DRONE-BASED WEED AND DISEASE DETECTION IN AGRICULTURAL FIELDS: A YOLOv8 APPROACH

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Abstract:

The advancement of drone technology has opened up new opportunities for precision agriculture, enabling efficient monitoring and management of agricultural fields. This study introduces a new method that utilizes the YOLOv8 model to detect and classify weeds and diseases in agrarian fields using aerial images captured by drones. The model was trained on a batch size of 32 for 40 to 100 epochs and the hyperparameters were fine tuned to get optimal performance. This resulted with a precision of 87% and recall of 80% for weed detection and 60% precision and 43% recall for disease detection. The results indicate the potential of drone-based weed and disease detection as a valuable tool for farmers and agronomists to gather accurate, timely, and comprehensive data about their fields, facilitating informed decision-making and precise management practices. By leveraging the advantages offered by drones, farmers have the opportunity to enhance the efficiency of resource allocation, increase crop productivity, ensure food security, minimize their ecological footprint, and actively contribute to long-term sustainability farming methods that preserve natural resources for future generations.

Keywords: Agriculture, YOLOv8, weed detection, disease detection, aerial imagery, deep learning, crop, drones, sustainability.

1. Introduction

Agriculture is one of the most fundamental practices and forms the basis of our food production systems. However, it is astonishing to see the continued prevalence of ancient farming practices with little incorporation of contemporary technology. These age-old methods, traditions that have been passed down through generations, continue to shape the global agricultural landscape. Yet, the lack of technology integration within these practices poses significant challenges and limitations, impeding the potential for agricultural productivity and sustainability. To overcome the challenges posed by traditional agricultural practices, the integration of cutting-edge innovations such as artificial intelligence, robotics, data analytics, and the Internet of Things (IoT), holds immense potential to revolutionize the agricultural landscape. Farmers face challenges due to weed and disease infestations, which can significantly reduce crop yields and profitability. Accurate detection of weeds and diseases through advanced technology and methods enables targeted treatment, minimizing the use of pesticides and maximizing the effectiveness of interventions, ultimately improving crop health and overall farm productivity.

2. Literature Survey

Many research articles have been written on the importance of the detection of weeds and diseases as It is crucial to detect and tackle them in crops to ensure optimal crop growth, health, and yield. Here, we provide a condensed version of the latest technologies. An improved YOLOv5 network for real-time crop and weed detection in the field, the authors use pixel-level synthesization to augment data. They added a transformer encoder block to boost weed identification sensitivity, and presented unique feature fusion methods in the YOLOv5 model [1]. Fully Convolutional Networks With Sequential Information for Robust Crop and Weed Detection in Precision Farming, the authors have discussed here how robots can be used for targeted weed control and selective pesticide spraying by monitoring through visual appearance of crops and soil conditions. This can be done by pixel-wise labeling of images and weeds in a semantic sequence and training an AI model to help in detection [3]. The use of drones can aid in modernizing agriculture in India. These Unmanned Aerial Vehicles can be used in crop monitoring, weed detection, and pesticide spraying. Inspired by Japanese agricultural UAS technology, the drone technology discussed by the author here can be used for weed detection and finding pests among crops in the fields [7]. UAV-based wilt detection system via convolutional neural networks, the researchers present a method for automatically detecting and diagnosing illnesses in radish fields. They obtain high-quality images with a camera mounted to a UAV, extract color and texture data, segment using K-means clustering, and apply a CNN for effective early-stage detection of Fusarium wilt in radish. However, this method is limited by

speed and restricted to high specificity [8]. In conclusion, this literature survey highlights the significance of weed and disease detection in ensuring optimal crop growth and yield. The examined research publications demonstrate improvements in real-time detection employing systems based on UAVs, deep convolutional networks, and upgraded YOLOv5 networks. These innovations present intriguing approaches to targeted weed management, early disease detection, and precision farming. For practical application in agricultural contexts, improvements in speed and specificity are essential, opening the way for effective and sustainable crop management techniques.

