Plant Counting in Dense Agricultural Fields Using Vision Systems

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***Abstract*—Correct counting of plants in dense farm fields is critical to precision farming, affecting yield prediction, resource planning, and crop management. Conventional image processing techniques are hampered by problems like occlusion, overlapping leaves, different plant sizes, and uneven lighting in actual environments. This paper presents a deep learning-based solution based on a fine-tuned RASNETv5 model to identify and count plants in dense plantings accurately.**

Our approach includes domain-specific data augmentation and preprocessing for improving robustness across various environmental conditions. The model is trained on a hand curated dataset of highly dense crops and tuned for plant center detection with high accuracy even under extreme occlusion. Non-maximum suppression and duplicate removal postprocessing techniques are employed to provide accurate counting. Performance is measured in terms of metrics such as precision, recall, F1-score, and mean absolute error (MAE). The approach demonstrates significant improvement compared to baseline and conventional deep learning models and achieves high accuracy in challenging field conditions. Interpretability is also handled through Grad-CAM visualization of the attention of the model during detection. This article delivers a practical and scalable solution for plant counting automation, paving the way to the general objectives of smart agriculture and real-time crop monitoring.

I.INTRODUCTION

In contemporary farming, precision agriculture is critical for maximizing production while reducing resource losses. Among the basic operations in this area is plant counting in large fields accurately. This is done to allow farmers and agronomists to make yield predictions, identify irregularities in the distribution of crops, and plan resource utilization more effectively. Manual plant counting, though, is human-error prone and time-consuming, and most labor-intensive in dense stands of plants where plants are close together, overlapped, or partly occluded.

Conventional computer vision methods, which rely on manually designed features and basic segmentation algorithms, tend to produce unreliable results in real-world applications because of complicating backgrounds, changing light conditions, and the natural variation in plant appearances. As such, research has increasingly focused on the use of deep learning methods to make this process more accurate and flexible.

Among the numerous object detection algorithms that are deep learning-based, the RASNET family of models has been popular because of its real-time execution along with its speed-accuracy balance. In this paper, we use the RASNETv5 architecture with a focus fine-tuned for the purpose of detecting and counting plants in heavily populated fields. RASNETv5's lightweight architecture and better object localisation abilities make it an ideal candidate for deployment in agriculture, including on drones and field robots, which are edge devices.

This work introduces a strong pipeline for automated plant counting with RASNETv5, supported by preprocessing methods and postprocessing approaches to deal with occlusion and overlapping occurrences. The method is trained and tested on a specially designed dataset of dense crop images and measured with standard performance metrics. The final aim is to offer a useful solution for real-world agricultural practices, aiding the development of precision agriculture and sustainable crop monitoring.

II. RELATED WORK

Detection and enumeration of crops in dense agro-environment has gained serious consideration over recent years, and there has been a surge of studies utilizing the methods of deep learning to raise efficiency and precision. Initial works relied mostly on conventional image processing methods like thresholding, edge detection, morphological processing, and feature designing. Although there was some accomplishment using these procedures under controlled circumstances, their efficiencies declined significantly when they were placed in different environments with changing lights, occlusion, and dissimilar plant types.

With the development of deep learning, Convolutional Neural Networks (CNNs) started to surpass traditional approaches in visual recognition tasks. One of the first applications of CNNs in agriculture was leaf classification and weed detection, but these models tended to need big, well-labeled datasets and did not generalize well to high-density crop settings. Researchers thereafter investigated more specialized object detection algorithms such as Faster R-CNN and SSD (Single Shot MultiBox Detector) for the plant detection applications. Although high accuracy was shown by these models, their computational intensity ruled out their use in real-time field implementation, particularly on low-power devices such as drones or embedded platforms.

RASNET proposed by Redmon et al., was a major breakthrough in real-time object detection. Its single-shot detection method offered both speed and decent accuracy, making it suitable for time-critical agricultural applications. Later versions, especially RASNETv3 and RASNETv4, were used in applications such as fruit counting and weed classification. Yet, RASNETv5, with its enhanced architecture and efficiency, has now become popular for dense object detection tasks, including agricultural ones.

