REAL-TIME MECHANICAL FLOWER THINNING EQUIPMENT, CONTROLLED BY ARTIFICIAL INTELLIGENCE
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ECHIPAMENT PENTRU RARIREA MECANICĂ A FLORILOR ÎN TIMP REAL, CONTROLAT FOLOSIND INTELIGENȚA ARTIFICIALĂ

Mihai Gabriel MATACHE[1], Robert CRISTEA*[1], Ana ZAICA[1], Radu CIUPERCĂ[1], Adrian IOSIF[2], Gheorghe VOICU[2]
[1] INMA Bucharest/ Romania;
[2] University "POLITEHNICA" Bucharest/ Romania;
Tel: +40 771 717 451; E-mail: robertcri@yahoo.com
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ABSTRACT
In this paper, the designing and development of a novel mechanical flower thinning equipment, destined to increase the fruit production in orchards, is presented. The system integrates a ZED 3D camera with a dedicated controller for artificial intelligence running a custom trained YOLO9 algorithm, for real-time flower detection and counting. Based on the flower density data, the rotational speed of the thinning rotor is automatically adjusted to achieve the desired thinning ratio. Laboratory tests were conducted to evaluate the efficiency and adaptability of the YOLO9 algorithm to control the equipment in simulated flower density conditions. Results demonstrated potential improvements in thinning accuracy, contributing to optimized fruit development, and reduced manual labor. The proposed equipment offers an innovative approach to orchard management, ensuring sustainable practices by enhancing flower thinning precision while reducing labor costs.

REZUMAT
În această lucrare se prezintă proiectarea și dezvoltarea unui echipament inovator pentru rărirea mecanică a inflorescențelor, destinat creșterii producției de fructe în livezi. Sistemul integrează o cameră 3D ZED cu un controler dedicat procesării programelor de inteligență artificială, care rulează un algoritm antrenat special YOLO9 pentru detectarea și numărarea în timp real a florilor. Pe baza densității florilor, viteza de rotație a rotorului de rărire este reglată automat pentru a obține raportul dorit de rărire. Au fost realizate teste în laborator pentru a evalua eficiența și adaptabilitatea algoritmului YOLO9 de a controla echipamentului în condiții simulate de densitate florală. Rezultatele au demonstrat îmbunătățiri potențiale în ceea ce privește acuratețea răririi, contribuind la optimizarea creșterii fructelor și la reducerea lucrărilor manuale. Echipamentul propus oferă o abordare inovatoare pentru gestionarea livezilor, asigurând practici durabile prin creșterea preciziei răririi florilor și reducerea costurilor cu forța de muncă.

INTRODUCTION
In modern orchard management, mechanical thinning of flowers is essential to optimize fruit production ensuring balanced nutrient allocation and reducing competition among fruits (*Smith et al., 2015*). Thinning is essential for increasing fruit quality and yield, and several methods have been developed to address this need, including mechanical, manual, and chemical/hormone thinning techniques. Each approach presents distinct advantages and limitations, which are important to consider when selecting a thinning strategy for specific orchard conditions.

Manual thinning is a more traditional approach, often favored for its precision and flexibility. Workers can selectively remove flowers or fruitlets, ensuring that most promising fruits receive enough space and adequate nutrients. However, manual thinning is highly labor-intensive and subject to human error, resulting in inconsistencies and inefficiencies, particularly in large-scale operations (*Hernandez et al., 2016*). Furthermore, as labor shortages continue to affect agricultural industries globally, reliance on manual thinning becomes increasingly unsustainable (*Gomez and Perry, 2019*).

Chemical and hormone thinning, using substances like auxins and cytokinins, represents another popular technique for managing flower density. This approach is advantageous because it can be applied over large areas with relatively low labor requirements (*Rodriguez et al., 2017*).

However, its efficacy is highly dependent on environmental conditions such as temperature and humidity, which could lead to results that are not always as expected (*Perez et al., 2018*). Besides, the overuse of chemical agents could have negative effects on tree health and on the environment (*Huang and Lee, 2020*), raising concerns about this method's long-term sustainability.