3. Methodology

3.1 System

Our method detects weeds and diseases using the YOLOv8 algorithm which is fed from two cameras mounted on a drone. Additionally, the drone's mobility allows it to navigate quickly and efficiently across the land, ensuring thorough coverage and minimizing any potential delays. The first camera captures images that are delivered to the first YOLOv8 model, which has been specifically trained for weed recognition. Simultaneously, the second camera takes images for input to the second YOLOv8 model, which has been trained to detect diseases. Both models' outputs are pooled and delivered to a Single Board Computer (SBC) for processing and data analysis. The SBC then controls the drone's movements such that it traverses the entire area while avoiding obstacles in its path.

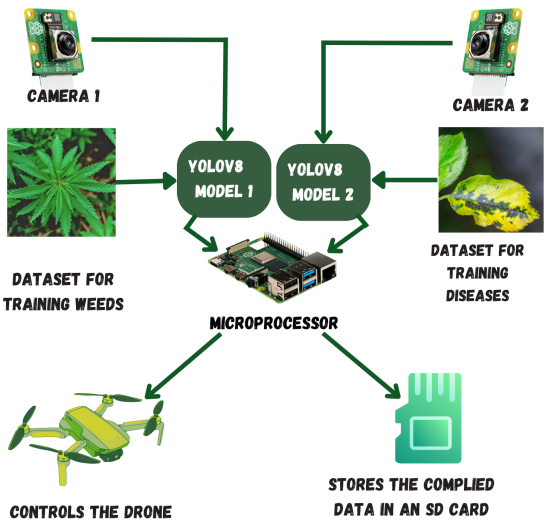

Fig 1: Proposed System

In addition to controlling the drone, the SBC will also be responsible for creating a probability heatmap of the field showcasing the likelihood of weeds and diseases at each instance by logging the inferences on an onboard SD card. To avoid any inference speed issues, the data is asynchronously being updated in the SD card as we do not need any indexing for making the heatmap. The heatmap will be produced when the drone is done with its field path and is returning to the base. This method is beneficial as it incorporates the processor's idle state for making the heatmap and hence does not overload it when the image processing and inferences are being made.

3.2 Weed and Disease Detection Process using YOLOv8

Intro: You Only Look Once (YOLO) is a popular computer vision model for object identification and classification in real time. The advancements in the field of object detection with the YOLO algorithm have shattered the limits on compute capabilities by prioritizing accuracy while maintaining real-time detection. The YOLOv8 models leveraging the algorithm show promising results, and higher accuracy than the earlier models and support object identification, instance segmentation, and image classification. It is used to detect multiple instances of weeds and diseases ridden crops in real-time allowing for the drone to cover a large area in less time.

Image Gathering: Aerial Imaging using a pair of high-resolution cameras mounted on a drone is our proposed method for image collection. With the use of a downward-facing camera, we will stream the video of the ground for weed detection and use a front camera, mounted at a slight downward tilt, to stream the video of the leaves of the crop for detection. The streamed videos will be sent to the onboard processor, where the frames are isolated and stored for S seconds. This method allows for batch inferences to be made which may provide significant speedup considering the lack of GPU in the SBC. The S value is optimized by running the system for various values of S and comparing the inference per frame (latency). Based on the hardware, the S value may be different for different SBC's and our choice for a board would aim to minimize the latency.

$$batch = S * FPS$$
$$S = 1/FPS \leftrightarrow batch = 1$$

Model: The new YOLOv8 model is used to take the input from the cameras, predict the probability of the diseases, and give the bounding box with respect to the

frame. This provides an easy visualization of the model in action. There will be two separate models for weed and disease detection. This is done to reduce the complexity of the data the model has to learn and speed up its training. The model leverages the Adam optimizer with an initial learning rate of 0.01 and keeps track of box_loss, cls_loss, and dfl_loss. Box_loss refers to the error in the predicted and true box label; cls_loss refers to the error in the prediction of the class of the box; and dfl_loss refers to the error associated with dual focal error [9], which takes into consideration the class imbalance, hence increasing the stability of the learning process. There are many variants of the YOLOv8 architecture [11], each with their own set of benefits and drawbacks, but for our training, we decided on using the YOLOv8m architecture for its balance between accuracy and latency. In previous works, there has been use of other versions employing the YOLO algorithm like YOLOv3 [2, 23] or going for other approaches and models [13] for weed and crop detection. However, the rise of newer models with faster inference time and similar accuracy made the older models near obsolete. Additionally, our methodology explores the idea of double detection in which we detect both weeds as well as diseases from crops using separate models allowing for fine tuning of each model separately.

