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An Automatic Identification of Agriculture Pest Insects and Pesticide Controlling

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Abstract: **Monitoring agriculture pest insects is currently a key issue in crop protection. Detection of pests in the farms is a major challenge in the field of agriculture; therefore effective measures should be developed to fight the infestation while minimizing the use of pesticides. The techniques of image analysis are extensively applied to agricultural science, and it provides maximum protection to crops, which can ultimately lead to better crop management and production. At farm level it is generally operated by repeated surveys by a human operator of adhesive traps, through the field. This is a labor- and time-consuming activity, and it would be of great advantage for farmers to have an automatic system doing this task. This project is a system based on identification of insects and to determine the quantity of pesticides to be provided according to the growth of the pest insect. The system will determine the quantity of pesticides according to the lifespan of the insect of common pests and will suggest methods of controlling. The proposed system classify the pest insects according to their categories using SVM classifier. This system is thus beneficial to farmers for providing pesticides in correct proportion.**

Keywords**: Insects; images; segmentation; Gabor; SVM classifier.**

I. INTRODUCTION

Agriculture is one of the most important sources for human sustenance on Earth. Not only does it provides the much necessary food for human existence and consumption but also plays a major role in the economy of the country [1],[2]. Millions of dollars are spent worldwide for the safety of crops, agricultural produce and good, healthy yield. It is a matter of concern to safeguard crops from Bio-aggressors such as pests and insects, which otherwise lead to widespread damage and loss of crops [3]. In a country such as India, approximately 18% of crop yield is lost due to pest attacks every year which is valued around 90,000 million rupees [4]. Without gathering information about the insect dynamics it is almost impossible to execute the appropriate pest control at the right time in the right place [5,6]. Conventionally, manual pest monitoring techniques, sticky traps, black light traps are being utilized for pest monitoring and detection in farms. Manual pest monitoring techniques are time consuming and subjective to the availability of a human expert to detect the same. Sticky traps and black light traps are less effective and also prone to cause harm to environmental friendly insects. As a preventive measure farmers spray pesticides in bulk which are detrimental and hazardous to the ecosystem [7].

In order to address these disadvantages, several present day pest detection and control methodologies exists which include image processing based pest identification. These two methodologies involve several complex image processing algorithms to achieve the same and are limited to a field environment. An average of pests accumulated on the trap on a particular day gives us the density of pest population in the field. Remedial measures can be taken based on the density. Integrated pest management relies on the accuracy of pest insects monitoring techniques. Without gathering information about the insects dynamics it is almost impossible to execute the appropriate pest control at the right time in the right place. Pests are those that directly damage the crop, and pest control has always been considered the most difficult challenge to overcome. A well-known technique to perform pest control monitoring is based on the use of insect traps conveniently spread over the specified control area.

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II. LITERATURE REVIEW

Various national, international and IEEE papers are surveyed and discussed below:

Tokihiro Fukatsu [8] proposed a system to monitor the occurrence of the rice bug, Leptocorisachinensis, in rice paddy fields as a means of reducing the burden of manual insect counting work with a high-resolution digital camera. One method is to filter extraneous image data containing no observed target insects (end-members) on the pheromone trap. In this method, the difference between collected image data and the reference image data was calculated, and the total number of pixels whose value was greater than a threshold value for the difference result (number of white pixels) was used for filtering. This method managed to maintain Sensitivity at 100% during the experiment. Accuracy was observed to be 89.1% on average. Using this method, the time spent looking at extraneous image data without L. chinensis can be reduced by 85%.

In [9], proposed by Chenglu Wen. An image-based orchard insect automated identification and Classification method was presented using three feature models: local feature model based on local invariant features; global feature model based on global features; and a hierarchical combination model for combining the results from the models above to achieve better performance under different image quality. Since some work has been done on automated identification and classification for good structured poses and similar size pest colonies images, our method aimed to propose an automated method which is more robust and can work on field insect images considering the messy image background, missing insect features, and varied insect pose and size which exist in such. Advanced analysis on time-dependent pose change of insects on traps was conducted in this research to study the pose change of insects on traps and the hypothesis that an optimal time to acquire and image after landing exists.

