Insect Pest Image Detection and Classification using Deep Learning

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1. ABSTRACT:

Abstract—Farmers' primary concern is to reduce crop loss because of pests and diseases, which occur irrespective of the cultivation process used. Worldwide more than 40% of the agricultural output is lost due to plant pathogens, insects, and weed pests. Earlier farmers relied on agricultural experts to detect pests. Recently Deep learning methods have been utilized for insect pest detection to increase agricultural productivity. This paper presents two deep learning models based on Faster RCNN Efficient Net B4 and Faster R-CNN Efficient Net B7 for accurate insect pest detection and classification. We validated our approach for 5, 10, and 15 class insect pests of the IP102 dataset. The findings illustrate that our proposed Faster R-CNN Efficient Net B7 model achieved an average classification accuracy of 99.00 %, 96.00 %, and 93.00 % for 5, 10, and 15 class insect pests outperforming other existing models. To detect insect pests less computation time is required for our proposed FasterR-CNN method. The investigation reveals that our proposed Faster R-CNN model can be used to identify crop pests resulting in higher agricultural yield and crop protection.

2. INTRODUCTION:

Agricultural production from field crops has advanced quickly in both quantity and quality, but the prevalence of pests and diseases on crops has limited the quality of agrarian output. If pests on crops are not thoroughly inspected and a sufficient, long-lasting treatment is not offered, the quality and amount of food production will be lowered, causing an increase in poverty and food shortages. Any country's economy might be negatively impacted by this, but it would be most harmful in places where 60-70% of the populace relies completely on income from the agricultural sector to support itself. Getting rid of pests that are growing and reducing crop production is a significant issue for agricultural producers. According to our research, a pest is any species that disperses disease and induces damage to the plants. Aphids, flax budworm, flea beetle, cabbage butterfly, peachtree borer, prodenia litura, thrips and mole cricket are the most frequent pests that attack plants. In order to prevent a large amount of loss and boost crop yields, it is necessary to identify these pests at all phases of their life cycles, whether they are nascent or advanced.

Understanding and classifying insects is the initial step in preventing crop damage caused by insect pests. This will allow us to distinguish between harmless insects and dangerous ones. In recent times, there has been a rise in awareness of automated pests' classification because this activity necessitates ongoing, intensive monitoring [1]. It is commonly known that distinct insect species may have phenotypes that are similar to one another and that due to various habitats and growth cycles, insects can have intricate morphologies [2] [3]. An outstanding method for recognizing insect images has been made possible by the development of machine learning techniques. Vehicle recognition and motion detection have seen considerable success utilizing computer vision as well as machine learning techniques [4] [5]. A sizable pest dataset of 40 high-grade pest categories was labeled using a multi-level classification framework of alignment-pooling method [6]. A dataset with 563 pest images partitioned into 10 categories was used. To classify the dataset, training was done on a Support Vector Machine for custom features [7]. Various image processing techniques to detect and retrieve insect pests by developing a machine-driven detection and removal system for evaluating pest concentration in paddy crops [8]. To identify the pest from a dataset of pest images K mean segmentation technique was implemented. In order to classify the pests, the discrete cosine transform method was implemented and the pest images were classified using an artificial neural network.Images were validated for five pests and obtained an accuracy of 94.00 % [9]. Deep learning techniques like convolutional neural networks have lately been used in agricultural production as a viable approach for fully automated pest classification [10].

The convolutional neural networks exert a significant influence on image elements and has their own feature extractor, which makes them superior to conventional image processing techniques and machine learning. Additionally, in several applications of medical image analysis, convolutional neural networks demonstrated their ability to manage picture noise and illumination change [11]. In this study, a Faster R-CNN framework to detect and classify insect pests is investigated. The main contributions of this work are as follows: 1) To detect and classify crop pests, a Faster R-CNN framework with Efficient Net is used. In order to improve the performance of the model the network drop connects is used to prevent over fitting and to increase regularization effect a swish function is utilized for Efficient Net. 2) The Region Proposal Network module and the bounding box regression can accurately predict the classes and locations of various crop pests. The computational time required for detecting the insect pests is less. 3) Compared to other methods, the evaluation results of insect pest classification using the proposed Faster R-CNN framework demonstrated superior performance

