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PEST DETECTION AND CLASSIFICATION FROM COTTON, SOYABEAN AND TOMATO PLANTS USING DWT, GLCM AND NEURAL NETWORK

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ABSTRACT

According to experts enormous amount of agricultural yield is lost every year due to rapid infection by pests, minimum 10% of crop yield to pigeon pea crop is lost due to pod borer (Helicoverpa armigera) pest attacks. To prevent this lost various methodologies were proposed earlier for identification and detection of agriculture pests but Most of work was done on identification of whitefly pest other than whitefly there is various pest like feabettle, bollworm, bug etc. Hence in this work we have proposed fast and accurate pest detection and classification technique including twenty different species of cotton, soyabean and tomato Plants field insect pests. As input 10 images per species from self generated, standard database and analysis of result out from images is done on the basis of two parameters DWT and GLCM. Result shows prototype system is reliable for rapid detection of pests. It is rather simple to use and exhibits the same performance level as a classical manual approach and it satisfy our main goal to detect the pests as early as possible and reduce the use of pesticides for the prevention of lost of agriculture yield.

Key Words—Pest Detection, Discrete wavelet transform (DWT), Gray Level Co-occurrence Matrix (GLCM), Neural Network(NN).

I. INTRODUCTION

The purpose of Agriculture is not only to feed ever growing population but it's an important source of energy and a solution to solve the problem of global warming. Plant diseases are extremely significant, as that can adversely affect both quality and quantity of crops in agriculture production. In Vidarbha region of India cotton soyabean and tomato is the most important cash crop grown on an area of 13.00 lacks hectors with production of 27 lack bales of cotton approximate. Diseases on these plants is the main problem that decreases the productivity. Plant disease diagnosis is very essential in earlier stage in order to cure and control them. Generally the naked eye method is used to identify the diseases. Previous literature describing to detect mainly pests like aphids, whiteflies, thrips, etc using various approaches suggesting the various implementation ways as illustrated and discussed[3]. We proposed an image processing based system that combines image processing, DWT, GLCM and Neural Network techniques. proposed techniques detect twenty species of cotton, soyabean and tomato Plants insect pests from different plant field such as cotton, Tomato and soyabean. For experimental purpose we have used 16 images as a test database and knowledge base for neural Network and mini- mum 10 images per species for the test purpose from this work tested on mixi-image which consist of self generated images and standard database. figure 1 below shows basic process of the detection of pest in which input image is live image taken by the camera and knowledge base is set of trained data then difference calculator calculates/detect difference in images and detect shape of pest if available. Implementation of the image processing algorithms and techniques to detect pests in controlled environment like greenhouse. Three kinds of typical features including size, morphological feature (shape of boundary), and color components were considered and investi- gated to identify the three kinds of adult cotton, soyabean and tomato Plants insects namely whiteflies, aphids and thrips[5]. classification using image processing has advantages to detect and classify the main agents that cause damages to soybean leaflets i.e., beetles and caterpillars using classifier and neural network for recognition of 20 species of cotton, soyabean and tomato Plants pests.

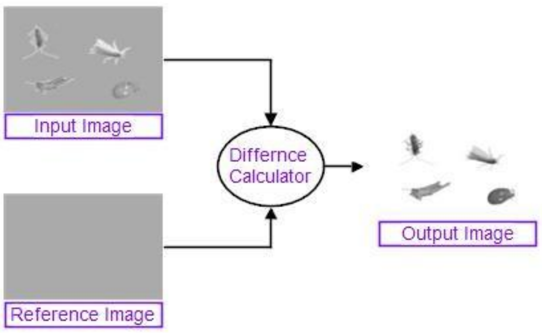

Figure 1: Process of Detection and classification pests.

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 images for pest detection. The rest of this paper is organized as follows, Section III consist of basic introduction of this approach and components. This section also describes the empirical evaluation with the experimental setup, a brief description of the data set and the testing results. Section IV consist result and discussion on the basis of DWT color features (normalized histogram of 24 bins) such as Mean, Variance, Skewness, area in pixel, shape of pest. Input images used are pest of cotton field, soyaben field, tomato field. and GLCM features Contrast, Homogeneity and Correlation Energy. Section V concludes the paper with a discussion of the findings towards future extensions[6][7].