M.Gonzalez [10] developed a system which is an implementation of a WimSN capable of taking images of plagues that attack fruits crops. It enables to implement early alerts systems in case of pest infection thus allowing performing localized fumigation in the crop with reduced pesticide usage and hence avoiding environmental and water pollution. It allows assessing pest populations' variability due to climate change and to identify the crops genetically more resistant to the lepidopterous insect pest (moths). The achieved design is low cost (around U$S 140 all included), it is of easy construction and quick maintenance and it enables to change the trap's floor while keeping the superior structure. It fulfills all requirements asked by the entomologists' partners of this project.

P. Tirelli, N.A. Borghese [11] elaborated a system based on a distributed imaging device operated through a wireless sensor network that is able to automatically acquire and transmit images of the trapping area to a remote host station. The station evaluates the insect density evolution at different farm sites and produces an alarm when insect density goes over threshold. The network architecture consists of a master node hosted in a PC and a set of client nodes, spread in the fields that act as monitoring stations. The master node coordinates the network and retrieves from the client nodes the captured images. The results of this study demonstrated the feasibility of pest insect automatic monitoring on the field, by wireless sensor networking.

III. SYSTEM DEVELOPMENT

3.1. Image Set:

Four insect species, Beet Armyworm, Cutworm, Stink Bug and Wasp were obtained from Agriculture College, Pune. Numbers of each species for lab-based images are given in Table 1.

Table 1NUMBERS OF EACH SPECIES FOR LAB-BASED IMAGES

Inset Name	Beet Armyworm	Cutworm	Stink Bug	Wasp
Stage I	10	10	10	7
Stage II	10	10	12	8
Stage III	13	11	10	12
Stage IV	12	11	11	12
Total	45	42	43	40

The general working of the pest detection system consists of following steps:

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3.2. Image Pre-Processing:

The purpose of image enhancement methods is to increase image visibility and details. Enhanced image provide clear image to eyes or assist feature extraction processing in computer vision system.

In RGB color model, each color appears in its primary spectral components of red, green, and blue. The color 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 and consume much time to process. In image processing it needs to process the three different channels so it consumes large time. In this study, grayscale image is enough for the method so the authors convert the RGB image into grayscale image with the following formula:

$I(x, y) = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$

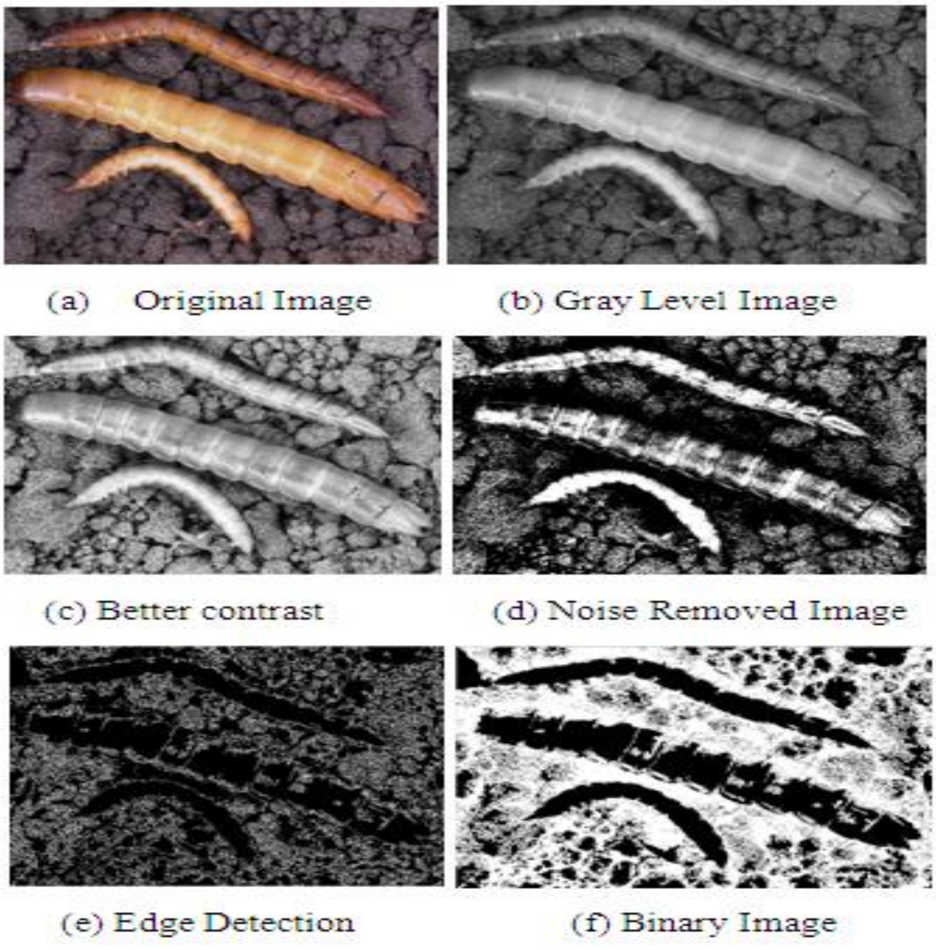

Fig.1 Results of preprocessing of an image.

Fig.1 (a) show original image captured in the field by camera. The various pre-processing techniques are applied on the image to get better results. The image is converted RGB to gray level, shown in fig.1 (b). The enhanced image gives better contrast, fig.1 (c). Noise in removed using bwareaopen(BW, P), which removes from a binary image all connected components (objects) that have fewer than P pixels, producing another binary image, shown in fig.1 (d).Edge detection is done using HPF, Fig.1 (e).To get better segmentation results convert image into binary image, fig.1 (f).

3.3. Segmentation:

The next step in the detection process is Segmentation. The image of the pest insect could be with complex background. So, segmentation is performed on the color converted image, to separate the object of interest from the background.

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Watershed transform, Otsu's Thresholding and Adaptive Thresholding algorithms are employed to extract the pest insect from the background. Segmentation is performed on the colour converted image, to separate the object of interest from the leaf and other complex background. The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represents the region boundaries. Water place on any pixel enclosed by a common local intensity minimum (LIM). Pixel draining to a common minimum forms a catch basin, which represent a segment.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), define as a weighted sum of variances of the two classes:

$$\sigma_\omega^2(t)=\omega_1(t)\,\sigma_1^2(t)+\omega_2(t)\,\sigma_2^2(t) \qquad (1)$$

Weights are the probabilities of the two classes separated by a threshold and variances of these classes.

Otsu shows that minimizing the intra-classes variance is the same as the maximizing inter-class variance:

$$\sigma_b^2(t)=\sigma^2+\sigma_\omega^2(t)\,\omega_1(t)\,\omega_2(t)[\mu_1(t)-\mu_2(t)]^2 \qquad (2)$$

Which is expressed in terms of class probabilities and class mean.

3.4. Feature extraction:

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. In image processing, image features usually included color, shape, size and texture features. In proposed system color, shape and texture features are extracted.

3.4.1. Color:

The color feature is one of the most widely used visual features in image processing. Color features have many advantages like robustness, effectiveness, Implementation simplicity, Computational simplicity, Low storage requirements. Color descriptors of images can be global or local and color descriptors represented by color histograms, color moments or color coherence vectors. [12].

The HSV (hue-saturation-value) system is a perception oriented non-linear color space. Color information is represented by hue and saturation values in HSV color space.

HSV color space is composed with hue saturation, value three components, Hue represent different colors, such as red, orange, green, with $0^\circ \sim 360^\circ$ measure and is determined by the dominant wavelength in the spectral distribution of light wavelengths. It is the location of the peak in the spectral distribution. The Saturation(S) indicates the depth of colour, for example, red can be divided into dark red and light red, measured in percentage from 0% to fully saturated 100%. Value indicates the degree of light and dark color, usually measured in percentage from black 0% to white 100%. In this paper, we study the H component of HSV color space, because the H component represents color information, can provide more obvious characteristics of the color image and can also be used as the semantic features of images to the image classification. The transformation from RGB color space to HSV color space is nonlinear; and the conversion formula is given as:

$$H=\begin{cases}\dfrac{(R-G)+(R-B)}{2\sqrt{([R-G)]^2+\sqrt{(R-B)(G-B)}}} & ,B\le G-1\\ 2\pi-across\,\dfrac{(R-G)+(R-B)}{2\sqrt{([R-G)]^2+\sqrt{(R-B)(G-B)}}} & ,B>G\end{cases} \qquad (3)$$

$$S=\frac{\max(R,G,B)-\min(R,G,B)}{\max(R,G,B)} \qquad (4)$$

$$V=\frac{\max(R,G,B)}{255} \qquad (5)$$

HSV is cylindrical geometries, with hue, their angular dimension, starting at the red primary at 0°, passing through the green primary at 120° and the blue primary at 240°, and then back to red at 360°. The HSV model is shown as Figure1,

