

Comparative Performance Assessment of a Transplanting Robot Equipped with Machine Vision under Different YOLO Algorithms

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Abstract

In this research, the performance of a greenhouse transplanting robot with a machine vision system based on the YOLO algorithms (YOLOv8s, YOLOv8n, YOLOv8m, YOLOv9c, YOLOv11s, YOLOv11m, and YOLOv11n) in handling pepper, lettuce, and tomato seedlings was evaluated in terms of detection accuracy, processing speed, and transplanting efficiency in a greenhouse environment. A robot was designed with a three-degree-of-freedom robotic arm, a dual-pin gripper, and a 1280×720 resolution camera, which was able to detect and transplant seedlings automatically. After comparing the different YOLO algorithms, the results showed that YOLOv8s had the best balance between accuracy (86.52%) and processing time (1'605.67 milliseconds), and the transplanting success rate was highest for tomato seedlings (92.38%) and lowest for pepper seedlings (81.11%). Statistical analysis confirmed that significant differences existed between the species. This system demonstrated a strong potential for precision agriculture by reducing labour costs and enhancing productivity. With future optimisations, it could deliver improved performance across diverse environmental conditions.

Keywords: Greenhouse, Machine vision, Robotic Transplanting, YOLO algorithm

Introduction

Agriculture is a fundamental pillar of the global economy, contributing to food security, employment, and sustainable development, and a key driver of rural development and livelihood improvement, but is challenged by natural resource degradation, climate change, and limits to water and soil availability (World Bank, n.d.). Greenhouse agriculture, which can accurately control environmental conditions and increase crop yields, has been a recent focus of interest, but traditional transplanting methods in greenhouses are not only costly and time-consuming, but often fail to produce desirable results. The main challenges of traditional transplanting are: (1) labour costs and shortages, skilled labour is difficult to access and rising wages drive up production costs; (2) human fatigue and errors, repetitive and time-consuming transplanting tasks cause worker fatigue and increase the potential for errors (Vougioukas, 2019); (3) low productivity and operational delays, handling tools and

seedlings are time-consuming, for example, although a single trip to retrieve a seedling tray may seem minor, it becomes costly and wastes time when repeated throughout the day (Garzón & de León, 2018); (4) inconsistent seedling quality, human handling and planting errors can lead to poor seedling quality, which is irreversible. These limitations demonstrate that traditional transplanting is inefficient for large-scale and modern greenhouse operations, and there is a need for technological solutions. One of the most promising solutions is the use of automated transplanting robots. These systems employ intelligent mechanisms to transfer seedlings from trays to their final growth medium with high precision (Bac, Van Henten, Hemming, & Edan, 2014). The advantages of such technology include reduced labour costs (Bac *et al.*, 2014), increased speed and accuracy (Hayashi, Ota, Kubota, Ganno, & Kondo, 2005), continuous and consistent performance (Kondo, Monta, & Noguchi, 2011), and minimised seedling root damage and waste (Li,

Zhang, Lei, Wang, & Guo, 2020). However, the adoption of transplanting robots also presents challenges, including high initial investment costs (Garzón & de León, 2018), the need for specialised expertise, maintenance expenses (Vougioukas, 2019), and reliance on energy and processing infrastructure (Shamshiri *et al.*, 2018). Machine vision is a critical technology for improving transplanting robots, which use cameras and image-processing algorithms to detect plant characteristics, fruits, weeds, and health indicators (Patrício & Rieder, 2018), and systems that process large volumes of visual data can aid in the intelligent management of resources like water and fertilisers (Liakos, Busato, Moshou, Pearson, & Bochtis, 2018). The YOLO (You Only Look Once) model is a popular machine vision algorithm widely used in agriculture that performs object detection and localisation in a single stage with a very high processing speed (Bochkovskiy, Wang, & Liao, 2020). The YOLO architecture consists of three main components: the backbone (feature extraction), the neck (multi-level feature fusion), and the head (class and position prediction) (Wang *et al.*, 2022). Different YOLO versions have introduced significant improvements in speed and accuracy, each with unique characteristics. YOLOv5 is lightweight and suitable for real-time applications (Jocher, 2020). YOLOv7 features the EELAN structure for higher accuracy with reduced computational demands (Wang, Bochkovskiy, & Liao, 2023). YOLOv8 is faster and more accurate, with capabilities for detection, segmentation, and classification (Jocher, Chaurasia, & Qiu, 2023). YOLOv11 is the latest version, offering enhanced accuracy and efficiency for computer vision tasks (Jocher & Qiu, 2024). The application of YOLO models in agriculture has been well documented. For example, the TIA-YOLOv5 model achieved real-time detection of weeds and cultivated plants with an F1 score of approximately 0.7 and a processing speed of 20 frames per second (Wang *et al.*, 2022). The design and development of automated transplanting systems using machine vision have garnered significant research interest in recent years. These systems aim to improve