3.RELATED WORK :

Several deep learning techniques have been used recently to categorize pests and develop cutting-edge outcomes in several applications for pest identification. Convolutional neural network and saliency techniques were used for classifying insect pests. Image processing algorithms known as saliency approaches emphasize the most important areas of an image. These techniques are based on the realization that the observer accurately distinguishes between the portions of its field of vision that are important and those that are not useful, rather than focusing on the entire range of vision. They obtained an accuracy of 92.43 % for the smaller dataset [12]. To classify the defected wheat granules for a dataset of 300 images, an artificial bee colony, performance tuning artificial neural network, and extreme learning machine techniques are used [40]. A deep learning framework for multi-class fruit detection which includes fruits images along with data augmentation based on Faster RCNN was proposed and the performance was evaluated [41].

For identifying pests and plant diseases in video content, a deep learning-based Faster RCNN was investigated along with video based performance metrics [42]. A survey paper of current innovations in image processing methods for automated leaf pest and disease recognition [43]. Adao et al. collected a dataset of cotton field images and implemented a deep residual design and classified the pests. F1-score of 0.98 was achieved by using Resnet 34 model [44]. A metric for accuracy degradation was utilized to analyze machine learning algorithms by enhancing benign samples [24]. The natural statistics model was applied to create saliency maps and identify regions of interest in an insect pest image. Further work was done on the bio-inspired Hierarchical model and X (HMAX) method in the accompanying areas to retrieve invariant features for representing pest appearance [13]. Convolutional neural network-based frameworks, such as attention, feature pyramid, and fine-grained modeling techniques for the IP102 dataset were implemented and obtained an accuracy of 74.00 % [14]. Chen. H. C et al. implemented the AlexNet-modified architecture-based convolutional neural network model on the mobile application in order to identify tomato diseases utilizing leaf images. For a 9-class disease, the Alexnet model had a precision of 80.3% [15]. Pest detection for 10 pest classes using an efficient system for deep learning achieved an average accuracy of 70.5 %. Yolov5-S model was used for the detection of pests and the dataset used was IP102 [16]. A comparison of KNN, SVM, Multilayer Perceptron, Faster R-CNN, and Single Shot Detector classifiers in distinguishing Bemisia Tabacii embryo and Trialeurodes Vaporariorum embryo tomato pest classes was implemented [17]. K. Thenmozhi used three types of the dataset which include NBAIR, Xie1, and Xie2 for insect classification for 40 classes and 24 classes.

Pre-trained deep learning techniques like AlexNet, ResNet, and VGGNet were used for insect classification and fine-tuned with pre-trained models by utilizing transfer learning and obtained an accuracy of 96.75, 97.47, and 95.97% [18]. Wang et al. implemented a Multi-scale convolution capsule network for crop insect pest detection. The advantages of MSCCN are that it is able to extract the multi-scale discriminative features, encode the hierarchical structure of size-variant pests and for pest identification, softmax function was used to determine the probability. They obtained an accuracy of 89.6% for 9 classes of insect species [19]. Nour et al. worked on the AlexNet model to recognize the pests for an IP102 dataset. The model accuracy was fine-tuned by data augmentation to obtain an accuracy of 89.6 % for an eightclass insect pest [20]. Balakrishnan et al. implemented a realtime IOT-based environment to detect pests using a faster RCNN ResNet50 model for object detection framework. The model used 150 test images for each class of insects, 8 classes of the IP102 dataset. The model average accuracy achieved for eight-class insects is around 94.00 % [21]. Kasinathan et al. implemented machine learning techniques such as ANN, SVM, KNN, Naïve Bayes, and the CNN model for pest detection and classification. The model achieved an accuracy of 91.5 % and 93.9 % for nine class and five class pests.

The drawback of this model they have used 50 images for each class even though more images of the pests were available in the dataset of IP102 [22]. Mohamed et al. developed a mobile application that uses deep learning to automatically classify pests and for the identification of insect pests, they used a Faster R-CNN model. The model achieved an average accuracy of 98 % for five pests. The drawback of this work, in training the image pests they have used a total of 500 image pests which results in poor approximation, and few test data will result in an optimistic and high variance estimation of prediction accuracy [23]. In order to overcome the above approach, the proposed work was implemented by using a Faster R-CNN for detection and classification of pests for around 1449 pest images for testing of five pest classes, similarly for 10 classes is 2921 images and 15 classes are 4321 pest images of IP102 dataset.