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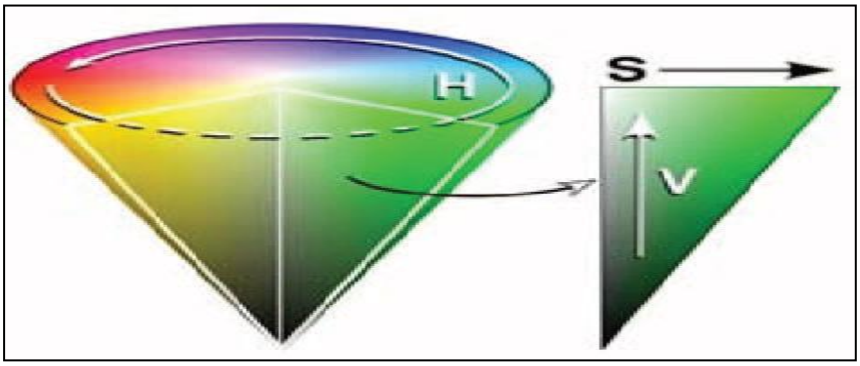

Figure 2. The HSV model

In our system, we employ the HSV color space instead of the RGB color pace in two reasons:

One is the lightness component is independent factor of images and second is the components of hue and saturation are so closely link with the pattern of human visual perception.

The proposed scheme contains three phases. First of all we resize all images to reduce the size of images and processing time. Secondly we convert each pixel of resized image to quantized color code. Finally we compare the quantized color code between the query image and database image.

3.4.2. Texture:

Shape features includes length, width, aspect ratio, rectangularity, area ratio of convexity, perimeter ratio of convexity, circularity and form factor, etc

The image analysis technique used for this study was the well-know Gabor wavelet transform. Wavelet transform could extract both the time (spatial) and frequency information from a given signal, and the tunable kernel size allows it to perform multi resolution analysis.

$$g(x, y) = s(x, y) * Wr(x, y) \quad (6)$$

In Eq. 1, g (x , y) is the Gabor Function, s (x , y) is the Gaussian Function and Wr (x , y) is the Window function.

Gabor transform equation of a signal x (t) is given by:

$$G_x(t,f) = \int_{-\infty}^{\infty} e^{-\pi(T-t)2} e^{-j2\pi ft} x(t)dt \quad (7)$$

The Gaussian function has infinite range and it is impractical for implementation. However, a level of significance can be chosen (for instance 0.00001) for the distribution of the Gaussian function.

$$e^{-\pi a2} \geq 0.00001; \ |a| \leq 1.9143 \quad (8)$$

$$e^{-\pi a2} < 0.00001; \ |a| > 1.9143 \quad (9)$$

Outside these limits of integration |a|>1.9143, the Gaussian function is small enough to be ignored. Thus the Gabor transform can be satisfactorily approximated as

$$G_x(t,f) = \int_{-1.9143+t}^{1.9143+t} e^{-\pi(T-t)2} e^{-j2\pi ft} x(t)dt \quad (10)$$

This simplification makes the Gabor transform practical and realizable.

The spatial frequency responses of the Gabor functions are:

$$f = N/P \quad (11)$$

where N is the size of the kernel and P is period in pixel.

Gabor filters increased the accuracy rate of the insect species recognition system.

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3.5. Classification and Recognition:

Support vector machine (SVM) is non-linear classifier. SVM is supervised machine learning method. Support Vector Machines (SVM) is a classification system derived from statistical learning theory [15]. The SVM estimates a function for classifying data into two classes. Using non-linear transformation that depends on a regularization parameter, the input vectors are placed into a high-dimensional feature space, where a linear separation is employed. To construct a non-linear support vector classifier, the inner product (x, y) is replaced by a kernel function K (x , y) as in

$$f(x) = sgn(\sum_{i=1}^{N} a_i y_i K(x_i x)+b) \quad (12)$$

Where, f(x) determines the membership of x.