speed and accuracy, and minimise seedling damage. Song *et al.* (2024) developed a non-destructive method for identifying horticultural seedling phenotypes using an improved YOLOv8 model, achieving 91% accuracy in bounding box detection and 91.3% in segmentation masks. The method utilised 3D reconstruction with Gaussian splatting for training data generation and was tested on watermelon seedlings in greenhouse settings. Khadatkhar, Magar, Sawant, and Modi (2024) designed an automated seedling extractor using mechanics and machine vision, reporting a 91–95% success rate in extraction and 86.3–90% in transplanting. This system, designed for nursery seedlings in controlled environments like greenhouses, minimised root damage. Tong, Shi, Wu, Jiang, and Yang (2018) developed a precise algorithm capable of detecting tomato (98.6%), cucumber (96.4%), eggplant (98.6%), and pepper (95.2%) seedlings, demonstrating the ability to distinguish between different plant types. Han *et al.* (2023) introduced a simple seedling transfer device with a lateral and horizontal pressure approach, achieving a 95.47% success rate for tomato seedlings in 128-cell trays. Syed *et al.* (2019) employed non-destructive monitoring of seedling biomass using a RealSense depth camera, demonstrating high success rates for lettuce and suitability for automated greenhouse transplanting systems. A review of prior studies indicates that machine vision in agriculture still requires further exploration. This research aims to develop a robot leveraging machine vision and robotics to explore approaches for addressing limitations, such as the need for rapid processing and reduced dependency on lighting conditions, including the use of a standard RGB camera (rather than specialised depth or multispectral sensors) operating under ambient lighting, aimed at reducing hardware costs, and to make a comparison between different versions of YOLO models.

Materials and Methods

In this study, a transplanting robot was designed, developed, and evaluated using the

YOLO algorithm to transfer seedlings of pepper (*Capsicum annuum*), lettuce (*Lactuca sativa*), and tomato (*Solanum lycopersicum*) from cultivation trays to individual pots under greenhouse conditions. The system combined machine vision and robotics technologies for seedling detection, classification, and transplantation. The hardware and software

components, materials, data collection and processing methods, model training, experimental design, and evaluation metrics are outlined in the following sections. The robot had two main components: hardware and software, which are explained in detail below. A schematic view of the robot is shown in Fig. 1.

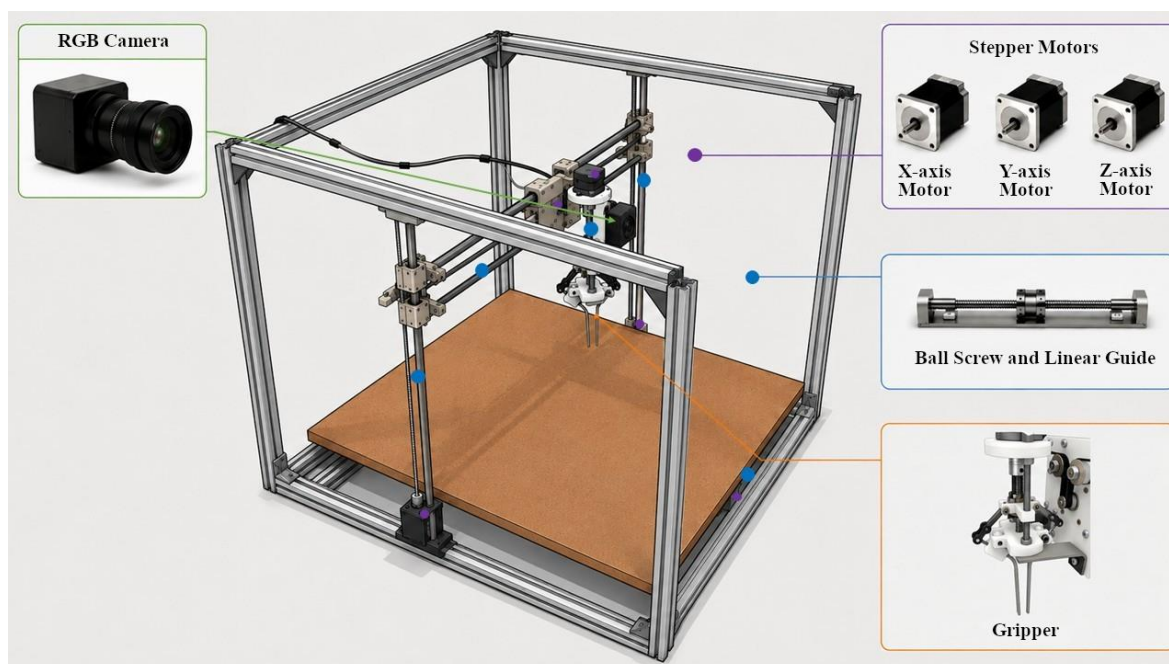


Fig.1. Overview of the Transplanting Robot

Structural Details of the Transplanting Robot

For this study, a small-scale transplanting robot was designed and constructed. A three-degree-of-freedom (3-DoF) robotic arm equipped with stepper motors was used, enabling movement along the X, Y, and Z axes. The general overview of the transplanting robot is shown in Fig.1. A camera with a resolution of 1280×720, connected via USB to a computer, was utilised. Fig.1 illustrates the camera's mounting position next to the gripper. A custom dual-pin gripper, controlled by a stepper motor, was designed to minimise damage to the roots and leaves of the seedlings.

