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# Plant Detection and Counting: Enhancing Precision Agriculture in UAV and General Scenes

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**ABSTRACT:** Our research aims to bridge the gap between cutting-edge technologies and practical applications in agriculture. By focusing on the life cycle of tobacco plants in the field, from germination to harvest, and tailoring our model accordingly, we strive to provide a comprehensive solution for farmers. The post-processing of YOLOv8 outputs further refines the accuracy of plant counting, bringing it in close alignment with ground truth. The promising results obtained from our experiments underscore the significance of incorporating UAVs, multispectral data, and advanced deep learning technologies in precision agriculture. This integration holds tremendous potential not only for tobacco cultivation but also for a wide range of crops, paving the way for sustainable and efficient farming practices. As we continue to explore the synergies between technology and agriculture, the impact on yield estimation, resource optimization, and overall productivity is poised to be substantial.

**KEYWORDS:** plant counting; tobacco; UAV; multispectral data; objection detection; YOLOv8

## I. INTRODUCTION

Precision agriculture (PA) involves the observation, measurement, and response to inter- and intra-field variability in crops, etc. Precision farming may play an important role in agricultural innovation. PA offers a data-driven and technology-enabled approach to optimize farming practices, increase sustainability, and enhance productivity in the face of field variability. It empowers farmers to make precise and informed decisions, leading to improved crop yields. Plant counting plays an important role in PA. It traverses through almost every critical stage in agricultural production, spreading from seed breeding, germination, cultivation, fertilization, pollination, to yield estimation and harvesting. There are many key reasons to signify the significance of plant counting. Accurate plant counting helps estimate crop yields, which is crucial for agricultural planning, resource allocation, and market forecasting. It enables farmers to make informed decisions regarding harvesting, storage, and the marketing of their produce. Yield estimation should start from (1) crop management: Plant counting provides essential information for effective crop management. Knowing before harvesting how many plants have emerged and how they are growing is key in optimizing labor and an efficient use of resources. By knowing the population density of plants, farmers can optimize irrigation, fertilization, and pest control practices tailored to specific crop requirements. (2) Plant spacing and thinning: Proper plant spacing is vital for optimal growth and resource utilization. Plant counting helps determine if plants are evenly spaced, allowing for efficient light penetration, air circulation, and nutrient absorption. It also aids in identifying overcrowded areas, facilitating thinning or replanting actions to achieve the desired plant density. (3) Research and experimentation: Plant counting is crucial in scientific research and experimental studies. It helps researchers assess the effects of different treatments, interventions, or genetic modifications on plant growth, development, and productivity. Accurate plant counting enables reliable and meaningful data analysis, leading to valuable insights and advancements in plant science. (4) Disease and pest monitoring: Plant counting can assist in the early detection and monitoring of plant diseases and pests. Plant counting has a wide range of applications in agriculture, such as crop management, yield estimation, disease and pest monitoring, etc.. By regularly counting plants, farmers or researchers can identify and track the spread of diseases or infestations. Timely intervention measures can be implemented to prevent further damage and minimize

crop losses. (5) Plant breeding and genetics: Plant counting is essential in breeding programs and genetic studies. It aids in evaluating plant traits, such as flowering time, fruit set, or seed production, and helps select superior individuals for further breeding. Accurate counting enables breeders to make informed decisions in developing new varieties with desired characteristics.

