Improved accuracy of pest detection using augmentation approach with Faster R-CNN

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Abstract. In agriculture, Pests are decreasing agricultural productivity. Identifying a pest is a challenging process and subject to expert opinion. Nowadays, lots of work carried out for automatic pest detection. It becomes possible because of emerging Deep Learning’s object detection architectures. This paper shows the multi-class pest detection using Faster R-CNN architecture and compared the performance results of image augmentation with focused on the accuracy performance along with small dataset. We have used Horizontal Flip and 90 Degree Rotation augmentation parameters for solving class imbalance problem. We found that trained pest detection model with augmentation options can perform better with an accuracy of 91.02% using Faster R-CNN architecture.

1. Introduction
Pest significantly reduces the quantity and quality of crops in agriculture. Pest identification is the basis of crop disease prevention to guarantee crop quality. Traditional diagnostic methods for pest identification are mainly based on naked-eye observation with low detectability and poor reliability as a result. Farmers are missing the best time for prevention due to lack of knowledge and unavailability of agricultural experts at the farm. Automated pest detection system provides a method to solve the problems effectively. In this study, we have selected three main flying insects viz. White grub, Helicoverpa and Spodoptera which affect groundnut, pepper and grain crops of Saurashtra region of Gujarat, India, respectively for classification.

Edge detection[1], pattern recognition[2], computer vision technology[3] and other technologies have developed rapidly in recent years. Fast growth and show the promising performance of convolutional neural networks (CNNs)[4] have been recorded.

In the previous study, our experiment concluded Faster-RCNN meta-architecture for further study among various deep learning meta-architecture[5]. The proposed research is focused on utilizing the Faster R-CNN model to achieve real-time detection of Pest in the natural environment. More ever, an unsupervised augmentation algorithm[6] was applied as pre-processing work for attaining the higher detection results of Faster R-CNN.

2. Related Work
There are many of advanced techniques developed and functional in the modern agricultural field such as plant diseases and pests recognition[7], Fruit Detection using a Robotic Vision System[8] and Whiteflies detection[9]. Although the pest classification methods have reached great success to some level, however, these features were too scrappy in the case of scale, rotation and size of data. CNN has been made a trust as object detection architecture of computer vision technology in recent years
In our previous study, we showed that state-of-the-art CNN meta-architecture Faster-RCNN is a better performer with classification accuracy among the three widely used deep learning meta-architectures viz. Faster R-CNN, SSD Inception and SSD Mobilenet[5]. Faster R-CNN works to efficiently classify objects using deep convolutional networks[11]. There is also plenty of work on object detection using Faster R-CNN in other domains like vehicle detection[12], signal detection[13] and human detection[14]. To improve pest detection accuracy, we proposed Faster R-CNN architecture for multi-class pest detection and classification based on deep learning using TensorFlow.

3. Material and Methods

To get truthful results, we have experimented with real conditions of pests. Hence, we had to choose targeted pests, pre-processing methods and pest detection architecture is detailed in the following sub-sections.

3.1. Choosing various pest classes as a model study

Groundnut, Cereal and Vegetable crops are significant crops grown in Saurashtra Zone (Agro-climatic Zone) of Gujarat[15]. White grubs are soil-inhabiting and feed on plant roots of groundnut crop. Spodoptera is significant damage to wheat, rice viz. cereal crops and vegetable crops. Helicoverpa is damaging the tomato crops. In our study, these are three different classes of pests (Viz. White Grub, Spodoptera and Helicoverpa) selected and collected images from near-by location of Saurashtra Zone of Gujarat, India. For more convenient during the experiment, identical names have been assigned to each Pest as per Table 1.

| Sr. | Pest         | Identical Name | Number of Images |
|-----|--------------|----------------|------------------|
| 1   | White Grub   | INS-A          | 319              |
| 2   | Spodoptera   | INS-B          | 131              |
| 3   | Helicoverpa  | INS-C          | 143              |

Table 1: Identical name for Pest which is used during the experiment

3.2. Faster R-CNN Architecture

Region-CNN (R-CNN) [11] is an object detection algorithm that targets to find and categorize multiple objects from a single image. R-CNN is very slow, and it can take time to process an image. Hence, it was making unstable real-time image detection environment. Faster R-CNN is an improved algorithm proposed by Shaoqing Ren et al. Which can directly let the network to acquire the region proposals. Inputted image is transmitted to CNN by Faster R-CNN [16]. It takes into account a significant number of potential areas which can use an effective in-depth learning method to estimate which areas have to be objects of interest. The predicted area of the region reshaped using the Region of Interest (RoI) pooling layer. Which layer generates the value for bounding box from classified and predicted image. In Previous work, our study shows that Faster R-CNN performs better based on accuracy performance with the small dataset of Pest[5]. Although, proposed study is improving result of pest detection using image augmentation.
3.3. **Image Augmentation**

Image augmentation is artificially creating variations in training images to expand an existing image data set. Certain pests are visible during relative seasons, so it is hard to capture images of each class of Pest equally. Hence, Due to limited dataset, the class imbalance problem described[17]. Our focus to expand limited datasets using image augmentation to achieve oversampling solutions. We have used Horizontal Flip and Rotation 90 Degree methods as data augmentation option of the configuration file of architecture in this study.

3.4. **Implementation**

High-Speed Quadro P5000 GPU workstation used for all the experiment for this study. All the pest Images captured using various regular mobile phone camera. Pest Image annotations saved as XML files using Labelimg[18] graphical tools. All experiments carried out on Tensorflow platform[19].XML Files are converted to TFRecords file for the training dataset and test dataset. Horizontal Flip and 90 Degree Rotation parameters used as data augmentation option in the configuration file of Faster R-CNN architecture to compare the performance of pest classification task during limited dataset. To scale up Faster R-CNN used Inception v2 as feature extractor during training the model[20]. TensorBoard provided Tracking and visualizing metrics such as loss and accuracy during the experiment.

