Development of a Harvesting Robot for Use in Soilless Greenhouses

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Abstract. This study aims to achieve fully autonomous fruit harvesting in greenhouses utilizing soilless agriculture by integrating artificial intelligence (AI)-driven deep learning algorithms and robotic arm systems. Based on a comprehensive literature review, a conceptual model has been proposed featuring an articulated harvesting arm mounted on a mobile platform. The system employs depth-sensing vision sensors and advanced object recognition algorithms (e.g., YOLO, Faster R-CNN) to detect fruits and extract their three-dimensional positional data. Using inverse kinematics and robot control algorithms, the robotic arm is guided to the target location and performs harvesting according to the fruit's ripeness level and optimal detachment point. The mechanical design incorporates adaptable gripper-cutter mechanisms to prevent fruit damage during the harvesting process. According to data from related studies, fruit detection accuracy typically ranges from 88% to 95%, while harvesting success rates vary between 80% and 100%. The average picking time per fruit ranges from 3 to 15 seconds, depending on the crop type and system specifications. Deep learning-based approaches have demonstrated high accuracy in both fruit detection and ripeness classification, while developments in adaptive end-effectors have significantly improved harvesting efficiency in robotic arms. This technical study explores the feasibility, constraints, and performance metrics of autonomous harvesting technologies in hydroponic greenhouses. It highlights the synergy between AI-based perception and precise mechanical actuation, offering insights into the integration of computer vision, robotics, and agronomic parameters in modern agriculture. By addressing both algorithmic precision and mechanical adaptability, this research contributes to the development of intelligent and scalable solutions for high-throughput and labor-efficient harvesting in controlled-environment agriculture.

Keywords: Harvest, Greenhouse, Artificial Intelligence, Robotic.

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1 Introduction

Increasing labor costs and labor shortages in the agricultural sector are accelerating the shift towards autonomous systems, especially for time-critical operations such as harvesting. Strawberries are a product that requires timely harvesting due to their delicate structure and short ripening period. The traditional method of picking ripe strawberries by hand is both laborious and can account for more than 50% of total production costs (Chang and Huang, 2024). In modern greenhouses using soilless farming (hydroponics or cocopeat), plants are typically grown on high beds or hanging systems, so automating the harvesting process will save labor and increase product standardization (Yu et al., 2024). With the development of smart farming technologies, digital image processing and artificial intelligence methods are finding opportunities for integration into agricultural applications. In particular, deep learning-based object detection algorithms have made it possible to obtain high-accuracy information about the location and ripeness of agricultural products in images (Pérez-Borrero et al., 2021). The YOLO ("You Only Look Once") algorithm has gained widespread interest in agriculture due to its success in real-time object detection. The YOLOv8 model, announced in 2023, stands out with its improved deep neural network architecture and higher accuracy/speed balance compared to previous versions (Tian et al., 2019; Chen et al., 2024; He et al., 2025). This model is effective in detecting strawberry fruits despite complex lighting conditions, such as in greenhouses, and partially hidden fruits behind leaves. On the other hand, merely seeing the fruit is not sufficient. For a harvesting robot to be successful, the fruit's spatial position must be precisely determined, and the robotic arm must reach and harvest the fruit through appropriate path planning. In recent years, specialized manipulator and gripper designs for agricultural harvesting have been developed for robotic systems (Han et al., 2024; Zhang et al., 2020). For delicate fruits such as strawberries, it is a common approach to design robotic end-effectors to cut and hold the fruit by its stem rather than grasping it directly. This allows harvesting to be carried out without touching the surface of the fruit, minimizing the risk of bruising or damage.