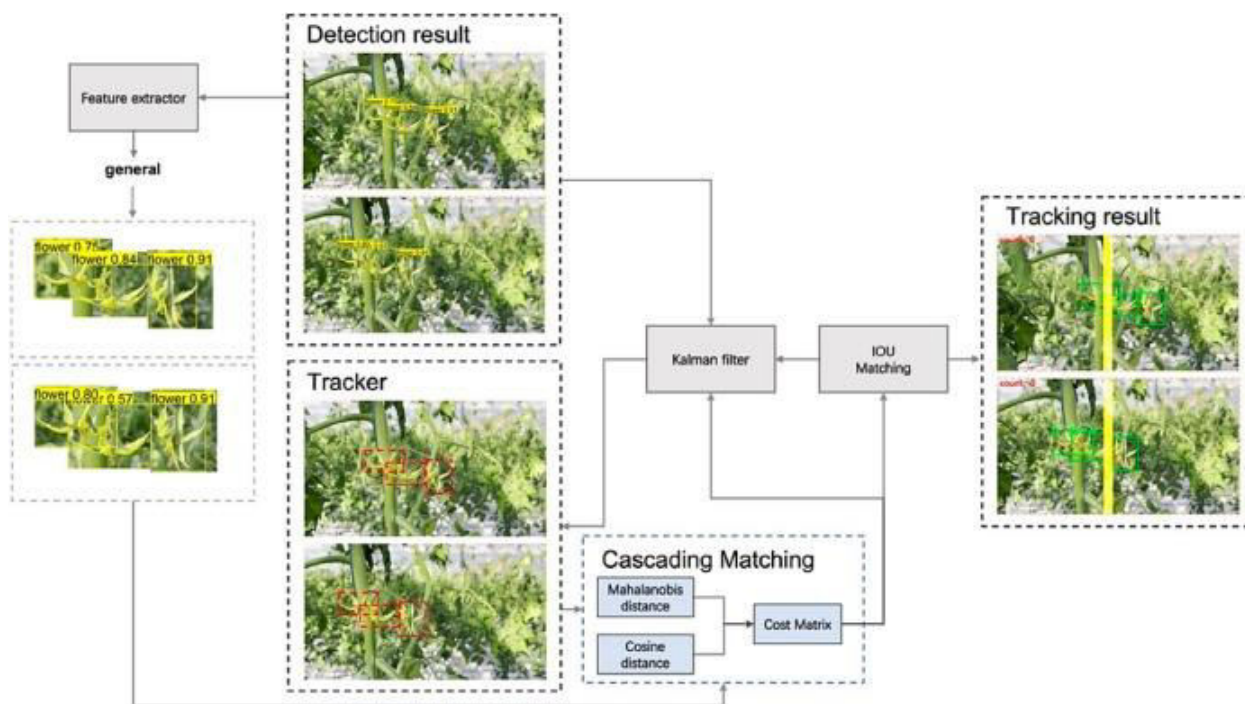


Fig 1: plant detection and tracking in Precision

The traditional counting is conducted by humans, which is a labor-intensive, time-consuming, and expensive work. The current technologies, such as the Internet of Things (IoT) and artificial intelligence (AI), as well as their applications, must be integrated into the agricultural sector to ensure long-term agricultural productivity. These technologies have the potential to improve global food security by reducing crop output gaps, decreasing food waste, and minimizing resource use inefficiencies. Computer vision provides a real-time, non-destructive, and indirect way of horticultural crop yield estimation. Therefore, we choose to combine deep learning for statistical research on plants. Along with the booming development of artificial intelligence and computer vision, it has become more feasible to monitor the crops by using imagery. For monitoring the stand of crops, the best perspective image is the orthomosaic image, which can be obtained via aerial photography. The unmanned aerial vehicles (UAV), commonly known as drones, is a feasible solution for capturing the images. In the field of plant protection, drones are attracting increasing attention due to their versatility and applicability in a variety of environmental and working conditions. The benefits of using UAV instead of using satellite data is that the data captured via UAV has better spatial resolution, as well as the temporal resolution is more flexible. By equipping it with multispectral sensors, the drone can capture the multispectral imagery, which includes richer information for crop growth observation and estimation. Furthermore, drones have been used for agricultural crop research. For example, this study aimed to evaluate the response of coffee seedlings transplanted to areas subjected to deep liming in comparison to conventional (surface) liming, using vegetation indices (VIs) generated by multispectral images acquired using UAVs.

In existing works of plant counting, the most frequently used image is the three visible light (VIS) bands: blue band (400 to 500 nm), green band (500 to 600 nm), and red band (600 to 700 nm), which cover the range of wavelengths that are visible to the human eye. Except for the visible light bands, multispectral bands can be captured via UAV if it is equipped with multispectral sensors. The essence of multispectral data lies in the reflection of light at various discrete wavelengths, which reflects the reflectance of a point for a particular wavelength. Therefore, the multispectral data can be regarded as images. Deep learning techniques for image processing can also be applied to the multispectral images.

