

A Methodology for Automatic Detection and Classification of Pests using Optimized SVM in Greenhouse Crops



Venkataramana Attada, Somesh Katta

Abstract: Digital revolution is taking place in every industry. The technologies namely Cloud Computing and the Internet of Things (IoT) are considered to be as a digital revolution. Comparatively with other industries Agriculture industry has less usage of these digital revolutionary technologies. In recent years Agriculture industry uses such type of digital revolution technologies to counterpart traditional practices which greatly influence the productivity. The IoT is set to push the future of farming to the next level by collecting the production data which includes weather and soil data, image data of crop, pests, etc. through internet enabled communication objects. Performing computation and providing advisory on this large scale of data that is collected by communication objects by Cloud Computing technologies in terms of Leaf is point of interest which has infestation problem with biological organisms such as pests observed by naked eye is time consuming. We make use of digital revolution device like Unmanned Aerial Vehicle (UAV) which collects the data from user point of interest, Digital Image Processing techniques, Pattern recognition Algorithms for above stated problem to develop an advisory based cloud system which provides advisory based on detection of pests present on off-seasonal crops rose, lengthy type crops cucumber which are cultivated in new agricultural farming i.e. limited space structure namely Greenhouse.

Index Terms: UAV, Greenhouse, Digital image processing, Pattern recognition, Off-seasonal crops

I. INTRODUCTION

A major challenge to Agriculture is it must be more efficient and sustainable if it is to provide enough food for a growing world population. But with the traditional practises agriculture not much efficient and sus-tainable to improve productivity so that it provides enough food for a growing world population. Agriculture has taken revolution over the traditional practises to made human being existence possible not only on the name of food scarcity but also at the cost of environmental damage. Agriculture is more productive when it is not affected by climate factors which include temperature means many crops are temperature sensitive, the growing

season, rainfall, wind, soil etc. We need to control these factors but in case of open fields it may not possible so greenhouses. Which are limited space structures for growing off-seasonal crops such as rose, cucumber.

The world change its face to Automation on the name of technology agriculture is no exception. Green-houses are designed with respective crop specific climate factors. To maintain respective climate factors at the cost of effective resource utilization in greenhouse is difficult task to human beings. With the advent of Internet of Things (IoT), the operations in protected structures can be automated according to the specific needs of farmers (Tomo Popović et al., 2017;). The important elements of an IoT environment are sensors and these sensors play a prominent role automated greenhouses to capture environmental parameters like soil moisture, humidity, temperature and etc. An IoT system may consists of either wired or wireless sensors to capture data from the environment. The sensor are connected to a microcontroller unit (MU) so that the MU collects data from sensors. The collected data of identifying the biological organisms such as pests and its impact on plants is done by human naked eye is time consuming in greenhouses. This need to be automated by an advisory based automated system which provides advisory based on identified pest so that user does effective resource utilization rather doing see and spray classic approach.

In this paper, an approach an automated pest detection in leaf images of a crop captured using an UAV is proposed and the detected pests are classified using an optimized SVM classifier. The proposed classification method serves as an effective solution for identification of pests not only in greenhouse crops but also in other crops.

II. LITERATURE REVIEW

A lot of research has been happening in Agriculture with respective new approaches over classical approaches in farming and incorporating technology in Agriculture as discussed in introduction i.e. Precision Agriculture. Advancement in technology and impact that created by biological organisms such as pests made re-searchers think about an automatic system for identifying pests present on crops. Sumit Vashisth et al conducted a survey in Himachal Pradesh for knowing the Insect-pest problems associated with off-seasonal crops such as capsicum, tomato, cucumber and rose are cultivated in greenhouses.

Revised Manuscript Received on October 30, 2019.

* Correspondence Author

Venkataramana Attada*, Department of Computer Science and Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh, India.

Somesh Katta, Department of Computer Science and Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh, India

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They surveyed eighty two greenhouses in Himachal Pradesh and they recorded the Insect-pests namely Whiteflies, Aphids, Mites Caterpillars, Leaf-Miners are commonly incident on crops [1].

J. Canny et al implemented a system which automatically detects the pests and use colour feature for train the SVM to classify the pest pixels and leaf pixels. They applied morphological operations to remove unwanted objects after detecting pests. They used erosion operation for removing unwanted objects after that they performed dilation operation to fill the holes[2].