II. PROPOSED METHOD

This section consist of introduction of proposed method and its components. This section also describes the empirical evaluation with the experimental setup, a brief description of the data set and tests. figure 2 shows basic block diagram of proposed method using DWT, GLCM and Neural Network.

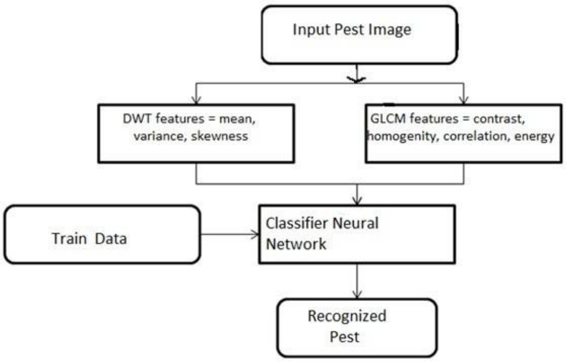

Figure 2: Block of proposed Method

A. Data Set:

Images of twenty species of Cotton , Soybean, and Tomatto field insect pests with 10 images per species from Google Images[2] and photographs taken by the Department of Agricultural Biology. This image set has significant viewpoint changes, different backgrounds, arbitrary rotations, and scale differences within each class. RGB (red, green, and blue) refers to a system for representing the colors to be used on a computer display. Input pest image is RGB image. Red, green, and blue (RGB) can be combined in various proportions to obtain any color in the visible spectrum. Levels of R, G, and B can each range from 0 to 100 percent of full intensity. Each level is represented by the range of decimal numbers from 0 to 255 (256 levels for each color), equivalent to the range of binary numbers from 00000000 to 11111111, or hexadecimal 00 to FF. The total number of available colors is 256 x 256 x

256, or 16,777,216 possible colors.), the color or a page background or text font is specified by an RGB value, expressed with six digits in hexadecimal format. The first and second digits represent the red level; the third and fourth digits represent the green level; the fifth and sixth digits represent the blue level.

B. 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 and texture features and these features are extracted from input image for further processing with the help of Following parameters are used to pest detection of DWT features such as Mean, Variance, Skewness.

1) **Mean:** It is the average value of all the elements in the matrix. It can be formulated as

$$\mu = \frac{1}{n}\Sigma_{i=1}^{m}\Sigma_{i=1}^{n}P(i,j) \qquad (1)$$

where, N is the number of pixels in the image, i and j are the values of corresponding row and column of the image respectively, m and n are the final values of the row and column of the image respectively, Pi,j is a matrix of the image.

2) **Variance:** The formula for the variance is:

$$\sigma = \frac{1}{n}\Sigma_{i=1}^{N}(x_i-\mu)^2 \qquad (2)$$

Where, N is the population size and is the population mean. V = var(X) returns the variance of X for vectors. For matrices, var(X)is a row vector containing the variance of each column of X. For N-dimensional arrays, var operates along the first non singlet on dimension of X. The result V is an unbiased estimator of the variance of the population from which X is drawn, as long as X consists of independent, identically distributed samples.

3) **Skewness:** Skewness is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. The skewness of a distribution is defined as

$$S = \frac{(E(x-\mu)^3}{\sigma^3} \qquad (3)$$

where, is the mean of x, is the standard deviation of x, and E(t) represents the expected value of the quantity t. Skewness computes a sample version of this population value. When you set flag to 1, the following equation applies

$$S_0 = \frac{\sqrt{(n(n-1)}}{n-2}S_1 \qquad (4)$$

This bias-corrected formula requires that X contain at least three elements. GLCM is sensitive to size of the texture samples on which they are estimated and the number of gray levels can be reduced. The commonly extracted textural features using GLCM are contrast, homogeneity, correlation, and energy.

4) Energy : Angular second moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM. Angular second moment measures the image homogeneity. Angular second moment is high when image has very good homogeneity or when pixels are very similar. Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment. It can be formulated as

$$Energy = \Sigma_{i=0}^{n-1}\Sigma_{i=0}^{n-1}C_{i,j}^2 \qquad (5)$$

5) **Homogenity:** Homogenity can measure the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It is mathematically represented as

$$Homogenity = \Sigma_{i=0}^{n-1}\Sigma_{i=0}^{n-1}\frac{C_{i,j}}{1+|i-j|} \qquad (6)$$