A. Insect Pests The proposed work, includes 15 classes of crop insect pests namely aphids, cicadellidae, flax budworm, flea beetle, cabbage butterfly, peachtree borer, prodenia litura, thrips, bird cherry-oat aphid, mole cricket, grub, wireworm, ampelophaga, lycoma delicatula and xylotrechus. Each class in the IP102 dataset is highly unbalanced, each class pest that contains more images in the dataset is taken into consideration for the study. The following insect pests framework cause considerable damage to the crops leading to a loss in crop productivity.

B. Faster R-CNN Faster R-CNN requires an image to be scaled to a certain length and width so that noise can be avoided and with the introduction of a region proposal network the detection speed of insect pests is vastly improved [37]. The feature map is generated by the convolution neural network layers for processing the images and the identified object undergoes location regression and classification. We evaluate the three important steps which are involved in Faster R-CNN. Feature maps were obtained from a pre-trained convolutional neural networks framework in particular Efficient Net [25], Resnet 50 [21], and Dense convolutional neural networks [38]. Next, the Region Proposal network generates the region proposals to detect the pest's locations in the image. The regression box provides the exact location of the insect pests. The insect pest image processed by the region generative proposal is sent to the region of interest pooling to identify and predict the accurate location of the insect pest image. Fig. 3 depicts the proposed Faster R-CNN framework for detection and classification

4.MATERIALS AND METHODS:

Efficient Net is a unique scaling method that uniformly scales all depth/width/resolution dimensions using a compound coefficient. Neural architecture search is used to generate a brand-new baseline network and scale it up to create the Efficient Nets family of modeling techniques, which outperform prior convolutional networks in both efficiency and accuracy, reducing parameter size and FLOPS [39]. Width scaling is the process of changing the width of an input image. The larger the image, the more feature maps/channels are possible, and thus the more information is available to process [36]. Resolution scaling is the process of changing the resolution of an image.

The higher an image's Dots per inch, the higher its resolution. Better resolution is simply an augmentation in the number of pixels in an image. To scale the three dimensions, a baseline model called Efficient Net B0 was introduced. There are seven Efficient Net models ranging from B0-B7, where B0 is the baseline model. The size of the incoming image varies between models. As the model level increases, so does the image's input size. This flexible scaling strategy can be utilized to effectively scale Convolutional Neural Networks and enhance the accuracy with a variety of frameworks.

The input image is processed by MBConv bottlenecks in which direct connections are used because between bottlenecks with significantly fewer channels than expansion layers in inverted residual blocks as shown in Fig. 1. MB Conv has an attention blocks and are made up of a layer that expands and then compresses the channels, mechanism that allows it to optimize channel features that contain the highest information while restricting less significant channel features.

The gradient of MBConv does not quickly vanish when the network depth is more thereby improving the model performance. The regularization effect can be increased by using a swish function with no upper limit wherein gradient saturation will not occur [25]. In order to improve the performance, the network drop connect is used to prevent over-fitting. The Efficient Net B4 and Efficient Net B7 model consists of nine phases with respect to Blocks. Blocks provide effective layers and their feature map is connected to the Region Proposal network and Region of Interest pooling as shown in Fig. 3.