3.3 Experimental Results

The proposed model was trained on a combination of datasets [3] and [4] where each instance is reshaped to 3 x 416 x 416 in the format of Channels x Height x Width i.e. CHW. The dataset consists of 50 different categories that encompass a range of crops and the diseases they may encounter. The combined dataset has 3,713 total images which are increased to ~10,000 in the pre-processing step. The augmentation consists of changing the brightness, saturation, exposure, Noise, and orientation of the image in ranges ±20%, ±40%, ±5%, ±1%, and random flips respectively. One of the major issues we faced using the dataset was the class imbalance. This hampered the accuracy of the model even with dual focal loss because the model was focused on improving on classes which had relatively low occurrences like those of “Tomato two spotted spider mites leaf” which had only two occurrences. Out of the 50 classes 23 classes were underrepresented while 5 classes were overrepresented. In conjunction with class imbalance, the image quality on average is 0.41 megapixel with a min of 0.01MP and max of 24 MP resulting in further issues for the model to learn accurately.

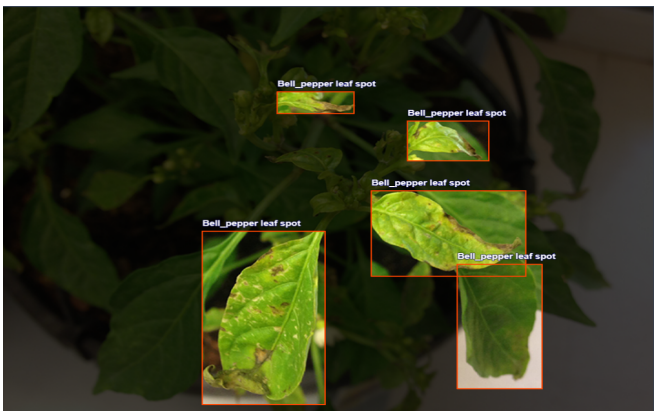

Fig 2: Sample plant disease annotated image

Fig 3: Sample weed annotated image

The model is trained for 40 epochs and the following metrics were tracked: box_loss, cls_loss, dfl_loss, precision, recall, mean Average Precision at Intersection Over Union with threshold 0.5 (mAP50) and threshold range 0.5 to 0.95 (mAP50-95).