4. **Result and Discussion**

Identifying pests is a significant factor in controlling crop damage and locating pests manually without the help of a specialized entomologist is a very cumbersome process, and the chances of error are high. With the advancement of Faster R-CNN architecture, it is possible to detect the pest in advance. This study objectives to compare the two experiments viz. augmented data and without augmented data to test the precision performance of the network using a small dataset of pest images.

To Visualization of Bounding Box output has been analyzed for all generated result. Few of visual output of with/without augmentation results in Figure – 2 to understand the detection accuracy.
Figure 2: Pest Detection output for experiments. (A) Without Augmentation (B) With Augmentation

Pest detection results for the experiments are summarized in the form of confusion matrices in Table 2. Customized parameters of the confusion matrix are: True Positives (TP) is the count of specific pest that predicted as a specific pest; False Negatives (FN) is the count of pest not predicted as a specific pest. True Negatives (TN) is the count of non-pest that not predicted as a pest, while False Positives (FP) is the count of non-pest predicted as a pest. As per the table, We found the higher detection accuracy in the evaluated model with augmentation. Due to image augmentation, Training model process becomes slower compared to without augmentation, but performance accuracy is improving [21].

| Faster R-CNN Training Model | TPR (%) | TNR (%) | PPV (%) | ACC (%) |
|----------------------------|---------|---------|---------|---------|
| Without Augmentation       | 89.56   | 97.49   | 97.44   | 93.40   |
| With Augmentation           | 91.02   | 99.45   | 99.44   | 95.07   |

Table 2: Confusion Matrix - Show the obtained result of different augmented and without augmented model
5. Conclusion
In this study, we compared pre-processing methods for pest detection and classification based on Faster R-CNN and evaluated the results. Faster R-CNN model with augmentation achieves higher accuracy with 91.02% in the case of pest detection. In the future, validate our finding with more classes of pests.

References
[1] R. Maini and A. Himanshu, “Study and Comparison of Various Image Edge Detection Techniques,” Int. J. Image Process., vol. 3, no. 1, pp. 1–12, 2009.
[2] J. O’Rourke and G. T. Toussaint, “Pattern recognition,” in Handbook of Discrete and Computational Geometry, Third Edition, 2017.
[3] K. Pulli, A. Baksheev, K. Kornyakov, and V. Eruhimov, “Realtime computer vision with OpenCV,” Queue, 2012.
[4] J. Teuwen and N. Moriaakov, “Convolutional neural networks,” in Handbook of Medical Image Computing and Computer Assisted Intervention, 2019.
[5] D. J. Patel and N. Bhatt, “Insect Identification Among Deep Learning ’s Meta-architectures Using TensorFlow,” Int. J. Eng. Adv. Technol., vol. 9, no. 1, pp. 1910–1914, 2019.
[6] Q. Xie, Z. Dai, E. Hovy, M.-T. Luong, and Q. V. Le, “Unsupervised Data Augmentation,” arXiv, 2019.
[7] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, “A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition,” Sensors (Switzerland), vol. 17, no. 9, 2017.
[8] S. Wan and S. Goudos, “Faster R-CNN for Multi-class Fruit Detection using a Robotic Vision System,” Comput. Networks, p. 107036, 2019.
[9] M. Wadhai, “AGRICULTURE PEST CONTROL USING COMPUTER VISION TECHNIQUE,” Int. J. Adv. Res., vol. 3, no. 8, pp. 309–314, 2015.
[10] D. J. Patel and N. Bhatt, “Analytical Review of Major Nocturnal Pests’ Detection Technique using Computer Vision,” Orient. J. Comput. Sci. Technol., vol. 11, no. 3, pp. 179–182, 2018.
[11] R. Girshick, “Fast R-CNN,” Proc. IEEE Int. Conf. Comput. Vis., vol. 2015 Inter, pp. 1440–1448, 2015.
[12] J. Fan, T. Huo, X. Li, T. Qu, B. Gao, and H. Chen, “Covered Vehicle Detection in Autonomous Driving Based on Faster RCNN,” pp. 7020–7025, 2020.
[13] K. N. R. S. V. Prasad, S. Member, B. D. Kevin, S. Member, V. K. Bhargava, and L. Fellow, “A Downscaled Faster-RCNN Framework for Signal Detection and Time-Frequency Localization in Wideband RF Systems,” vol. 19, no. 7, pp. 4847–4862, 2020.
[14] Y. H. Yeu, “Investigation on Different Color Spaces on Faster RCNN for Night-Time Human Occupancy Modelling,” no. December, pp. 13–14, 2019.
[15] S. Teams, “State Agriculture Plan and State Infrastructure Development Plan,” Gandhinagar, 2019.
[16] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2017.
[17] J. L. Leevy, T. M. Khoshgoftaar, R. A. Bauder, and N. Seliya, “A survey on addressing high-class imbalance in big data,” J. Big Data, vol. 5, no. 1, 2018.
[18] Tzutalin, “Labelling.” Labelling. 2015.
[19] M. Abadi et al., “TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems,” in 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI ’16), 2016, pp. 265–283.
[20] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the Inception
Architecture for Computer Vision,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2016-December, pp. 2818–2826, 2016.

[21] C. Shorten and T. M. Khoshgoftaar, “A survey on Image Data Augmentation for Deep Learning,” J. Big Data, vol. 6, no. 1, 2019.