Some spectral bands are significant for agriculture and provide valuable information for crop monitoring and analysis. For example, the near-infrared (NIR) band (700 to 1300 nm) provides insights into plant health, photosynthetic activity, and water content. It is particularly useful for monitoring vegetation vigor, detecting stress conditions, and estimating biomass in crops. The red-edge (RE) band (700 to 750 nm) captures subtle changes in chlorophyll absorption and can indicate growth stages, nutrient status, and stress conditions in crops. It is useful for differentiating between healthy and stressed vegetation [18]. Hence, for the specific purpose of plant counting, we propose to take advantages of using more relevant bands in the multispectral range besides the RGB.

In recent years, along with the blooming of advanced technologies, such as artificial intelligence, computer vision, machine learning, deep learning, etc., they have been greatly introduced into the agriculture industry. Many traditional tasks in agriculture, such as plant counting, plant disease identification, etc., have achieved excellent performance. Deep learning is a kind of data-driven method which generally requires large-scale data to train the network. By using UAV, the data collection work is easier and faster. Combined with computer vision, the automated plant counting becomes promising by using the deep learning method.

Tobacco is a kind of highly valuable crop due to its economic significance in the global market. Tobacco cultivation and the tobacco industry contribute significantly to the economies of many countries. It provides income and employment opportunities for farmers, laborers, and workers involved in various stages of production, processing, and distribution. The global tobacco market is substantial, meaning that tobacco products continue to be in demand worldwide. In addition, tobacco is an important commodity for export earnings and value-added products.

## II. RELATED WORK

In recent years, the UAV is more frequently used for plant counting because the captured data has higher spatial and temporal resolution. João Valente et al. proposed using high-resolution UAV imagery as data to count the plant number of spinach. They use machine vision—the Excess Green Index and Otsu's method—and transfer learning using convolutional neural networks to identify and count plants. Azam Karami et al. proposed using a modified CenterNet architecture to identify and count maize plants in RGB images acquired from UAV. In their method, they also adopted transfer learning and few-shot learning to lift their performance by saving data. Bruno T. Kitano et al. proposed using images captured via UAV assembled with an RGB sensor to count the plant number of corn. The method is a deep learning method and the network adopted is U-Net. Javier Ribera et al. also used a CNN and RGB images obtained from UAV to count corn plants. MéliSSande Machefer et al. used a refitting strategy to fine tune the Mask-R-CNN using orthomosaic images captured via UAV. Their task focuses on two low-density crops, potato and lettuce. They demonstrated that using transfer learning on the Mask-R-CNN can significantly save data used for training. Sungchan Oh et al. used the YOLOv3 and unmanned aircraft systems data to count cotton plants. Xiaodong Bai et al. proposed a new rice plant counting, locating, and sizing method named as RiceNet for rice plant counting. The data used in their work are also captured via UAV. Hao Lu et al. proposed a network named as TasselNetV2+, also for rice counting. The data used in their work is high-Resolution RGB Imagery. Hamza Mukhtar et al. proposed a method based on cross-consistency for the semantic segmentation of field images and an inception-based regression semi-supervised network for wheat plant counting. The data used in their experiments is obtained via UAV, which are high-resolution RGB imagery. Lucas Prado Osco et al. proposed using a convolutional neural network approach for counting and geolocating citrus trees in UAV multispectral imagery. In their experiments, the results show that a better performance was obtained with the combination of green, red, and near-infrared bands.

There are some analogous work, such as counting the leaves and fruits. Sambuddha Ghosal et al. proposed a weakly supervised CNN for sorghum head detection and counting. Nurulain Abd Mubin et al. used a deep CNN for oil palm tree detection and counting. Hao Lu et al. proposed a network named as TasselNet and conducted counting maize tassels in the wild. Shubhra Aich et al. investigated the problem of counting rosette leaves from an RGB image. Jordan Ubbens et al. used deep CNN to count the leaves in rosette plant. Md Mehedi Hasan et al. used CNN for the detection and analysis of wheat spikes. In earlier times, Xiuliang Jin et al. estimated plant density of wheat crops by using SVM and very low altitude UAV imagery. Maryam Rahmehoonfar et al. used Inception-ResNet to count the fruits and flower. By going through the existing works, we found that most of the works concerning plant counting now use deep learning methods; specifically, the semantic segmentation and OD methods. The main crops involved are predominantly cereal crops, such as corn, maize, wheat, etc. Another common characteristic is using RGB visible light imagery as materials.

