

pass filters are sharpening filters. Smoothing filters are used for smoothing of the edges. Sharpening filters are used for enhancing the edges in the image.

In our system we are using smoothing 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 smoothing filter is average filter. It consists of a 3X3 matrix of 1 and it is divided by 9.

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.

Advanced 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, advanced SVM's introducing 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 advanced 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 is given in following table 1.

4) Pests identification and marking The pests identification is done by the support Vector machine classifier. There are two categories are formed such as affected leaf and unaffected leaf. Some data from data base provided to train the support vector machine and based on the data provided to support vector machine we can identify whether the testing data is affected and marked if affected.

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
Energy	Returns the sum of squared elements in the GLCM.

5) Pest 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 an input to the support vector machine; Based on the comparison with the parameters of database support vector machine generates the output.

6) Classification of Pests If the leaf is found to be infected then the next step is to find out the type of pest. Here we are classifying them into two categories which are whiteflies and aphids. For identification, after the averaging filtering, a special type of mask is used. Then the filtered image is convolved with the mask. Then extracting the region properties and gray co-occurrence matrix properties the classification is done in two types, whiteflies and aphids. For identification we are considering region properties like standard deviation and contrast. For deciding the category we are using SVM classifier again. The database which is provided for the training of second SVM is shown in figure. 4

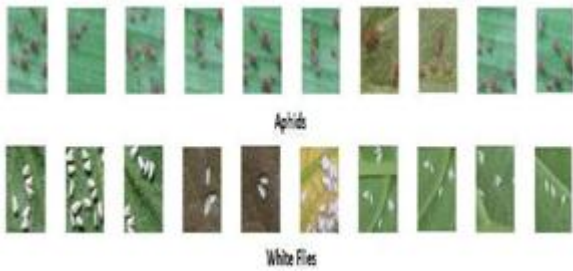


Figure 4: Database for classification

4. Flowchart

The flow chart for the propose system is given in fig.5. The flowchart gives the complete idea about the system.

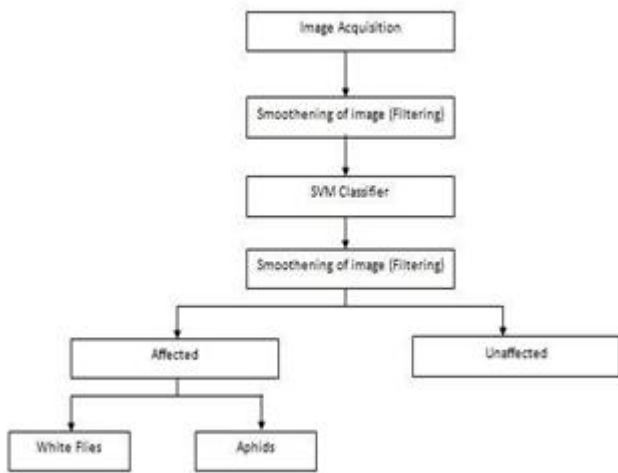


Figure 5: Flowchart of the system

5. Result

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. 6 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.7 shows that the training to the advanced SVM done with 100% accuracy. We have divided it into two categories affected and unaffected. Here 1 represents unaffected and 0 represents affected. Also further the affected

category is divided into two classes, aphids and whiteflies. For this classification we have used one more advanced SVM classifier. The different properties which decide that they are whiteflies or aphids are shown in table 3. Based on this the advanced SVM is trained and input image of affected leaf is given to the second support vector machine which will generate the output as 1 or 0 based on the parameters of the input image. 1 is for aphids and 0 is for whitefly.

Parameters	Entropy	Mean	Standard deviation	Contrast	Correlation	Eccentricity
Unaffected Images	5.111022	128.9804	8.784494	0.099495	0.788207687	0.88005621
	5.704047	122.7276	13.36848	0.088384	0.817424865	0.0369198
	5.356719	119.6399	11.23865	0.085354	0.77523552	0.06858617
	4.956636	118.4778	7.783343	0.053232	0.666828028	0.98068627
	5.266736	107.8551	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	11.68826	0.063838	0.825014884	0.07977056
	4.706327	120.4082	6.939394	0.046646	0.774875913	0.06434645
	5.169737	120.4206	19.33133	0.18697	0.713766094	0.10776177
Affected Images	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
	6.064404	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
	5.549607	136.7810	17.02995	0.123131	0.808520036	0.0907478

Table 2: Different Parameters

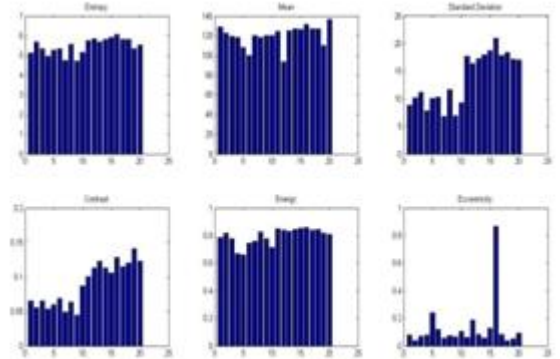


Figure 6: Graph of different Parameters

Parameters	Entropy	Standard Deviation	Contrast	Eccentricity	Euler's Number
Affected with Aphids	0.241974	0.1958067	0.040022	0.47946715	112
	0.241974	0.1958067	0.040789	0.303154	124
	0.244457	0.1970767	0.040899	0.5103298	115
	0.243465	0.1965699	0.040899	0.29788011	111
	0.241974	0.1958067	0.039912	0.47548961	109
	0.242968	0.1963159	0.041009	0.36370833	99
	0.24693	0.1983371	0.042105	0.56804004	84
	0.243465	0.1965699	0.041228	0.50649518	98
	0.243465	0.1965699	0.042544	0.3016139	113
	0.243961	0.1968235	0.041667	0.31537708	111
Affected with Whiteflies	0.327893	0.2377087	0.069956	0.51147809	76
	0.357723	0.251445	0.07182	0.418625	44
	0.305539	0.2271689	0.066667	0.45601103	63
	0.301057	0.2250285	0.060855	0.39285678	106
	0.285105	0.2173283	0.049452	0.39021232	110
	0.296089	0.2226441	0.064474	0.59140669	75
	0.28741	0.218449	0.056031	0.32758873	146
	0.280933	0.2152929	0.055811	0.54562806	178
	0.281398	0.2155203	0.055044	0.39666599	151
	0.275793	0.2127727	0.054167	0.50532207	160

Table 3: Different Parameters to decide Aphids or white

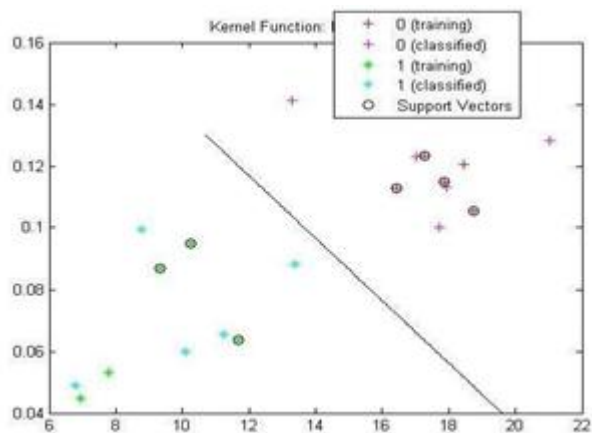


Figure 7: Output of the SVM

6. Conclusion

Image processing technique plays an important role in the detection of the pests. Our first objective is to detect whiteflies, aphids and 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.

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