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Insect classification and detection in field crops using modern machine learning techniques

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A B S T R A C T

The agriculture sector has an immense potential to improve the requirement of food and supplies healthy and nutritious food. Crop insect detection is a challenging task for farmers as a significant portion of the crops are damaged, and the quality is degraded due to the pest attack. Traditional insect identification has the drawback of requiring well-trained taxonomists to identify insects based on morphological features accurately. Experiments were conducted for classification on nine and 24 insect classes of Wang and Xie dataset using the shape features and applying machine learning techniques such as artificial neural networks (ANN), support vector machine (SVM), k-nearest neighbors (KNN), naive bayes (NB) and convolutional neural network (CNN) model. This paper presents the insect pest detection algorithm that consists of foreground extraction and contour identification to detect the insects for Wang, Xie, Deng, and IP102 datasets in a highly complex background. The 9-fold cross-validation was applied to improve the performance of the classification models. The highest classification rate of 91.5% and 90% was achieved for nine and 24 class insects using the CNN model. The detection performance was accomplished with less computation time for Wang, Xie, Deng, and IP102 datasets using insect pest detection algorithm. The comparison results with the state-of-the-art classification algorithms exhibited considerable improvement in classification accuracy, computation time performance while apply more efficiently in field crops to recognize the insects. The results of classification accuracy are used to recognize the crop insects in the early stages and reduce the time to enhance the crop yield and crop quality in agriculture.

1. Introduction

Agriculture, which is considered the backbone of the economy, contributes to the country's economic growth and determines the standard of life. The agriculture and food processing industry is among the major sectors in any country and plays an essential role in expanding the export quality of agricultural and food products. In developing countries, the increase in food processing transformations is mainly due to the impact of export earnings and domestic market demands. In specific conditions, it requires storage, constant maintenance of equipment, and workspaces very frequently. Pest attack is one of the significant problems in the agriculture sector that results in degradation of crop quality. Pests,

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germs, and weeds cause massive loss to crops and results in a low market for the final products. Finding new ways to gain even small increases in efficiency can make the difference between turning them into a profit or a loss. It has to take care of the pest attack on crops that affects the growth of the field crops. The highly essential cash crops mostly contribute to the vast quantities of production. The insects are the main reason behind crop quality degradation and reduce the productivity of crops, therefore. Hence, monitoring and evaluating the losses due to insects is necessary to ensure crop quality and safety in agriculture.

Machine vision applied in monitoring of crop and soil, fruit grading, plant disease detection, insect pest recognition, and detection. Recently, many developments have been made in the agriculture sector, using machine learning to detect and classify the insects under stored grain conditions [1]. Fruits and vegetables quality evaluation performed using computer vision-based quality inspection comprising four main steps, such as acquisition, segmentation, feature extraction, and classification [2]. Moment invariant techniques applied for extracting shape features and neural networks were developed to classify 20 types of insect images [3]. Yue et al. [4] proposed a super-resolution model based on a deep recursive residual network for agricultural pest surveillance and detection. Pest identification in the complex background using deep residual learning was developed to improve the recognition performance for ten classes of crop insects [5]. Various unsupervised feature learning methods and multi-level classification frameworks were developed for the automatic classification of field crop pests [6]. More recent studies [7,8] reported that image processing applied effectively for insect detection due to less computation cost, fast detection, and easy to distinguish insects with similar color and shape. In [9], clustering segmentation with descriptors is implemented to detect the pests in grapevine with different orientations and lighting environments. The contour-based and region-based segmentation are combined and applied for detecting individual moths and touching insects [10].

In recent years, advanced models in machine learning were successfully achieved the best performance in pest classification and detection [3–6]. Among these works, the various models were trained by using extracted features from the insects and different categories of insect images were classified. It is very difficult to classify and detect insects with similar feature types and different positions in the natural environment. Wang [11] and Xie [12] used ANN and SVM model for the classification of insects in the crops. Wang et al. reported that ANN performed with good stability, and the results of SVM were showed better classification for seven geometrical features. Recently, Yang et al. [13] used SVM based method for the identification of insects with different proportions of the wings. Xie et al. [12] used the SVM model for 24 common pest species of field crops for color, texture, and shape and proposed the effective feature description for insect images. It is well known that ANN and SVM model are provided better classification results that can be applied for insect classification. In contrast, the parameters in existing insect-classification methods influence the process of low-level features [14] and increase the computation time [15]. Hence, the different parameter sets for SVM and ANN algorithms applied successfully to classify insects to achieve state-of-the-art performance. The deep learning model with low classifier has poor performance in image classification applications; hence, it is needed to improve the performance. Liu et al. [16] systematically applied state-of-the-art methods such as VGG, GoogleNet, ResNet, OverFeat, and compare the classification performance with their stack sparse autoencoder model for the improvement of the classification effect of the deep learning model. Nanni et al. [17] also investigated handcrafted and learned descriptors for data augmentation to improve the performance of CNNs. The improvement was obtained by combining local features, dense sampling features, and deep learning approaches using augmented images.

This study aims to classify and detect the insects in corn, soybean, and wheat, etc. using machine learning and insect pest detection algorithm at the early stage of crop growth. The different shape features were used for insect classification by applying ANN, SVM, KNN, NB, and CNN models. The performances of machine algorithms for two datasets were compared to provide insect class information and detection of insects performed with four datasets. The insect pest detection algorithm is simple and efficient in terms of computation time for detecting insects in agriculture fields. Image processing techniques applied to segment the foreground insect and locating the position of the insect in the image with a bounding box. The experiments were conducted on a 2.3 GHz Intel corei5 processor with 16 GB of RAM. The work is implemented in MATLAB2018a, Python, and other supporting frameworks such as Keras and Tensorflow for the analysis of detection and classification of insect images in the agriculture field.