Mechanical thinning, including the method discussed in this paper, addresses many of the limitations of manual and chemical thinning. By using advanced technologies such as AI-based flower detection and real-time adjustments, mechanical thinning offers high precision and efficiency (*Miller et al., 2018*). Unlike chemical methods, mechanical thinning does not depend on environmental conditions and avoids the potential ecological risks associated with chemical agents (*Jensen and Roberts, 2021*). Additionally, it significantly reduces the labor costs associated with manual thinning while providing more consistent results across large orchards (*Zhang and Collins, 2019*).

In summary, traditional manual thinning methods are labor-intensive and subject to inconsistencies, especially in large-scale orchard operations (Adam and Brown, 2008). Chemical thinning is less labor-intensive but could cause variable results and potential environmental harm. Mechanical thinning methods, particularly with AI enhancements, provide high efficiency and precision without the need for chemicals, making them promising solutions for modern orchard management. Studies have shown that effective thinning, including spatially managed approaches, can optimize crop load distribution, indicating potential benefits of precision strategies in orchard management (*Manfrini et al., 2009*).

Over-thickened flower clusters can limit the quality and yield of fruits, because they compete for vital resources needed for growth. This fact has driven the demand for automated solutions, which are increasingly being adopted for precision agriculture (*Lee et al., 2021*).

Latest advancements in automation, particularly the integration of artificial intelligence (AI) and machine learning algorithms, have revolutionized agricultural practices (*Kramer et al., 2000*). Systems equipped with AI technologies offer real-time decision-making capabilities, enabling more precise interventions in vegetable crops, especially orchard management (*Werner et al., 2005; Matache et al., 2022*). Recent advancements also illustrate how non-destructive sensing technologies can further improve precision agriculture, integrating real-time data to optimize processes like thinning (*Biegert and McCormick, 2024*). Object detection algorithms such as YOLO (You Only Look Once) have been proven effective in real-time recognition tasks, including the detection and counting of flowers and fruits (*Brown, 2010; Stern and Lars, 2009; Chen et al., 2024*). These algorithms, combined with advanced imaging systems like the ZED 3D camera, provide higher accuracy and adaptability in detecting flower clusters under varying conditions (*Gonzalez and Turner, 2020*).

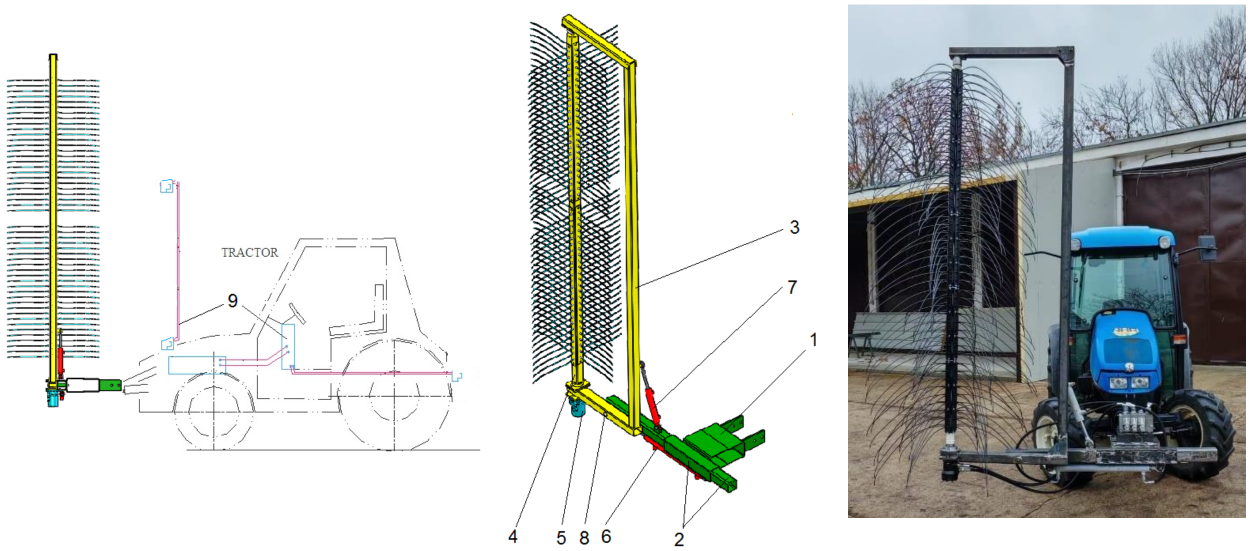
The development of AI-controlled mechanical thinning equipment offers several advantages, including increased operational efficiency, reduced labor costs, and enhanced precision in thinning flower clusters (*Miller and Zhang, 2018*). These systems ensure optimal thinning, promoting consistent fruit development and improved yields by automatically adjusting the rotational speed of the thinning rotor, based on real-time flower density detection (*Lee et al., 2021*). Moreover, they contribute to the orchards sustainability, reducing the need for manual labor, which is increasingly scarce in agricultural sectors worldwide (*Smith et al., 2015*).

