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DEEP LEARNING-BASED COTTON PEST CLASSIFICATION USING COMPUTER VISION

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Abstract
Images are used in agricultural sciences to monitor plant health and detect pests. This study addresses the issues of identifying cotton pests, specifically Whitefly, Jassid, Thrips, and Spotted Bollworm, using a proposed vision-based methodology that combines handmade and deep learning techniques. The project aims to extract statistical texture parameters from cotton field photos using 2D Gabor filters and co-occurrence matrices, such as smoothness, kurtosis, entropy, contrast, mean, and homogeneity. These features were refined by experimental pruning and classified using a Support Vector Machine (SVM) using a Fine Gaussian kernel. Performance was evaluated using metrics such as precision, recall, F-measure, ROC-AUC, mean absolute error, and root mean square error, resulting in a pest classification accuracy rate of 94.3%. This research makes a significant contribution to the development of automated and precise pest detection technologies, boosting sustainable agricultural practices, particularly in locations like Southern Punjab, Pakistan.

1 INTRODUCTION

In the agrarian sciences, pictures are the critical wellspring of information and data. Computerized picture investigation and picture preparing innovation go around these issues in view of the advances in PCs and microelectronics related with conventional photography [1].

Observing of wellbeing and identification of infections and vermin is basic in plants trees for practical agribusiness [2]. In this advanced period of calculation, a computerized recognizable proof of cotton pests, i.e., White fly, Jassid, Thrips and Spotted Bollworms from images stayed vital in agriculture fields. It is yet a major test looked at by worldwide group that should be tended to. Discover pests in an open scene and adequately recall that they have been a vivacious subject in PC vision for a significantly long time. An ethnicity announcement of the ethnicity grouping issue can be characterized as takes after. Although cotton pest's identification and acknowledgment are yet an unsolved issue centrality there is no 100% exact area and characterization structure, however amid the previous decade, numerous strategies and systems have been slowly made and associated with handling the issue. Before considering the arrangement of the cotton diseases there is important to amass the pests from pictures known as the readiness set [3-26].

These are several approaches reported by the researchers working in the same domain of cotton pest's classification and recognition worldwide. A few of them have reported their methods that could be able to detect and classify the exact type of cotton pests or even diseases. Appearance based highlights which are known as Global highlights, and the shape-based highlights which are known as features. The purpose of this research is to probe the methods to auto identify and classify cotton pests directly from digital images. There is cotton pests' detection and classification. There is hardly any exaggeration that automated protocols performing human assistance in different fields of life like agriculture etc. are beneficial for human beings. Statistical texture parameters along with machine learning techniques have been used to develop a tool that will auto detect and classify cotton pests cultivated in Pakistan especially in Southern Punjab [27-47].

During the last decade, different approaches have been proposed for cottons pest's detection and classification based on the design methodology and data collection process. These approaches fall into vision-based, non-visual sensor-based, and multi-modal categories. Indeed, cotton pest's detection and classification systems are complex in nature and comprised of different sub-systems [48-79]. This thesis is aimed at developing novel techniques by adopting vision-based approach to cottons pests' detection and classification using handcrafted and deep learning-based techniques. Detailed objectives of the thesis are as follows:

- O1. comprehensive review of state-of-the-art techniques based on handcrafted and deep learning approaches, to decide which one works the best;
- O2. understanding the limitations of state-of-the-art techniques, and identifying the gaps in contributions;
- O3. development of a novel method for cotton pest's detection, recognition and classification, which is considered as one of the major challenges in different application domains of agriculture;
- O4. development of an innovative method for detection and classification using a supervised deep learning or a transfer learning model;
- O5. development of an innovative method for cottons pest's detection and classification using an unsupervised deep learning model;
- O6. comparison between the supervised and unsupervised deep learning models on the same dataset;
- O7. production of better results than the existing ones in terms of accuracy and efficiency on standard benchmark datasets.
- O8. The purpose of this research activity is to develop an automated tool for the analysis or interpretation of happening events and their context from video data or images.
- O9. To design a procedure for accuracy and validity on dataset for pest classification.

In this research work, a method of cotton pest's detection, recognition and classification, i.e., White fly, Jassid, Thrips and Spotted Bollworms and many more from images has been proposed using machine learning techniques. To recognize cotton pests, the research is initiated by exploring and investigating the texture parameters of cotton field's images. Smoothness, Kurtosis, Entropy, Contrast, Mean and Homogeneity. Texture features of image $I(x, y)$ have been calculated from each training image by convoluting it with 2D Gabor filters.

In this research work, I have adopted the following steps as my research methodology. These steps have been executed to achieve the target of classification of activities from the given set of activities. The dataset consisting of images belongs to cotton pests that have been input into the developed system. The most appropriate features (pruned through a lot of experiments), i.e., Gabor Texture has been used to represent the texture of the input images. Co-occurrence matrix as feature representative has been used allied with statistical moments. SVM with Fine Gaussian kernel has been used to train and test the proposed system. Following standard evaluation, True False Rate (TFR), (False Negative Rate) FNR, (Positive Predictive Vale) PPV, (False Discovery rate) FDR, Precision, Recall, F-Measure, ROC(AUC), Mean Absolute Error and Root Mean Square Error have been used for the evaluation of the proposed system. The result achieved by the proposed system as per these evaluation measures remained accuracy with SVM obtaining 94.3% accuracy.

The rest of the article has been organized as follows: portion 2 contains literature reviewed. Methodology of the proposed framework has been outlined in portion 3, while portion 4 contains results obtained through proposed method and their discussion. Conclusion and future work has been represented in portion 5.

2 Literature Review

Automated cottons pest's detection and classification play an important role in agriculture field. Its goal is to recognize the pests of cotton from the sensors and/or video data, including the knowledge of the context in which these take place. Due to the advancement in sensor and visual technology, cottons pest's detection and classification-based systems have been widely used in many agriculture applications. Specifically, the proliferation of small size sensors has enabled smart devices to recognize the cotton pests in a context-aware manner. Based on the design methodology and data collection process, these approaches are categorized into visual sensor-based, non-visual sensor-based, and multi-modal categories [80]. The major difference between the visual and other types of sensors is the way of perceiving the data [81]. Visual sensors provide the data in the form of 2D or 3D images or videos, whereas other sensors provide the data in the form of a one-dimensional signals [82].

