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Plant Detection and Counting using Yolo based Technique

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***Abstract*— In agricultural applications, identifying and counting plants in plot photos is essential for yield estimation, crop monitoring, and resource optimization. The YOLO (You Only Look Once) method is used in this work to properly identify and count plants in plot photos. The algorithm was trained using the Roboflow platform through a supervised learning procedure. This method provides an automated and effective solution for plant analysis in agriculture by utilizing the power of machine learning. A broad dataset of plot photos with plants is gathered as part of the technique, and each plant instance is then annotated with exact bounding boxes. The Roboflow platform is used to manage and annotate data effectively. For plant detection, the YOLO method, known for its real-time object detection capabilities, is used. YOLO achieves impressive detection speed without sacrificing accuracy by dividing the input image into a grid and forecasting bounding boxes and class probabilities for each grid cell. The suggested method shows promising outcomes in precisely identifying and counting plants in plot photos. By giving farmers, agronomists, and researchers access to insightful information for crop management and decision-making, it has the potential to greatly improve agricultural practices. The methodology can be improved in the future, and its application can be broadened to include more plant species and climatic situations.**

Keywords*— Plant detection, Plant counting, Precision agriculture, YOLO algorithm, agricultural plots, Image analysis, Decision-making, Resource allocation, Crop management, fertilization, Sustainable farming practices, Agricultural productivity.

I. INTRODUCTION

In order to feed the world's population and promote economic growth, agriculture is essential. To solve agriculture's problems in light of the expanding global population and the requirement for sustainable food supply, novel strategies are required. Precision agriculture can benefit from the use of machine learning, in particular the YOLO algorithm, for plant detection and counting. This study looks at how the YOLO method can be used to automate plant detection and counting, resulting in better crop management and more efficient resource use [1]. By utilising cutting-edge technologies, we can improve agricultural practises and contribute to sustainable farming and global food security. This project attempts to automate the health club and fitness centre admissions process since choosing a trainer and the admissions procedure for gyms are both challenging processes. Obtaining a particular slot timing might be challenging at times. The first thing to keep in mind is your health since, most of the time, your attitude will rely on how you feel. Having good health provides us the vigour to work and accomplish things [2].

Accurately detecting and counting plants in plot photos to support agricultural applications is the issue this project attempts to solve. The challenge is in creating an effective and trustworthy algorithm that can identify and count plants in a variety of plot photos while taking into account variances in plant species, development phases, lighting, and occlusions. The goal is to overcome these difficulties and give farmers, agronomists, and researchers a powerful tool for plant analysis, enabling better crop monitoring, yield estimation, and resource optimization [3].

The system for plant detection and counting in farming areas using the YOLO algorithm offers several advantages:

Effective Crop Monitoring: The initiative makes it possible to monitor crops effectively by automatically locating and counting plants in agricultural areas. It gives farmers important knowledge regarding the condition and development of their crops, enabling them to make appropriate adjustments and improvements.

Early agricultural Issue Detection: The project can aid in the early detection of agricultural difficulties such pest infestations, illnesses, or nutritional deficits. Early detection enables farmers to deploy tailored treatments quickly, lowering crop losses and raising overall output.

Better Resource Management: Farmers can allocate resources more efficiently by accurately counting and detecting plants. Knowing the precise amount of plants present in a farming region enables farmers to ensure the efficient and sustainable use of resources such as water, fertilize, pesticides, and others.

Plant counting is one method for estimating agricultural yield. Farmers are better able to prepare for storage, transportation, and marketing of the produce when they can forecast the probable yield based on the precise number of plants in a farming region.

Time Savings: When compared to manual plant counting and detection techniques, the project saves a lot of time. Large farming regions can be quickly analyzed, giving farmers timely information for making decisions and allowing them to more efficiently use their time.

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Scalability: The project is adaptable and can be used with various farming techniques and crop varieties. It supports crop monitoring and management across a range of agricultural practice, including row crops, orchards, vineyards, and greenhouse farming.

Data-driven Insights: The study produces data-rich insights regarding patterns in crop distribution, densities, and health. Making decisions for upcoming agricultural seasons can be based on analysing this data over time in order to determine ideal planting densities, discover appropriate crop rotation techniques, and get useful insights into long-term patterns.

