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Original Research Article

Utilizing Machine Learning to Detect Whiteflies on Tomatoes in a Controlled Environment

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Abstract: The tomato is the vegetable crop with the most economic impact globally, and its production has expanded significantly over time. Recent years have seen the discovery of whiteflies as a serious loss-maker in producing fresh-market and greenhouse tomatoes. Tomato plants are harmed both directly and indirectly by whitefly nymphs and adults. The leaves are attacked by whiteflies, causing them to turn yellow and curl up, resulting in their destruction. Currently, early whitefly migrations are detected using yellow sticky traps. However, executing this activity takes a lot of time and effort. In order to identify plant pests more rapidly and precisely, a method of early detection that significantly reduces economic losses was created. In this research, we proposed to use an image analysis and machine learning technique to develop a model for detecting whiteflies on tomatoes in a greenhouse. Images of leaves covered in whiteflies were obtained, and the EfficientDet-D0 model was used to train the machine learning algorithm. Results indicate that this new method might detect whiteflies with acceptable precision and an F1 score of 0.40, indicating that EfficientDet-D0 models reliably recognize the distinctive characteristics of whiteflies.

Keywords: whitefly; detection; EfficientDet-D0; machine learning; F1 score

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1. Introduction

The tomato whitefly, or Bemisia tabaci, is a widespread insect. Whiteflies are a tiny, soft-bodied homopteran insect that belongs to the Aleyrodidae family (Arthurs & Bruck, 2017; Flint, 2021). Tomato plants are harmed both directly and indirectly by the whitefly, Bemisia tabaci, nymphs, and adults. Whiteflies eat on leaves, making them yellow and curling, which destroys them (Flint, 2021), as shown in Figure 1: (a), (b), and (c). An easy visual inspection using yellow sticky traps is the most popular technique for monitoring pest populations in crop health surveys, and it can help recognize early migrations of whiteflies into fields (Pinto-Zevallos & Vanninen, 2013; Flint, 2021), as shown in Figure 1: (d). This task will require a lot of time and effort to complete.

Developing an early detection method that reduces economic losses could result in a more effective and precise method of identifying plant pests (Pinto-Zevallos & Vanninen, 2013). This technology has been extensively utilised in the food and agriculture-based industries, where it provides automated solutions like pest and disease identification (Santhosh Kumar *et al.,* 2022). AI systems may assess pest activity and behaviour data to develop pest-specific treatment programs. This may lead to reduce the number of treatments required and the use of hazardous chemicals. Computer vision techniques can be used to effectively monitor pests in farms and greenhouses in order to get around these limitations. Machine learning techniques were used for pest identification and detection [Santhosh Kumar *et al.*, 2022; Chaudari & Waghmare, 2020). This involved training a classifier on image datasets of the pest to familiarize it with its distinctive features. Subsequently, the trained model was employed to predict new inputs, classifying them as pests if they surpassed a predefined threshold.

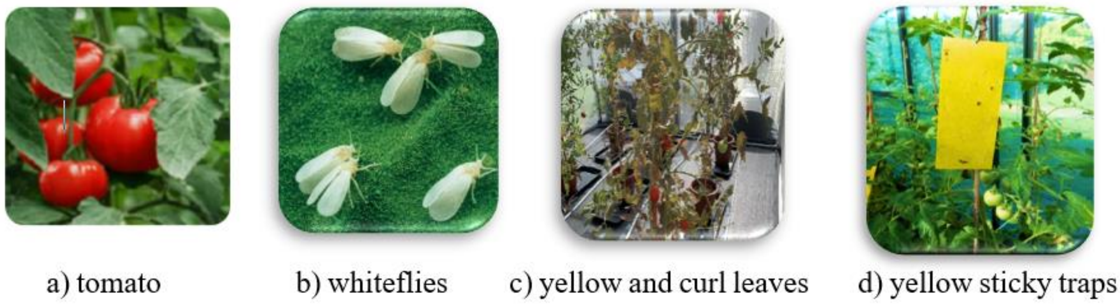

Figure 1: Tomato (a), affected whitefly (b-c), and trap catches (d)

2. Materials and Methods

2.1. Image Data Acquisition

Figure 2. Images of whitefly-infested

To train the whitefly detectors, 2825 pictures of tomato plants were collected, as shown in Figure (2) grown in a greenhouse at Laman Sayur, Malaysia Agro Exposition Park Serdang (MAEPS), Serdang, Selangor. Whiteflies are purposely introduced to plants during the reproductive stage to conduct various studies on their effects. The number of whiteflies was at its maximum during the second week after the plants were exposed. Images of the leaves covered in whiteflies were taken in these fields. The wholly developed leaves on a plant were turned to reveal the underside, where the whiteflies reside, and this view was captured during the image-capturing process using randomly chosen plants. Images were taken with various cameras and resolutions, such as cell phones or digital cameras. A laptop was used to store all the photos taken.