6) Correlation: Correlation calculates the linear dependency of the gray level values in the co-occurrence matrix. Measures the joint probability occurrence of the specified pixel pairs. It is represented as

$$Correlation = \Sigma_{i=0}^{N-1}\Sigma_{j=0}^{N-1}\frac{((1-\mu_i)(1-\mu_j)C_{i,j})}{\sigma_i\sigma_j} \qquad (7)$$

Contrast is a measure of the local intensity level variation which gives higher value for high contrast image. It is given by

$$Contrast = \Sigma_{i=0}^{N-1}\Sigma_{j=0}^{N-1}(i-j)^2C_{i,j} \qquad (8)$$

C. Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform is a time/frequency analysis algorithm which has the characteristic of multi-resolution analysis. It not only analyzes signals in the time domain or frequency domain but in the combined domain with time and frequency so that the signal has a good frequency resolution in the low frequency sub-band and a good time resolution in the high frequency sub-band. Discrete Wavelet Transform for two-dimensional image is to perform multi-resolution decomposition for the image, which decomposes the image into the low frequency sub-band and the high frequency sub- band as shown in figure 3 whose resolutions are different. The main energy of the image is accumulated in low frequency sub-band where records the feature information of the image. Equation 1 shows formula for calculation energy value of the

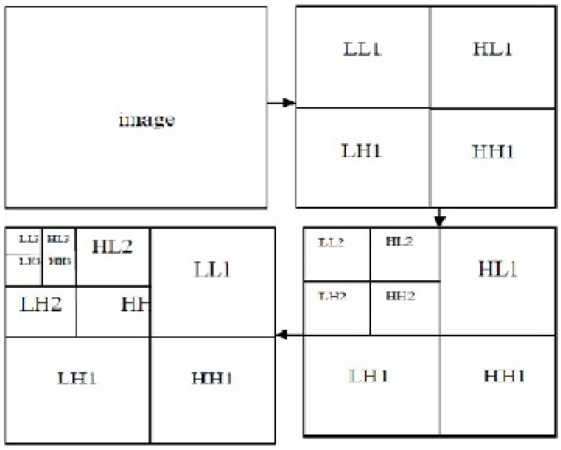

Figure 3: level 3 discrete wavelet decomposition

low-frequency sub-band E,

$$E = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} X_{(i,j)}^2 \qquad (9)$$

Where N denotes the low frequency sub-band size of color component after wavelet transformed, X(i,j) denotes the po- sition coefficient of the low-frequency sub-band (i, j). This feature vector is stored in database with respective image of pests. Next stage will be classification stage.

D. Gray Level Co-occurrence Matrix:

A method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM)/ray-level spatial dependence matrix. This functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, After you create the GLCMs, you can derive several statistics from them using the gray co-props function. These statistics provide information about the texture of an image such as Contrast: Measures the local variations in the gray-level co-occurrence matrix.

Correlation:Measures the joint probability occurrence of the specified pixel pairs. Energy: Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment. Homogeneity: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal

E. Classification (Feed Forward Neural Network):

With the help of feed forward neural Networks, we would be identifying type of pest which is present in image by comparing input image with trained set of data and give preventive as well as control measure to it. It can move to meet a given input / output relation from the direction of the organization neural network, the typical structure is shown in Figure 4. A typical Feed forward neural network consists of three parts: input layer, hidden layer and output layer. At last stage with help different features extracted from images type of pest is recognized which is important for the decision for preventive measure on that[27]. Process of flow of pest detection using DWT is shown in figure 5 it shows input images of the selected twenty species of insect pests that are mostly found in Jaffna cotton, soyabean and tomato Plants fields are used for pre-processing after prepossessing important features required for identification are extracted from input images then extracted features are compared with trained data se*t and result of identified pest is use forward for calculation of mean variance and skewness then rather these properties processing such as RGB to Gray conversion[22-24], Sobel edge Detection, Dilation and image filling for region calculation properties Area and perimeter which are used to calculates accuracy of pest detection image using discrete wavelet transform.

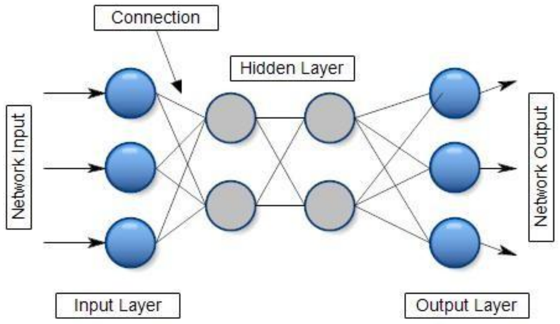

Figure 4: Architecture of a feed-forward neural network.