A dedicated board based on the ESP32 microcontroller, capable of simultaneously controlling multiple stepper motor axes and equipped with various sensor inputs for

collision detection, was used to coordinate the robot's components. TB6600 drivers were employed to control the stepper motors. A personal computer was selected for image processing and running YOLO models due to its high computational power and compatibility with deep learning algorithms. The general hardware specifications are listed in Table 1.

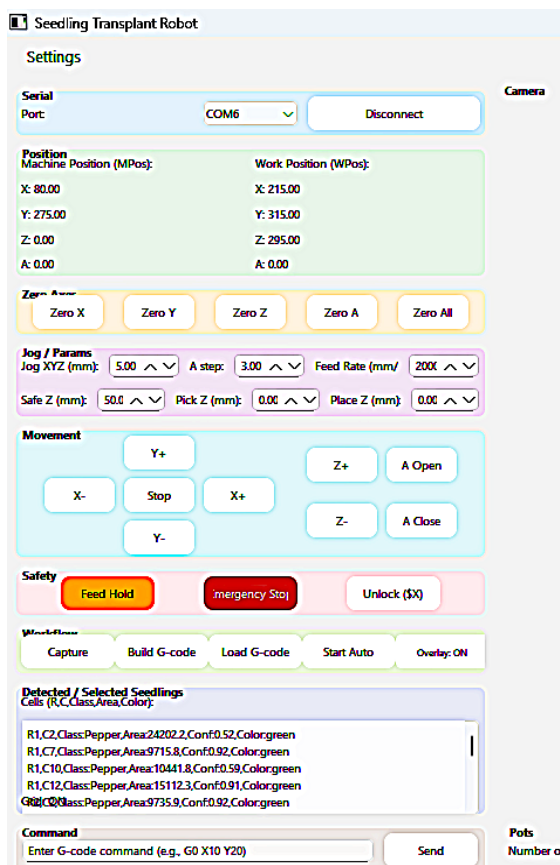
Table 1- Hardware Specifications of the Robot

Component	Specifications	Description
Robotic Arm	Three Degrees of Freedom (3-DoF), Stepper Motor	Movement along X, Y, and Z axes
Gripper	Dual-pin (needle-type), Stepper-controlled	Designed to minimise damage to roots and leaves
Camera	1280×720 resolution, USB interface	Image acquisition
Control Board	ESP32 + TB6600 Drivers	Controls axes and sensor inputs
Processing Unit	Personal computer (i5 CPU, 8GB RAM)	YOLO processing and system control

Modelling

Machine Vision Models: Various versions of YOLO (YOLOv8s, YOLOv8n, YOLOv8m, YOLOv9c, YOLOv11s, YOLOv11n, and YOLOv11m) were evaluated for the detection and classification of three types of seedlings and empty cells. The optimal model was ultimately selected for the robot. Additionally, Python-based software was developed for this study to coordinate the outputs of the vision

system with the movements of the robotic arm. This software utilised the OpenCV library for image processing and PyTorch for running the YOLO models. The software included various components for connections, axis control, displaying axis positions, camera visualisation, seedling detection, pot definition, G-code extraction for sending programs to control the robot's hardware, and more. The user interface of this software is shown in Fig. 2.

**Fig.2.** Display Interface of the Robot Controls

Experimental Procedure and Details

Three types of seedlings pepper, lettuce, and tomato were selected at the two-to-four true-leaf stage. A total of six seedling trays were used for the experiment. Cultivation Trays were standard 72-cell trays with cell dimensions of 4×4×5 cm. Pots were individual plastic pots

with a diameter of 8 cm and a height of 12 cm. The soil in the trays was a mixture of 60% peat moss, 20% perlite, and 20% vermiculite, and for the pots, a mixture of 50% loamy soil, 30% compost, and 20% sand was used. The seedling specifications are listed in Table 2.

Table 2- Seedling Specifications

Species	Root System Type	Root Density (Qualitative)	Total Root Length (Average)	Dry Root Mass (Average)
Tomato	Dense fibrous, high branching	Very high	25–35 cm in 4–5-week-old seedlings	150–250 mg
Lettuce	Medium fibrous, rapid but less dense	Medium	15–25 cm in 3–4-week-old seedlings	80–150 mg
Pepper	Sparse fibrous, slow growth	Low	10–18 cm in 5–6-week-old seedlings	50–120 mg

Note: "Total Root Length" refers to the cumulative length of all fibrous root branches within the root system, not the vertical root depth; this value can exceed the physical cell depth (5 cm) because fibrous root systems grow densely and with high branching within a confined volume.