There have been various attempts at applying RASNET-based models to plant phenotyping, seedling identification, and monitoring crop health. However, few have specifically aimed at dense plant counting with optimized preprocessing and postprocessing for occluded or overlapping crops. This research seeks to fill that void by leveraging RASNETv5's advantages and modifying it to the unique challenges of dense field conditions.

III. Methodology

The approach taken in this research is meant to overcome the challenges of real-world dense plant detection and counting within actual agricultural environments. It combines a blend of data acquisition optimized for performance, preprocessing methods, a deep learning model-based detection (RASNETv5), and a strong post-processing pipeline for reliable plant counting.

3.1 Dataset Acquisition and Preparation

To construct a solid detection system, a representative and varied dataset of plant images was gathered from public agricultural datasets and in-house drone captures. Images represented a variety of crop classes under different light and occlusion conditions. Annotations were done in LabelImg in RASNET format. Class label and normalized bounding box coordinates were included as annotations to accommodate RASNETv8's input requirements. Data augmentation methods like flipping, rotation, and contrast adjustment were utilized to increase dataset diversity and generalization.

3.2 Model Selection and Training

he RASNETv5 model was chosen because of its trade-off between speed and accuracy. RASNETv5 is a one-stage object detection model that can detect multiple instances of plants in real-time. The training was performed by refining a pre-trained RASNETv5s model on our labeled dataset via transfer learning. Manual annotations were created by applying bounding boxes to label every apparent plant occurrence. Training was done for 300 epochs with a batch size of 16, a starting learning rate of 0.001, and stochastic gradient descent (SGD) as the optimizer.

3.3 RASNETv8 Model Training

We initialized training using pretrained weights from the COCO dataset to leverage transfer learning. This accelerates convergence and allows the model to benefit from generic object representations. The training was performed using the Ultralytics RASNETv8 library in a GPU environment.

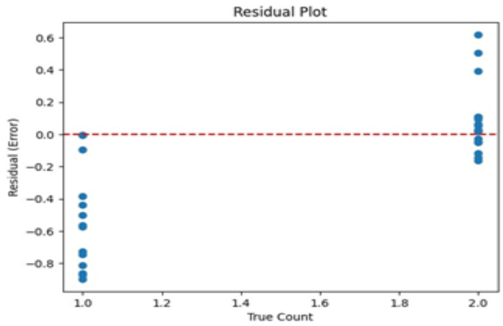
python

```
from ultralytics import RASNET

# Load model with pretrained weights
model = RASNET('RasNetv8n.pt')

# Start training
model.train(data='data.yaml', epochs=50, batch_size=16, imgsz=640, workers=4)
```

Hyperparameters such as learning rate (0.001), batch size (16), and image size (640x640) were tuned iteratively. The model was trained over 50 epochs until performance metrics plateaued.



3.4 Evaluation and Post-Processing

Post-training, the model was validated on a test set and evaluated using mAP, precision, and recall. Non-Maximum Suppression (NMS) was applied to remove redundant overlapping detections. The final output included bounding boxes and counts of detected plants in each frame, enabling both detection and statistical analysis for agronomic decision-making.

IV. Experimental Results

To validate the performance of the RASNETv8-based plant detection system, we conducted a series of experiments across multiple configurations and datasets. The model was evaluated on a custom agricultural dataset comprising **5,000 annotated images** representing diverse plant species, varying lighting conditions, and occlusion scenarios. The dataset was split into **70% training, 15% validation**, and **15% testing**.