O. P. Verma et al. discussed about a new approach needed over classical approach manual detection of pests and counting of them which is not accurate. They propose a methodology for integrated pest management which uses digital image processing algorithm using extended region grow for identifying pests and have to counting the pests. They make use of this pest count to predict the pesticide to be used. They conduct a survey on agricultural crops namely Paddy, Wheat, Cotton, etc. To knowing which crop is mostly affected by pests and they found that paddy field is affected by pest in a large scale. So, they selected paddy to detect and count the plant hoppers[3].

J. C. Bezdek et al. discussed about the two hot points in the Internet field that are Cloud Computing and Internet of Things. The impact of both technologies is less in the field of agriculture. They study and analyse the both techniques and discussed ideas that have a great influence in agriculture with the combination of both technologies Cloud Computing and Internet of Things. They discussed different applications with combination of two hot points. Among those applications one application is related to forest pests' control which is serious problem in the china[4].

G. Kumar et al discussed about chemical farming problem. In their words chemical farming problem is spraying chemicals for controlling pests to whole field rather affected area of pests[5].

Sushma R.Huddar et al discussed about infestation problem by pests and insects. They proposed a novel and unique algorithm to segregate and detect pests using image processing which involves less computation and also their system is not particular to greenhouse environment it also aims in open field environment. They chosen whitefly as point of interest and they tested different whiteflies affecting different leaves with the accuracy of 96%[6].

All the above work and a lot of work related to pest identification system which is not included is either particular pest like whitefly identification as point of interest or particular crop like paddy crop pests as point of interest. Their work differ by change in methodology with respect to different digital image processing techniques, feature extraction algorithms and classification algorithms. This paper aims to detect the pests which are common in the greenhouses and provide advisory to tackle such pest.

III. METHODOLOGY

The proposed system shown in above figure has the following modules:

1. Image Acquisition Module
2. Data Centre
 - Data Storage Unit

- Pest Image Analysis (Edge Detection and Feature Extraction)
- Pest Classification

3. Advisory System

4. User

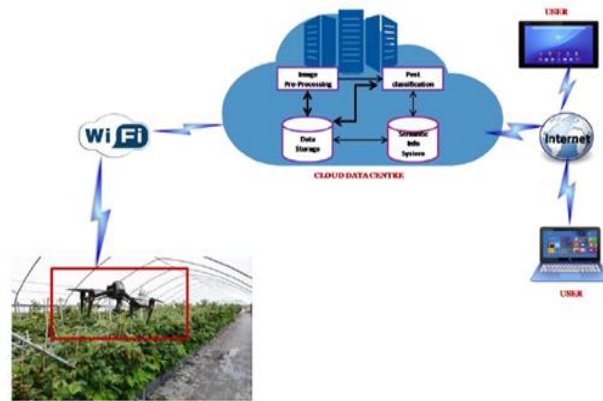


Fig.1. Proposed System Architecture

1. Image Acquisition Module

For doing image analysis, acquisition of images need to be done either it could be done by collecting from Internet or acquisition of images using some equipment. Advancement in technology made acquisition simple through equipment like IP Webcam, Unmanned Aerial Vehicle (UAV) which is shown in proposed system architecture figure. Placing Internet equipped cameras in the greenhouse and captured images with 5 or 10 frames per second at some megapixel resolution and processing in local machine happened in normal green-houses.

But it is not a good solution in the aspect of bushy type crops, long crops because those cameras placed in fixed location and they captured image with some percentage of zoom only[7]. To handle this type of problems Unmanned Aerial Vehicle (UAV) used. UAVs carry different sensors such as optical, multispectral modules to gaining knowledge about the development of a crop. UAV broadcast the video where it operates but it is operator responsibility capturing the frames as of his interest and send it to the data centre.

Availability of greenhouses is less and not functioning of those in our region made us go for alternative i.e., IP Webcam mobile application which has same functioning of UAV. Capturing of pests (Whiteflies, Aphids, and Mites) present on leaves in greenhouses using IP Webcam mobile application and pest images from Internet are collected[8]. The digital colour images which are collected from Internet and using IP Webcam are in JPEG format with a resolution of 1024 x 900 and gray scale of 255.