2. Materials and methods

2.1. *Insect pest classification*

2.1.1. *Insect dataset for classification*

Insect classification and insect detection were performed for Wang [11] and Xie [12] dataset for different field crops. Wang dataset with nine insect classes and Xie dataset with 24 classes used in this work. Wang dataset has a total of 225 images, which means that there are 25 insect images per class, and it was divided into 70–30% train-test ratio. In Wang dataset, the training set contains 162 insect images, and testing set contains 63 insect images. Xie dataset contains 785 insect images in the training set and 612 insect images in the testing set, in which each class has about 60 insect images. The details of insect classes of these two datasets are given in supporting information S-Tables 1 and 2.

2.1.2. *Image pre-processing*

In image pre-processing, image enhancement techniques applied to reduce noise in the images and sharpen the images for better accuracy [18,19]. It improves the quality of the image for better detection and classification of insects. The datasets used here are already pre-processed and segmented [20].

2.1.3. Image augmentation

Since fewer insect images are available in both Wang and Xie datasets, image augmentation is applied. The insect images were rescaled to the size of 227 × 227 pixels. Image data augmentation techniques such as rotation, flipping, and cropping operators are used to increase the training set for achieving improved accuracy and eliminate the problems of overtraining [21,22]. As shown in Fig. 1, *Nephotettix bipunctatus* insect image from the Xie dataset is converted into multiple images in the augmented dataset by applying eight different operators.

After using augmentation on the training set, the Wang and Xie datasets contain 1 296 and 6 280 augmented training insect images, respectively. The details are given in supporting information S-Tables 1 and 2.

2.2. Insect classification methodology

Insect classification involves various steps to be performed. The flow of steps for insect classification is illustrated in Fig. 2. Image augmentation is applied to insect dataset images to expand the training dataset. Then, shape features extracted from the insect images and ANN, SVM, KNN, and NB machine learning algorithms are applied to classify the insect classes. CNN based insect classification adapted for comparison performance. The experiment is conducted with 9-fold cross-validation for both Wang and Xie dataset to evaluate the performance of the machine learning algorithms.

2.2.1. Insect classification with image processing and machine learning techniques

2.2.1.1. Shape feature extraction. Shape features are the essential features which are not affected due to scaling, rotation, and translation and applied in computer vision and automatic object recognition systems. Classification of insects is performed based on the finite shape features extracted from the insect images. The insect images in the form of RGB converted to grayscale images for further feature extraction. Image processing techniques are applied to extract the shape features using the Sobel edge detection algorithm and morphological operations [23]. The nine shape features include area, perimeter, major axis length, minor axis length, eccentricity, circularity, solidity, form factor, and compactness [23] stored in feature vectors and then applied to the classifier models.

2.2.1.2. Insect classification with ANN, SVM, KNN, and NB. The insects are classified into various classes using the four machine learning techniques such as ANN, SVM, KNN, and NB classifier and described as follows.

1. *ANN classifier* – A simple neural network contains an input, hidden, and output layer with linkages. Initially, random weights are assigned. The final linkage weights determined, and activation rates of the output layer were calculated. A feed-forward multi-layer artificial neural network is designed to automatically identify and classify adult-stage whiteflies and thrip in greenhouses [24]. The insect

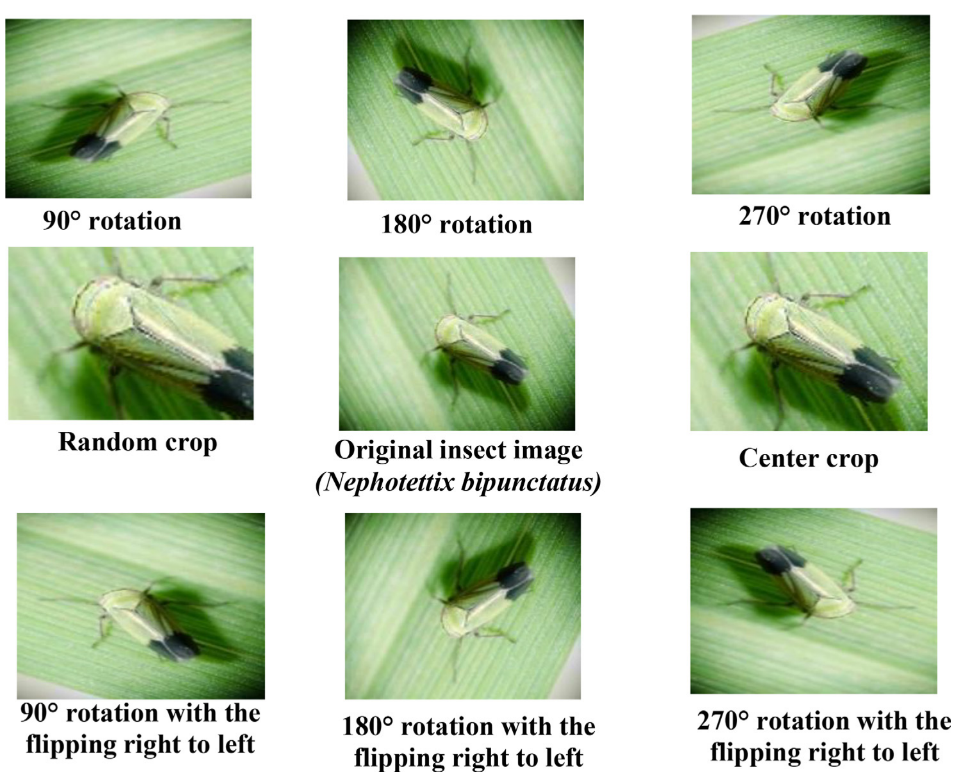


Fig. 1 – Image augmentation.