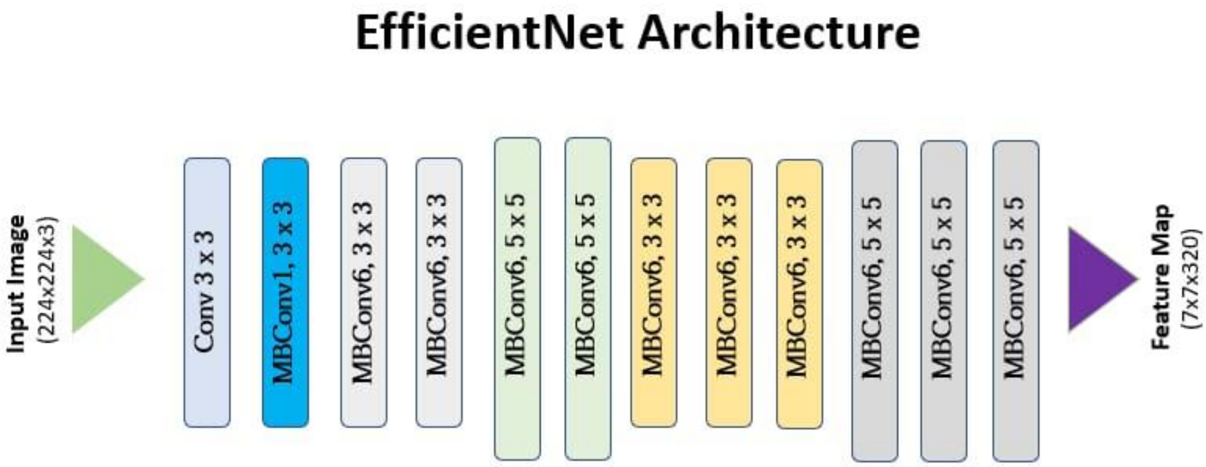


Fig. 1. Efficient B7 Architecture.

A. Dataset Capturing pest images is a difficult task although all insect pests go through several phases during their entire life, based on the species and category of pest. IP102 dataset is commonly used to test the insect pest for classification and detection based on deep learning methods [22]. As a result, we utilized pest images from the public IP102 dataset. The dataset has around 75000 images pertaining to 102 insect pest species. For detection and classification, we have chosen 5, 10, and 15 classes of insect pests. Dataset of 14490 pest images for the training of five pest classes, 29210 images for 10 pest classes, and 43210 images for 15 pest classes. The pest images were split in the ratio of 80 % training, 10 % validation, and 10 % for testing. Sample images of insect pests are shown in Fig. 2.

B. Proposed Framework for Detection and Classification The pest images of the IP102 dataset are passed to Efficient Net network and are pre-trained on ImageNet to generate feature map. In order to improve the performance, network Drop connect and Swish function is utilised in Efficient Net. The feature map is passed to the RPN network to generate the bounding box and proposal score for the pest images. The output of RPN network and feature map obtained from the Efficient Net algorithm is passed to ROI pooling for detection and classification of pest images. Further the flow of the Proposed Faster R-CNN framework for Pest detection and Classification is explained in detail in the below following Section 3C and 3D.