This paper presents the design and development of an innovative mechanical flower thinning system that integrates a ZED 3D camera with a custom-trained YOLO9 AI algorithm on an open source dataset of apple flowers. The system was designed to detect and count flowers in real-time, adjusting its thinning action dynamically based on flower density. Laboratory tests were conducted to evaluate the system's accuracy and adaptability under controlled conditions. The results demonstrated potential improvements in thinning accuracy and operational efficiency, offering a promising solution for modern orchard management.

MATERIALS AND METHODS

Technical Equipment for Flower Thinning in Orchards, ERI-0, is designed for the thinning of flower clusters on fruit trees in orchards to optimize fruit development and production. The equipment can be used in orchard farms by commercial entities engaged in orchard maintenance, manufacturers of technical equipment for orchards, dealers, distributors, etc. The technical equipment for flower thinning, symbolized as ERI, performs the mechanical thinning of flower clusters on fruit trees, a necessary operation when the productivity of orchards is reduced because all nutrients are consumed for vegetative growth rather than fruiting. It also aims to reduce the costs of technological operations in plantations.

Figure 1 presents the componence of the experimental model - technical equipment for flower thinning.



a) b)

1. Welded support; 2. Guide assembly; 3. Rotor support; 4. Rotor shaft assembly; 5. Hydraulic motor; 6. Hydraulic cylinder, 500 mm stroke; 7. Hydraulic cylinder, 150 mm stroke; 8. Coupling bolt; Flower detection system – ZED 3D camera + controller

Fig. 1 - Technical Equipment for Flower Thinning in Orchards, ERI-0, in aggregate with the working tractor

a) Component elements; b) ERI-0 experimental model

The technical equipment for flower thinning in orchards, ERI, operates in combination with agricultural tractors with a power of approximately 45 HP. The equipment is mounted at the front of the tractor and is driven by its own hydraulic system, which is powered by the tractor's hydraulic outlets.

After coupling the ERI equipment to the tractor, it is transported to the work site. The equipment is raised to the maximum position using the tractor's hydraulic system, and adjustments are made to the rotor's inclination (position 4, fig. 1), the working distance of the rotor relative to the tree crown, and the penetration depth of the rotor equipped with wires. These adjustments are performed by operating the two hydraulic cylinders (positions 6 and 7, fig. 1) of the equipment.

Once these adjustments are made, the hydraulic motor that drives the rotor is connected to the tractor's hydraulic system, and the tractor transmission is initially set to a lower gear. The tractor-ERI unit is then set in motion, performing the flower thinning. Depending on the situation, the speed of movement and the position of the ERI equipment relative to the rows of trees can be adjusted.

The rotational speed of the thinning rotor is continuously and automatically adjusted, controlled by the flower detection system. This system is equipped with an intelligent video camera that records the density of the flower clusters, transmits the information to the analysis system, which then sends commands to the equipment's proportional distributor, thereby varying the rotor's speed. The rotor speed is programmed based on the flower density.