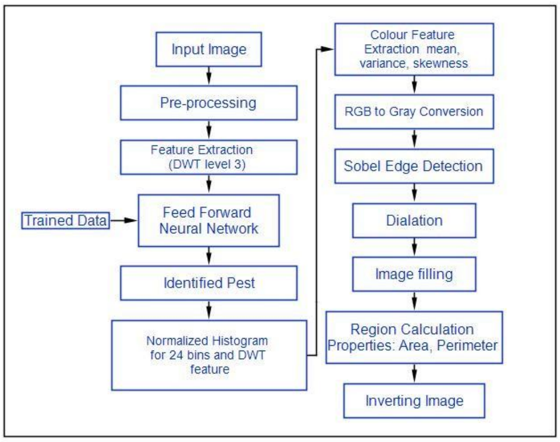

Figure 5: Process flow of proposed system using DWT.

Process of flow of pest detection using GLCM is shown in figure 6 it shows input images of the selected twenty species of insect pests that are mostly found in Jaffna cotton, soyabean and tomato Plants fields are used for pre-processing after prepossessing important features required for identification are extracted from input images then extracted features are compared with trained data set and result of identified pest is use forward for calculation of GLCM [11]Feature Contrast, Homogeneity[16-21], Correlation, Energy then rather these properties processing such as Sobel edge Detection, Dilation and image filling for region calculation properties Area and perimeter which are used to calculates accuracy of pest detec- tion image using Gray Level Co-occurrence Matrix.

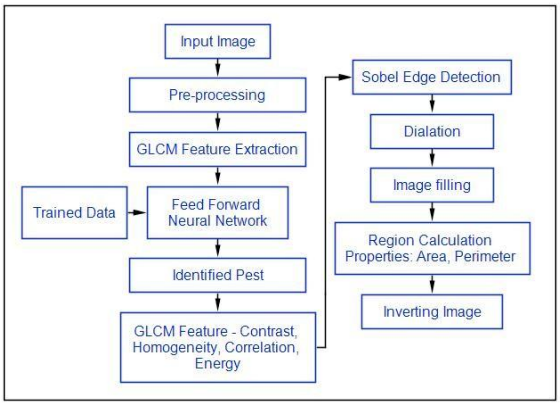

Figure 6: Process flow of proposed system using GLCM.

III. RESULTS AND PERFORMANCE COMPARISON:

A. Results

This section consist result and discussion on the basis of DWT color features (normalized histogram of 24 bins) such as Mean, Variance, Skewness, area in pixel, shape of pest[14][15]. Input images used are pest of cotton field, soyaben field, tomato field. and GLCM features[11]Contrast, Homogeneity and Correlation Energy. table 1 shows that Results of Pest Detection using Discrete wavelet Transform on basis of Mean, Variance, Skewness and Size such as table

2 shows accuracy of proposed method by using different training sets. table 3 shows that Results of Pest Detection using gray-level co-occurrence matrix on basis of Contrast, Homogeneity, Correlation and Energy such as table 4 and Table 5 shows accuracy of proposed method by using different training sets[12][13].

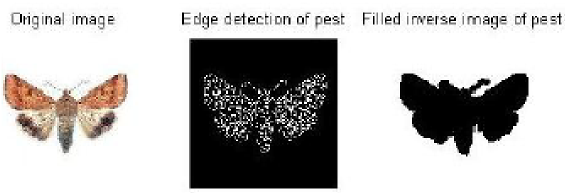

Figure 7: contains (a)original image (b) Edge detection of pest (C)Filled inverse image of pest.

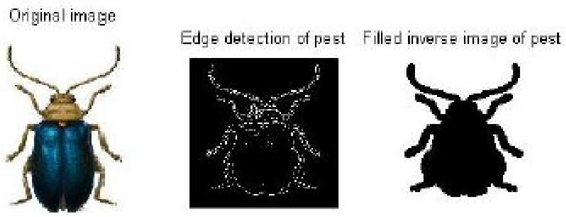

Figure 8: contains (a)original image (b) Edge detection of pest (C)Filled inverse image of pest

B. Result Comparison

In figure 7 and figure 8 shows result of selected pest both figures are divided into three parts 1st original second edge detection of pest third filled inverse image. Table 3 represent result of accuracy from both method GLCM and DWT form table we noticed that proposed system better work with GLCM, from figure 9 it is clear as data set is increased such as images 8 out of 16 to 16 out of 16 and so on accuracy is increased for the both cases proposed with GLCM and Proposed with DWT that means if we want more accurate result proposed system delivers more accurate result with large set of data. From results proposed system calculated mean results are 81.94% and 83.34% for DWT and GLCM respectively. From figure 9 it is clear that if more contrast image gives higher level of Homogeneity and same higher correlation and energy.

