of the different parameters is also shown in fig. 4 and from the analysis of that we have decided to choose Standard deviation and contrast as deciding or classification factors. The graph shown in fig. 5 shows that the training to the SVM is done with 100% accuracy. We have divided it into two categories affected and unaffected. Here 1 represents unaffected and 0 represents affected.

Parameters	Entropy	Mean	Standard deviation	Contrast	Correlation	Eccentricity
Unaffected Images	5.111022	128.9804	8.784494	0.099495	0.788207687	0.08005621
	5.704047	122.7276	13.36848	0.088384	0.817424865	0.0369198
	5.356719	119.6399	11.23865	0.065354	0.775523552	0.06858617
	4.956636	118.4778	7.785343	0.053232	0.666828028	0.08068627
	5.266736	107.8553	10.09207	0.06	0.661228997	0.24282954
	5.335025	99.7185	10.26094	0.094747	0.7433882	0.11856729
	4.750367	120.2329	6.788967	0.04899	0.759140928	0.05610738
	5.552168	118.4309	11.68626	0.063838	0.825014884	0.07377056
Affected Images	4.706327	120.4082	6.939394	0.044646	0.774875913	0.06434045
	5.169737	120.4206	19.33133	0.18697	0.713766094	0.10776177
	5.743359	124.3191	17.72068	0.100303	0.849842034	0.06283355
	5.849869	93.6361	16.42084	0.112828	0.841796732	0.18596007
	5.703574	125.1937	17.29079	0.123232	0.830376481	0.08401726
	5.826912	127.2926	17.94776	0.113232	0.844825531	0.05584843
	5.902958	126.3397	18.74501	0.105556	0.85344753	0.12640911
	6.084404	131.414	21.01807	0.128182	0.859443699	0.86873436
	5.825271	127.2334	17.8611	0.115051	0.841136478	0.08528723
	5.809195	126.9435	18.45275	0.120606	0.842934082	0.03635498
5.336148	110.0158	13.31124	0.14101	0.816806901	0.05226187	
5.540607	136.7816	17.02995	0.123131	0.808520036	0.0907478	

Table 1: Different Parameters

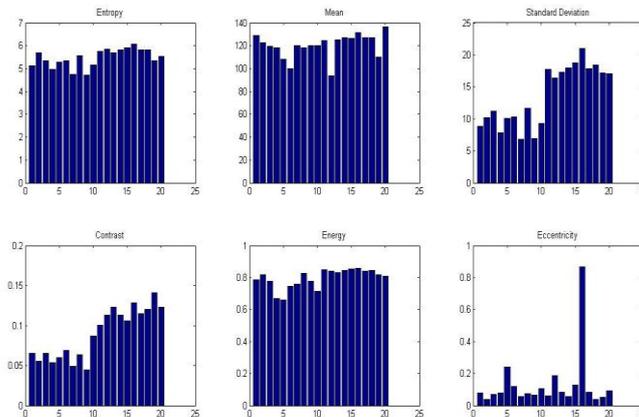


Figure 4: Graph of different Parameters

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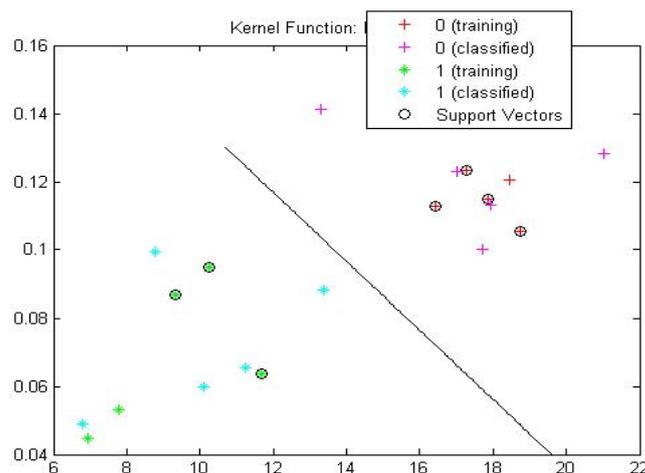


Figure 5: output of the SVM.

VII. CONCLUSION

Image processing technique plays a important role in the detection of the pests. Our first objective is to detect whiteflies, aphids, thrips on greenhouse crops. We propose a novel approach for early detection of pests. To detect objects we use pan tilt camera with zoom. So without disturbing the pests we are able to take the image. It illustrates the collaboration of complementary disciplines and techniques, which led to an automated, robust and versatile system. The prototype system proved reliable for rapid detection of pests. It is rather simple to use and exhibits the same performance level as a classical manual approach. Our goal is to detect the pests as early as possible and reduce the use of pesticides.

REFERENCES

- [1]. Martin,V.Thonnat,“A Learning Approach For Adaptive Image Segmentation.” In Proceedings of IEEE Trans.Computers and Electronics in Agriculture.2008.
- [2]. Vincent Martin and Sabine Moisan, “Early Pest Detection in Greenhouses”. INRIA Sophia Antipolis M’editerrann’ee, PULSAR team 2004 route des Lucioles, BP93
- [3]. Jayamala K. Patil , Raj Kumar, “Advances In Image Processing For Detection Of Plant Diseases” Journal Of Advanced Bioinformatics Applications and Research ISSN 0976-2604 Vol 2, Issue 2, June-2011, pp 135-141
- [4]. Ikhlef Bechar and Sabine Moisan, “On-line counting of pests in a greenhouse using computer vision”. published in "VAIB 2010 - Visual Observation and Analysis of Animal and Insect Behavior (2010)"
- [5]. Paul Boissarda, Vincent Martin, “A cognitive vision approach to early pest detection in greenhouse crops”. computers and electronics in agriculture 6 2 (2 0 0 8) 81–93
- [6]. B.Cunha.“Application of Image Processing in Characterisation of Plants.” IEEE Conference on Industrial Electronics.2003.
- [7]. Santanu Phadikar, Jaya Sil.“Rice Disease Identification Using Pattern Recognition Techniques.” IEEE 10th International Conference On I.T.E.2007.
- [8]. Rafael C. Gonzalez, Richard E. Woods. “Digital Image Processing”,2nd edition, Pearson education (singapore) pte.ltd.2003.
- [9]. T.F.Burks, S.A.Shearer and F.A. Payne, “Classification of weed species using color texture features and discriminant analysis,” Trans. ASAE, vol.43, no.2, pp.441–448, Apr. 2000.
- [10]. R.Pyidipati, T.F. Burks and W.S. Lee, “Identification of citrus disease using color texture features and discriminant analysis,” Comput. Electron. Agric., vol.52, no.1, pp.49-59, June 2006.
- [11]. Laaksonen, J.Koskela, M.Oja, E. , “Self-organizing maps for content-based image retrieval,” International Joint Conference on Neural Networks, vol.4, pp.2470-2473 ,1999.
- [12]. R.M. Haralick, K. Shanmugam and I.Dinstein, “Textual features for image classification,” IEEE Trans. Syst. Man Cybern., vol.3, no.6, pp. 610–621, Nov. 1973
- [13]. H. Ritter and T.Kohonen. “Self-organizing semantic maps”, Biological Cybernetics, vol.61, pp.241-254, 1989.