During one pass, the equipment thins half of the tree crown, with the other half being thinned on the return pass.

Main Technical Specifications of the Experimental Model:

- Purpose: .... for flower thinning
- Type of Equipment: .... mounted, three-point linkage
- Power Source / Required Power: .... minimum 45 HP wheel tractor
- Maximum Working Height, mm: 3000
- Height Adjustment, mm: .... hydraulic
- Oblique Rotor Inclination for Adjusting the Working Angle: .... approx. 18°
- Equipment Weight, kg: .... approx. 120
- Minimum Width, mm: .... approx. 2093
- Maximum Width, mm: .... approx. 2593

- Length, mm: .... approx. 875
- Height, mm: .... approx. 2220

The logical flow of the application for flower counting and controlling the thinning rotor speed follows a continuous cycle, starting from real-time image capture and ending with automatic adjustment of the rotor speed based on flower density.

The process begins with the ZED 3D camera, which captures images of the flowers in the orchard. ZED 3D camera provides enhanced depth perception, allowing for more accurate detection of flower clusters in complex environments like orchards. These raw images are then sent for pre-processing. In this stage, the application automatically adjusts the orientation of the images to ensure correct alignment, resizes the image to 640x640 pixels for compatibility with the YOLO9 model, and applies augmentations such as rotations and exposure adjustments. After the images have been pre-processed, they are sent to the YOLO9 model. The model analyzes the images to identify and count flower clusters. During this analysis, YOLO9 divides the image into grids and makes predictions for each section. If flower clusters are detected, the application proceeds to count them, comparing the identified visual characteristics with the reference patterns in the pre-trained model to ensure accuracy.

Based on the visual analysis results of YOLO model, the application adjusts the rotational speed of the thinning rotor in real-time. If the density of flowers is high, the rotor speed is increased to ensure effective thinning, while a lower density results in a slower rotor speed. This adaptive control mechanism allows the equipment to maintain optimal thinning, promoting balanced fruit development across the orchard.

The entire flow of the application operates in a continuous cycle, capturing images, pre-processing them, analyzing them to count flowers, and adjusting the rotor speed as needed. This ensures an efficient and automated system for managing flower thinning, reducing the need for manual intervention, and optimizing the overall process.

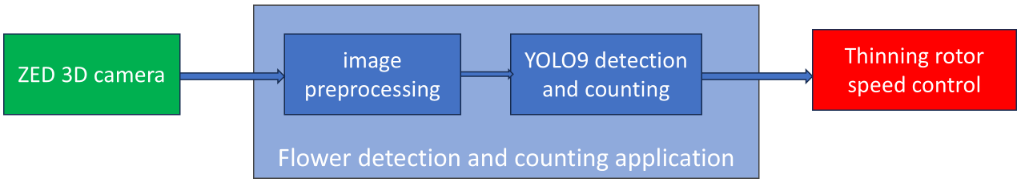


Fig. 2 – Flow diagram of the software application for the thinning equipment control

In order for the YOLO9 model to detect and count the flowers, it was trained using a dataset with pictures of apple flowers (*Addineduws, 2024*). Training the YOLO9 model involved optimizing the loss function to minimize errors in detecting and counting flower clusters. The model was trained using stochastic gradient descent (SGD) with an initial learning rate of 0.01, a momentum of 0.937, and a weight decay of 0.0005. The batch size was set to 16, and training was conducted for 300 epochs.

The performance of the YOLO9 model was evaluated using several metrics: **Precision (P), Recall (R), mean Average Precision (mAP), inference time,** and **visual assessment.** These comprehensive evaluation metrics ensured a thorough assessment of the model's performance in counting flowers, enabling reliable and effective control of the rotor speed based on real-time flower density. The calculation of these metrics considered the number of true positive samples (TP), false positive samples (FP), and the total number of samples (N). The **Average Precision (AP)** for each flower cluster category was derived using a specific formula, providing detailed insights into the model's accuracy across different categories.