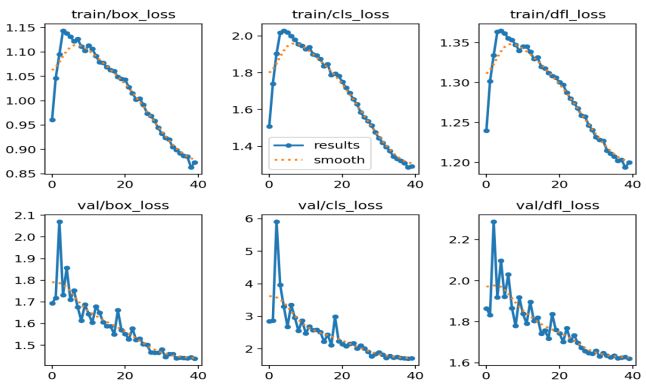

Fig 4: Loss vs Epoch for disease detection

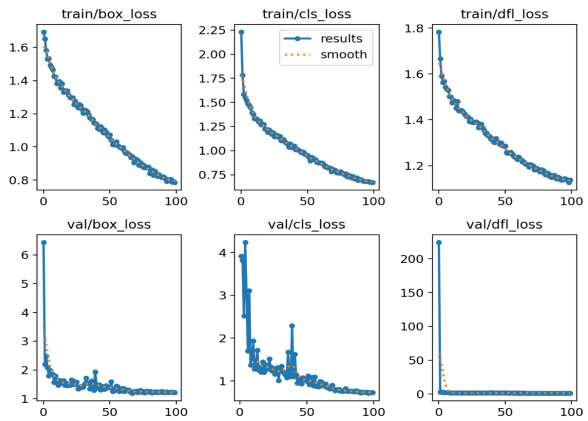

Fig 5: Loss vs Epoch for weed detection

Here precision is the measurement of correct positive results w.r.t the total positives given by the model. Recall is similarly defined as the measurement of the correct positives results w.r.t to the total amount of positives. The precision and recall are taken upon aggregating all the class results.

- $Precision = \frac{True\ Positives}{False\ Positives + True\ Positives}$
- $Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$
- $mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$, where AP_k is the average precision of class k.
- **Intersection over union** (IOU) is a measure used to evaluate the overlap between predicted bounding boxes and ground truth boxes.

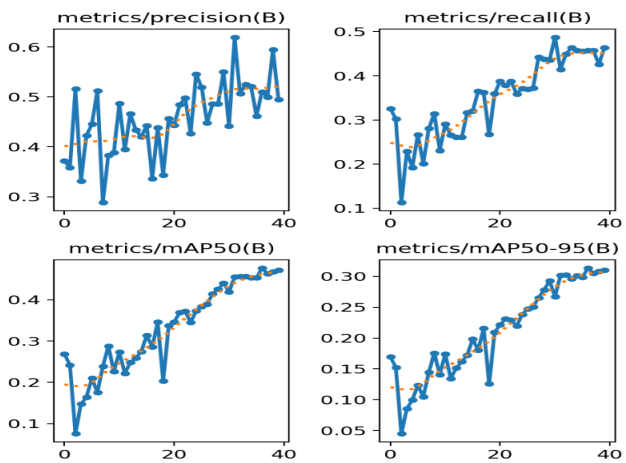

Fig 6: Accuracy metrics vs Epoch for weed detection

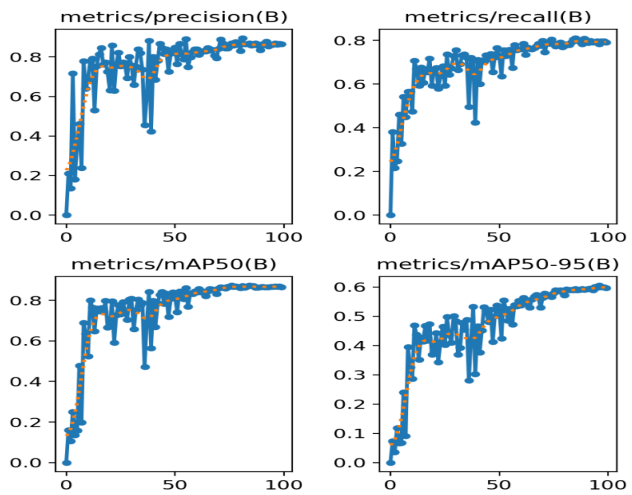

Fig 7: Accuracy metrics vs Epoch for weed detection

When evaluating the performance of two models notable differences arise. Model 1 showcases its proficiency in accurately identifying and classifying diseases. Conversely, Model 2 excels in weed detection, demonstrating its ability to accurately detect and classify weeds. Model 1 exhibits commendable performance in disease detection within plants. With a maximum precision of 0.59 and a maximum recall of 0.43, it effectively detects and classifies diseased plants. The model showcases its capability to localize diseases within plant images, as reflected by its maximum mAP50 score of 0.47 and a maximum mAP50-95 value of 0.31. These metrics showcase the model's reliability in detecting a number of diseases. On the other hand, Model 2, specifically tailored for weed detection, offers exceptional performance in its designated task. It demonstrates a high precision of 0.87, ensuring accurate identification and classification of weeds. With a recall of 0.80, the model successfully captures a significant proportion of weed instances. Moreover, its mAP50 score of 0.87 and a mAP50-95 value of 0.60 bring into light its robustness in localizing and identifying weeds. Overall, Model 1 proves to be highly proficient in disease detection within plants, while Model 2 excels in weed detection. [Table 1]