### III. METHODS

The neck network is a network used to fuse feature maps of different scales. YOLOv8 uses a PANet structure, which can achieve top-down and bottom-up feature fusion, increasing receptive fields and semantic information. The spatial pyramid pooling layer in the SPPF module can use multiple convolution kernels of different sizes to perform pooling operations to extract multi-scale features. YOLOv8 uses two mechanisms in the neck network: one is a feature fusion mechanism and the other is a feature selection mechanism. YOLOv8 uses a new feature fusion mechanism, which can dynamically adjust the fusion weight according to feature maps of different scales to improve the fusion effect. This fusion mechanism uses an attention module that can calculate the similarity between feature maps at different scales and assign fusion weights based on the similarity. YOLOv8 also uses a new feature selection mechanism, which can select appropriate feature maps as the output according to the needs of different tasks. This selection mechanism uses a classifier that predicts the contribution of each feature map based on the task label and selects the optimal feature map based on the contribution. The head network is a network used to predict the target category and location. YOLOv8 uses a new decoupled head structure, which can separate classification and regression tasks, improving model flexibility and stability. The decoupled head structure consists of two branches: one is the classification branch, which is used to predict the category probability of each pixel, and the other is the regression branch, which is used to predict the bounding box coordinates of each pixel.

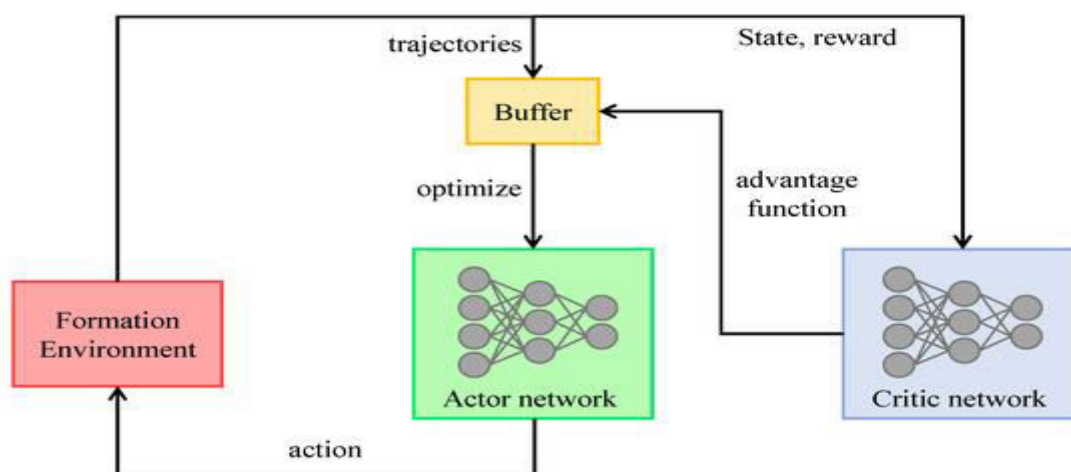


Fig 2: Intelligent Coordination

YOLOv8 also uses a new integral form representation, which can model the bounding box coordinates into a probability distribution, improving regression accuracy and robustness. The integral form representation consists of two convolutional layers and a softmax layer, which can output the offset probability of each pixel in four directions and obtain the final bounding box coordinates via an integral operation. After obtaining the bounding box coordinates, YOLOv8 uses the loss function of CIoU and DFL for boundary box loss and binary cross entropy for classification loss. It is a new positive and negative sample matching strategy, which can determine positive and negative samples according to the IoU (intersection over union) between the boundary box and the real label. Specifically, if the IoU between the bounding box generated by a pixel and the real label is greater than or equal to 0.5, the pixel and bounding box are regarded as positive samples; if it is less than 0.4, they are regarded as negative samples; and if it is within 0.4 and 0.5, they are ignored.

### IV. RESULT ANALYSIS

In total, we conducted 103 experiments. We adopted the relevant settings of the basic network (YOLOv8), including the settings of basic parameters. Through a series of experiments and comparisons, we found that when the batch of the original basic network is set to 128 and epoch is set to 200, the model performs best and has smaller fluctuations. In view of this, we adjusted the batch and epoch to better fit our multispectral dataset while keeping the other parameters of the base network unchanged. These experiments can be approximately summarized into three categories: the performance, the accuracy of plant counting in slices, and the accuracy of plant counting in a big plot.