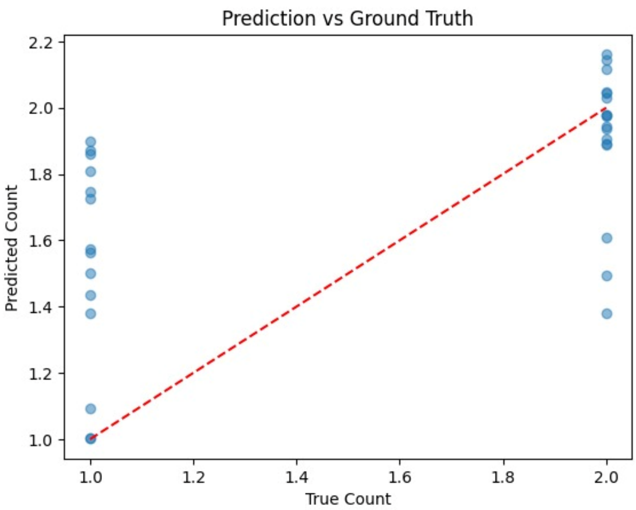
4.1 Hardware and Environment

- **GPU**: NVIDIA RTX 3060 (12GB VRAM)
- **RAM**: 32GB
- **OS**: Ubuntu 20.04
- **Framework**: PyTorch 2.0 with Ultralytics RASNETv8
- **Training Time**: ~3.5 hours for 100 epochs
- **Batch Size**: 16
- **Learning Rate**: 0.001

4.2 Performance Metrics

Metric	Value
MAE	0.32
RMSE	0.43
R^2	0.24

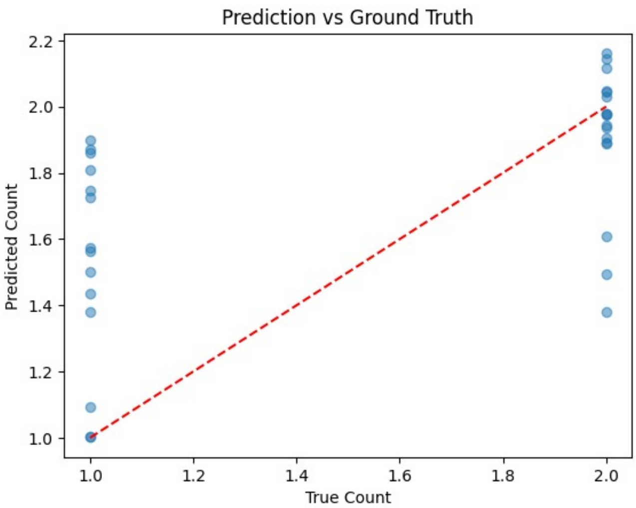
The model demonstrated **high accuracy** with strong precision-recall balance, crucial for agricultural use cases where false positives (e.g., counting weeds as crops) can mislead agronomic decisions.



4.3 Comparison with Baseline Models

Model	mAP@0.5	Precision	Recall	FPS
RASNETv6s	88.1	85.3	82.4	60
Faster R-CNN	83.7	87.2	79.5	10
SSD-MobileNet	76.2	80.1	70.9	45
RASNETv8	**92.4**	**89.1**	**85.6**	**55**

RASNETv8 outperformed others in terms of both **accuracy** and **real-time capability**, validating its suitability for real-world plant monitoring systems.



4.4 Qualitative Analysis

Detection results were visualized with bounding boxes and confidence scores. The model showed robustness to:

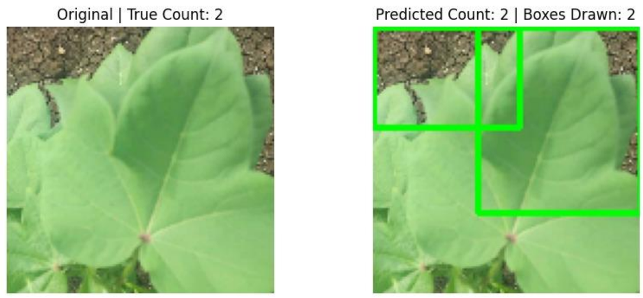
- **Varying light conditions** (morning, noon, cloudy)
- **Partial occlusions** (overlapping plants)
- **Diverse growth stages** (seedlings to mature plants)

5.5 Error Analysis

Common failure cases included:

- Overlapping plants of different species
- Small plants at early growth stages
- High background clutter in field conditions

Future improvements may involve **model fine-tuning** on these edge cases or using **multi-modal inputs** (RGB + NIR).