The main concept of SVM are to transform input data into a higher dimensional space by means of a kernel function and then construct an OSH(Optimal Separating Hyper Plane) between the two classes in the transformed space. For insect identification it will transform feature vector extracted insect's contour.

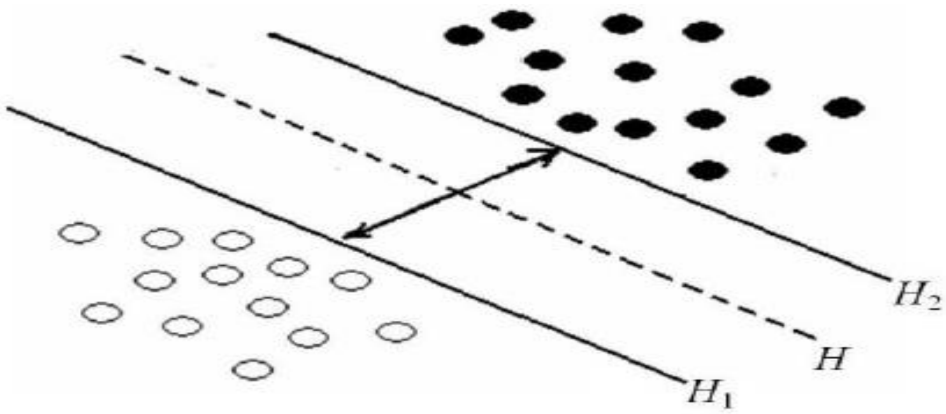

Figure 3.The optimal plane of SVM in linearly separable condition

Different types of features extracted from insect's images and asynchronous calculate distance to achieve successive similarity matching; the last one is the final recognition results. This structure can be called multifeature cascade structure, by a higher similarity comparison of the output match to become the next set of feature extraction and comparison of input similarity measurement done by calculating distance between features. This structure has the following problems: (1) in every query similarity measure should be carried out repeatedly, impact the retrieval efficiency. (2)To assume that the similarity of each feature value in a unified domain, otherwise it would be calculated from a linear combination of similarity that does not make sense. Features characteristic normalized into two parts between internal and features. It will be directly applied to calculate the similarity as it cause significant error without going through the normalization. Images of the collected insects cut, zoom in and change and improve photo quality and gray scale processing, to achieve uniform size of the image, the image for a given size image, select the part of the insect images as training set, training set contains images own name and subject name and insects.

Table 2. CLASSIFICATION RESULTS UNDER OPTIMAL MODELS FOR EACH SPECIES WITH FIELD-BASED IMAGES FOR TRAINING

Species	Sample number	Correct number by feature extraction	Correct number by SVM Classification
Beet Armyworm	45	44	43
Cutworm	42	42	39
Stink Bug	43	40	40
Wasp	40	38	35
Correct Rate		80%	82%

IV. RESULT AND DECISION

The 30 field sample images were used for testing, and the images Of 169 lab-based images were used for training. The insect identification and classification model, which is mentioned in Section 3.3, was used for features extraction and classification. The feature extraction and classification results are shown in Table 2. The model correctly extracted 80% of pest insect images. The SVM based classification model using lab-based images for training and field-based images for testing correctly classified 82% of the insect images.

V. CONCLUSION

From the above results it is concluded that automatic identification of pest insects on the field is done by using SVM classifier.

In this paper, an automatic detection and extraction system was presented, different image processing techniques were used to detect and extract the pests in the captured image.

The mechanism used to extract the detected objects from the image is simple, the image was scanned both horizontally and vertically to determine each coordinates and save the object image. The result presented in this paper is promising but several improvements on both materials and methods will be carried out to reach the requirements of fully automated pest detection, extraction and identification system.

VI. FUTURE SCOPE

In the future, other image processing techniques may be used to enable the detection and extraction more efficient and accurate. Other future work may include the identification system of the extracted objects.

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