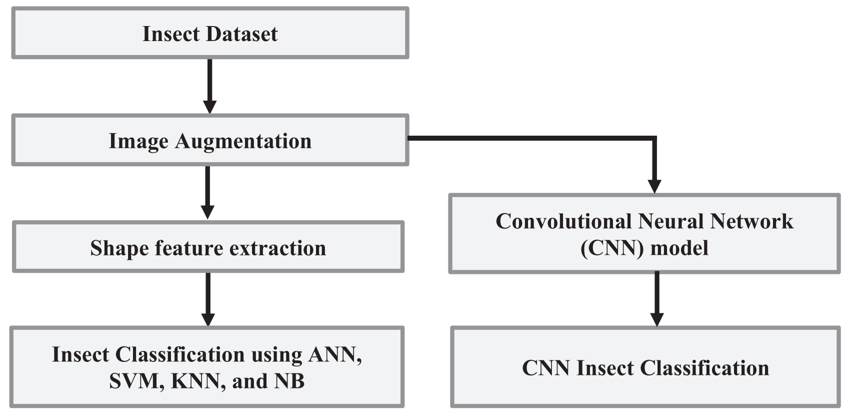


Fig. 2 – Framework for insect classification.

recognition model's ability was improved using a back-propagation ANN model for identifying Beet armyworm *(Spodoptera exigua)* from other species [25].

2. *SVM classifier* – It is a supervised machine learning algorithm. Here, the dimensional space based on the number of features that we have. The data items plotted as a point in a k-dimensional space where we have 'k' features with the value of a particular coordinate representing corresponding feature value. Insect classification is performed by identifying the hyper-plane, which differentiates the classes very well. The SVM classifiers were effectively applied to minimize the overall interspecific error rates for identifying mosquitoes [26] and Fruit flies [27].
3. *KNN classifier* – It is a lazy learning algorithm which does not use any parameters. Here, weights are assigned to the neighbors' contributions, such that nearer neighbors contribute more to the average than the farther ones. In processing classification problems with high dimensions and small samples, the KNN algorithm achieves a better identification rate for butterfly species [28].
4. *Naive Bayes* – This is based on Bayes Theorem of probability and assumes independence among all the predictors. This classifier simply follows the assumption that the presence of a particular feature is not related to the presence of any other feature in an insect class. Naive Bayesian classification was applied to predict the insect class probabilities that a given tuple from the soybean crop insect dataset belongs to a particular insect class [29].

2.2.2. *Insect classification with CNN model*

The CNN model developed to train with RGB insect images from Wang and Xie dataset. The CNN model comes under the class of deep, feed-forward neural networks applied to analyze visual imagery of insect images and computationally efficient due to automatic feature learning and weight sharing [30–33]. The CNN model contains five convolutional layers and three max-pooling layers, a flatten layer, a fully connected layer, and a softmax output layer to classify insect images, as illustrated in Fig. 3.

The size of the insect image is rescaled to 64 × 64. The CNN model can run over each insect image pretty fast and reduce the computational operations per layer and memory requirements. Each convolution layer and max-pooling layer use 3 × 3 and 2 × 2 filter sizes, respectively. A fully connected layer is designed in such a way to learn high-level features for final insect classification.

2.3. *Insect pest detection*

2.3.1. *Insect dataset for detection algorithm*

In this work, the insect pest detection algorithm is applied to Wang, Xie, Deng [34], and IP102 [35] datasets contain insects with different field background. The 24 classes and nine classes of insects were selected from Xie datasets and Wang dataset, respectively. The details of insect images are provided in supporting information S-Tables 3 and 4. The nine classes of insect dataset were used for detection from the Deng data set [34]. The details of the images of the Deng data-set are shown in Table 1.

The nine classes of insects are mainly collected in agriculture tea plants and other plants from Europe and Central Asia. The IP102 datasets images were collected from various online sources such as Mendeley Data, IPM images, Dave's Garden, and other sources. The 12 classes of insects from IP102 datasets are shown in Table 2. Some samples of images from the Deng and IP102 dataset appeared in Fig. 4(a) and 4(b).