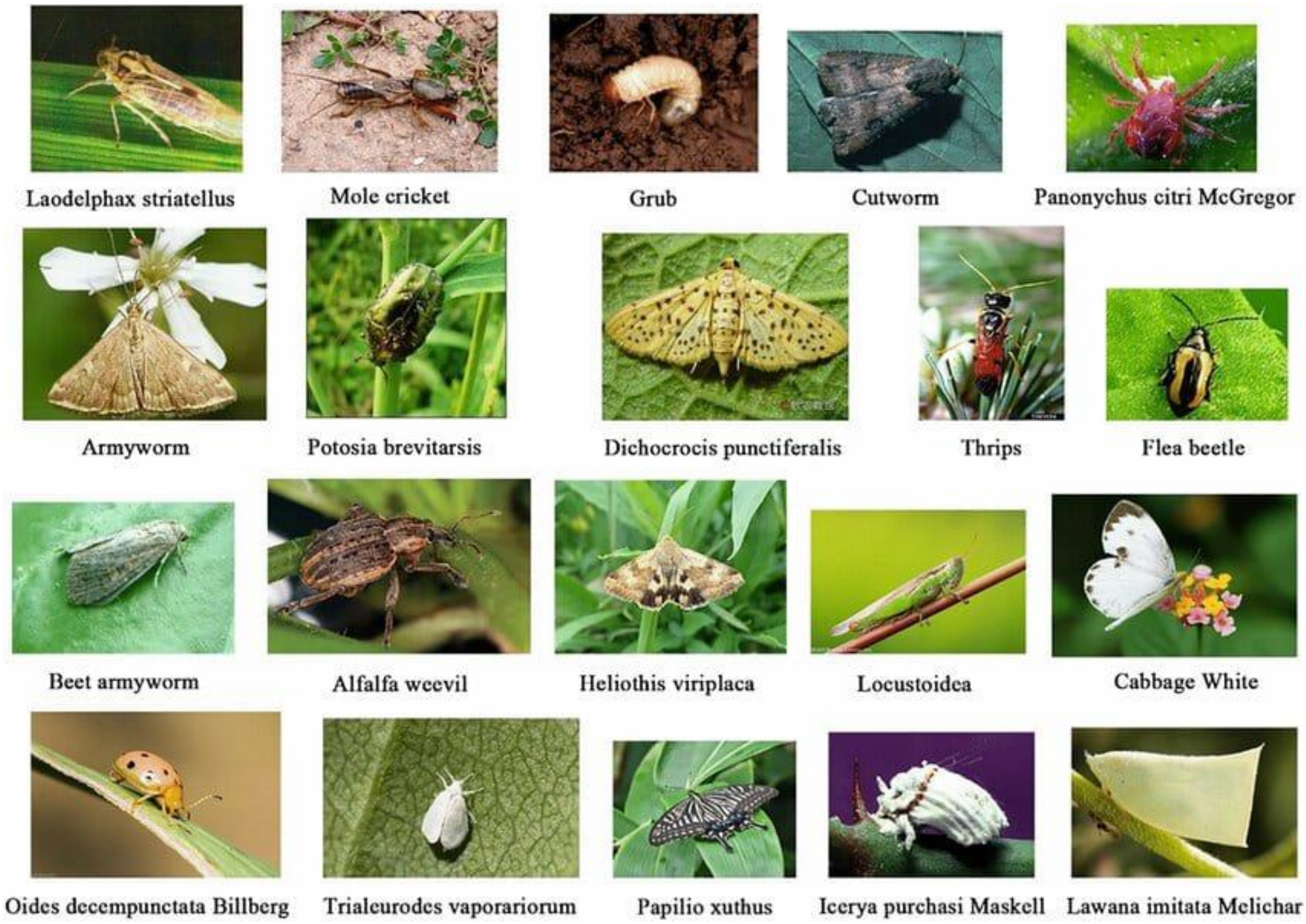


Fig. 2. Samples of Pests Images from the IP102 Dataset.