In recent years, the wearable devices have been featured with many small non-visual sensors, which have enabled the development of pervasive applications. The wearable devices such as smart-phones, smart-watches, and fitness wristbands are worn all day long by many people [83]. These devices have computing power, communication capability, and are available at low cost, which make them suitable for cottons pests detection and classification. Currently, various techniques have been proposed for sensor-based cotton pest's recognition in daily monitoring, rehabilitative training, and disease prevention [84]. They used Artificial Neural network to identify cotton insects that is ideal and problem-solving model. This article basically discussed only Assassin Bug, Alfalfa Hopper, Hippodamia Ladybug Larva, Hippodamia Lady Beetle Adult. The investigator collected custom data from United States. The accuracy of the system is not up to mark that is 95.6%. The empirical features are used for the processing of images to identify of the insect that are complex and complicated for processing point of view.

On the other hand, visual sensor-based approach is one of the most popular cottons pest's detection and classification approach in the computer vision and machine learning research community. This approach has been employed in a wide range of application domains [85]. In particular, the past decade has witnessed enormous growth in its applications [86]. Multi-modal cottons pest's detection and classification approach has also become popular during the last decade. In this approach, visual and non-visual sensors are used at the same time to recognize the cotton pests [87]. This approach is specifically useful in situations where one type of sensor is not enough to meet the user's requirements. For example, a visual sensor, like camera can cover the subject and the context in which the activity takes place, but it may not be enough to analyze the sensitive information such as temperature, user heart rate, and humidity in the environment. To overcome, these limitations, multi-modal approach is employed [88].

However, non-visual sensors in general and wearable sensors in specific have several limitations. Most of the wearable sensors need to be worn and run continuously, which may be difficult to implement in agriculture application scenarios due to many practical and technical issues. The major practical issues are acceptability and willingness to use wearable sensors, and technical issues include battery life, ease of use, size, and effectiveness of the sensor. In addition to this, in some application domains such as video surveillance where continuous monitoring of the people is required for suspicious activities, non-visual sensor-based approach might not be effective [89]. Therefore, the ultimate solution lies in adopting vision-based cotton pests recognition approach as it can be applied to most of the application domains [90]. This is the rationale for the proposed work to focus on the vision-based cotton pest's recognition. Depending on the complexity and duration, vision-based activities fall into four categories, i.e., White fly, Jassid, Thrips and Spotted Bollworms [84].

Human vision framework can get the arrangement of perceptions in regards to the development and state of the bugs [91]. Pests such as White fly, Jassid, Thrips and Spotted Bollworms have been classified [92]. Scientists contributed much exertion amid the previous couple of decades on this important issue to address it [93]. What we have accomplished so far might be a small amount of what a develop human vision framework can do [94].

The state of the methods presented by different researchers have been reviewed and are presented in this chapter as follows; They used Artificial Neural network to identify cotton insect that is ideal and problem-solving model. This article basically discussed only Assassin Bug, Alfalfa Hopper, Hippodamia Ladybug Larva, Hippodamia Lady Beetle Adult. The investigator collected custom data from United States. The accuracy of the system is not up to mark that is 95.6%. The empirical features are used for the processing of images to identify of the insect that are complex and complicated for processing point of view.

The author Ram parsed et al, (2016) [95] have proposed an automated system to symmetrically classify harmful and non-harmful cotton pests using neural network. The idea of neural network introduced by the group of researchers of California University in 1950. This led to the thinking that science must be settled to report the problem of pest control. Although science is referred to as Integrated Pest Management (IPM). The aim of IPM is not remove all pest [96]. IPM is used to reduce the cotton pest that they harmful some of the pests are not harmful for cotton they are tolerable and crucial because their natural enemies persist in cotton [97]. It is most important for the author to identify correct cotton insects to utilize his approach. They captured the images of the insects from fields in different angles and in different environments. Because insects appear in crops in different strictures crop type, weather factor, wetness, season, hot plant. They used soft computing technique to classify cotton insects [98]. They used Artificial Neural Network for classification process. The identification of cotton pests based on feature extraction that are collected possible known pests of cotton in different environments. After that they used these extracted features to train ANN [99]. Then the automated system identified desirable and undesirable pest. The desirable pest belongs to biological control species, and the undesirable pests belong to pest species. This desirable and undesirable approach provides a framework to control biological tests. After that they converted images of pests into binary form by applying image enhancement methodology. They used dilation and erosion operators for morphology of binary images [100]. Basically, the dilation operation increases the size of the object whit respect to its background. When dilation operation is performed on objects it increases the size of white objects it is useful when white objects are deified in an image. The erosion operation is used when the size of object is too reduced. In image processing when erosion operation is performed on images it reduces size of white object. It erosion operation is continuously used on images the white objects may disappear from images. After applying enhancement technique through dilation and erosion operators they extracted useful features to train ANN. They used Empirical features extraction method to identify cotton insect pest. These features are Form Factor, Roundness, Aspect Ratio, Compactness, and Extent. These are the basic features that are used to classify insect [101].

Overall, the survey of literature review has been ordered in Table 1 as shown following.

Table 1: State of art of cotton pests' classification

Sr.	Author name and year	Problem addressed	Methodology	Dataset	Evaluation measures	Limitations
1	Ram Prasad and Joe Ellington 2000	Insect Classification In Cotton Ecosystems	Empirical Features (Form Factor, Roundness, Aspect Ratio, Compactness, Extent) + Artificial neural network (ANN)	Custom Southwestern United States.	Accuracy=95.6%	1. Evaluation measures are not up to mark. 2. It classifies only limited cotton pests.
2	J.M Mckinion Et all J.N Jenkins J.L Willers A. Zumanis 2009	cotton insect pest's detection	Line intercept methodology using GIS- map	Mississippi (USA) Spatially variable insecticide application using GIS-based map scouting. Images are captured using cameras mounted on fixed wing.	Accuracy=95%	1. Evaluation measures are not up to mark. 2.working with WLAN 3. The experiments performed on images are captured with cameras having low resolution, so the method is not robust no noise.
3	1.P. Revathi 2.M.Hemalatha 2013	Identification of cotton leaf spot disease	Cross information Neural network based on PSO features selection	South zone Tamil Nadu at Andhiyaur, leaves are captured using a digital mobile phone.	Accuracy=95%	1. Evaluation measures are not up to mark. 2. it classifies only a limited cotton pest.
4	1.Abhishek Dey Et all 2.Debasmita Bhoumik 3.Kashi Nath Dey 2016	detection of white fly by using statically method GLRLM and GLCM	Images are captured through digital camera	West Bengal India	Accuracy =98.46%	1.A complex methodology is used for identification of white fly. 2. it classifies only white fly.