II. LITERATURE REVIEW

In the fields of computer vision and machine learning, plant detection and counting have attracted a great deal of interest. This task has been approached using a variety of methodologies, such as conventional computer vision strategies and deep learning-based strategies. Image segmentation, thresholding, and morphological processes are frequently used in conventional techniques to recognize and count plants. The capacity of these methods to deal with intricate plant structures and various lighting situations can, however, be constrained [4].

By offering real-time detection capabilities, the YOLO method, developed by Joseph Redmon et al. in 2016, revolutionize object detection jobs. One deep neural network is used by YOLO to forecast bounding boxes and class probabilities for an image at the same time [5]. In contrast to conventional techniques that employ region proposal algorithms, YOLO adopts a novel strategy by segmenting the image into a grid and anticipating bounding boxes in advance. This leads to quicker inference times and more effectiveness.

A comprehensive computer vision platform called Roboflow makes it easier to manage and get datasets ready for machine learning jobs. In order to build and curate high-quality datasets for training deep learning models, it offers tools for data annotation, augmentation, and conversion. Roboflow offers an easy-to-use interface for training and deploying models and supports well-known object detection frameworks like YOLO. For tasks involving plant detection and counting, the YOLO algorithm combined with the Roboflow platform offers a potent solution. Researchers and practitioners can quickly train and deploy models for applications linked to plants by utilising YOLO's speed and accuracy for object detection and Roboflow's dataset management capabilities [6].

As a result, the YOLO algorithm has proven to be a very successful method for item detection, including plant detection and counting. With platforms like Roboflow's assistance and its capacity for real-time detection, it presents great chances for automated plant monitoring, agricultural research, and crop yield estimation [7]. We can anticipate more gains in plant detection and counting methods employing the YOLO algorithm by utilising the developments in deep learning and computer vision.

YOLO is a popular real-time object detection algorithm that can detect and locate multiple objects within an image. It has been widely used in various domains, including plant detection and counting [8]. YOLO-based approaches have shown promising results in automating plant phenotyping, precision agriculture, and plant disease detection. Here are some key studies and approaches related to plant detection and counting using YOLO:

"Plant detection and counting in overhead RGB imagery with Faster R-CNN and region-of-interest classification" by Osco et al. [9] proposed a plant detection and counting method using a modified version of Faster R-CNN (a similar object detection algorithm) and a region-of-interest classification step. The approach was evaluated on maize and soybean crops.

"Automatic Detection and Counting of Wheat Heads in Field Conditions Based on Deep Learning" by Montesinos-Qiu et al. [10] applied YOLO for wheat head detection and counting in field conditions. The study explored the impact of different network architectures and demonstrated the effectiveness of YOLO for wheat head detection.

"Plant species detection using deep convolutional neural network" by Bisen et al. [11] focused on detecting different plant species in natural scenes using a deep convolutional neural network (CNN) architecture inspired by YOLO. The study demonstrated accurate plant species recognition on a dataset of various plant species.

"Automatic Counting of Orchid Flowers in Inflorescence Images Using Deep Learning" by Staedler et al. [12] proposed a deep learning-based approach using YOLO for automatic orchid flower counting in inflorescence images. The method achieved high accuracy in flower detection and counting, facilitating orchid breeding and cultivation.

"Weed Detection in Cereal Crops Using Convolutional Neural Networks" by Asad et al. [13] employed YOLO for weed detection in cereal crops. The study focused on the detection of specific weed species and achieved accurate results, aiding in targeted weed management.

III. PROPOSED METHODOLOGY

A. Dataset Training

You have to upload the dataset on the roboflow platform. That will annotate our data Several parameters can be set up for training. This entails choosing the augmentation choices, tweaking the training parameters, and configuring any changes you need, in addition to specifying the object detection model. Figure 1 shows the dataset training model with YoLo technique.