The automated transplanting process included the following steps. First, the camera moved toward the centre of the seedling tray and was positioned 20 cm above the seedling surface. Then, using the YOLO model, the planted seedlings were detected and classified.

Subsequently, seedlings evaluated as superior based on leaf surface area were selected. The corresponding G-code was then generated and sent to the controller to execute the planting process in the pot. The diagram of the process flow is shown in Fig. 3.

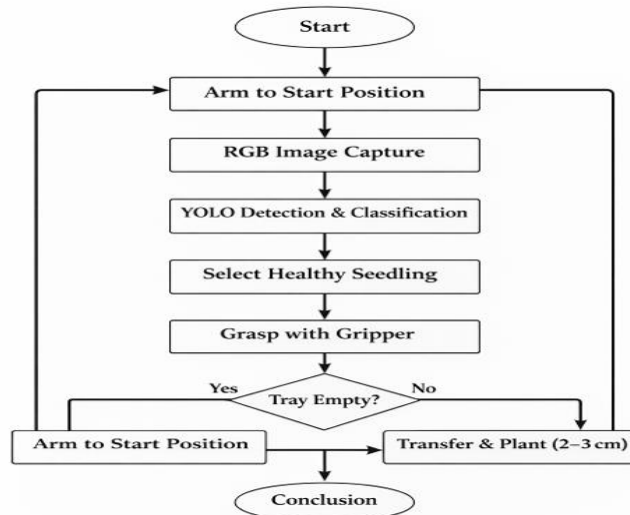


Fig.3. Flowchart of the transplanting operation process

The evaluation criteria included: 1. Performance of selected models, 2. transplant success rate (percentage of healthy seedlings transferred), and 3. overall efficiency (number

of seedlings transferred per hour). The independent variables were seedling type, lighting conditions (morning, afternoon, or evening), and tray density (full or half-full). Manual seedling transplantation was used as the

control group. Each experiment was repeated five times. Analysis of variance (ANOVA) was used to compare the mean values of the indices under different conditions, and the Tukey HSD test identified significant differences. Analyses were conducted using Python with the SciPy and Matplotlib libraries.

Results and Discussion

This section presents and analyses the results of evaluating deep learning models based on the YOLO architecture (including YOLOv8n, YOLOv8m, YOLOv8s, YOLOv9c, YOLOv11n, YOLOv11m, and YOLOv11s) on a dataset of images of pepper, tomato, and lettuce seedlings in a greenhouse environment. The complete annotated dataset, after augmentation, comprised approximately 4771 seedling instances, split into training (80%), validation (10%), and test (10%) subsets. All images were resized to 640×640 pixels, and data augmentation was applied using horizontal flipping, 90-degree rotations, and random brightness ($\pm 20\%$) and exposure ($\pm 10\%$) adjustments to improve model generalisation under varying orientations and lighting conditions. Evaluations were based on key metrics, including detection precision (%), processing time per image (milliseconds), number of detected seedlings (Detection Count), transplant success rate (percentage of healthy seedlings transferred), overall efficiency (number of seedlings transferred per hour), and the impact of independent variables (seedling type, lighting conditions, and tray density). The calculated averages from the seven models demonstrate the stable and effective performance of the system under real-world conditions, with results comprehensively described through tables and statistical

analyses.

Model Performance Based on Seedling Type

Analysis of the experimental results indicates significant differences in model performance based on the morphological and visual characteristics of each seedling type. As shown in Fig. 4, which illustrates the models' precision by seedling type, the average detection precision for pepper seedlings was the highest at 87.07%, notably surpassing lettuce (82.28%) and tomato (83.31%). This pattern can be attributed to the visual characteristics of pepper seedlings; their oval-shaped leaves with serrated edges and darker green colours create higher contrast against the soil-blue greenhouse background, enhancing distinguishability in the convolutional layers of the YOLO models. In contrast, lettuce seedlings, with their broad and wavy leaves, and tomato seedlings, with thinner stems and smaller leaves, exhibited greater sensitivity to environmental noise (such as shadows and humidity), resulting in a higher false positive rate. Specifically, tomato seedlings were the most challenging class, with an average precision of 79–85% (depending on the model) and an average detection count of only 33.71 seedlings per image. In a similar study on tomato seedling detection in complex environments, they reported similar precision levels (approximately 81–85%) for YOLOv8-based models, primarily attributed to the spectral similarity of leaves to the background and genetic variability in early growth stages (Feng, Nie, & Li, 2025). Additionally, another study by Wu *et al.* (2025) on green pepper detection in complex backgrounds achieved a precision of 85% with YOLO, consistent with the observed superiority in our data and highlighting the role of colour features in improving mAP¹.