2.3.2. *Insect pest detection algorithm*

A detailed procedure chart for insect pest detection algorithm is shown in Fig. 5 and described as follows. The insect image is loaded and resized to 227 × 227. *OpenCV* reads the color image in the order of BGR (Blue, Green, and Red) format. The mask image named '*mask*' is created that contains an array of zeroes with the same size of the input insect image. The foreground and background array models are created with zero-filled arrays. These two arrays are used internally when the foreground insect is segmented from the background. The co-ordinates of the bounding box are defined. It comprises the region in which we want to segment the insect in the input image. The GrabCut algorithm [36] is adapted by applying a mask image '*mask*' to the input image for separating the foreground insect from the colored background image. The bounding box initialization mode is selected, and the algorithm runs for five iterations. The

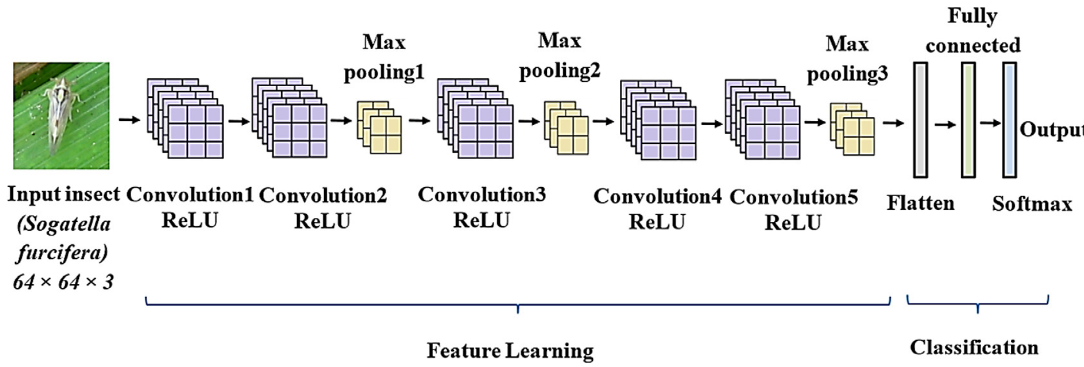


Fig. 3 – Insect classification with CNN model.

Table 1 – Details of insects used from the Deng dataset.

Insect class	Number of insects
Locusta migratoria	77
Parasa lepida	14
Gypsy moth larva	10
Empoasca flavescens	20
Spodoptera exigua	53
Chrysocus chinensis	27
Laspeyresia pomonella larva	14
Atractomorpha sinensis	10
Laspeyresia pomonella	57

Table 2 – Details of insects used from the IP102 dataset.

Insect class	Number of insects
Rice leaf roller	50
Rice leaf caterpillar	50
Paddy stem maggot	50
Asiatic rice borer	50
Yellow rice borer	50
Rice gall midge	50
Rice Stemfly	50
Brown plant hopper	50
White backed plant hopper	50
Small brown plant hopper	50
Rice water weevil	50
Rice leafhopper	50

output mask image '*mask_output*' is generated such that all definite background and probable background pixels are set to zero, and definite foreground and probable foreground pixels are set to one in the mask image '*mask*'. The BGR channels of the input image were multiplied with the output mask image '*mask_output*' to get the segmented insect image '*image_seg*'. Another mask named '*background_img*' is created similar to the size of the input image with an array consists of zeroes. Then all the pixels in the '*background_img*' mask are changed to white pixels. This '*background_img*' mask is added with the '*image_seg*' to generate the '*image_segmented*' image. The segmented image '*image_segmented*' is processed further by converting it into HSV [Hue, Value, and Saturation] color model, and the Gaussian blur is applied to remove the Gaussian noise. The contrast of the image enhances by using histogram equalization. The inverted binary thresholding is adapted in this study. The *findContours* function in OpenCV is applied to identify the contours in the binary image. After finding the contours, the largest counter is selected, and the remaining trivial contours are eliminated. The minimum-area bounding rectangle for the largest contour is calculated using *minAreaRect* function, and its co-ordinates are used to draw the rotated rectangle in the input image that contains the insect.

2.4. Classification accuracy

The classification accuracy of the model is calculated by the following Eq. (1),

$$Classification\ accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (1)$$

The TP, FP, FN, and TN represent the true positive, false positive, false negative, and true negative. The insect appears in the image is considered as TP if it is classified correctly; otherwise, it is regarded as FN. The insect which is not present in the image is considered as TN if the classification is done incorrectly; otherwise, it is referred as FP.