2. Data Centre

A. Data Storage Unit

Unlike Informative Systems, some systems undergo multiple stages while processing different kinds of data like image data used in this paper in real time projects. Those intermediate results need to be stored for further analysis. Images that are collected using image acquisition module are stored in a local system where those has to be used for further analysis explained in coming sections.

In case of fixed camera as acquisition module it continuously captured the images and send to local machine on average it can send frames up to 24 per second. Sometimes this continuous flow of data may also a major problem in terms of storage[9]. If it is the case then go with Storage as a Service of Cloud technology.

B. Pest Image Analysis:

The steps followed in pest image analysis shown in the figure 2. By considering pests as objects present in images rather considering them as living organisms so that those can be further analysed by considering each part of it. An object can be identified by detecting its edges which is characterized by change in intensity with some direction behaviour. An edge plays a prominent role in the process of detecting the objects present in images. Noise present in image differentiates edges as strong or weak edges[10].

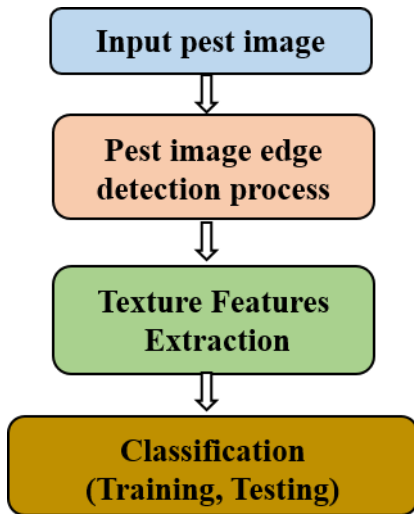


Fig.2 Block diagram for Image Analysis

Because of noise in images, image pre-processing is primary and mandatory step in image analysis. Gaussian mask, interpolation algorithms (bicubic etc) used as pre-processing steps to eliminate noise and then apply some edge detection filters like Sobel, Prewitt and Canny which are good at identifying strong edges. In this paper fuzzy based Bacterial foraging algorithm approach is used for pest object detection[11]. This approach uses the Univalve Segment Assimilating Nucleus (USAN) area histogram-based Gaussian membership function to extract primitive edge information which reduces the noise information. For enhance weak edge information parametric fuzzy intensification operator (FINT) used. Both strong and weak edge qualities assessed by fuzzy measures. Next, the nature-inspired optimization bacterial foraging algorithm is used to optimize the parameters such as sharpness factor and fuzzy entropy. Finally, defuzzification done by applying adaptive thresholding to get binary edge map which is obviously pest identified edge map[12].

The USAN area is calculated using SUSAN principle, with a mask of 37 pixels. The 37-pixel circular mask approximation in a digital image is shown Fig.3. The central pixel is compared with other pixels within the mask using the following equation:

$$C(r, r_0) = \exp \left(-\frac{|I(r) - I(r_0)|}{t} \right), r \neq r_0$$

Where I(r) is the intensity of a pixel at position r, within the

mask, I (r₀) is the intensity of the nucleus of mask at position r₀. ‘t’ is the brightness threshold. t=20 for 8-bit images. The value of δ is taken as “6” experimentally.

The USAN area k at position r₀ calculated as

$$K(r_0) = \sum_r C(r, r_0)$$

USAN area histogram constructed so that pixels that are having same area comes into their respective groups. The probability having USAN area ‘k’ calculated using below formula.

$$P(k) = \frac{h(k)}{\sum h}, k = 0, 1, \dots, 36.$$

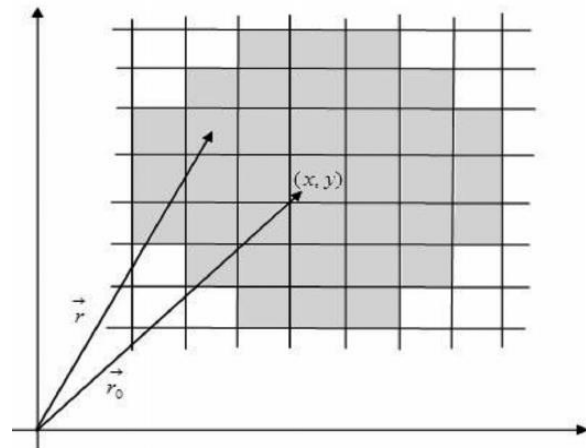


Fig.3. Circular mask approximation in digital images, with 37 pixels.