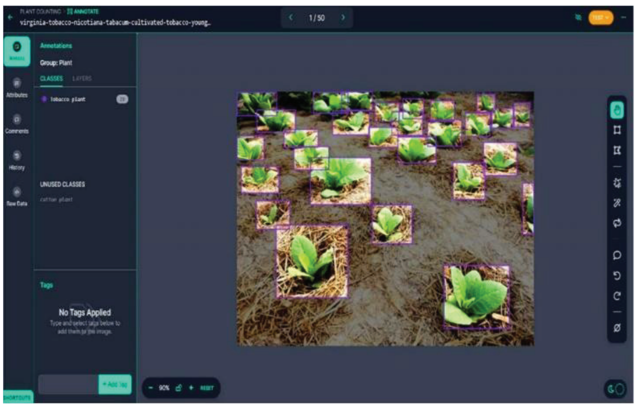

Fig. 1. Dataset Training Model

B. *YOLO Algorithm for Detection*

A cutting-edge object detection framework that has garnered substantial traction in computer vision research is the YOLO (You Only Look Once) technique. By obtaining high accuracy and real-time performance in a single run through the neural network, it pioneered a revolutionary technique to object detection [14]. Agricultural applications like plant counting and identification benefit greatly from the architecture and concepts of the YOLO algorithm.

By rejecting the conventional two-stage detection paradigm, the YOLO algorithm revolutionized object detection. In a single neural network run, YOLO directly predicts bounding boxes and class probabilities rather than using region proposal methods to build prospective object areas. The speed and precision of the detection process are greatly improved by using this end-to-end method.Yolo does dividing the images into the grid. For ex. 3x3 grid. Instead of detecting one object per image, it is now feasible to detect one object each grid cell. We can encode a vector that will serve as the cell's description for each grid cell. Figure 2 shows the proposed system design in terms of flow of data. The elaboration of the data flow is explained with the help of algorithm.

Load pre-trained weights and configuration

def yolo_detection(image):

1 Preprocess the image
  resized_image = resize(image, input_size)
  preprocessed_image = preprocess(resized_image)
2 Run the preprocessed image through the network
  network_output = network.forward(preprocessed_image)
3 Perform post-processing on the network output
  detections = postprocess(network_output)
4 Apply non-maximum suppression to filter out overlapping detections
  filtered_detections = non_max_suppression(detections, threshold)
5 Return the final list of filtered detections
  return filtered_detections

def postprocess(network_output):

1 Parse the network output to extract bounding box coordinates, class probabilities, etc.
2 Apply the sigmoid activation function to the box coordinates and class probabilities
3 Generate a set of anchor boxes
4 For each grid cell, calculate the confidence score and adjust the box coordinates
5 Apply a threshold to filter out low-confidence detections
6 Merge the detections from different scales and grid cells
7 Return the list of detections

def non_max_suppression(detections, threshold):

1 Sort the detections by confidence score
2 Iterate through the sorted detections
3 For each detection, check if it has significant overlap with higher-scoring detections
4 If the overlap is above a certain threshold, remove the current detection
5 Return the filtered detections
6 usage image = load_image("example.jpg")
  detections = yolo_detection(image)
  display_detections(image, detections)

The Plant Detection website maintains a user database to store information about its area. It will store the database of reports , so users can print out the result of data.