For apple flowers on trellis systems, required density after thinning aims to balance the tree's capacity to support fruit growth while preventing overloading. Proper thinning typically retains about 5-10 cm of spacing between clusters, which effectively reduces the initial flower density by approximately 70-80%. This practice ensures that about 20-30% of the flowers are left, promoting optimal fruit quality and size (NIAB, 2024; Valent, 2024). This enhances light penetration and air circulation, leading to improved fruit quality.

Fruits spacing and load reduction also help to mitigate risks such as reduced flowering in the following seasons and potential damage to tree limbs (ISHS, 2024).

To correlate the YOLO9 output with the control thresholds for the thinning equipment, an adaptive mechanism was implemented to adjust the rotor's speed based on detected flower density. After analyzing the images captured by the ZED 3D camera, the YOLO9 model provided a real-time count of flower clusters, which was then used to determine the appropriate speed setting for the thinning rotor.

The system was designed around three predefined thresholds corresponding to 50%, 75%, and 100% of the nominal rotational speed, set at 400 rpm. These thresholds were directly linked to specific density ranges, which were set empirically for the purpose of laboratory tests of the equipment:

1. **Low Density:** When the YOLO9 model detected a low number of flower clusters (e.g., 0-10 per frame), the system activated the rotor at 50% speed, or 200 rpm. This ensured minimal thinning where fewer flowers were present.
2. **Medium Density:** For a moderate count (e.g., 11-20 clusters per frame), the rotor speed was adjusted to 75% (300 rpm), allowing more substantial thinning without full intensity.
3. **High Density:** If the model identified a high density of flowers (21 or more per frame), the equipment automatically operated at the maximum 400 rpm to ensure effective thinning across dense clusters.

This setup allowed for continuous real-time analysis in laboratory conditions, where the YOLO9 model was fed with test pictures to monitor the flower density as the equipment simulated the moving along the orchard rows. The control system dynamically adjusted the rotor speed based on the model's output, creating a simulated thinning process. This was done through a variable command signal for the hydraulic proportional valve which controlled the hydraulic motor.

The simulation tests were designed to evaluate how effectively the mechanical flower thinning equipment could adapt to different scenarios by using real-time data from the YOLO9 model. The laboratory tests aim was to see how well the system adjusted the rotor speed based on varying flower densities detected in the orchard.

Four distinct scenarios were set up to represent low, medium (usually met in orchards, 2 scenarios), and high flower densities, each testing the equipment's adaptive control mechanism.

- **Scenario 1: Low Density** In the first test, the YOLO9 model detected a low number of flower clusters, specifically 5 clusters, which was categorized as a low-density situation. Based on this input, the control system set the rotor speed to 200 rpm, or 50% of the nominal speed of 400 rpm. This ensured minimal thinning, which was appropriate for areas where fewer flowers were present, preventing over-thinning.
- **Scenario 2: Medium Density** The second scenario simulated a moderate density, with the YOLO9 model identifying 15 flower clusters per frame. This was classified as medium density, prompting the system to adjust the rotor to 300 rpm, or 75% of the nominal speed.
- **Scenario 3: High Density** In the third test, a high-density scenario was simulated. The YOLO9 model detected 25 flower clusters, indicating a dense area that required more intensive thinning. The control system responded by setting the rotor to its maximum speed of 400 rpm, ensuring thorough thinning across the dense clusters.
- **Scenario 4: Medium Density Revisited** The final scenario revisited a medium-density situation, where the YOLO9 output showed 18 clusters. As with the earlier medium-density test, the system adjusted the rotor speed to 300 rpm, providing a consistent thinning performance.

To simulate the presence of flowers on branches, artificial markers representing flower clusters were placed in the lab setup, for the 4 scenarios. These included, bright pink and white colored stickers mimicking the size and positioning of real flower clusters. The YOLO9 model detected these markers, and the equipment responded as if they were actual flowers. After the thinning operation, the remaining markers were counted to verify the thinning efficiency.

