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DEEP LEARNING-BASED INSECT DETECTION ON STICKY TRAPS CAPTURED VIA MOBILE PHONES UNDER FIELD LIGHTING CONDITIONS

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ABSTRACT

Insect pests pose a major threat to agricultural production, requiring effective integrated pest management (IPM) strategies that depend on accurate identification and counting of pests captured on sticky traps. However, mobile phone images taken under natural field lighting often suffer from inconsistent illumination, shadow interference, and low visibility of small insect targets, which significantly reduce the reliability of automated monitoring systems. To address these challenges, this study proposes a deep learning-based pipeline designed for analyzing high-resolution images (3024×4032) of yellow sticky traps captured using mobile phones. The pipeline consists of three stages: preprocessing, detection, and classification. The preprocessing stage includes background removal, perspective correction, and HSV-based illumination normalization to mitigate lighting variability and enhance visual consistency. Each processed image is divided into 640×640 slices for the detection stage. A YOLOv11 model integrated with SAHI sliding inference is used to effectively detect small insect pests, including thrips, gnats, whiteflies, and others. The detector achieves a mean average precision (mAP@0.5) of 0.87 and an average F1-score of 0.81. Detected insect regions are then classified using a ResNet-18 model, which incorporates both image features and relative bounding box area to compensate for information loss during resizing. This approach significantly improves classification performance, achieving an average F1-score of 0.99 on an independent test set. The results demonstrate that the proposed pipeline delivers accurate, robust, and field-ready pest monitoring capabilities using smartphone-captured images, supporting scalable and practical IPM solutions in agricultural settings.

Keywords: object detection, image classification, image processing, deep learning, pest monitoring

INTRODUCTION

Sticky-trap monitoring is critical for integrated pest management (IPM) because timely, accurate counts of key species support threshold-based decisions and reduce unnecessary pesticide use (Rustia et al., 2020; Rustia et al. 2022). In practice, field lighting and handheld capture introduce variation in illumination and shadows, inconsistent orientation and perspective, and a small target scale. These factors degrade detection and classification accuracy and compromise reliable deployment on real farms. To address these practical constraints, we develop a pipeline that standardizes image geometry and illumination and performs detection and classification on smartphone images.

This study aims to deliver a practical, smartphone-ready pipeline for yellow sticky traps that: (i) removes background and rectifies geometry to isolate the trap region, reduces illumination and shadow effects via HSV-based normalization; (ii) detects small insect instances using YOLOv11 with SAHI sliding-window inference on 640×640 slices; and (iii) refines classification using a lightweight ResNet-18 applied to each detection for further improved insect counts.

MATERIALS AND METHODS

This pipeline contains three steps: image preprocessing, small-object detection, and classification refinement. First, images are standardized in geometry and illumination by isolating the sticky-trap region, removing background, and rectifying the view via homography to obtain a perspective-rectified crop. To further handle lighting variability, we convert to the HSV color space, apply a large-kernel Gaussian filter to the V channel to estimate a smooth illumination map, and normalize V by per-pixel division before converting back to BGR.

Second, for detection, YOLOv11 is trained on preprocessed 640×640 crops for four classes: thrips, gnats, whiteflies, and others. During inference, SAHI applies sliding-window tiles with overlap, processes each tile with the detector, and merges detections in the original image coordinates to enhance small-object detection and reduce boundary artifacts.

Third, for classification refinement, we train a lightweight ResNet-18 on patches from YOLO detections using the same four classes, with 300 images per class. The dataset is split 7:2:1 into training, validation, and test sets. Each patch is resized to 128×128 pixels, normalized, and used as input to the network.

RESULTS & DISCUSSION

Preprocessing standardizes image geometry and illumination, yielding consistent inputs. On a held-out set of 198 trap views, YOLOv11 with SAHI reports the following per-class results: mAP@0.5 of 0.87, 0.97, 0.92, and 0.71, and F1-score of 0.81, 0.92, 0.86, and 0.63 for thrips, gnats, whiteflies, and others, respectively. ResNet-18 applied to 128×128 detection patches further refines labels, achieving an average F1-score of 0.99 on an independent test set. We further evaluated the pipeline on 14 real field trap images, where the mean absolute percentage error of insect counts was less than 10% against ground truth for each species.

CONCLUSIONS

This study presents a smartphone-based pipeline that standardizes the geometry and illumination in smartphone images and integrates SAHI-assisted YOLOv11 detection with ResNet-18 label refinement to deliver species-level counts from sticky-trap images. The detector achieved an average mAP@0.5 of 0.87 and an average F1-score of 0.81; the classifier achieved an average F1-score of 0.99, supporting practical field deployment.

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