USAN area histogram which is calculated above fuzzify by using histogram-Gaussian membership function so that noise effect is reduced. The Gaussian membership function is given by below equation.

$$\mu_1(k) = \exp \left(-\left(\frac{k - k_{\min}}{2f_h^2} \right)^2 \right)$$

is the minimum USAN area. The fuzzifier parameter is determined as below.

$$f_h^2 = \frac{1}{2} \frac{\sum_{k=0}^{L-1} (k - k_{\min})^4 p(k)}{\sum_{k=0}^{L-1} (k - k_{\min})^2 p(k)}$$

Noise removed by using Gaussian membership function. But, still some edges not that much prominent to get into strong edges list. To detect such weak edges and enhance those weak edge information in the image by using parametric fuzzy intensification operator as shown in below.

$$\mu_2(k) = \begin{cases} \alpha [\mu_1(k)]^\beta & 0 \leq \mu_1(k) < 0.5 \\ 1 - \alpha [1 - \mu_1(k)]^\gamma & 0.5 \leq \mu_1(k) \leq 1 \end{cases}$$

In the above formula 0.5 used which is a cross over point. This cross over point made a division as strong edges or weak edges. After made a division two fuzzy measures sharpness factor, fuzzy entropy are defined to assess the edge quality of both strong edges and weak edges so that those can optimized to get good quality edge map. By using above two membership functions μ₁(k), μ₂(k) to de-fining the fuzzy measure sharpness factor in terms of strong edge sharpness, weak edge sharpness as shown in below.



The fuzzy edge sharpness factor for the weak edges of the image is given by below equation

$$F_w = \sum_{k=0}^{L-1} [\mu_2(k) - c]^2 p(k)$$

The average fuzzy edge sharpness factor for the weak edges of the image is given by

$$F_{avgW} = \sum_{k=0}^{L-1} [\mu_2(k) - c] p(k)$$

The fuzzy edge sharpness factor for the strong edges of the image is given by

$$F_s = \sum_{k=0}^{L-1} [\mu_1(k) - c]^2 p(k)$$

The average fuzzy edge sharpness factor for the weak edges of the image is given by

$$F_{avgS} = \sum_{k=0}^{L-1} [\mu_1(k) - c] p(k)$$

After that quality factor of the weak edges is calculated.

$$Q_w = \frac{F_{avgW}}{F_w}$$

Similarly quality factor of the strong edges is calculated by Favgs, FS. Total edge sharpness factor includes strong, weak edges of a edge map is calculated by dividing the 'QS' with 'QW'. Another fuzzy measures 'fuzzy entropy' which measures the randomness pre-sent in the image.

$$E = \frac{-1}{L \ln 2}$$

$$\sum_{k=0}^{L-1} [\mu_2(k) \ln(\mu_2(k)) + (1 - \mu_2(k)) \ln(1 - \mu_2(k))]$$

To get quality edge map both fuzzy measures need to be optimized which are intuitively depends the parameters α , β , γ , and f_h . For optimizing those values the objective function is defined in terms of both fuzzy measures.

$$J = E + \sigma |S_{df} - S_f|$$

Bacterial Foraging Algorithm used for optimizing the parameters α , β , γ , and f_h . by searching in the 4-D search space on image in terms of reducing the objective function value.

The main steps in Bacterial Foraging Algorithms(O. P. Verma et al., 2017) are: Chemo taxis, Swarming, Reproduction, Elimination and Dispersion. The $J(i, j, k, l)$ is defined to represent the fitness of the 'i'th bacterium at the position $\Theta_i(j,k,l)$ in 'j'th chemotaxis, 'k'th reproduction and 'l'th elimination-dispersion step. Initially all bacteria placed randomly. The parameters after doing optimization are used to modify above defined membership functions which include optimized parameters. After that this fuzzy domain values need to be transferred to spatial domain values which is defuzzification. That means using fuzzy membership values characterizing edge pixel as '1'and background pixel as '0' by adaptive thresholding rather consider-ing single threshold, double threshold used in canny edge filters. Adaptive thresholding follow localized area criteria. Each image pixel value compares with its localized area which is a