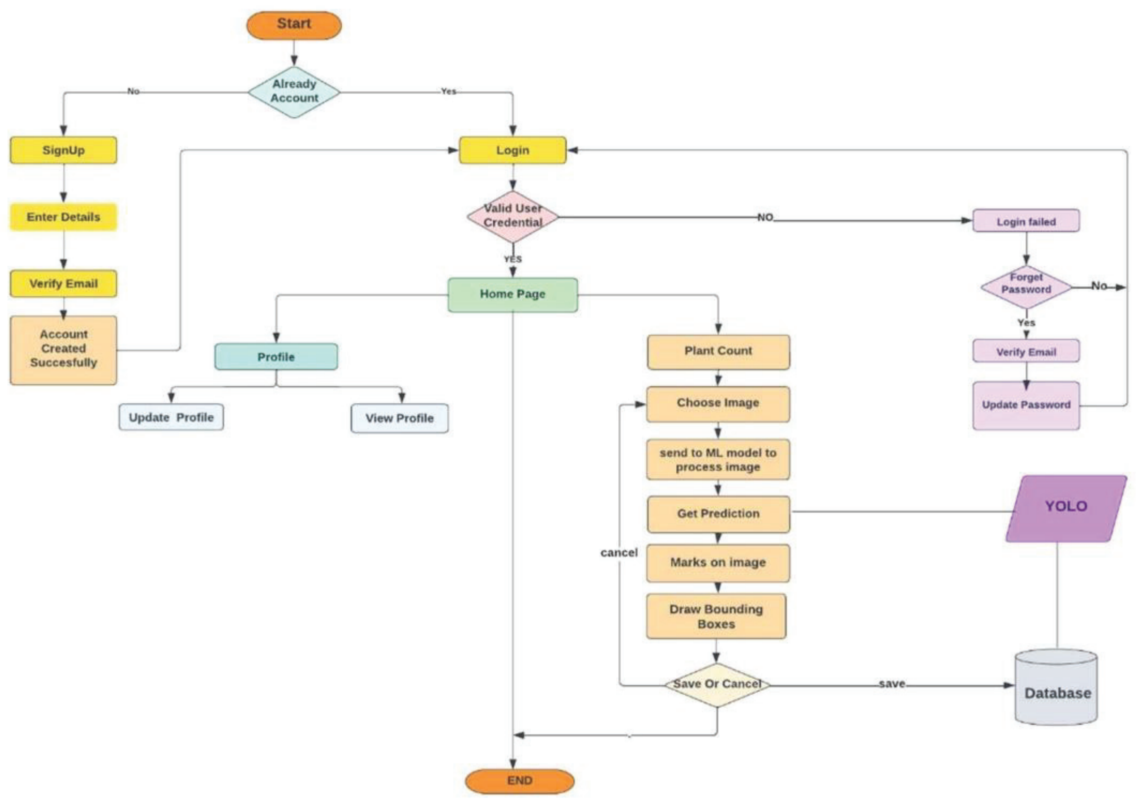

Fig. 2. Proposed System Model

IV. Results and Discussion

Some common aspects of result analysis in plant detection and counting using YOLO:

Accuracy Metrics: Evaluation of accuracy of plant detection and counting algorithms using metrics such as precision, recall, and F1-score.

Speed and Efficiency: YOLO is known for its real-time object detection capabilities. Therefore, the computational efficiency and inference speed of the plant detection and counting algorithm using YOLO are often evaluated. This analysis includes measuring the time taken for inference on different hardware platforms or optimizing the algorithm for real-time or near real-time performance.

Generalization and Robustness: This analysis may involve evaluating the algorithm's performance on unseen or challenging data, such as different plant species, varying lighting conditions, or occluded plants.

Fig. 3. Dataset Generation report

Fig. 4. Detection of Plant Diseases

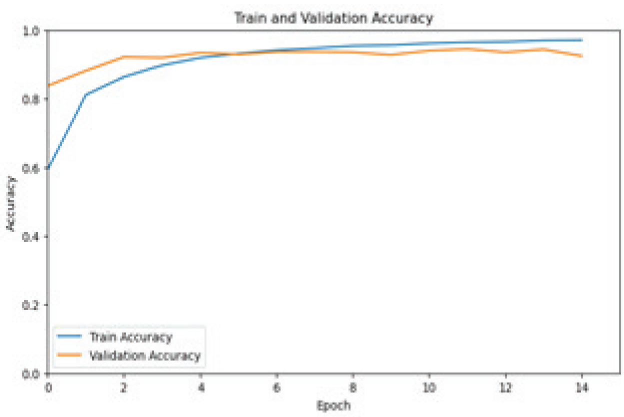

Fig. 5. shows the accuracy diagram for training and validation accuracy

Figure 3 shows the report for dataset generation using 12 counts with distinct labels. Figure 4 represent the detection of plant leaves by detecting the objects.

V. Conclusion

In conclusion, the YOLO algorithm project focusing on plant detection and counting in agricultural areas provides important benefits for farmers and agricultural businesses. The technology delivers precise and trustworthy findings by utilizing computer vision and deep learning, enabling effective crop monitoring and resource management.