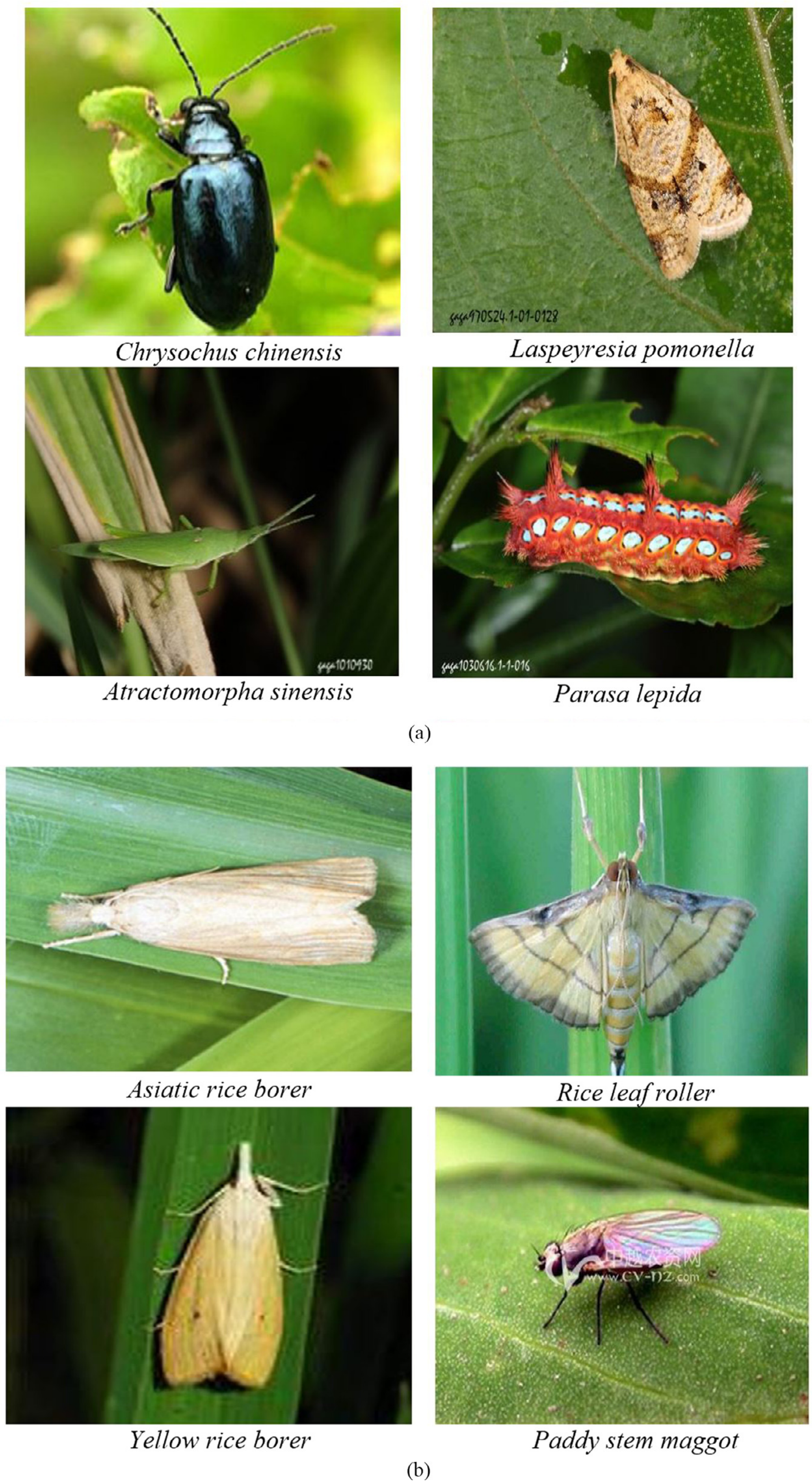


Fig. 4 – (a) Samples of images from the Dengt datasets. (b) Samples of images from the IP102 datasets.

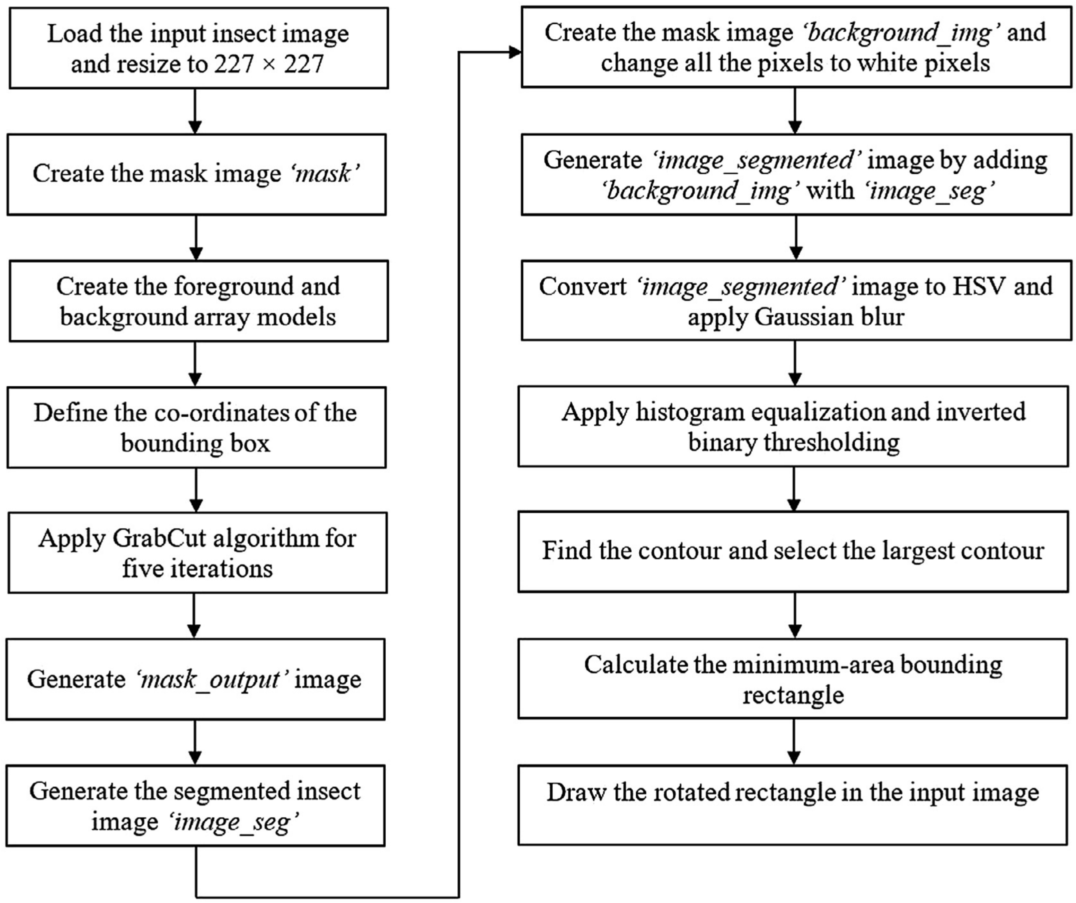


Fig. 5 – The flow chart of insect pest detection algorithm.