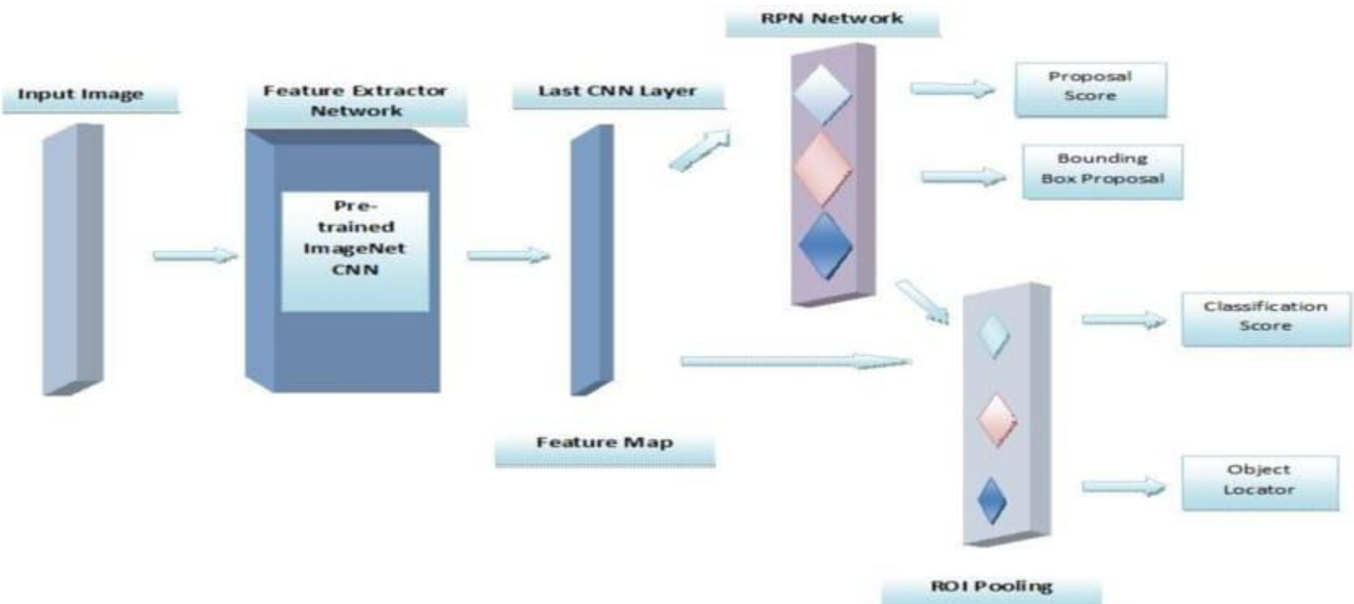


Fig. 3. Proposed Faster R-CNN Framework for Pest Detection and Classification.

C. Image Preprocessing and Augmentation

Images are transformed to (600,600) in the pre-processing stage phase to retain the same aspect ratio, and images are normalized to maintain the standardized data distribution [25]. The importance of data augmentation for image classification analysis has previously been proven due to insufficient datasets. The categories of each insect pest in the IP102 dataset are highly unbalanced. To increase the data while avoiding the over-fitting problem, various data augmentation techniques such as rescaling, zooming, and horizontal flipping have been used. Gaussian filter is first used to smooth the image. The images were rescaled, created a mask for every image, and then applied segmentation to each sample. Each image in the dataset is subjected to the processing pipelining by a function.

D. Insect Pest Detection & Classification

The above-proposed learning architecture is used for image processing and to detect and classify pests using the Efficient Net and Faster R-CNN approach as shown in Fig. 3. The convolutional neural network layers of Efficient Net B4 and Efficient Net B7 has been used as feature extractor in this research and for Faster R-CNN because of their added advantage of lightweight and its processing speed which is critical for our end application. The pre-trained weights of Efficient Net were trained on the Image Net dataset. The size of the input image for this methodology is fixed at 224 x 224. Hence using the EfficientNet model we generate feature maps for an input image and pass it to the RPN.

The RPN takes these feature maps as an input to it and provides a set of rectangular proposals (bounding box) identifying the object i.e, a pest in the convolutional neural network feature map as an output along with the objectness score. Grid-anchor having aspect ratio [0.25, 0.5, 1.0, 2.0] is started with a 16x16 pixel size during this stage. These anchors point to available objects of different sizes and aspect ratios at the corresponding location. Intersection over Union determines how well the bounding box matches with the ground truth of the insect pest image, where A and B are two sections of region proposals as given in (1). To improve the performance of the model and to reduce the noise, nonmaximum suppression is utilized for identifying the bounding boxes with the highest confidence so that the small overlaps are ignored. The thresholds were kept at 0.7.

$$IoU = A \cap B \ A \cup B$$

To create the proposals for the object, the Faster R-CNN architecture is utilized. It has a specialized and unique architecture that has got classifier and regressor. The Faster RCNN is robust against translations, it's one of the important properties that it is translational invariant.

When multi-scale anchors are present, Faster R-CNN creates a "Pyramid of Anchors" rather than a "Pyramid of Filters," which consumes less time and is more cost efficient compared to various other architecture. The next step is to pass the proposals to Region of Interest pooling layers. To create a single feature map for each of the proposals provided by RPN in a single pass, Region of Interest pooling is utilized. It is implemented to address the issue of fixed image size difficulties with object detection. ROI pooling is utilized to create fixed-size feature maps against non-uniform inputs by applying max-pooling across the inputs. This layer needs two inputs: (i) A feature map obtained from a backbone of EfficientNet B4 or EfficientNet B7 used in our research methodology after multiple convolutions and pooling layers. (ii) 'N' proposals or Region of Interests from region proposal network (RPN).

The benefit of Region of Interest pooling is that we can utilize the corresponding feature map across all proposals, allowing us to pass the whole image to the convolutional neural networks rather than passing each proposal separately. The sub-windows have a size of (N, 7, 7, 512) which has been created by the Region of Interest pooling layer by applying max pooling over the next stage, where N represents the number of region proposals obtained by the RPN network. The features are moved into the classifier and regression sections after moving via two fully connected layers. Using the softmax function, the classification division evaluates the probability of a region proposal comprising an insect pest. Additionally, Intersection over Union values are used to evaluate the accuracy of the bounding box generated surrounding the insect pest. The anchor box coordinates are provided by the bounding box regression.