Table 1: DWT features, size and Shape of selected pest out all 17 species.

Original images	Mean	Varience	Skewness	Size (pixels)	Shape of Pest
	0.100790	0.032878	1.882365	13272	
	0.070846	0.038241	4.355419	24472	
	0.140110	0.022994	2.374718	30422	
	0.057060	0.040081	4.569857	17634	
	0.053004	0.040547	4.580889	14341	
	0.057261	0.040057	4.576978	17379	
	0.058240	0.039939	4.579469	17313	
	0.058240	0.038246	4.562807	29952	

Table 2: Table contain original image, GLCM feature like contrast, homogeneity, correlation and energy of selected pest out all 17 species.

Sr. No.	original image	contrast	homogeneity	correlation	energy
1		0.050997	0.063023	0.979670	0.975839
2		0.188638	0.276698	0.928768	0.910899
3		0.247016	0.292784	0.914956	0.900259
4		0.530481	0.676150	0.927978	0.925250
5		0.561547	0.646284	0.952420	0.946220
6		0.915816	0.844196	0.923189	0.911559
7		0.455463	0.568006	0.919517	0.904389
8		0.369494	0.580770	0.956364	0.940461
9		0.720626	0.636503	0.914012	0.916029

Table 3: Accuracy of proposed system using GLCM and DWT.

Sr. No.	Specification	DWT Accuracy(%)	GLCM Accuracy(%)
1	Number of Specimen: 1 Training: 4 out of 20 images	60	65
2	Number of Specimen: 3 Training: 6 out of 20 images	65	65
3	Number of Specimen: 3 Training: 7 out of 20 images	75	65
4	Number of Specimen: 1 Training: 8 out of 20 images	76.66	75.75
5	Number of Specimen: 3 Training: 9 out of 20 images	78.33	80.80
6	Number of Specimen: 1 Training: 11 out of 20 images	85.00	86.66
7	Number of Specimen: 2 Training: 14 out of 20 images	85.33	88.34
8	Number of Specimen: 3 Training: 15 out of 20 images	88.84	90

Table 4: Result of proposed system with DWT.

Query image	No. of test image	No. of relevant images	DWT Accuracy (%)
cotton	20	17	80%
soyabean	20	19	95%
tomato	20	19	95%
Average of DWT	60	54	90%

Table 5: Result of proposed system with GLCM.

Query image	No. of test image	No. of relevant images	GLCM Accuracy %
cotton	20	17	80%
soyabean	20	19	95%
tomato	20	19	90%
Average of GLCM	60	55	91%

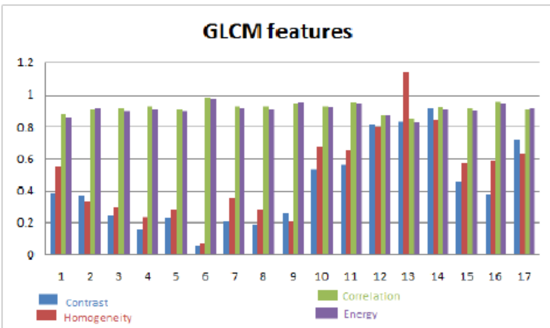

Figure 9: Graphical representation of GLCM features.

IV. CONCLUSION

From previous literature review and result comparison its clear that As previous literature is limited only on whitey detection our work is better from previous because by using proposed user can easily detect over 17 types of pest from any type of cotton, soyabean and tomato Plants field. As per result comparison it is clear that proposed method is best suitable for GLCM with 83.34% accurate. proposed system is best suitable for Tomato, Soyabean and Cotton plants. After identification particular pests, system would give preventive as well as control measures which help the farmers to take correct action to increase production. 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 presented system is simple and yet efficient. Image processing technique plays an important role in the detection of the pests.

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