5	1.L.O.Solis-Sanchez Et al, 2008	Machine vision system that classify white fly.	Identification of white fly through machine vision using IMP.	Dataset is collected from greenhouse Mexico	Accuracy =97%	1.images are captured using omputerized pansonic camera 2. personal computer is used for image processing with specification Pentium IV CPU (Intel, Santa Clara, CA, USA) with 1 Gb in RAM memory. 3.matlab 7.0 is used for application software.

2.1 Research gap

From the literature reviewed, it has been established that none of the study is able to address the luminance effect. Moreover, most of the studies used one dataset for their experiments. Most importantly none of the reported study has gained standard evaluation measures as up to the mark. Still there is enough space to investigate the procedures that could be able to address the problem of illumination effect, with improved accuracy and validated on cross datasets. From the writing investigated, it has been set up that none of the investigation can address the influence of luminance. Additionally, a large portion of the investigations utilized one dataset for their trials. None of the detailed examinations has increased standard assessment measures as up to the check. Still there is sufficient space to explore the techniques that might address the issue of light impact, with enhanced precision and approved on cross datasets. Standard evaluation measures adopted by the international community working form gender classification are accuracy, specificity, sensitivity and precision.

3 Research Methodology

In chapter 2 different pest identification methods have been going through with their pros and cons. In this chapter, theoretical framework of my innovative proposed method of pest identification is discussed in detail. The top-down approach of my proposed method wherein pre-processing, algorithm and flow cottons pest's detection and classification of proposed method has also been discussed in this chapter. I have applied my proposed cotton pest's method initially dataset and then obtained results are those are grateful. As an experimental purpose the proposed cotton pest's algorithm is also applied on different images obtained from different datasets, discussed in this chapter too. The results and their deliberations are illustrated in section 4. In this article, a pest Identification method for different facial images is proposed but it can be applied on a diversity of imaging modalities. In this research work, I have adopted the following steps as my research methodology. These steps have been executed to achieve the target of classification of activities from the given set of activities.

1. The dataset consisting of images belongs to activities that have been input into the developed system.
2. The most appropriate features (pruned through a lot of experiments), i.e., Gabor Texture has been used to represent the texture of the input images.
3. Co-occurrence matrix as feature representative has been used allied with statistical moments include the following;
4. SVM with Fine Gaussian kernel has been used to train and test the proposed system.
5. Following standard evaluation, True False Rate (TFR), (False Negative Rate) FNR, (Positive Predictive Vale) PPV, (False Discovery rate) FDR, Precision, Recall, F-Measure, ROC(AUC), Mean Absolute Error and Root Mean Square Error have been used for the evaluation of the proposed system.
6. The result achieved by the proposed system as per these evaluation measures remained accuracy with SVM obtaining 94.3% accuracy.

3.1 Image acquisition

For research and experiments, we have used customized dataset obtained through digital camera with high dimensions and higher mega pixels with no compression ratio. Table 2 shows detail of the images used for research and experiments with each cotton pest, as shown in figure 1. A total of 2400 (600 images of each of the categories of cotton pests) images belonging to different cotton pests have been used for research and experiments. Out of these 2400 images, a total of 1584 (396 of each category of cotton pests) images have been used for training of the proposed method, while a total of 816 (204 images of each of the category of cotton pests) have been used for testing of the reported method.

Table 2. No. of Images used for training and testing of the proposed method

Cotton Pests	Total number of images	No. of Images used for Training	No. of Images used for Testing
White fly	600	396	204
Jassid	600	396	204
Thrips	600	396	204
Spotted Bollworms	600	396	204
Total	**2400**	**1584**	**816**

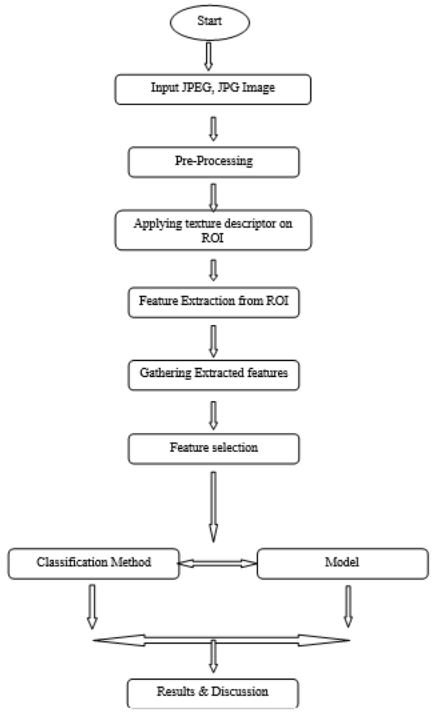

Figure 1: Showing top-down approach of the proposed system

3.2 The Proposed method

In this exploration work, a novel strategy for pest classification order, i.e., white fly and jassid and spotted Bollworm from facial pictures has been proposed utilizing texture parameters and support vector machine (SVM). The analysis started by investigating and exploring the texture parameters of facial pictures. Gabor filter is observed to be more suitable to exploit textural data of visual articles [102]. Accordingly, Gabor filter has been utilized to extract texture attributes from the facial images of the thrips and jassid and spotted Bollworm. These attributes include Contrast, Kurtosis, Entropy, Mean, Smoothness and Homogeneity. Texture attributes of picture I (x, y) were figured from each preparation cut by convoluting it with the help of 2D Gabor filter [33], demonstration of the proposed work has been drawn in Figure 3.1.

3.2.1 Pre-processing

Pre-processing includes different procedures on an image. Primarily, the images of the datasets listed in Table 3.1 were changed from TIF format to JPEG being appropriate image format to exploit the texture information for feature extraction and classification [103]. Although, dataset images are inclined with noise, however, as discussed earlier, artifacts are also observed in the white fly, thrips and jassid and spotted Bollworm images, which are an open issue to be addressed. To remove the noise existing in both training and testing slices, Gaussian filter [104] was employed and to increase the contrast, local histogram equalization [105] was used. The effects of the Gaussian filtered applied on Figure 2 and enhances its quality and shown in Figure 3. Histogram equalization has been adopted to enhance the image having different categories and different cotton pests performed by human beings. The details of the local histogram equalization is as below. Although, MRI produces outputs of high determination and quality, in any case, as talked about prior, curios are likewise seen in the sweeps, which are an open issue to be tended to. Upgrade is the modification of a picture to modify effect on the watcher. By and large improvement adjusts the first advanced esteems to bring out highlights of a picture and feature the specific qualities of a picture. The handled picture is more reasonable than the first picture for a specific application. For the change of differentiation and to evacuate the clamor introduce in MRI cuts utilized as a part of both preparing and testing, histogram evening out was utilized, which has a decent execution for customary pictures, for example, pest representations or common pictures. Change or mapping of every pixel of information picture into comparing pixel of prepared yield picture is called Histogram Equalization (HE) [106]. HE collects the histogram of the pixel esteems in the picture as indicated by the foreign made unique picture and afterward dislodges all picture pixel esteems. It likewise changes the first pixel esteems to improve the picture differentiate. In a HE-prepared picture, the brilliant territory is probably going to be excessively strengthened; thus, the picture feature areas are overexposure, the distinction in picture differentiation is expansive, and the conveyance of pixels is unnatural. The working process of histogram equalization is as below;