The laboratory tests involved capturing "before" and "after" images during the simulation. By comparing the number of markers detected by YOLO9 before the equipment was activated and after the thinning process, the percentage of simulated flower clusters removed was calculated. Efficiency was assessed using a simple formula:

$$TE\ (\%) = \frac{NBT - NAT}{NBT} \qquad (1)$$

where:

TE – thinning efficiency, NBT- number of detected clusters before thinning,

NAT – number of detected clusters after thinning.

Through this laboratory-based approach, the effectiveness of the thinning equipment was tested even in the absence of flowering trees. This method provided a comprehensive evaluation of the system's performance, ensuring it was ready for real-world deployment during the flowering season.

RESULTS

The YOLOv9c model was trained on a laptop ASUS ROG Strix SCAR 18, G834JY-N6046X, 18-inch, QHD+ 16:10 (2560 x 1600, WQXGA), 13th Gen Intel® Core™ i9-13980HX Processor 2.2 GHz (36M Cache, up to 5.6 GHz, 24 cores: 8 P-cores and 16 E-cores), with NVIDIA® GeForce RTX™ 4090 graphic card and DDR5 64GB RAM, on UBUNTU 22.04.4 LTS operating system. The software environment comprised PyTorch 2.0.0, Cuda 11.8, Cudnn 8.6.0, and Python 3.8.

In figure 1, the confusion matrix created after model training is presented.