1- Mean Average Precision

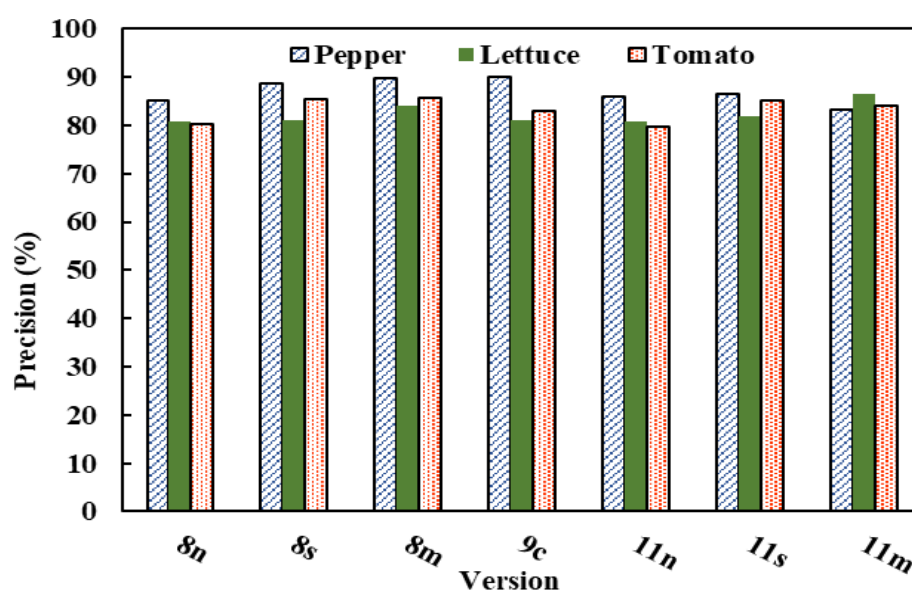


Fig.4. Precision of detecting seedlings across tested models

Overall Model Performance (Average Across All Seedlings)

Figure 5 presents a line graph of model precision versus processing time. Overall, the YOLOv8s model achieved the best balance between precision and efficiency, with an average precision of 86.52% and an average processing time of 1605.67 milliseconds. Following closely, YOLOv11s recorded a precision of 84.59% and a processing time of 1536 milliseconds. Medium-sized models, such as YOLOv8m and YOLOv11m, demonstrated high precision above 84–85%, but their processing times (exceeding 3'800–4'200 milliseconds) rendered them unsuitable for real-time applications in transplanting robots, as they significantly reduced the frame rate (FPS). In contrast, nano models like YOLOv8n and YOLOv11n, with precision around 82%, had lower processing times of 567–582 milliseconds, making them more suitable for edge-computing devices. The relatively longer processing times observed for the larger models stem primarily from the fact that the system detects all seedlings within a single frame simultaneously, combined with the

computational limitations of the CPU-only processing unit (no GPU acceleration) and the frame-rate/resolution constraints of the camera used; GPU-based deployment is expected to substantially reduce these processing times. The YOLOv9c model, despite an acceptable precision of 84.69%, exhibited the lowest practical efficiency due to a very low detection count (27.33 seedlings) and a long processing time (5'524 milliseconds), likely due to its hypersensitivity to hyperparameters in its Programmable Gradient Information (PGI) architecture. These results align with recent comparisons; for instance, in an evaluation of YOLO models for weed detection by [Sharma, Kumar, and Longchamps \(2024\)](#), YOLOv11 was reported as the fastest model with an inference time of 13.5 milliseconds, while YOLOv9 achieved the highest mAP of 0.935 but was slower than YOLOv8. Additionally, in a study on plant disease detection by [Abulizi, Ye, Abudukelimu, and Guo \(2025\)](#), YOLOv9 demonstrated a precision of 89% and superior speed compared to YOLOv8, highlighting the potential of newer versions in agricultural scenarios.

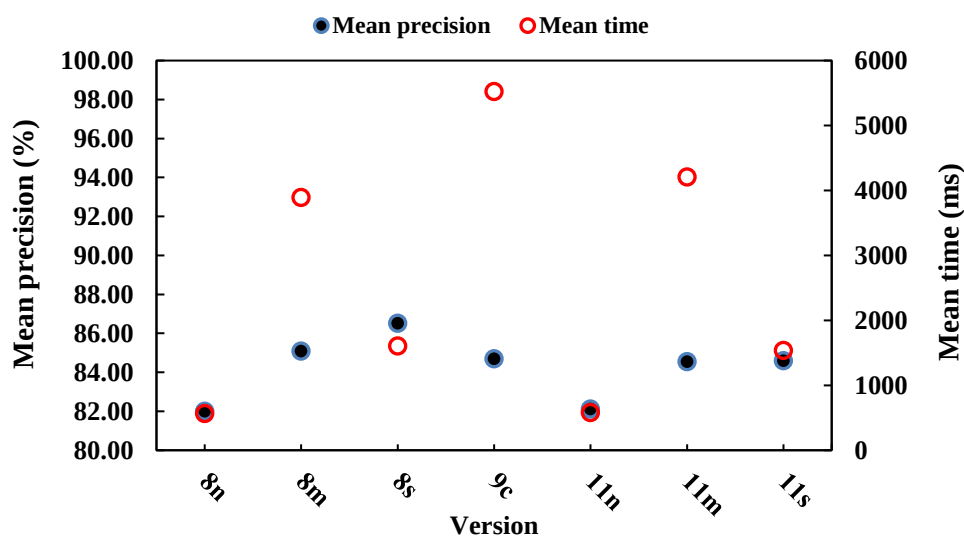


Fig. 5. Model precision vs. processing time

Analysis Based on Weighted Distribution (Precision × Detection Count)