Given the frequency distribution (instead of image):

- Using above transformation, average intensity and contrast are increased.
- Repeated histogram equalization does not change image.
- Frequencies of gray-levels in histogram equalized image are not exactly same due to the discrete values and round off.
- If the transformation is monotone increasing, grey level order of the image is preserved, such that for any two grey levels t_1 and t_2 , and their corresponding transformed values $T[t_1]$ and $T[t_2]$:

$$t_1 < t_2 \quad \text{if and only if } T[t_1] < T[t_2]$$

Figure 1. Original Image

Figure 2. Histogram Equalized Image

3.2.2 Feature extraction

Texture descriptors are commonly used in this field to decompose the facial images, Popular texture descriptors include Local Binary Pattern (LBP) [107], Binary Rotation Invariant and Noise Tolerant (BRINT) [108], Weber Law Descriptor (WLD) [109] and Gabor [110] [111] [112] [108] [113, 114] [110]. Generally, Gabor filter requires five parameters i.e. (1) *Wavelength* (λ) (2) *Orientation* (θ) (3) *Phase offset* (φ) (4) *Sigma* (σ) and (5) *Gamma* (γ).

The choice of these factors was essential to this training and empirically the values of λ, φ, σ and γ were set to 3.5, 0, 2.8 and 0.3 respectively, where $\theta \in \{0, \frac{\pi}{2}, \frac{\pi}{3}, \frac{\pi}{4}\}$ resulting in four images at these orientations.

GLCM is a quantifiable system for taking a test at the surfaces that contemplates the spatial relationship of the pixels. The GLCM capacities describe the surface of a picture by figuring how regularly matches pixel with esteems and in a predetermined spatial relationship happen in a picture, making a GLCM, and afterward separating factual measures from this framework. The graycomatrix work in MATLAB makes a GLCM by computing how regularly a pixel with the force esteem happens in a particular spatial relationship to a pixel with the esteem j. As a matter of course, the spatial relationship is cottons pest's detection and classification as the pixel of intrigue and the pixel to its prompt right (on a level plane neighboring), however you can indicate other spatial connections between the two pixels. Every component (I, j) in the resultant GLCM is basically the aggregate of the circumstances that the pixel with esteem I happened in the predefined spatial relationship to a pixel with esteem j in the info picture [115].

GLCM features:

- Typically, GLCM is calculated at four different angles: 0, 45, 90, 135 degrees.
- For each angles different distances can be used, d= 1, 2, 3 etc.
- Size of GLCM of 8-bit image: 256*256(2^8). Quantizing the image will result in smaller matrices. A 6-bit image will result in 64*64 matrices.
- 14 features can be calculated for each GLCM. The features are used for texture calculations.

An overview of GLCM at 0 and 45 degrees is shown in Figure 4.

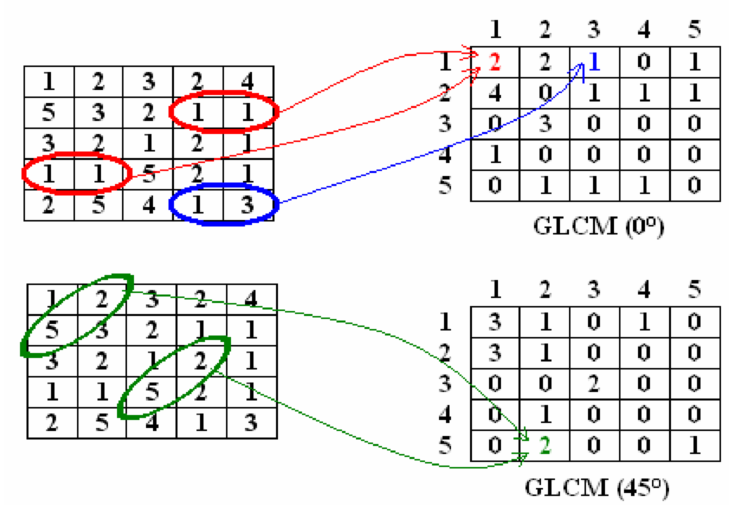

Figure 4: GLCM overview at 0 and 45-degree angle

The Gabor Filter is applied on different sample images from the database at different angles and gets results, when the Gabor filter is applied on the original image when angle is 0 as described in Figures 5.

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Figure 5: Input image

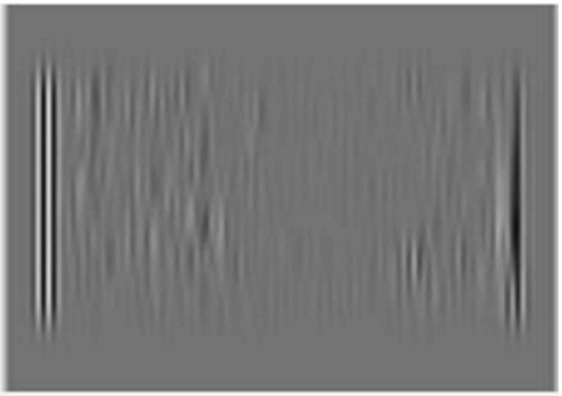

Figure 6: Gabor Filter at 0 angle

The results of the Gabor Filter is also based upon the angle applied on input images, Figure 6 , Figure 3.7 and Figure 3.8 respectively show the results of the Gabor Filter when angle changes from 0 to $\frac{\pi}{2}, \frac{\pi}{3}, \frac{\pi}{4}$.