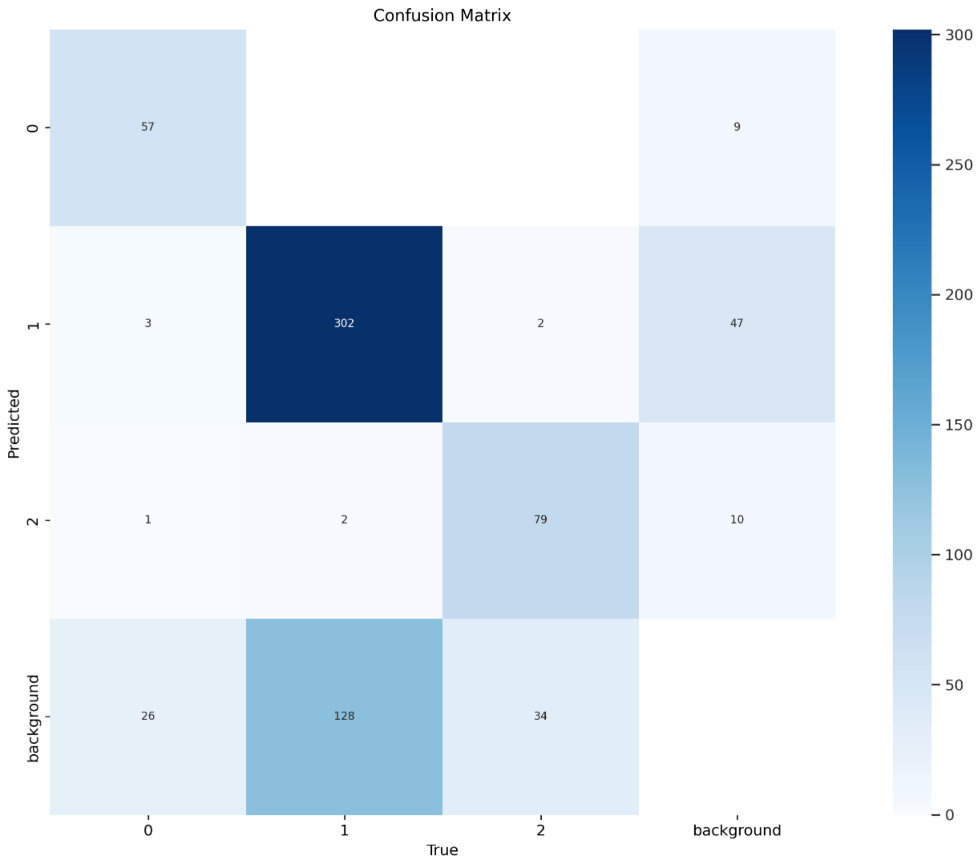


Fig. 3 – Confusion matrix after YOLO9c training

The confusion matrix offered valuable information about the performance of the model across different flower-related classes. The dataset included three main classes: bud (Class 0), flower (Class 1), and middle (Class 2), along with a category for background elements. For the **Class 0 – Buds, t**he model showed a reasonable ability to identify buds, correctly classifying 57 instances. However, there were some misclassifications, with 9 buds incorrectly labeled as background. This suggests that while the model was able to recognize the features of buds effectively, there was still some confusion, likely due to overlapping characteristics or background elements that closely resembled buds. Flowers, classified as Class 1, were the most accurately detected, with 302 instances correctly identified. This high true positive rate indicates that the model learned to distinguish flowers effectively. However, there were still a few misclassifications: 3 were mistaken for buds (Class 0), 2 for the middle section (Class 2), and 47 were classified as background. The relatively high number of misclassifications as background suggests that, in certain situations, the model might have struggled to differentiate flowers from non-floral elements, possibly due to environmental noise or the complexity of the scene. The middle sections of the flower, or Class 2, were recognized with moderate success, with 79 instances correctly classified. There were minor misclassifications: 1 instance was mistaken for a bud, 2 for flowers, and 10 were labeled as background.

These errors indicate that the model could be facing challenges in distinguishing the middle parts, which might require more training data or clearer feature separation from other classes. The background category experienced significant misclassifications. Although 34 instances were correctly recognized as background, there were considerable errors where background elements were incorrectly labeled: 26 as buds, 128 as flowers, and 34 as the middle section. The high misclassification rate, particularly with flowers, suggests that the model may over-detect objects, interpreting random patterns or elements in the background as flowers. This could point to a need for further training to improve background discrimination or to refine the dataset with more diverse background examples. In table 1 are presented the metrics obtained after model training.

Table 1

Metrics obtained for the trained model

Metrics	YOLOv9c
Precision – P (%)	0.8306
Recall – R (%)	0.6861
F1-score (%)	
mAP50 (%)	0.7803
mAP50-95 (%)	0.4861
Inference time	1.1ms preprocess, 64.5ms inference, 0.8 ms postprocess per image at shape (1, 3, 512, 640)

The performance metrics obtained from the YOLOv9c demonstrate strong precision and solid average precision, but they also highlight areas for potential improvement.

Precision was high at 83.06%, indicating that the model accurately identified buds, flowers, and middle sections without many false positives. This level of precision is important for ensuring that the thinning equipment responds correctly to actual flower clusters, avoiding unnecessary adjustments based on incorrect detections. However, the **recall rate**, at 68.61%, was a little bit lower, meaning that the model missed some instances that should have been detected. Improving recall would help ensure that no significant clusters are overlooked during the thinning process. The model's performance was also reflected in the **mean Average Precision (mAP50)** score of 78.03%, which describe its reliability in detecting and localizing flower components across different conditions. A score above 75% indicates that the model has learned to generalize well, effectively recognizing objects even in complex scenarios. However, the **mAP50-95 score**, which was 48.61%, was low. This metric considers a wider range of intersection over union (IoU) thresholds, highlighting that the model's localization accuracy could still be improved. Still, for our equipment which has a more general approach on the all vertical side of the tree, this metric value is acceptable. In terms of **inference time**, the model demonstrated impressive efficiency, with 1.1 ms for preprocessing, 64.5 ms for inference, and 0.8 ms for post-processing per image. These quick processing times indicate that the system can operate in near real-time, which is essential for the adaptive control of the thinning equipment. This speed allows the equipment to respond dynamically to changes in flower density, ensuring smooth and consistent thinning.