value of average all pixel values or some other. If the pixel value greater than the local value it can be treated as edge and '1' in terms of binary edge map. Otherwise, it was background pixel. This can be done in adaptive way for some other pixel the threshold value is some other value. After this step final edge map obtained. The diagram of edge detection approach shown in Fig.4. In image analysis, detecting the pest object edges are of no use. By having the edges of object, the object cannot differentiated. For that it has to undergone for further process called feature extraction where one object distinguish from others by using feature set which contains discriminating information. This discriminating information can be colour, texture, etc. Considering dominant colour information is not suitable because all are leaf images and the dominant colour is green with the small variation of pest colour in the image cannot differentiate objects. So, Texture features extractions suitable which are computed from statistical distribution of pixel intensities at specified positions in relative to each other pixel in the image. Because of considering gray level distribution only while extracting features Second order statistical features extraction i.e. gray Level Co- occurrence preferred in this paper. GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P(i, j | $\Delta x, \Delta y$) is the relative frequency with which two pixels, separated by a pixel distance ($\Delta x, \Delta y$), occur within a given neighbourhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P(i, j | d, θ) contains the

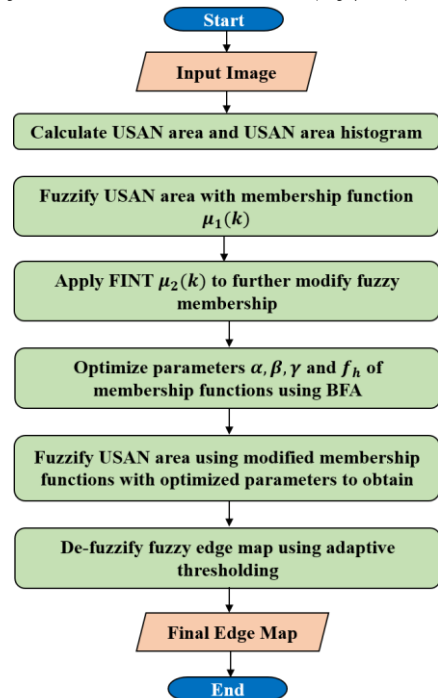


Fig.4. Block diagram of Edge Detection Algorithm

second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance (d) and at a particular angle (θ). Four GLCM matrixes are constructed based on angles(0,45,90,135) with distance 1. The final GLCM matrix element P(i, j) is taken as average of P(i,j | 1,0), P(i,j | 1,45), P(i,j | 1,90), P(i,j | 1,135).

From this final GLCM matrix entropy, contrast, angular second moment, inverse difference moment, dissimilarity are the five texture features are get extracted from each and every image which is used as pest image dataset attributes which can be used to train the classifier which can explained in next section. Contrast feature gives the information of local variation present in the image. Contrast feature can be calculated by using below formula.

$$\text{Contrast} = \sum_{i=1}^n \sum_{j=1}^n (i - j)^2 \log P(i, j)$$

Entropy texture feature measures the disorder of an image. Entropy can be computed by using following equation.

$$\text{Entropy} = - \sum_{i=1}^n \sum_{j=1}^n P(i, j) \log P(i, j)$$

Angular Second Moment also called energy measures the uniformity of an image. Angular second moment can be computed by using following equation.

$$\text{ASM} = \sum_{i=1}^n \sum_{j=1}^n \{P(i, j)\}^2$$

Inverse Difference Moment measures image homogeneity.

$$\text{IDM} = \sum_{i=1}^n \sum_{j=1}^n \frac{1}{1+(i-j)^2} P(i, j)$$

Final texture feature Dissimilarity can be computed by following equation.

$$\text{Dissimilarity} = \sum_{i=1}^n \sum_{j=1}^n P(i, j) |i - j|$$

C. Pest Classification

Pest classification is the problem of identifying in which set of pest images a new pest image belongs, on the set of training set of images computation of 5 texture features has to be done and used as dataset which is training data for building a classifier. Choosing attributes for classifier and choosing classifier which is fit for data are main considerations in this type of problems. Features which are extracted in section B strong relevance means even change of one feature also greatly influence the accuracy classifier. For this purpose statistical learning apps present in MATLAB are used. Classifiers which are used to test which fit for pest image dataset as shown in below table 1.