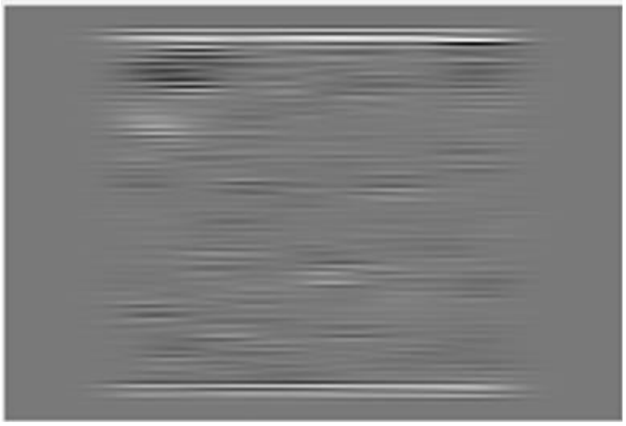

Figure 7: Gabor Filter at Gabor Filter at $\frac{\pi}{2}$

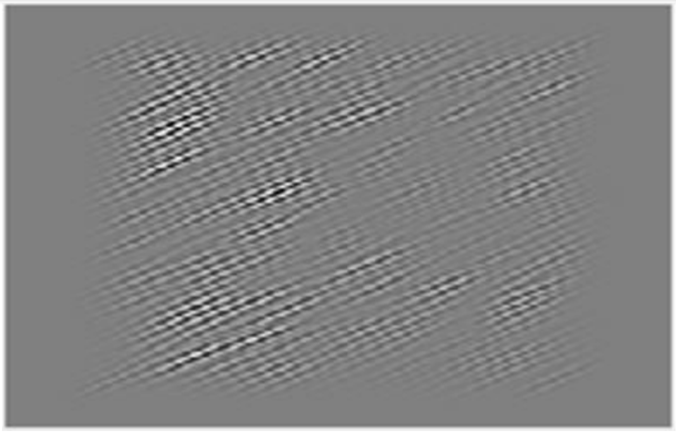

Figure 8: Gabor Filter at $\frac{\pi}{3}$

Figure 9: Gabor Filter at Gabor Filter at $\frac{\pi}{4}$

The 2D Gabor filter is mathematically defined in Eq. 1.

$$g\lambda,\theta,\varphi,\sigma,\gamma(x,y)=\exp(-\frac{x'+\gamma^2 y'}{2\sigma^2})\cos(2\pi\frac{x'}{\lambda}+\varphi) \quad (1)$$

Where x' and y' have been designed using Eq. 2 and Eq. 3 respectively.

$$x'=x\cos\theta+y\sin\theta \quad (2)$$

$$y'=y\cos\theta-x\sin\theta \quad (3)$$

Related studies are using machine learning approaches for addressing the same issue of cotton pests classification [116].

The motivation behind element extraction is to decrease the first information by estimating certain properties, or highlights, that recognize one information design from another example [117]. The extricated highlight ought to give the attributes of the information compose to the classifier by thinking about the portrayal of the applicable properties of the picture into include vectors [118]. We extract the following;

- **Contrast:** Contrast is 0 for a constant image. Contrast is calculated by using the equation given below:

$$C = \sum_{i,j} |i-j|^2 P(i,j)$$

- **Homogeneity:** Homogeneity is evaluated using the equation given below:

$$H = \sum_{i,j} \frac{P(i,j)}{1+|i-j|}$$

- **Mean:** The mean can be calculated using the formula:

$$\mu = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j)$$

- **Kurtosis:** K measures the peakness or flatness of a distribution relative to a normal distribution. The conventional definition of kurtosis is:

$$K = \left\{ \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[\frac{p(i,j) - \mu^4}{\sigma} \right] \right\} - 3$$

- **Smoothness:** Relative smoothness, R is a measure of grey level contrast that can be used to establish descriptors of relative smoothness. The smoothness is determined using the formula:

$$R = 1 - \frac{1}{1+\sigma^2}$$

- **Entropy:** Entropy is a statistical measure of randomness that can be used to cottons pests' detection and classification:

$$h = -\sum_{K=0}^{L-1} Pr_k(log_2 Pr_k)$$

3.2.3 Classification of cotton pests

Artificial Neural Networks (ANN), SVM [116], Deep learning and its variants, Naïve Bayes frameworks, Decision Trees etc. [119]. are among the most popular classifiers used for image classification.

Cotton pests as shown in following has been recognized using the proposed method of classification.

- **White fly**
- **Jassid**
- **Thrips**
- **Spotted Bollworms**

The sample of the images having different cotton pests are shown in the following figure 10.

Figure 10: Showing images of the activities used for both training and testing of the proposed system

3.3 Evaluation measures used for the evaluation of the proposed method of cotton pest's classification

Evaluations measures are used to assess the performance and effectiveness of any applied methodology. The detail of standard evaluation measures we used for the evaluation of our proposed method is given below.

- Accuracy: The accuracy of a test is its ability to differentiate the tumorous and non-tumorous cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

- Sensitivity or True Positive Rate (TPR) or Recall: The sensitivity of a test is its ability to determine the tumorous cases correctly. To estimate it, we should calculate the proportion of true positive in tumorous cases. Mathematically, this can be stated as:

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

- Specificity: The specificity of a test is its ability to determine the non-tumorous cases correctly. To estimate it, we should calculate the proportion of true negative in non-tumorous cases. Mathematically, this can be stated as:

$$\text{Specificity} = \frac{TN}{TN+FP}$$

- False Negative Rate (FNR): The fraction of positive examples that are classified as negative.

$$\text{FNR} = \frac{FN}{TP+FN}$$

- Positive Predictive Value (PPV) or Precision is the probability that subjects with a positive screening test truly have the disease.

$$\text{Precision} = \frac{TP}{TP+FP}$$

- False Discovery Rate (FDR): It is the expected percent of false predictions in the set of predictions.
- ROC curve: is a single value used to evaluate the performance of a classifier on given dataset. It is a graphical representation of the balance between TPR and FPR at *every* possible decision boundary.
- False Positive Rate (FPR): The fraction of negative examples that are classified as positive.

$$\text{FPR} = \frac{FP}{FP+TN} \text{ or 1- accuracy}$$

- F-measure is a cottons pest's detection and classification mean of precision and recall.

4 Results and Discussions

The development of applications to extract distinctive features from images having different cotton pests is the motivation behind most studies in the field of security surveillance. Table 4.1 shows detail of the images used for research and experiments with each cotton pest. A total of 2400 (600 images of each of the categories of cotton pests) images belonging to different cotton pests have been used for research and experiments. Out of these 2400 images, a total of 1584 (396 of each category of cotton pests) images have been used for training of the proposed method, while a total of 816 (204 images of each of the category of cotton pests) have been used for testing of the reported method.