In figure 4 are presented the results obtained by YOLO9c model after it was fed the test images with various instances of apple flowers. The results displayed in the image represented the outcomes of the YOLO model after training, showing how effectively the model was able to detect and classify different components of apple flowers. The bounding boxes in the images indicated where the model detected instances of each class, providing a visual representation of its performance. YOLO model demonstrated a strong capability to identify and differentiate between buds, flowers, and middle sections. In many cases, the bounding boxes accurately and tightly surrounded the relevant objects, highlighting that the model had learned to localize these features effectively. For example, the buds (Class 0) were consistently detected in images showing early-stage flowers, and full blooms were correctly identified as flowers (Class 1). This indicated that the model could reliably classify each class across different scenarios. The detection was observed to be consistent across multiple environmental conditions, including different lighting scenarios and varied backgrounds, proving that the training process, which included data augmentation, helped the model generalize well. Even in more complex scenes, where flower clusters were dense, the model was able to identify multiple instances of flowers, showing it could handle scenarios with close-packed objects. Despite the overall strong performance, there were some instances where the model misclassified objects or incorrectly labeled them. For example, in certain images, buds might have been mistakenly classified as middle sections, or the bounding boxes overlapped significantly, suggesting the model sometimes struggled to distinguish overlapping features. These issues pointed to areas where further fine-tuning could improve accuracy, especially in distinguishing subtle differences between classes.

Fig. 4 – Identification results after YOLO9c training

To evaluate the performance and adaptive capabilities of the mechanical flower thinning equipment, a series of simulation tests were conducted under controlled laboratory conditions. Given the absence of flowering trees during the testing period, the system was tested using bright pink and white colored stickers mimicking the size and positioning of real flower clusters. In table 2 are presented the results observed during these tests, highlighting the equipment's ability to adapt to different levels of flower density.

Table 2

Simulation tests for the system functioning

Test Scenario	Detected Flower Clusters (YOLO9 output)	Density Classification	Rotor Speed Setting (rpm)	Thinning Efficiency (%)	Comments
Scenario 1	5	Low density	200	30	Minimal thinning, suitable for low-density sections.
Scenario 2	15	Medium density	300	60	Moderate thinning, appropriate for medium-density areas.
Scenario 3	25	High density	400	90	Maximal thinning, effective in dense flower clusters.
Scenario 4	18	Medium density	300	65	Consistent thinning achieved for medium-density patches.

The simulation tests demonstrated that the adaptive control system of the thinning equipment could effectively adjust rotor speeds based on real-time flower density data from the YOLO9 model. The system responded appropriately across different scenarios, from low to high-density areas, ensuring that the thinning process was efficient and precise. By fine-tuning the rotor speed to match the detected flower density, the equipment was able to optimize thinning, promoting uniform fruit development and reducing the need for manual intervention.

CONCLUSIONS

The development and testing of the mechanical flower thinning equipment demonstrated the potential of using artificial intelligence to enhance precision and efficiency in orchard management. The integration of a ZED 3D camera and the YOLO9 model enabled real-time detection and counting of flower clusters, providing accurate data to control the thinning process in an adaptive manner. Laboratory simulations showed that the system effectively adjusted rotor speeds based on detected flower densities, ensuring consistent thinning across various scenarios.

The results indicated that the adaptive control mechanism could reliably manage low, medium, and high-density flower clusters by setting appropriate rotor speeds, from minimal thinning at 200 rpm to maximum thinning at 400 rpm. This feature is mandatory for maintaining optimal flower spacing, promoting uniform fruit development, and reducing the need for manual intervention. Furthermore, the YOLO9 model achieved a high degree of accuracy in identifying and classifying apple flower components across various conditions. While the model performed well, some misclassifications, especially concerning background elements, suggested that further refinements could enhance performance. Expanding the dataset to include more diverse environmental conditions and refining the model's ability to differentiate overlapping features would likely reduce errors and improve reliability.

This study has shown that AI-enhanced mechanical thinning equipment can be a promising solution for modern orchard management, offering a balance of precision, adaptability, and efficiency. Future developments should focus on real-world field testing during the flowering season to validate laboratory results, and fine-tuning the system to address any challenges that arise under natural conditions. This approach will help ensure that the technology is ready for practical deployment, enabling sustainable and cost-effective orchard practices.

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