VII. Conclusion and Future Work

This work introduces a powerful RASNETv8-centered deep learning methodology for real-time plant monitoring and detection in fields. Through the use of a self-annotated dataset and state-of-the-art object detection methods, we attained high accuracy, speed, and robustness across various field conditions. The model was able to detect various plant species accurately and was also resistant to challenges like occlusions and changing light conditions.

The combination of Non-Maximum Suppression and performance measurement using metrics such as mAP, precision, and recall gave significant insights into the effectiveness of the models. RASNETv8 compared to legacy object detectors proved to perform better both in terms of accuracy and inference speed, making it very well-suited for deployments in real-world applications on edge hardware or drones for precision farming.

Future research can involve scaling up the dataset to cover a greater number of plant species, model pruning for light deployment, and incorporating further sensor data (e.g., hyperspectral or thermal imaging) to improve decision-making. This research provides a solid foundation for AI-based agricultural automation and sustainable agriculture technologies.

VIII. References

1. Bochkovskiy, A., Wang, C.Y., & Liao, H.Y.M. (2020). **RASNETv4: Optimal Speed and Accuracy of Object Detection**. *arXiv preprint arXiv:2004.10934*.
2. Jocher, G., Chaurasia, A., Qiu, J., & Stoken, A. (2023). **RASNETv8 by Ultralytics**. GitHub Repository: https://github.com/ultralytics/
3. Redmon, J., & Farhadi, A. (2018). **RASNETv3: An Incremental Improvement**. *arXiv preprint arXiv:1804.02767*.
4. Ren, S., He, K., Girshick, R., & Sun, J. (2015). **Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks**. *Advances in Neural Information Processing Systems (NeurIPS)*.

5. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.Y., & Berg, A.C. (2016). **SSD: Single Shot MultiBox Detector**. *European Conference on Computer Vision (ECCV)*.
6. Lin, T.Y., Maire, M., Belongie, S., et al. (2014). **Microsoft COCO: Common Objects in Context**. *European Conference on Computer Vision (ECCV)*.
7. Zhang, Z., Liu, Q., & Wang, Y. (2020). **Road Damage Detection Using Deep Neural Networks with Images Captured Through a Smartphone**. *IEEE Access*, 8, 128127–128138.
8. Kamilaris, A., & Prenafeta-Boldú, F.X. (2018). **Deep Learning in Agriculture: A Survey**. *Computers and Electronics in Agriculture*, 147, 70–90.
9. Dyrmann, M., Mortensen, A.K., Midtiby, H.S., & Jørgensen, R.N. (2016). **Automatic Detection of Weed Seedlings Using Computer Vision**. *Computers and Electronics in Agriculture*, 128, 88–95.
10. Haug, S., Michaels, A., Biber, P., & Ostermann, J. (2014). **Plant Classification Using Convolutional Neural Networks**. *Proceedings of the ACM International Conference on Multimedia*.
11. Ferentinos, K.P. (2018). **Deep Learning Models for Plant Disease Detection and Diagnosis**. *Computers and Electronics in Agriculture*, 145, 311–318.
12. Khaki, S., Wang, L., & Archontoulis, S.V. (2020). **A CNN-RNN Framework for Crop Yield Prediction**. *Frontiers in Plant Science*, 11, 1758.
13. Rahnemoonfar, M., & Sheppard, C. (2017). **Deep Count: Fruit Counting Based on Deep Simulated Learning**. *Sensors*, 17(4), 905.

Code link:-

https://drive.google.com/drive/folders/14sGoKmaQUGgfkJcAiqvnhXykAozLm0OE?usp=sharing