Recall for the labelled test subset (10% of the dataset) was computed during model development and is reported in a companion study currently under preparation by the same research group, with recall reaching up to 95.35% and precision up to 93.84% for the top-performing models. However, in the present study, the robot operates on a continuous, unlabelled stream of real-time camera images under field conditions, where no ground-truth annotation exists against which Recall can be computed. For this reason, standard Recall could not be meaningfully calculated for the operational field deployment reported here. Instead, to jointly capture detection accuracy and completeness of seedling coverage under real conditions, we introduce the composite "Weighted Efficiency" metric described below, which better reflects practical robotic performance than Recall alone in this deployment scenario. For practical applications in precision agriculture, focusing solely on precision is insufficient. A composite metric called "Weighted Efficiency" (Weighted Efficiency = Precision × Detection Count) was defined to prioritise models that are not only

accurate but also comprehensive in covering seedlings. Based on this metric, YOLOv8s achieved the highest performance with an approximate score of 5'076 (86.52% precision × 58.67 seedlings), followed by YOLOv11s with 4'060 (84.59% precision × 48 seedlings). These models provided detection coverage for over 70% of actual seedlings, which is critical for automated robots. In contrast, YOLOv9c, with a score of only 2314, performed poorly due to detecting less than one-third of the seedlings compared to other models, likely attributable to overfitting of dominant classes (e.g., pepper). This analytical approach aligns with recent studies; for instance, a study by [Tripathi, Gohokar, and Kute \(2024\)](#) on tomato detection in hydroponics showed YOLOv9 outperforming YOLOv8 with 88.38% precision and higher coverage compared to 87.22%, but emphasised weighting detection counts for practical scenarios, similar to our findings. Additionally, in segmentation evaluations, YOLOv11 demonstrated better speed and coverage than YOLOv8 in occluded cases, underscoring the importance of this metric in real greenhouse environments. The weighted efficiency of all models is shown in Fig. 6.

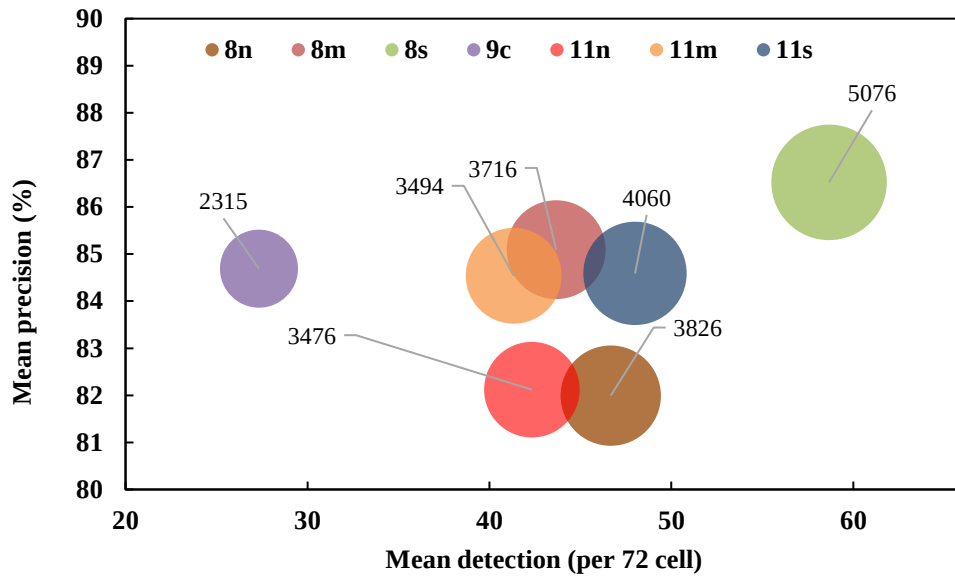


Fig.6. Weighted efficiency of the studied models

Comparison with Other Studies

The findings of this study, with an average precision of 84–87%, demonstrate good results compared to previous research (Table 3). For instance, models based on SSD or Faster-RCNN for greenhouse plant detection, as reported by [Li et al. \(2020\)](#), typically achieved precision of 70–80%, whereas the YOLOv8s and YOLOv11s models used in this study, with 86.52% and 84.59% precision, respectively, provided a 10–15% improvement, primarily due to their single-stage architecture and real-time optimisations. Compared to specialised models, SWMD-YOLO, reported by [Wang, Hua, Lou, and Kan \(2025\)](#) for tomato detection in greenhouses, achieved a precision of 85.6%