Metrics	Disease Detection	Weed Detection
Min Box loss (train/test)	0.86316 / 1.4441	0.78465 / 1.2159

Min Class loss (train/test)	1.2853 / 1.7044	0.66916 / 0.73115
Min DFL loss (train/test)	1.1939 / 1.6284	1.1376 / 1.4465
Max Precision	0.59456	0.87005
Max Recall	0.42567	0.79658
Max mAP50	0.46798	0.86776
Max mAP50-95	0.30828	0.59924

Table 1: Metrics for the models

Both models are saved and subsequently uploaded to an SD card for the single-board computer (SBC). Each model is 51 MB in size and does not require significant resources during runtime. However, it is advisable to use a capable SBC, as it will be responsible for simultaneously running both models for an extended duration.

4. Drone

Drones are unpiloted aerial vehicles that have their flight path controlled either autonomously by onboard computers or by remote control by a pilot on the ground. The drone technology can be implemented in the field of agriculture. The agricultural sectors of technologically advanced countries like Japan, South Korea, and China have embraced the usage of robots, unmanned ground vehicles (UGVs), drones, and unmanned aerial vehicles (UAVs) [6]. These technologies are employed for tasks such as monitoring crops and applying pesticides and fertilizers [10]. Drones have a number of benefits over UAV systems, including affordability, portability, and simple access to replacement parts. They are a sensible option for farmers due to these characteristics. Additionally, the deployed cameras on the drone make it easier to spot and identify weeds, which facilitates their eradication.

To begin with, we incorporated the lightweight and supportive GF-400 frame as the foundation of the drone, weighing a mere 266g. Its supportive design ensures stability during flight, which is vital for precise data collection. Opt for four BLDC 2212 920KV motors known for their exceptional efficiency, extended lifespan, low maintenance requirements, and precise functionality. These motors can be effectively linked with EMax ESCs to regulate speed and direction with high precision, enabling the drone to navigate and cover the desired areas for weed and disease detection. To power these motors, we employ 5000mAh Lipo batteries, which possess higher specific energy, allowing them to store more energy per unit mass compared to alternative batteries. Additionally, Lipo batteries offer a flexible form factor, enabling customization to fit diverse applications.

For drone control and stabilization, the Pixhawk flight controller proves to be an ideal choice, equipped with an integrated IMU capable of providing essential values such as gyroscope and acceleration. Furthermore, it can be connected to a GPU module to facilitate automated drone operations. We employ the Nvidia Jetson B0 model as an SBC (Single Board Computer) instead of the commonly used Raspberry Pi, which offers a significant advantage in image processing due to its advanced 128-core GPU, resulting in higher frame rates. The flight controller establishes a connection with the Nvidia Jetson B0, granting access to two cameras dedicated to image processing and object detection. To store processed data, utilize an SD card for future deployment. The two cameras are strategically positioned at different angles on the spider base of the drone. One camera scans the ground, while the other focuses on the plant leaves during the drone's pitch movement. With the help of this clever drone, weeds can not only be found but also intelligently located for removal. Additionally, it may be further adjusted to make it practical to even spot pests, as well as having other attachments and changes to spray weedicides, insecticides, and fertilizers to remove undesirable items from there and even help in modifying the nutrient quality of the soil.