Table 3: No. of Images used for training and testing of the proposed method

Cotton Pests	Total number of images	No. of Images used for Training	No. of Images used for Testing
White fly	600	396	204
Jassid	600	396	204
Thrips	600	396	204
Spotted Bollworms	600	396	204
Total	**2400**	**1584**	**816**

In this experiment, results concerning cotton pest's detection and classification recognition have been gathered based on three different types of descriptors. In the datasets, the results are averaged over five folds of each method for cottons pest's detection and classification recognition rates in percentages (i.e. the rate of correct decisions to the number of overall decisions. In addition to this, these methods are tested on 1584 images and consist of images taken under a variety of lightings and illustrating various expressions. Texture, shape and color features were extracted for every image in each dataset and then concatenated into a single feature vector. The 115 most informative feature bins amongst all resulting vectors were selected in the dataset. These selected features later were applied for face representation datasets. Furthermore, it was found that applying an Ensemble (Bagged Trees) to the database representing the selected feature vectors begets out performances of all other strategies in terms of accuracy. The results of Gabor Jets, raw pixel values and LBP combined with PCA are provided in last three rows of table below.

In addition to the previous tests, we performed another experiment to demonstrate that increasing the number of features would not necessarily increase recognition rate. This experiment has been conducted on a set of features extracted by LBP for gender recognition.

Although there are many different branches in the field of face processing, face recognition is an essential component. In general, solving this problem requires overcoming certain difficulties, such as differing image qualities, background clutter, poses, facial expressions, and varying levels of lighting. This chapter summarizes some popular methods for facial recognition and proposes a face recognition approach that is robust, simple, and efficient to use when compared to other existing methods.

For experiments and study purposes, a large dataset for the study of each of the cotton diseases, i.e., White fly, Jassid, Thrips and Spotted Bollworms of a hand texture is used. A total of 2400 (600 images of each of the categories of cotton pests) images belonging to different cotton pests have been used for research and experiments. Out of these 2400 images, a total of 1584 (396 of each category of cotton pests) images have been used for training of the proposed method, while a total of 816 (204 images of each of the category of the cotton pests) images have been used for testing the reported method. Following texture features were used to extract information to yield parameters.

1.	Autocorrelation	13.	Sum_of_Squares
2.	Contrast	14.	Sum_Average
3.	Correlation_matlab	15.	Sum_variance
4.	Correlation_p	16.	Sum_entropy
5.	Cluster_Prominence	17.	Difference
6.	Cluster_Shade	18.	Difference_entropy
7.	Dissimilarity	19.	Information_measure_of_correlation1
8.	Energy	20.	Information_measure_of_correlation2
9.	Entropy_shade	21.	Inverse_difference
10.	Homogeneity	22.	Inverse_difference_Maleized
11.	Homogeneity_p	23.	Inverse_difference_moment_Maleized
12.	Maximun_probability		

A number of experiments were performed for the selection of regions of interest i.e. rectangular or square of size 8, 16, 32, 64 and 128 respectively. ROI of following dimensions were used to extract the features mentioned earlier.

Table 4. Annotated extracted features used for Training and Testing of proposed system

F1	F2	F3	F4	F5	F7	Class
0.0262	0.1619	1123.0676	1261804.219	3792.80038	$1.23E^{-11}$	**White fly**
0.00335	0.0579	1135.4243	1298358.962	1086.4791	1.12E-11	**Jassid**
0.01803	0.1343	1139.2756	1310854.581	3017.4763	1.84E-11	**Thrips**
0.02198	0.1482	1125.7581	1265970.178	3417.4743	1.56E-11	**Spotted Bollworms**

Since natural images contain large texture (analyzed through several experiments), after experiments it was concluded that 128X128 size of ROI is the best to describe its texture successfully. Therefore, in this research, ROI with size 128X128 were used to extract out texture features and label the data set for performed supervised machine learning. After having valid annotated featured space, several classifies were used to train the learning model. According to machine learning ethic 66% of total data was used to train the learning model while 34% of the available dataset was used to test the training model. For classification purposes the following classifies were used;

- Ensemble (Bagged Trees)
- KNN (Weighted KNN)
- Ensemble (Subspace KNN)
- KNN (Fine KNN)
- SVM (Fine Gaussian SVM)

As a quantitative comparisons purpose between these classifies, the following parameters of pests and weighted average classes were taken into consideration. To assess the performance and effectiveness of the proposed method, large number of experiments will be performed in this research study by considering many combinations of different image representations and transformations. The performance is given in terms of true negative rate (specificity), true positive rate (sensitivity), and accuracy.

$Sensitivity$=100∗ (TP+FN) (1)

$Specificity$=100∗ (FP+FN) (2)

$Accuracy$=TP+$TNTP$+TN+FN+FP∗100 (3)

The classification results obtained through MATLAB 2016b have been evaluated as per accuracy, true positive rate, as depicted in Table No. 5

Table 5: Classification Results obtained through MATLAB 2016b

Classes used for classification	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	AUC-value
White fly	95%	97%	97%	93%	.93
Jassid	96%	93%	95%	95%	.92
Thrips	93%	96%	96%	96%	.95
Spotted Bollworms	95%	94%	96%	99%	.92

Table 6: Classification Results obtained through Weka 3.8

Sr#	Classifier	Accuracy	TPR (avg)	FNR (avg)	PPV (avg)	FDR (avg)	ROC-Value (avg)
1	Ensemble (Bagged Trees)	94.4%	89%	11%	94%	6%	0.98
2	KNN (Weighted KNN)	94.3%	90%	10%	94%	5%	0.98
3	Ensemble (Subspace KNN)	92.6%	85%	15%	93%	7%	0.98
4	KNN (Fine KNN)	93.5%	90%	10%	91%	9%	0.93
5	SVM (Fine Gaussian SVM)	93.3%	86%	14%	96%	4%	0.98

Morever, when the Ensemble classifier is applied on the dataset as discussed in Table 6 to evalaute the proposed system and evalaute different parameters, i.e, TPR, TNR, PPV, FDR, ROC curve also displayed through figure for better visualization and understaing.
So the ROC curve obtained by Ensemble (Bagged Trees) classifiers on proposed model as shown in Figure 11.