E. Classification Performance Metrics

The performance for identifying the insects is measured by using rotation estimation for validating the insect pests of tested images with predicted classification results of the Faster R-CNN technique [26]. The Confusion Metrics are evaluated by True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The TP indicates the current predicted insect pest class category that is correctly classified. The TN pertains to other groups that do not belong to the existing insect pest class category. The FP pertains to other insect pest class category incorrectly classified as the current insect pest class type. The FN relates to the current insect pest class category that was incorrectly classified and did not belong to the existing class. Precision metric indicates out of all points that are predicted to be positive, how many are actually Positive. The recall metric indicates out of all positive points, how many are actually positive. The classification metrics is given below.

$$accuracy = tp+tn\ tp+fp+tn+fn \quad (2)$$

$$precision = tp\ tp+fp \quad (3)$$

$$recall = tp\ tp+fn \quad (4)$$

$$f1score = 2*precision*recall\ precision+recall \quad (5)$$

5. RESULTS AND DICUSSIONS

For this experiment, we have used an i7 processor with GPU (Nvidia RTX 3080 Ti) along with other supporting tools such as Keras and Tensor flow for the detection and classification analysis of insect pest images of the IP102 dataset. The performance of the insect detection and classification method was implemented on 5, 10 and 15 classes of insects. The insect pest images were split into the ratio of 80% training, 10% validation, and 10 % for testing. The proposed Faster R-CNN model is trained using Stochastic Gradient Descent as an optimizer with 0.9 momentum value, region proposal network weights, and the last fully connected layer weights. The learning rate tells about the learning progress and updates with weight parameters to reduce the loss. The learning rate is varied from 0.0005, 0.0001, 0.001.The maximum no of epochs trained to 40 steps. The detection and classification results are shown in Fig. 4 based on Faster RCNN. The proposed Faster R-CNN technique can correctly detect insect pests in the image and identify the categories. For all test datasets of pest species, classification accuracy ranged from 97.0 to 100.00%.