2.2. Development of Whitefly Detection Model

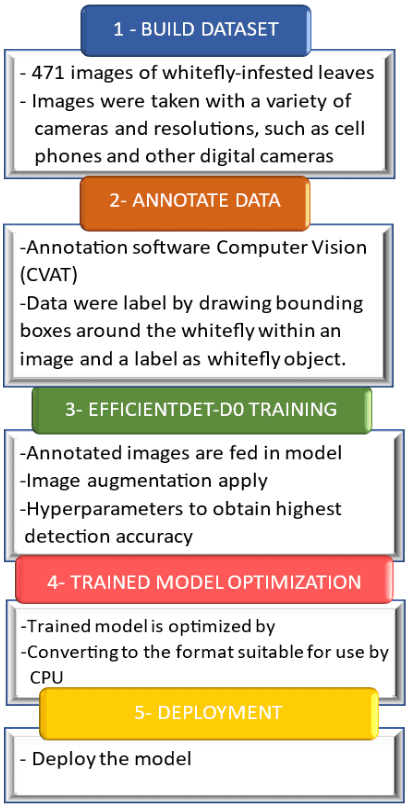

Figure 3. Development of whitefly detection model

The methods for finding whiteflies on tomato leaves are discussed in detail, as shown in Figure 3. This method's main objective is to locate and identify the whitefly on a tomato crop accurately (Fuentes *et al.*, 2017; Chen *et al.*, 2021). The raw images are then manually annotated and labelled for training data. Before training models, image annotation is an important image pre-processing step (Aljabri *et al.*, 2022). A feature is information collected from an image, and the input is assigned to the labelled features based on the chosen features. During training, a machine might learn about the labelled features. As a result, the training model's accuracy is greatly affected by how accurately the features are labelled. Labelling the location of the pest in the image is a step in the image annotation process, and the outputs of the labelled results are the pest's coordinates and bounding boxes. An open-source graphic image annotation application called Computer Vision (CVAT) allows users to manually locate and save an image's position of a pest as a *.xml file. The machine learning model typically performs significantly better with additional data. Limited data sources are a concern, as a lack of data impacts the overfitting phenomenon during training. Data augmentation could solve the overfitting issue in addition to data inadequacy. Some techniques, including geometrical (resizing, cropping, rotating, horizontal flipping) and intensity (contrast and brightness augmentation, colour, noise) alterations of images, were used to increase the input data in enhancing the sample size and variation. Due to its better performance in object detection, which needs annotated images as training data, machine learning approaches are highly regarded. Using this labelled data, we use machine learning algorithms to identify the whiteflies on the tomato crop images. Our dataset has been split into an 80% training set, a 10% validation set, and a 10% testing set to execute the experiments. The training is carried out on the training set, followed by the evaluation on the validation set, and the testing set is used for the final evaluation once it indicates that the experiments have achieved the expected result. For the task of locating and detecting the whitefly on a tomato crop, we used an “EfficientDet-D0”. This model provided strong detection. Input data for this method involved converting the images and their corresponding annotations stored as XMLfiles from the base dataset into TF (Tensorflow) Recordfiles. This specific data format is required as the input for training when using the Tensorflow Object detection API (Application Programming Interface) utility utilized for this experiment. The model was trained and evaluated in this experiment using the EfficientDet-D0 implementation from the Tensorflow Object Detection API, a Google Deep Learning platform. Transfer learning, a method used for machine learning, was especially used. The 312 photographs utilized as the test set for the models before the evaluation made up the testing TF record. The remaining photos were utilized for train and validation. Various parameters can be defined for training a model using the Tensorflow object identification API. The model was trained using the Google Cloud Platform Machine Learning Engine, and the training process was analyzed using a tensor board. Recall and Precision are performance indicators for object detection that apply to information retrieved from a data set. The Recall was used to detect how many whiteflies our models misclassified as whiteflies. The Precision was used to determine how many whiteflies existed compared to our models' predictions. The number of detections for the EfficientDet-D0 detector that overlap with annotated bounding boxes from the base dataset was calculated using a Python script, and the number of non-overlapping detections formed the false positives (FP) (false positives). The detection result and classifier performance are the major indexes to evaluate the model's performance in object detection approaches. In order to measure the efficiency of bounding box positioning, the standard measurements of Intersection over Union (IOU), precision, recall, and F1 score are typically used. Equations 1 and 2 define precision, recall, and F1 score. Precision is a measure of the ability to recognize negative datasets. The model's ability to recognize a negative dataset is stronger when the precision score is higher. Recall is a measure of the ability to recognize positive datasets. The model performs better at distinguishing a positive dataset with a higher precision score. The F1 score is a measured indicator that includes the mean of the precision and recall and could balance the model's precision and recall. A higher F1 score demonstrates the model's greater robustness. The general analytics technique for describing the effectiveness of a classifier is the confusion matrix. Confidence level or confidence score ranges from 0% to 100%; the higher the number, the more confident the model can predict the result.