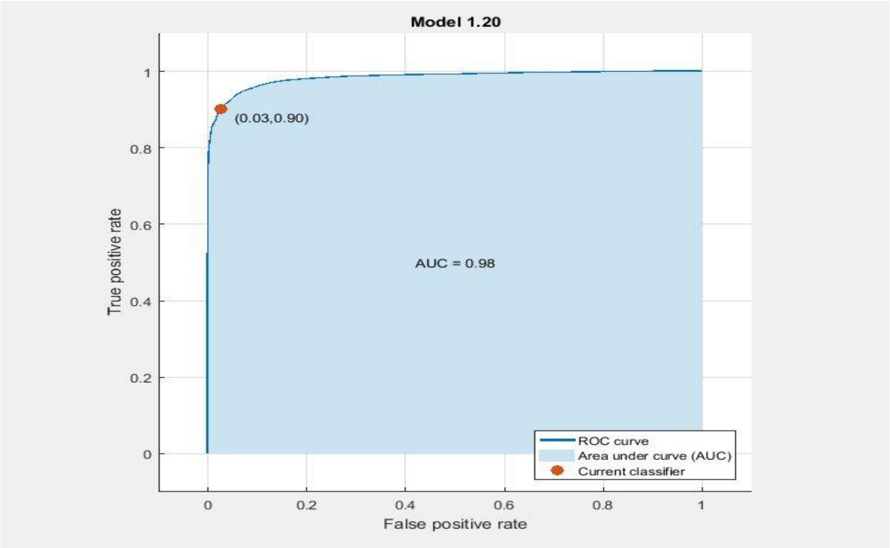

Figure 11: ROC Curve on Ensemble Classifier

When the KNN (Weighted KNN) classifier is applied on the dataset. to evalaute the proposed system and evalaute different parameters, i.e, TPR, TNR, PPV, FDR, ROC curve also displayed through figure for better visualization and understaing.
Figure 12 describes the ROC value of the proposed model while the proposed model is being evaluated through the Ensemble (Subspace KNN) classifiers.

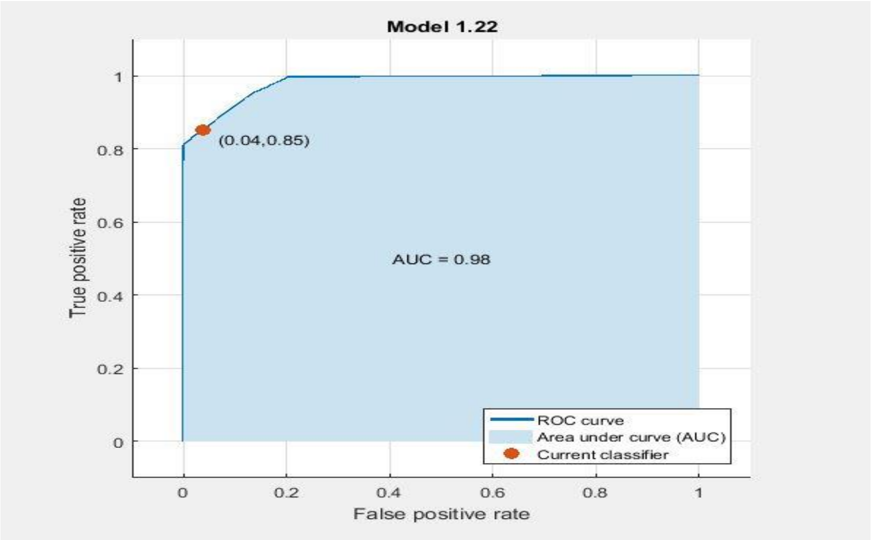

Figure 12: ROC Value on Ensemble Subspace KNN

Figure 13 describes the ROC value of the proposed model while the proposed model is being evaluated through the SVM (Fine Gaussian SVM) classifiers.

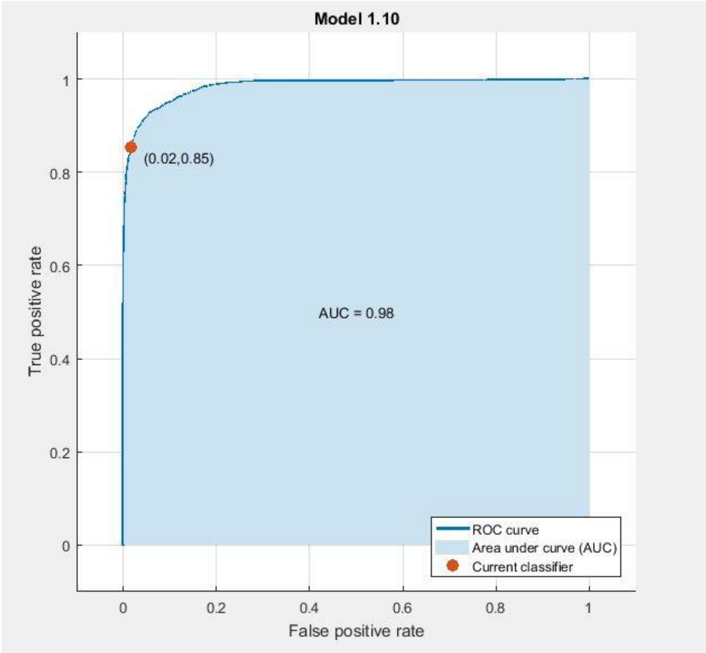

Figure 13: ROC Value on SVM (Fine Gaussian SVM)

The method of cotton pests classification proposed by [120] has achieved accuracy of 95.05% with SVM. They have used LDP techniques for the development of their method. The main disadvantage of this scheme is that the LDP machinist is applied on the facial images to get LDP picture and then histogram is extricated from every neighborhood region of LDP picture to construct the nearby representation of the face. Second major limitation in that method with classification is that it is not up to the mark. Further the dataset used by the researchers has very limited number of images for training and testing the proposed model. The proposed model also used only one evaluation parameter which is accuracy there are many others evaluation parameters to evaluate system. While, the proposed method by us has achieved greater evaluation measures and used many evaluation parameters to evaluate the proposed model, as per accuracy which is 94.4%, 97% TFR for white fly & 89 % for thrips, 3% FNR for s & 11% for jassid, 95% PPV for thrips & 94% for jassid and spotted Bollworm, 5% for white fly & 6% for jassid and spotted Bollworm, by using Ensemble (Bagged Trees) as a classifier. The reported method has used a large volume of facial images from ferret dataset for its training and testing. The procedure of converting images in LDP images is more computational cost, hence in our case no computational cost is required.