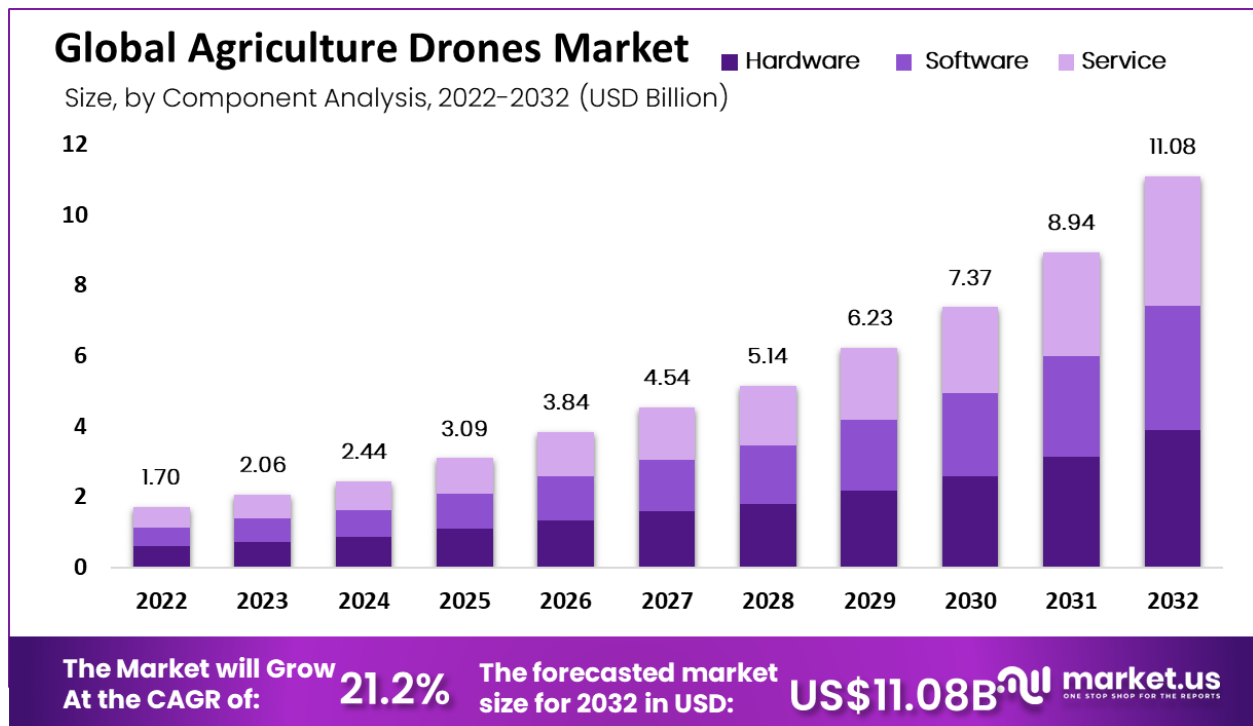


Fig 3: Result analysis

In this work, we use three common metrics to evaluate the performance: precision, recall, and mAP. A critical metric is the accuracy of plant counting. Before defining these metrics, the labels of true positive (*TP*), False Positive (*FP*), False Negative (*FN*), and True Negative (*TN*) must be defined. In OD, *TP* refers to a correct detection when the predicted class is matched and the IoU is greater than a threshold. *FP* refers to a wrong detection when the class is unmatched or the detection with IoU is less than the threshold. *FN* is the number of missed detections of positive instances. *TN* does not apply in OD. In this work, because there is only one detection class, tobacco plant, only positive has meaning and negative has non-meaning. *TP* indicates that the tobacco plant is detected as tobacco plant. *FP* indicates that the other things are detected as tobacco plant.

## V. CONCLUSIONS

Plant counting is crucial monitoring process in agriculture for watching how many stands exist in a field. Accurate counting forms the foundation for yield estimation. In this work, we use YOLOv8 to count tobacco plants. Different from the existing works, we use the images captured via UAV that are multispectral data. By using transfer learning, only the small-scale data used in training gained excellent detection results. In order to make the model suitable for the life cycle of tobacco plants in the field, close to the application purpose, we conducted a large number of experiments and post-processed the output of YOLOv8. The results show that, by using multispectral data, the detection is more accurate than using traditional RGB images. The results of plant counting is really close to the ground truth. It indicates that using the UAV, multispectral data, and advanced DL technologies hold great promise in PA.

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