Table 1 Classifiers and Accuracy

Classifier	Accuracy (%)
KNN (Num Neighbours=10)	37.5
KNN (Num Neighbours=6)	41.1
KNN (Num Neighbours=5)	50
SVM (Kernel Function=Linear)	29.2
SVM (Kernel Function=Quadratic)	50
SVM (Kernel Function=Gaussian)	33.3
SVM (Multiclass Method=OVO)	38.5
SVM (Multiclass Method=OVA,RBF Kernel)	80

Basically Support Vector Machines classifier is a binary classifier. But, later it can be implemented in two different variants One vs one (OVO), One against the others (OVA) which are used different kernel functions for Non-linear data which is having multi classes here in this paper multiple pest names(White fly, Aphids, Mites). In the “one against the others” algorithm, n hyper planes are constructed, where n is the number of classes. Each hyper plane separates one class from the others classes. Transformation of non-linear data to linear data by constructing hyper plane with one side of one class and another side of all other classes’ instances also

called support vectors. For this purpose RBF kernel function used and shown in below equation.

$$\text{RBF Kernel: } k(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|^2}{2\sigma^2}\right) \sigma > 0$$

In this way, we get ‘n’ decision functions (f_k)_{1≤k≤n} of the form . The class of a new point x is given by arg max_k f_k(x), i.e. the class with the largest output of the decision function. This classifier One vs All Support Vector Machines classifier builds the model with the accuracy 80% with given sample dataset as shown in below table 2.

Table 2 Pest Image Dataset

Contrast	Energy	Dissimilarity	Correlation	Homogeneity	Class label
0.00380562	0.99241087	13.000000	-0.001855	0.99809719	Aphids
0.00177846	0.99644783	14.000000	-0.00089	0.99911077	Aphids
0.00233236	0.99534344	12.000000	-0.0011675	0.99883382	Aphids
0.00115664	0.99768874	7.000000	-0.0005727	0.99942168	Aphids
0.00127574	0.99745097	7.000000	-0.0006317	0.99936213	Aphids
0.00221945	0.99556853	16.000000	-0.0011022	0.99889028	Aphids
0.0018001	0.99640466	21.000000	-0.0008998	0.99909995	Leaf
0.00081616	0.99836868	4.000000	-0.0004083	0.99959192	Leaf
0.00239918	0.99521029	21.000000	-0.0011997	0.99880041	Leaf
0.00205811	0.99589014	17.000000	-0.0010283	0.99897094	Mites
0.00133988	0.99732293	12.000000	-0.0006704	0.99933006	Mites
0.0026137	0.99478286	10.000000	-0.0013086	0.99869315	Mites
0.00152699	0.99694952	17.000000	-0.0007628	0.9992365	Mites
0.00193263	0.99614037	7.000000	-0.0009573	0.99903368	Mites
0.00217707	0.99565297	6.000000	-0.0010897	0.99891147	Mites
0.0014312	0.99714069	7.000000	-0.0007088	0.9992844	White fly
0.0017762	0.99645233	10.000000	-0.0008889	0.9991119	White fly
0.00143301	0.99713707	6.000000	-0.000717	0.9992835	White fly
0.00215418	0.99569861	14.000000	-0.0010783	0.99892291	White fly
0.0018188	0.99636738	16.000000	-0.0009031	0.9990906	White fly
0.00165107	0.99670195	15.000000	-0.0008244	0.99917446	White fly
0.00170673	0.99659091	12.000000	-0.0008541	0.99914664	White fly
0.0011325	0.99773693	7.000000	-0.0005608	0.99943375	White fly
0.00064613	0.99870838	3.000000	-0.0003047	0.99967693	White fly

D. Advisory System




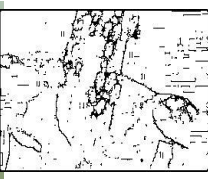

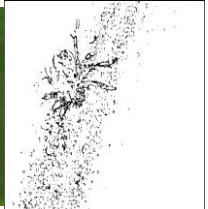
By knowing the type of pest present in the image provided to the system user cannot identify the actual infestation problem. For that, user needs some assistance in terms of damage caused by identified pest, fertilizers that could be given by this advisory module. This advisory collected from greenhouses people.