The gender classification through DCT, LBP and GDF is suggested by [121] through images by using AR & ethnic database and obtained accuracy 84.6% and 80.3% on ethnic & AR databases, respectively. They have used combination of three techniques DCT, LBP & GDF as described for the development of their method. But the proposed model also has some drawbacks with respect to their methodology and the number of images used for training and testing their proposed model. The main drawback of this technique is that they used very little dataset for training and testing, they used 126 no of images in which there were 56 images for jassid and spotted Bollworm and 70 images for thrips and white fly. Second disadvantage of DCT is that while the input from preprocessed 8 x 8 blocks is integer-valued, the output values are normally real-valued. So, we need a quantization step to draw some conclusions about the values in each DCT block and produce output that is integer valued. Another disadvantage of their proposed model is their evaluation parameters such as accuracy not up-to the mark which is accuracy 84.6% and 80.3% on ethnic & AR databases, respectively. On the other hand, our proposed model covers all the issues as described above, first we used dataset contains images which is sufficient to train and test our proposed model, the second important feature of our proposed model is accuracy is almost up-to the mark which is 94.4%, 97% TFR for jassid and spotted Bollworm & 89% for jassid and spotted Bollworm, 3% FNR for white fly, thrips & 11% for jassid and spotted Bollworm, 95% PPV for white fly & 94 % for jassid and spotted Bollworm, 5% FDR for white fly & 6% for jassid and spotted Bollworm and 0.98 ROC value on Ensemble (Bagged Trees) classifier. Our proposed model also gives good classification rate on another classifier, i.e., by using KNN (Weighted KNN) it gives 94.3% accuracy, 97% TFR for jassid and spotted Bollworm & 90% for jassid and spotted Bollworm, 3% FNR for thrips & 10% for jassid and spotted Bollworm, 94% PPV for white fly & 94 % for jassid and spotted Bollworm, 6% FDR for thrips & 5% for jassid and spotted Bollworm and 0.98 ROC value.

When the same features were used for classification through a machine learning tool Weka 3.6, the classification results were evaluated as per following standard measures;

The classification rates as per above mentioned parameters have been presented in Table No 7.

Table 7: Shows the Comparisons of performance measuring parameters by different classifiers

Classifier Used for Classification	TP-Rate	FP-Rate	Precision	Recall	F-Measure	ROC(AUC)	Mean Absolute Error	Root Mean Square Error	Class
Meta (RandomCommitte) 97.28%	0.989	0.057	0.97	0.989	0.979	0.996	0.0353	0.1368	**White fly**
	0.943	0.011	0.978	0.943	0.96	0.996	0.0353	0.1368	**Jassid**
	0.973	0.041	0.973	0.973	0.973	0.996	0.0353	0.1368	**Thrips**
	0.977	0.045	0.976	0.977	0.977	0.945	0.03	0.1716	**Spotted Bollworms**
Meta (RandomSubSpace) 92.84%	0.955	0.023	0.957	0.955	0.956	0.956	0.03	0.1716	**White fly**
	0.969	0.037	0.969	0.969	0.969	0.969	0.03	0.1716	**Jassid**
	0.98	0.168	0.916	0.98	0.947	0.978	0.2297	0.2803	**Thrips**
	0.832	0.02	0.957	0.832	0.891	0.978	0.2297	0.2803	**Spotted Bollworms**
Trees (J48graft) 90.91%	0.928	0.116	0.93	0.928	0.927	0.978	0.2297	0.2803	**White fly**
	0.925	0.128	0.931	0.925	0.928	0.951	0.0948	0.29	**Jassid**
	0.872	0.075	0.862	0.872	0.867	0.951	0.0948	0.29	**Thrips**

	0.906	0.11	0.907	0.906	0.906	0.951	0.0948	0.29	**Spotted Bollworms**
Meta (END) 90.63%	0.932	0.133	0.929	0.932	0.93	0.952	0.0922	0.286	**White fly**
	0.867	0.068	0.872	0.867	0.87	0.952	0.0922	0.286	**Jassid**
	0.909	0.11	0.909	0.909	0.909	0.952	0.0922	0.286	**Thrips**
	0.925	0.128	0.931	0.925	0.928	0.951	0.0948	0.29	**Spotted Bollworms**
Multi-Layer Perceptron	0.872	0.075	0.862	0.872	0.867	0.951	0.0948	0.29	**White fly**
	0.906	0.11	0.907	0.906	0.906	0.951	0.0948	0.29	**Jassid**
	0.925	0.128	0.931	0.925	0.928	0.951	0.0948	0.29	**Thrips**
	0.973	0.041	0.973	0.973	0.973	0. 996	0.0353	0.1368	**Spotted Bollworms**
Multiclass Classification	0.872	0.075	0.862	0.872	0.867	0.951	0.0948	0.29	**White fly**
	0.906	0.11	0.907	0.906	0.906	0.951	0.0948	0.29	**Jassid**
	0.973	0.041	0.973	0.973	0.973	0. 996	0.0353	0.1368	**Thrips**
	0.973	0.041	0.973	0.973	0.973	0. 996	0.0353	0.1368	**Spotted Bollworms**

Since the accuracy of Decision Trees, Bayes (Bayes Net) and Rule Riders are highest i.e. 99.28% than other classifiers used for machine learning purpose, so it is therefore proposed that either Decision Trees, Bayes (Bayes Net) or Rule Riders is best classifiers for the analysis of image texture analysis. It is concluded from the reviewed literature that very few approaches exist that might be able to classify gender through their facial images as white fly or jassid and spotted Bollworm accurately in general. There remains a need for a more robust model to solve the problem of gender classification.
Rate for thrips & 0.11 for white fly and 0.041 weighted average, 0.97 Precision for thrips & 0.978 for jassid and spotted Bollworm and 0.973 for weighted average, 0.989 Recall for white fly & 0.943 for jassid and spotted Bollworm and 0.973, 0.976 F-Measure for thrips & 0.96 for jassid and spotted Bollworm and 0.97 for weighted average, 0.99 ROC vale, 0.035 Mean Absolute Error and 0.136 Root Mean Square Error.

5 Conclusion

The maturity of machine learning and computer vision models has made it possible to develop automated tools to perform classification. The practicality of these methods in security surveillance units is based on the ease of computation and the reduction of operator involvement. Resultantly, machine learning, computer vision and digital image processing are now assisting department of law and order, enforcement agencies and security handling institutes. In this study, a method was proposed using these multidisciplinary approaches to classify different cotton pests, i.e., White fly, Jassid, Thrips and Spotted Bollworms.

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