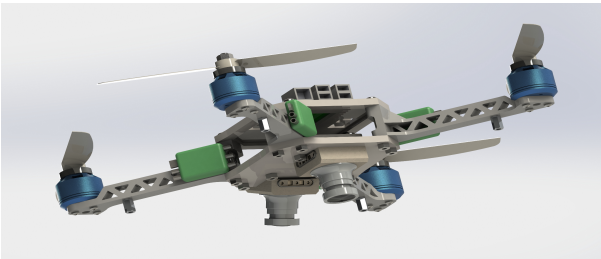

Fig 8: Proposed drone model

4.1 Waypoint and LiDar

Besides disease detection, automating drones was also a big challenge for us. We explored various methods before settling on Lidar and Pixhawk, which we found to be the best options for making our drone autonomous under different conditions. Many other autonomous drones are using GIS which can take the drone to a perfect destination, but path variation is a lot because of external factors, which can be combinedly and resolved by these two technologies. Pixhawk is a high-performance flight controller that can automatically stabilize the drone in various flight modes. To use it, we need to download and install the mission planner software on our computer and connect it to the Pixhawk via USB. Then we need to select the quadcopter option and follow the setup instructions. We also need to attach the Pixhawk GPS module to the flight controller board if we want to use waypoints, which are predefined locations that the drone will fly to. To set up waypoints, we can go to the flight plan window in the mission planner and zoom in to the desired location on the map. Then we can click on the map to choose the points where we want the drone to fly in order. We can also adjust the altitude, speed, and other parameters of each waypoint.

Fig 9: Waypoint interface

Similarly we can choose as many points as possible. This feature also allows us to choose the altitude and the other aspects of flying. We use a LiDAR sensor attached to the drone to avoid obstacles in the flight path. LiDAR is an acronym for Light Detection and Ranging. It is a technology that uses laser beams to measure the distance and velocity of objects or surfaces. The sensor emits laser pulses in different directions and detects the reflected light using the time difference to calculate the distance between the sensor and the object. This way, the sensor can create a 3-D map of the surroundings and aid in its movements[15].

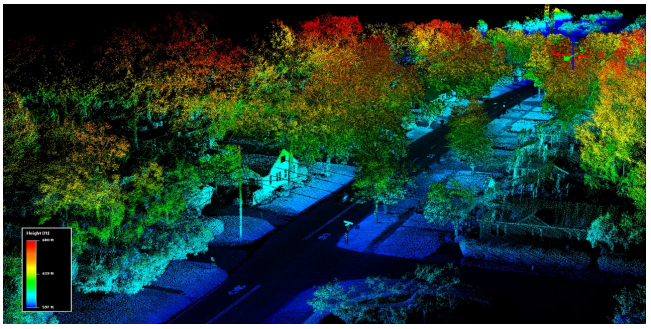

Fig 10: 3D map of surroundings using LiDAR

5. Conclusion

Agriculture is our society's key practices and is vital for maintaining sustainable food production. However, traditional farming methods have faced limitations due to the lack of integration of contemporary technology. Integrating cutting-edge technologies like artificial intelligence, robotics, and data analytics holds enormous potential for reshaping the farming industry in order to address these issues. One of the significant hurdles faced by farmers are weeds and diseases, which can considerably impact crop yields. Precise identification and timely action are essential for efficient control and handling. Our work introduces a fresh approach that utilizes the YOLOv8 model and aerial imagery captured by autonomous drones for the detection and classification of weeds and diseases in agricultural fields. By harnessing deep learning and object detection techniques, the objective of this approach is to ensure precise identification and classification of various weeds and diseases, helping farmers and agronomists to make well-informed decisions and implement specific management strategies. The current technologies used for detecting weeds and diseases have limitations related to their speed, accuracy, and reliance on human supervision. The proposed system addresses these drawbacks by leveraging the YOLOv8 model and UAVs. The AI model, trained using a variety of datasets, Improves the ability to learn and apply knowledge to various

situations, enabling effective detection across various crops and diseases. Moreover, integrating an automated drone system improves efficiency. Equipped with high-resolution cameras, the drone captures aerial images, offering a comprehensive field view for weed and disease detection. The drone's movement, controlled by the SBC, fosters seamless data collection and analysis. The AI model achieved promising recall and precision rates for weed and disease detection. The drone's autonomy and ability to avoid obstacles are further improved by integrating LiDAR technology, making it a useful tool for reliable agriculture. Overall, this study highlights the potential for using cutting-edge technologies in agriculture to improve production, decrease environmental damage, and provide reliable assessment and resource allocation. Technology integration has the potential to improve sustainability, protect natural resources, and ensure food security**.**