3. Results and discussion

The experimental data and developed codes are shared at https://github.com/Then-mozhi-2007/Classification-and-detection. The performance of the insect classification and detection model studied on 9 and 24 different classes of insects and discussed in Sections 3.1 and 3.2.

3.1. *Insect classification results*

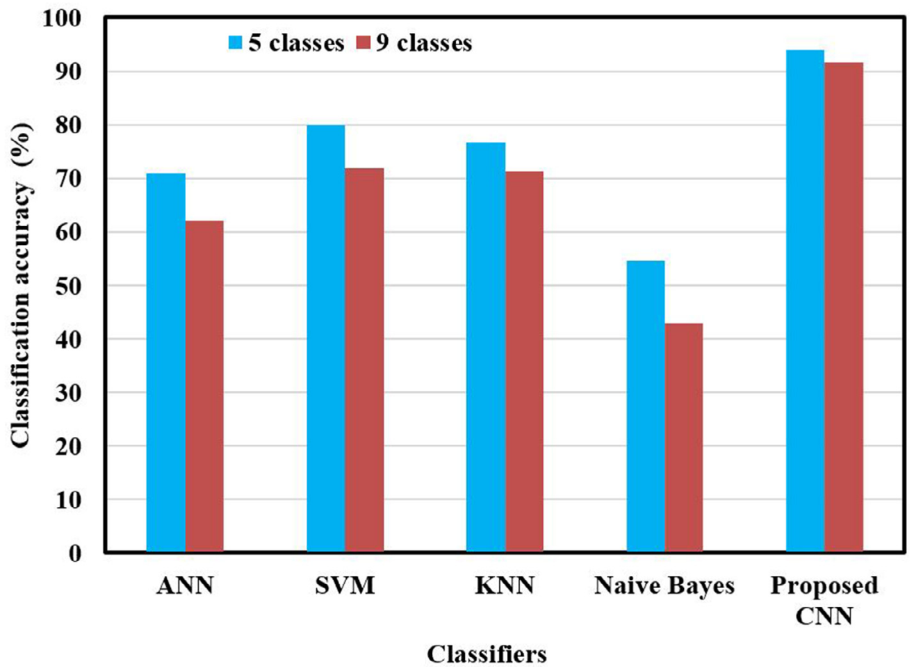
Classification performed using shape features obtained from image processing technique with machine learning algorithms includes ANN, SVM, KNN, and Naive Bayes. CNN models are also used in insect classification to compare the classification accuracy with each technique. Nine-fold cross-validation applied on both Wang dataset for 1 359 insect images and Xie dataset for 6 892 insect images include augmented train ant test images to achieve an improved model for insect classification. The following parameters were selected using random search parameter tuning method [37] for classification of insects: In ANN classifier, the number of neurons in the input, hidden1, hidden2, and output layer are 9,150,60 and 9 for Wang dataset and 9,150,60 and 24 for Xie dataset; Activation function applied in input and hidden layers are sigmoid, and softmax used in the output layer; Stochastic gradient descent optimizer is adapted and back-propagation training algorithm performed with a learning rate of 0.01. SVM classifier uses a radial basis function (RBF) kernel. In KNN, the number of neighbors selected as 10 and Euclidean distance metric is applied. The Gaussian Naive Bayes algorithm adapted to generate classification results with minimum training time. The CNN model trained with a batch size of 64, the number of epochs as 50, and a learning rate of 0.001.

A comparison of various techniques performed after the results were collected. Fig. 6(a) and 6(b) illustrates the results obtained for insect classification for Wang and Xie datasets using various machine learning algorithms.

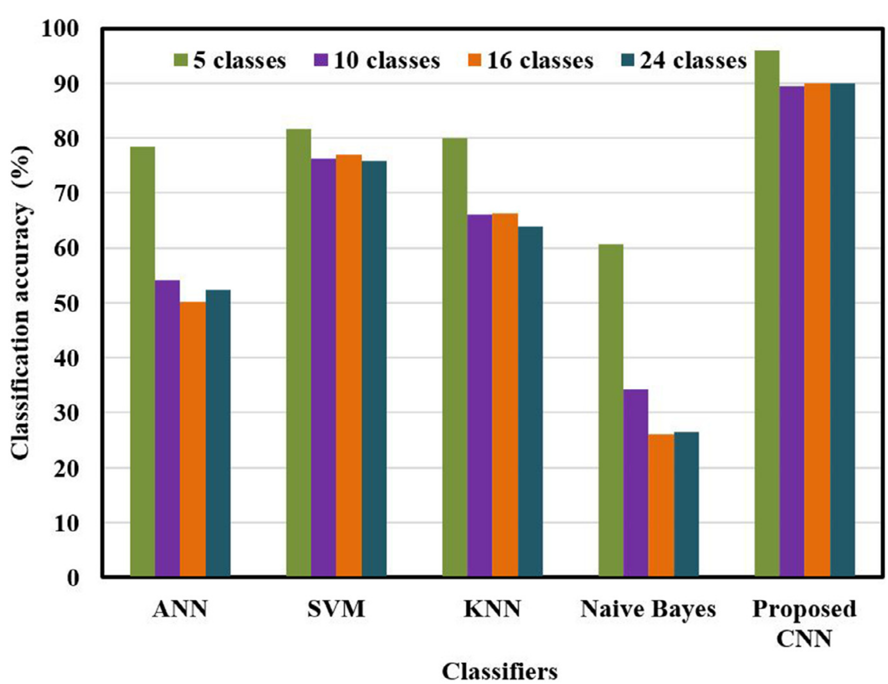
Fig. 6(a) showed that the classification accuracy of 79.9% and 71.8% for 5 and 9 classes of insects observed with nine shape features from the RBF kernel SVM classifier. The applied shape features in SVM showed better accuracy for insects with quite similar structures in wings and body shapes such as Auchenorrhyncha, Heteroptera, Hymenoptera, Coleoptera, and Lepidoptera. The results of the Gaussian Naive Bayes classifier resulted in low accuracy for both datasets due to feature independence, and it weights all the features equally. The similar better accuracy of insects with wing structures and body shapes while classify using SVM model was obtained by Wang et al. [11] for seven geometrical features.