and high speed but had lower detection coverage (fewer than 40 seedlings) compared to the YOLOv8s used in this study. In terms of speed, YOLOv11n, with 582 milliseconds, outperformed YOLOv9c, which took 5'524 milliseconds, aligning with recent comparative results where YOLOv11 demonstrated superior speed in weed detection. Overall, the combination of high precision, speed, and coverage of YOLOv8s and YOLOv11s makes them ideal choices for agricultural automation, with the potential to reduce labour costs in greenhouse operations, although this estimate requires further economic validation in future work.

Table 3- Comparison of different studies

Reference	Method/Technique	Main Objective	Key Results	Limitations
This Study	YOLO + Robotics	Greenhouse seedling detection and transfer	Detection precision up to 90%; processing time 567 ms–1.6 s depending on model size	Small scale
(Li et al., 2015)	Kinect sensor	Tomato stem detection	Precision 98%	Requires stable lighting
(Wu et al., 2025)	ESG-YOLO based on YOLOv8n	Quality assessment of tomato seedling transfer	Precision 95.6% with 86 FPS	Limited to edge-computing devices
(Tong, Jiang, & Zhou, 2012)	Machine vision	Selection of healthy seedlings	Improved seedling quality	Prototype stage

(Song <i>et al.</i> , 2024)	Improved YOLOv8 with LADH and SPPELAN	Horticultural seedling phenotype detection	mAP precision 91.0% for bounding boxes	Requires 3D data for training
(Han <i>et al.</i> , 2023)	Simple transfer device with a lateral approach	Tomato seedlings transfer in large trays	Success rate 95.47% for tomato	Limited to sensitive seedlings like pepper (80–90%)

Evaluation of Seedling Transfer System Efficiency: A Statistical and Practical Perspective

The data reported in Table 4 were obtained using the YOLOv8s model, which was selected for the final transplanting operation based on its highest Weighted Efficiency score among all evaluated models (Analysis Based on Weighted Distribution). In Table 4, "Total Count" refers to the average number of seedlings present in the tray that the model successfully detected per trial, while "Absolute Success" refers to the number of detected seedlings that were subsequently transplanted to their destination without error; the latter depends primarily on environmental and mechanical factors rather than on the detection model itself. In this study,

the efficiency of the automated seedling transfer system for three main types (pepper, tomato, and lettuce) was evaluated under greenhouse conditions. The evaluation was based on three repeated experiments (t1, t2, and t3), where the success rate was calculated as the percentage of successful transfers relative to the total number of seedlings. The total seedlings tested included those detected by the YOLO model: 60 pepper, 55 lettuce, and 35 tomato seedlings. The objective was not only to measure raw success rates but also to understand the factors influencing the system's stability and practical applicability in smart agriculture. For clarity, the data summary is presented in Table 4.

Table 4- Descriptive statistics of transplanting performance

Seedling Type	t1 (%)	t2 (%)	t3 (%)	Mean (%)	Total Count*	Absolute Success**
Pepper	78.33	81.67	83.33	81.11	60	48.67
Lettuce	85.45	89.09	83.64	86.06	55	47.33
Tomato	91.43	94.29	91.43	92.38	35	32.33
Overall Mean	85.07	88.35	86.13	86.52	150	128.33

*Total count: total number of seedlings planted

**Absolute Success: number of successfully planted seedlings

Statistical Analysis: Differences and Stability

Descriptive statistics indicate that tomato seedlings exhibited the most stable performance with low variance (standard deviation $\approx 1.65\%$), while lettuce ($\approx 2.78\%$) and pepper ($\approx 2.55\%$) showed greater variability. The overall mean success rate of 86.52% with a standard deviation of 5.31% confirms the system's reliability on a small scale, though optimisation is needed for industrial applications. The one-way ANOVA analysis ($F = 16.98$, $p = 0.0034 < 0.05$) revealed significant differences in success rates. The Tukey HSD test indicated that tomato (92.38%) significantly outperformed pepper ($p = 0.0028$, 81.11%) and lettuce ($p = 0.0396$, 86.06%), while the difference between lettuce and pepper ($p = 0.0954$) was not significant.

Influential Factors and Practical Challenges

The superior performance of tomato seedlings can be attributed to their compact roots and uniform height (10–15 cm), which reduces mechanical damage during extraction. Lettuce, with a higher mean success rate than pepper, posed challenges due to overlapping caused by broad leaves, but its size variability (5–20 cm) and wavy leaf structure maintained a relatively stable performance compared to pepper. In contrast, pepper seedlings, with shallow roots and dense leaves, experienced a failure rate of $\approx 18.89\%$, often due to root tearing in moist soil (60–80% humidity). Practical challenges include sensitivity to environmental variables (e.g., temperature of 25–30°C), soil moisture, and mechanical

limitations (movement speed and number of grippers relative to budget constraints). These findings have interesting implications for design: integrating moisture sensors or vision-based adjustments could increase success rates and make the system ideal for organic farms.