6. References

[1] Wang, A., Peng, T., Cao, H., Xu, Y., Wei, X., & Cui, B. (2022). TIA-YOLOv5: An improved YOLOv5 network for real-time detection of crops and weeds in the field. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.1091655

[2] Dandekar, Y., Shinde, K., Gangan, J., Firdausi, S., & Bharne, S. (2022). Weed Plant Detection from Agricultural Field Images using YOLOv3 Algorithm. In *2022 6th International Conference On Computing, Communication, Control And Automation (ICCUBEA*. https://doi.org/10.1109/iccubea54992.2022.10011010

[3] sample Object Detection Dataset (v1, 2023-02-11 1:18am) by Institute of Southern Punjab. (n.d.). Roboflow. https://universe.roboflow.com/institue-of-southern-punjab/sample-ixosm/dataset/1

[4] PlantDoc Object Detection Dataset - resize-416x416. (2023, May 18). Roboflow. https://public.roboflow.com/object-detection/plantdoc/1

[5] G. Jocher, A. Chaurasia, and J. Qiu, "YOLO by Ultralytics."https://github.com/ultralytics/ultralytics", 2023.

[6] Lottes, P., Behley, J., Milioto, A., & Stachniss, C. (2018, October). Fully Convolutional Networks With Sequential Information for Robust Crop and Weed Detection in Precision Farming. *IEEE Robotics and Automation Letters*, *3*(4), 2870–2877. https://doi.org/10.1109/lra.2018.2846289

[7] Dutta, G., & Goswami, P. (2020, October 1). Application of drones in agriculture: A review. International Journal of Chemical Studies, 8(5), 181–187.

[8] Dang LM, Hassan SI, Suhyeon I, Sangaiah AK, Mehmood I, Rho S et al. UAV Based Wilt Detection System Via Convolutional Neural Networks. Sustain. Comput. Inform. Syst., 2018.

[9] Hossain, Md Sazzad, et al. "Dual Focal Loss to Address Class Imbalance in Semantic Segmentation." Neurocomputing, vol. 462, Elsevier BV, Oct. 2021, pp. 69–87, doi:10.1016/j.neucom.2021.07.055.

[10] Budiharto, W., Chowanda, A., Agung, A., & Suroso, J. S. (2019). A Review and Progress of Research on Autonomous Drone in Agriculture, Delivering Items and Geographical. . . ResearchGate.

[11] Terven, J., & Cordova-Esparza, D. (2023). A Comprehensive Review of YOLO: From YOLOv1 and Beyond. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2304.00501

[12] Longzhe Quan, Wei Jiang, Hailong Li, Hengda Li, Qi Wang, Liqing Chen,Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding, mode, Biosystems Engineering, Volume 216, 2022, Pages 13-31, ISSN 1537-5110, https://doi.org/10.1016/j.biosystemseng.2022.01.019.

[13] Nitin Rai, Yu Zhang, Billy G. Ram, Leon Schumacher, Ravi K. Yellavajjala, Sreekala Bajwa, Xin Sun, Applications of deep learning in precision weed management: A review, Computers and Electronics in Agriculture, Volume 206, 2023, 107698, ISSN 0168-1699

[14] Rai, N., Zhang, Y., Ram, B. G., Schumacher, L., Yellavajjala, R. K., Bajwa, S., & Sun, X. (2023). Applications of deep learning in precision weed management: A review. Computers and Electronics in Agriculture, 206, 107698. https://doi.org/10.1016/j.compag.2023.107698

[15] Remondino, F., Barazzetti, L., Nex, F., Scaioni, M., & Sarazzi, D. (2011). UAV photogrammetry for mapping and 3d modelling: current status and future perspectives. UAV Photogrammetry for Mapping and 3D modeling-Current Status and Future Perspectives, 1–6. https://re.public.polimi.it/handle/11311/614334