IV. RESULTS

The whole process of pest detection and classification in crop images is done in MATLAB environment with the images stored in data centre. The results are shown in below.



Table 3 Results of Edge Detection Algorithm

Input Pest image	Edge Detected Pest image	Pest Image Name
		White fly
		Aphids
		Mites

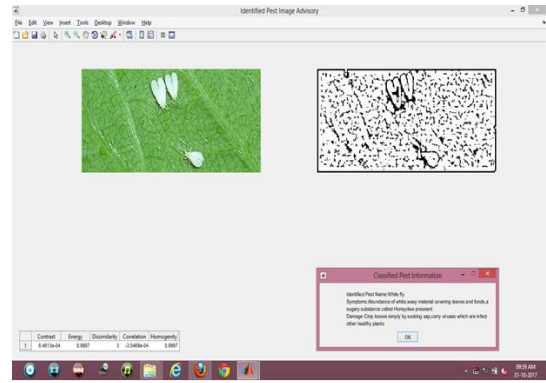


Fig.7 The whole process of the system

V. CONCLUSIONS AND FUTURE SCOPE

The whole process which is followed in this paper identifies the common pests present in greenhouses with the accuracy of 80%. Future work will concentrate on crop specific pest identification and classification system and a centralized system so that all crops pest identification has done by offering as Software as a Service to the user then the users can capture the pest image from their mobile and upload to the system and get advisory.

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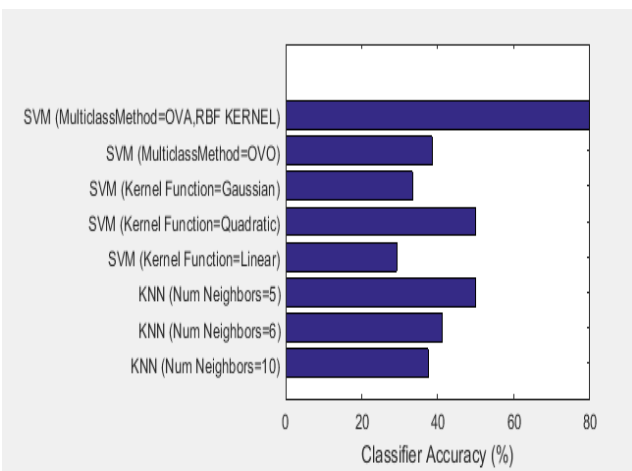


Fig.6 Accuracy of different classifiers applied on pest image dataset

The whole process of the system shown in Fig.7 in terms of input given test image it undergone step edge detection process, texture features extraction and classify the test image by its features with SVM classifier model and provides advisory means symptoms shown by leaf, what extent the damage caused by identified pest, what types of diseases caused by it and fertilizers used to reduce the effect of identified pest

AUTHORS PROFILE



Dr. Venkataramana Attada born in 1977 and received his UG, PG degrees in Computer Science from Andhra University, Visakhapatnam. He received his Ph.D. from Andhra University under the supervision of Prof. S. Pallam Shetty. He is having 19 years of teaching experience. Since 2004 he is working as Associate Professor in the Department of Computer Science and Engineering, GMR Institute of Technology. Currently, he is heading

the Department of CSE. He is a Member of various professional bodies like ACM, CSI and ISTE. He has published/presented more than 24 papers in various national and International Journals and Conferences. He received five times best faculty awards in GMR Institute of Technology for his commendable performance in academics. He also received faculty excellence award from Infosys under Industry–Institute Partnership program. His research areas include Wireless Communication Networks, Internet of Things, Software Engineering and Data Analytics.



Mr. Somesh Katta, working as Assistant Professor in the Department of CSE, GMR Institute of Technology, Rajam, AP, India. He has 6 years of teaching experience. He received Bachelor of Technology and Master of Technology from Andhra University in the years 2010 and 2013 respectively. He is pursuing his Ph.D from Bennett University, Greater Noida. Mr. Somesh is a professional member of ACM and IEEE. His research areas include Machine Learning, Internet of

Things and Cyber Physical Systems.