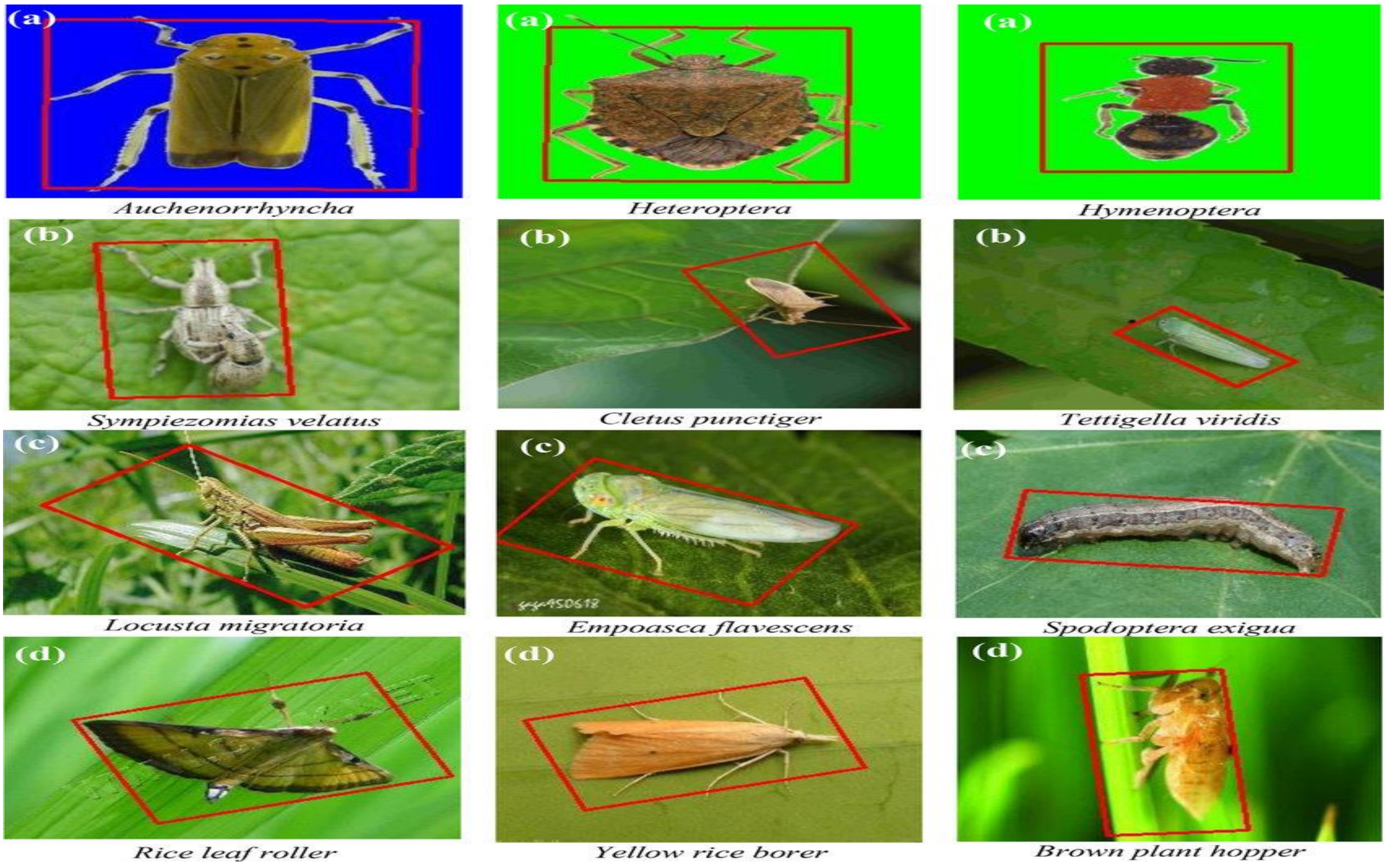
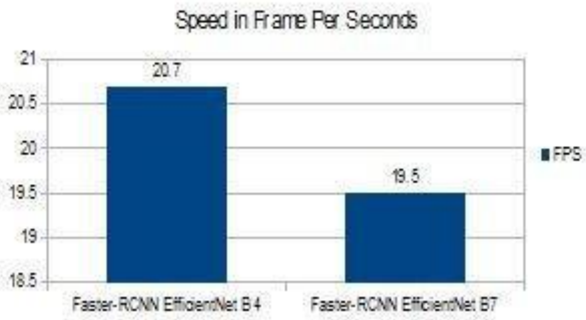


Fig. 4. Sample of Pest Detection Results for the IP102 Dataset.

The performance indicator for Pest detection is shown in Fig. 5, such as the two methods' average inferential speed. As shown in Fig. 5, Faster R-CNN Efficient Net B7 speed along with accuracy takes around 19.5 frames per second compared to the other model which takes 20.7 frames per second.



The model performance for five pest classes based on Faster R-CNN Efficient Net B7 and Faster R-CNN Efficient Net B4 model is shown in Fig. 6 and Fig. 7. The learning rate was reduced by a factor of 0.5 when the improvement during training went negative.

The model continued to be trained with a stop patience of seven, i.e, if for seven continuous epochs there was a negative improvement, the training was halted automatically. The Validation accuracy of around 99.00 % was achieved during training, and the validation loss decreased progressively up to 0.4 % for the Faster R-CNN Efficient Net B7 model. Similarly, the Validation accuracy of 98.00 % and loss of 0.6 % are obtained for the Faster R-CNN Efficient Net B4 model.

6. CONCLUSION:

In this study, the investigation was done on the Faster RCNN method to detect and classify different insect pests for 5, 10, and 15 classes, and the results were compared. To improve the performance and accuracy, each one of the pest images has been resized, pre-processed, and augmented to increase the dataset. When the image background is more challenging and the insect classes are more numerous, as in the IP102 dataset, our proposed Faster R-CNN Efficient B7 model achieved an average classification accuracy of 99.00 %, 96.00 %, and 93.00 % for 5, 10, and 15 class insect pests outperforming other existing models such as SSD Mobile Net, Bio-inspired method and Faster R-CNN ResNet 50. In future work, the proposed Faster R-CNN model will be used for higher number of insect classes and subclasses of insect pests that will be useful for farmers to detect insect pests for detection and classification.

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