The CNN model is applied to improve the classification accuracy by automatically extracted features. As seen in Fig. 6(a), the CNN model explores high-level features of the insect images, and the results prove that higher classification accuracy is achieved with five convolutional layers and three max-pooling layers with a learning rate of 0.001. CNN model has brought to 93.9% and 91.5% accuracy for 5 and 9 insect classes because it deals with more discriminate features in the insect images.

The extracted shape features from the 24 insect classes of Xie dataset applied for various classifiers. As a comparison with [12], the authors applied moment-invariant features with SVM classifier and obtained an accuracy of 70.5% on 24 insect classes. Further, Cheng et al. [38] used ten classes of insects from Xie dataset and obtained 25.3% classification accuracy by applying SVM classifier. When compared with Cheng et al. [38] and Xie et al. [12], our results showed an improved accuracy of 75.8% for the 24 insect classes using the nine shape features in the SVM classifier as shown. From Fig. 6(b), the higher accuracy of 90% obtained from the CNN model favors for fast identification of insects and investigate



(a)



(b)

Fig. 6 – (a) Insect classification results for Wang dataset. (b) Insect classification results for Xie dataset.

the appearance of insects in the crops. Table 3 shows the computation time to process the 9 and 24 class insect datasets in various classifier models.

The computation time required to process the classifier models depends on the respective type and size of the images. The time required for the computation may vary for different algorithms and various processing units. From Table 3, it is clearly shown that computation time varied for all the algorithms with respect to the insect dataset images. The computation time for ANN, SVM, KNN, Naive Bayes was lesser than the proposed CNN. The lowest classification accuracy was obtained for ANN, SVM KNN, Naive Bayes classifiers. However, proposed CNN is achieved higher accuracy when compared to other classifiers for both dataset images. The order of classification accuracy was NB < ANN < KNN < SVM < proposed CNN. While the proposed CNN required more computation time for classification, the higher accuracy was achieved that can be useful to recognize the insects according to classes and family.

3.2. Insect detection results

The insect pest detection algorithm focusses on detecting the insects with complex background by applying segmentation followed by finding the effective contour in the insect image. This algorithm is applied to insect datasets from Wang, Xie, Deng, and IP102. The sample detection visualizations of insects are shown in Fig. 7(a–d).

The Wang insect classes in Fig. 7(a) were detected precisely using the pest detection algorithm due to pure background color. The challenging issue for the attainment of well detection output depends on the insect images with a complicated background in the presence of shadow and dirt. The proposed pest detection algorithm segments the insect from the background and selects the contour of the insect to achieve a high detection performance.

Fig. 7(b) shows that the pest detection algorithm performed well for Sympiezomias velatus, Cletus punctiger and Tettigella viridis insects of Xie dataset with constrained and unconstrained poses of insect images as well as for different background and orientations of insects. In our approach, 225 images of 9 classes from Wang dataset, 1599 images of 24 types from Xie dataset, 282 images of 9 different classes from the Deng dataset and 600 images of 12 different classes from IP102 dataset used for insect pest detection algorithm. In case of IP102 dataset, the insect images were collected from different agriculture fields with different illumination and image quality. The Deng, and IP102 datasets were applied by [39] using cluster-based saliency and graph-based visual saliency for insect detection from tea plants and other agriculture plants around the field in Europe and Central Asia.

As shown in Table 4, the computation time of Wang, Xie, Deng and IP102 datasets is varied for all the images during the detection of insects. The reason for variation in computation time for the detection of different insect datasets is mainly due to the size differences of the images. The segmentation algorithm is applied to compute the exact insect image boundaries by evolving an initial contour to detect the insects in all the datasets. All the images were rescaled to 227×227 in the pre-processing stage in the pest detection algorithm. Due to the pre-processing of insect images, the algorithm detects the insects faster with different image dimensions and reduces the computation time. The pest detection algorithm is processed with resized images to reduce the computation time that may be suitable for real-time detection in agriculture sectors. Abdullah et al. [40] obtained the average computation time for the segmentation process of 100 images and concluded that computation time varied due to the different image sizes.