$$Precision = \frac{Number\ of\ true\ detections}{Total\ number\ of\ detection} \tag{1}$$

$$Recall = \frac{True\ detection\ object}{True\ detected\ object + True\ undetected\ object}$$

$$F1\ Score = \frac{2\ \times (Precision \times Recall)}{Precision + Recall} \tag{2}$$

3. Results and Discussion

3.1. Whitefly Detection Model

A custom dataset containing 471 images was curated and annotated with bounding boxes on whitefly objects. By typical dataset standards, the dataset size is relatively small. Image augmentation techniques were applied to overcome this, including rotations and flips. The final dataset consists of 2825 images, where 2513 photos are in the training dataset and 312 in the testing dataset. This augmented dataset is then used to train the efficient D0 model. The parameters used to train the model are listed in Table 1. Images are pre-processed and resized to the [512×512×3] input size. The batch size was the most significant functioning value based on the training hardware available. The number of epochs was selected based on the training and validation loss trajectory.

Table 1. Training parameters specified for the EfficientDet-D0 model

Parameter	Value
Image Size	512 x 512 x 3
Batch	15
Epochs	30

The Precision was used to calculate the number of actual whiteflies that our model predicted, and the Recall was used to calculate how effectively the model identified whiteflies from other objects. The number of detections that overlap with the base dataset's annotated bounding boxes was counted using a Python script to determine the TP (true positives) and the amount of non-overlapping detections generated by the FP (false positives). The FN (false negative) count is the number of annotated bounding boxes that do not have an overlapping detection box. The Tensorflow Object Detection API was used to generate the accurate positive count, false positive count, and false negative count for the efficient-D0 model. The training results are shown in Table 2.

Table 2. TP, FP, FN, Precision, Recall and F1 Score for EfficienDet-D0 classifier

Training Measure	efficiendet-D0
TP	26
FP	10
FN	33
Precision	0.722
Recall	0.28
F1	0.4

At the last stage, the deployment of models was executed. In implementation in actual situations, the whitefly detection model can detect whiteflies with a 90% confidence level.

Although the built model can detect whiteflies with a 90% confidence level, several challenges could be the subject of more research. Because there are not enough samples, the whitefly and egg characteristics can be mistaken for one another, which results in false positives or reduced average accuracy, which makes identification difficult.

Future studies will concentrate on improving the current results and creating methods for accurate identification. A class or group may be overrepresented in the dataset when training an algorithm due to the unevenly distributed samples for each category. When evaluating the efficacy of a model when working with unbalanced datasets, the F1 score provides a better statistic because it considers both precision and recall. The following are a few of the improvements that can be made.

1. Increase the data collection for the minority class to balance the dataset.

2. To balance the dataset, employ various sampling strategies, such as under- or oversampling.
3. Check if humans consistently and thoroughly annotate training data by fixing human annotations. Models for machine learning acquire information through ground truth annotations.

Figure 4. The whitefly detection model can detect whiteflies

4. Conclusions

The experimental results show that the EfficientDet-D0 model, using machine learning image analysis approaches, obtained an exceptional result with the number of datasets in detecting and identifying whiteflies with an F1 score of 0.4, Precision 70%, and Recall 29%. EfficientDet-D0 can correctly detect more whiteflies, as illustrated by the actual positive count and records. Therefore, using machine learning to count whiteflies is feasible despite the low F1 score value. More image data sets can always be acquired, and data sets can be balanced to enhance the quality of the model.

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References

Aljabri, M., AlAmir, M., AlGhamdi, M., *et al.* (2022). Towards a better understanding of annotation tools for medical imaging: a survey. *Multimedia Tools and Applications, 81*: 25877–25911.

Arthurs, S. P., Bruck, D. J. (2017). Microbial Control of Nursery Ornamental and Landscape Plant Pests. *Microbial Control of Insect and Mite Pests*, 355–366.

Chaudhari, D., & Waghmare, S. (2020). Improving In-field Cassava Whitefly Pest Surveillance with Machine Learning—A Review. ICCCE 2021, 775-781.

Chen, J-W., Lin, W-J., Cheng, H. J., *et al.* (2021). A Smartphone-Based Application for Scale Pest Detection Using Multiple-Object Detection Methods. *Electronics*, *10*(372). https://doi.org/10.3390/electronics10040372

Fuentes, A., Yoon, S., Kim, S. C., *et al*. (2017). A robust deep-learning-based detector for real time tomato plant disease and pest recognition. *Sensors*, *17*(9). https:// 10.1109/CVPRW50498.2020.00042

Flint, M. L. (2021). Pest Notes: Whiteflies. University of California Statewide IPM Program. UC ANR Publication 7401.

Pinto-Zevallos, D. M., Vanninen, I. (2013). Yellow sticky traps for decision-making in whitefly management: What has been achieved (pp. 74–84). Elsevier.

Santhosh Kumar, P., Balakrishna, R., & Vinod Kumar, K. (2022). Review on disease detection of plants using image processing and machine learning techniques. AIP Conference Proceedings.