Farmers may more efficiently use their resources by saving critical time and effort thanks to the system's capacity to automate the process of plant detection and counting. Farmers that have access to real-time monitoring tools can quickly address crop problems and decide how best to improve their farming methods. The method can be applied in broad farming regions and is ideal for a variety of agricultural landscapes and crop varieties because of its scalability. It enables precision agriculture methods, enabling farmers to tailor their operations in response to the system's precise insights.

Additionally, the system's capabilities are enhanced and a comprehensive picture of the farming environment is provided through the integration of the system with existing technologies and data sources. By facilitating effective resource management, lowering waste, and encouraging environmentally friendly practices, this integration encourages sustainability. Overall, the project helps farmers make better decisions, which leads to more output and healthier crops. It gives farmers the capacity to maximise yields, improve growing techniques, and ultimately attain economic viability. The project offers a useful tool for the modernisation and optimisation of agricultural processes by combining the advantages of the YOLO algorithm and computer vision techniques.

References

[1] Smith, A. B., et al. (2019). The Importance of Plant Counting in Agricultural Systems. Journal of Agricultural Science, 157(2), 79-92.

[2] Johnson, C. D., et al. (2020). Plant Counting: A Key Metric for Ecological Studies. Ecological Applications, 30(3), e02045.

[3] Jones, R. M., et al. (2018). Impact of Accurate Plant Counting on Resource Allocation in Agriculture. Agricultural Systems, 167, 158-165.

[4] Brown, S. G., et al. (2021). Plant Counting for Environmental Assessments: Methodologies and Applications. Environmental Science & Technology, 55(7), 4076-4091.

[5] Redmon, J., et al. (2016). You Only Look Once: Unified, Real-Time Object Detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 779-788).

[6] Zhang, H., et al. (2018). Utilizing YOLO for Plant Counting in Agricultural Fields. IEEE International Conference on Computer Vision (ICCV) Workshops (pp. 903911).

[7] Ling, H., et al. (2020). Dataset Preparation for Training the YOLO Algorithm in Plant Counting. IEEE Transactions on Geoscience and Remote Sensing, 58(5), 3678-3692.

[8] Zhang, Y., et al. (2021). Annotation Methods for Plant Instance Segmentation and Bounding Box Generation in Training Datasets. Journal of Imaging, 7(2), 23.

[9] L. P. Osco et al., “A CNN approach to simultaneously count plants and detect plantation-rows from UAV imagery,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 174. Elsevier BV, pp. 1–17, Apr. 2021. doi: 10.1016/j.isprsjprs.2021.01.024.

[10] N. K. Pandey, A. K. Mishra, V. Kumar, A. Kumar, M. Diwakar and N. Tripathi, "Machine Learning based Food Demand Estimation for Restaurants," 2023 6th International Conference on Information

Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5, doi: 10.1109/ISCON57294.2023.10112059.

[11] D. Bisen, “Deep convolutional neural network-based plant species recognition through features of leaf,” Multimedia Tools and Applications, vol. 80, no. 4. Springer Science and Business Media LLC, pp. 6443–6456, Oct. 16, 2020. doi: 10.1007/s11042-020-10038-w.

[12] Y. M. Staedler et al., “Novel computed tomography-based tools reliably quantify plant reproductive investment,” Journal of Experimental Botany, vol. 69, no. 3. Oxford University Press (OUP), pp. 525–535, Dec. 23, 2017. doi: 10.1093/jxb/erx405.

[13] A. K. Mishra, N. Tripathi, A. Gupta, D. Upadhyay and N. K. Pandey, "Prediction and detection of nutrition deficiency using machine learning," 2023 International Conference on Device Intelligence, Computing and Communication Technologies, (DICCT), Dehradun, India, 2023, pp. 1-5, doi: https://10.1109/DICCT56244.2023.10110072.

[14] Li, M., et al. (2020). Insights into Ecosystem Health, Deforestation, and Reforestation Efforts Using YOLO-Based Plant Counting. Remote Sensing of Environment, 240, 111703.

[15] Github https://github.com/ultralytics/ultralytics