4. Conclusion

In this paper, different insect datasets were classified and detected by applying the machine learning and insect pest detection algorithm, and the results were compared. All the insect images were rescaled, pre-processed, and augmented to increase the dataset to improve the accuracy. Achieving the insect classification with higher accuracy in the real-time field is a challenging issue in the presence of shadow, leaves, dirt, branches, and flower buds, etc. in major agriculture field crops. The classification accuracy compared between various machine learning techniques include ANN, SVM, KNN, Naive Bayes, and the CNN model. The results proved that the CNN model provides the highest classification accuracy of 91.5% and 90% for 9 and 24 classes of insects from Wang and Xie datasets, respectively. The achieved classification accuracy helps to reduce the computation time for better insect recognition. The detection of insects from Wang, Xie, Deng, and IP102 datasets was performed using insect pest detection algorithm with less computation time. In future, deep learning technique will be applied for the recognition of multi insects and insect images with different periods of growth in agriculture field crops. The pest detection algorithm will be implemented in deep Convolutional Neural Network (CNN) model to detect the insects with class labels for larger insect datasets.

Table 3 – Computation time for different classifiers for Wang and Xie dataset.

Algorithm	Computation time (min)	
	Wang dataset	Xie dataset
ANN	<3	<5
SVM	<1	<2
KNN	<1	<2
Naive Bayes	<1	<2
Proposed CNN	~120	~180

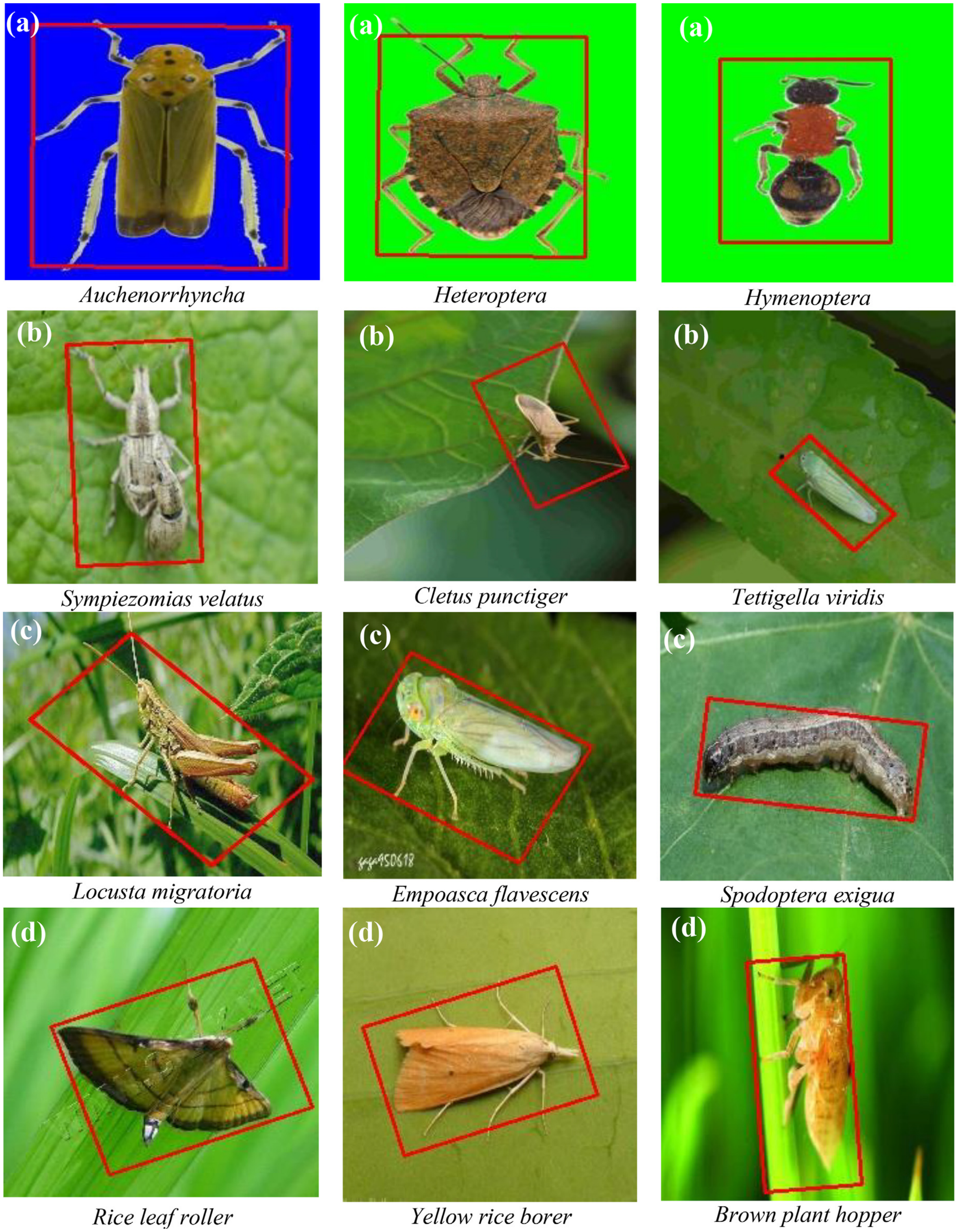


Fig. 7 – Sample of insect detection results for (a) Wang, (b) Xie, (c) Deng, and (d) IP102 dataset.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 4 – Computation time of Wang, Xie, Deng and IP102 datasets for insect detection.

Insect Dataset	Total number of insects	Computation time / min
Wang	225	<5
Xie	1 599	<38
Deng	282	<6
IP102	600	<9

ports from Machine Learning and Data Analytics Lab, Department of Computer Applications, National Institute of Technology, Tiruchirappalli, Tamil Nadu, India.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.inpa.2020.09.006.

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