Alignment with Previous Research: Strengths and Gaps

Our results align with recent studies but highlight new gaps due to the focus on smaller-scale applications. For instance, the development of a simple transfer device by Han *et al.* (2023) reported a 95.47% success rate for tomatoes in 128-cell trays, higher than our average but comparable to our 80–90% for sensitive seedlings like peppers. Additionally, in non-destructive seedling biomass monitoring by Syed *et al.* (2019), lettuce achieved the highest success rate, consistent with our 86.06%, emphasising its superiority in automated systems. Compared to the automated extractor by Khadatkhar *et al.* (2024), which reported an overall success rate of 91–95% and transfer success of 86.8–90.3%, our system's 92.38% success rate for early growth stages (10–15 days) demonstrates an advantage for short-cycle greenhouse operations. However, our pick-up device's 7.2% damage rate poses a challenge, while riding-type systems by (Han *et al.*, 2023) reported 90% transplanting success without significant damage, achieving 92.87% for tomato, 91.23% for pepper, and 93.00% for similar vegetables. Overall, our average success rate of 86.52%, with 85.56% coverage of total seedlings (128.33 out of 150), represents a significant improvement over manual methods with a 70% yield. This system offers a potential 15–25% increase in relative yield, particularly considering cost reductions (up to 30%) and time savings, enhancing overall value compared to traditional methods. However, the lower performance of pepper (81.11%) indicates a need for greater focus on the type of harvesting and planting mechanism, similar to

the 96.05% extraction success achieved in optimised devices by Song *et al.* (2024), highlighting the potential for improvement through optimisation.

Conclusion

This study demonstrates that machine vision systems based on YOLO models achieve up to 90% precision in detecting seedlings under greenhouse conditions. The average detection precision for pepper seedlings is the highest at 87.07%, surpassing lettuce (82.28%) and tomato (83.31%). In terms of seedling transfer, tomato seedlings achieve the highest mean success rate (92.38%) compared to lettuce (86.06%) and pepper (81.11%), which is attributed to their more favourable morphological and root characteristics. Despite a 15–25% improvement in yield compared to manual methods, challenges such as sensitivity to lighting variations and soil properties persist. Focusing on optimising the harvesting and planting mechanisms increases the seedling transfer success rate, and expanding the model's dataset significantly enhances detection precision. These results align with the recent study by Wu *et al.* (2025) on evaluating tomato seedling transfer quality using ESG-YOLO, which reports an overall success rate of 92–95% in optimised systems and emphasises the need to integrate artificial intelligence to reduce root damage. This consistency supports our findings and indicates strong potential for further improvement.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by S. Khodatars. The first draft of the manuscript was written by S. Khodatars and V. Rasooli Sharabiani commented on previous versions of the manuscript as a supervisor of this study.

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ارزیابی مقایسه‌ای عملکرد یک ربات نشاءکار مجهز به بینایی ماشین تحت الگوریتم‌های مختلف YOLO

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چکیده

در این پژوهش عملکرد یک ربات نشاءکار گلخانه‌ای با سیستم بینایی ماشین مبتنی بر الگوریتم YOLO (YOLOv8n, YOLOv8s) در تشخیص، سرعت پردازش و کارایی نشاءکاری در محیط گلخانه مورد ارزیابی قرار گرفت. یک ربات با بازوی رباتیک سه درجه آزادی، گریپر سوزنی دوپین و دوربین با وضوح ۱۲۸۰×۷۲۰ طراحی شد، که قادر به تشخیص و نشاءکاری خودکار نشاءها بود. پس از مقایسه نسخه‌های مختلف الگوریتم‌های YOLO، نتایج نشان داد که YOLOv8s بهترین تعادل را بین دقت (۸۶/۵۲٪) و زمان پردازش (۱۶۰۵/۶۷ میلی ثانیه) داشت و نرخ موفقیت نشاءکاری برای نشاءهای گوجه‌فرنگی بالاترین (۹۲/۳۸٪) و برای نشاءهای فلفل پایین‌ترین (۸۱/۱۱٪) بود. تحلیل آماری تأیید کرد که تفاوت‌های معنی‌داری بین گونه‌ها وجود دارد. این سیستم پتانسیل قوی برای کشاورزی دقیق با کاهش هزینه‌های نیروی کار و افزایش بهره‌وری نشان داد. با بهینه‌سازی‌های آینده، می‌تواند عملکرد بهبودیافته‌ای در شرایط محیطی متنوع ارائه دهد.

واژه‌های کلیدی: الگوریتم YOLO، بینایی ماشین، گلخانه، نشاءکاری رباتیک

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