Researchers around the world have developed autonomous robot prototypes for strawberry harvesting. Japan is one of the countries where the first strawberry picking robots were developed, and since the 1990s, robots suitable for different greenhouse cultivation systems have been introduced. For example, a strawberry picking robot was developed that adapts to different cultivation arrangements (soil-covered field ridges and raised beds) (Kondo et al., 1996). In a field trial by Hayashi and colleagues (2010), a strawberry robot using color thresholding-based visual perception was reported to have achieved limited success. This robot struggled in situations where the fruit was covered by leaves or where the background plant parts were of a similar color. Furthermore, while it achieved 76% success in detecting ripe strawberries in a real field, it was unable to detect green (unripe) strawberries. With the development of machine vision techniques in subsequent years, deep learning-based solutions began to be introduced to the fruit detection problem. For example, a study using the Mask R-CNN architecture succeeded in detecting strawberries at different ripeness levels with an F1 score of up to

94% (Sun et al., 2023). With the increasing success of deep learning, the "image recognition" module, which is a fundamental component of autonomous harvesting robots, has been significantly enhanced. This article comprehensively examines how YOLOv8-based detection techniques are used in strawberry harvesting and how their integration with robotic arms has been implemented in the literature. It also discusses the performance metrics of existing systems, the technical challenges encountered, and areas for future improvement.

2 Technical Design

The design of an autonomous strawberry harvesting system is fundamentally based on the integrated operation of image processing and robotic control components. This section examines the technical design of systems defined in the literature at the component level.

2.1 Image Acquisition and Preprocessing

Variable lighting and dense vegetation in greenhouse conditions can create parasitic effects on raw images. For this reason, most systems collect images from different angles using one or more cameras. In addition to RGB cameras, infrared (IR) or depth (RGB-D) cameras can also be used for fruit detection (He et al., 2022). For example, a study using multiple images taken from above by a drone estimated strawberry yield, but this method focused on ripe fruits (Oliveira et al., 2023). In current systems, images are fed directly into the deep learning model with as little noise filtering and basic color/contrast adjustments as possible, as they will be processed in real time. However, some studies have combined different spectral bands (e.g., ultraviolet images under UV illumination) to detect post-harvest damage and bruising in strawberries that are not visible to the naked eye (Lu et al., 2017). The main focus for autonomous harvesting is determining ripeness and location information; therefore, it is important to diversify the images to include different lighting conditions and partial overlaps. In a study by Chen et al. (2024), they trained a YOLOv8-based model using a dataset created by collecting images under different light and viewing angles, thereby improving detection performance in complex greenhouse environments.

2.2 Object Recognition and Maturity Detection

This part, which can be described as the "eye" of the harvesting robot, is responsible for detecting strawberry fruits and, preferably, their ripeness levels on the images coming from the camera. The YOLOv8 model continues the single-stage detection approach of previous YOLO versions, while incorporating a deeper architecture and advanced feature fusion techniques. For example, components introduced in YOLOv8, such as CSP (Cross Stage Partial) and Path Aggregation, improve object detection at different scales. Various improved versions of YOLOv8 for strawberry detection have been proposed in the literature. In a study called CES-YOLOv8, some modules in the model's backbone layer were replaced with the ConvNeXt v2 architecture, and the Efficient Channel Attention (ECA) mechanism was added to better capture the features of strawberries at different stages of ripeness (Chen et al., 2024). This improved model achieved higher accuracy and F1 score compared to the original YOLOv8 in complex environments (92.1%, F1=0.8899). Similarly, the RLK-YOLOv8 study increased the model's spatial perception ability by integrating large-core convolutional blocks (RepLKNet) into YOLOv8. Thus, an average performance of 95.4% was achieved in detecting strawberries partially hidden between leaves or at different growth stages (He et al., 2025). This model can also estimate yield by counting individual strawberries at different developmental stages (such as flower, green fruit, and ripe fruit). Another critical function of the object recognition module is to determine the ripeness of the fruit. Since classic methods based on color and texture are highly affected by environmental conditions (light, shadow, color differences depending on variety, etc.), deep learning-based ripeness classification has been found to be more reliable. For example, a system has been developed that detects the stem point of each strawberry and classifies its ripeness based on color characteristics using a “pose” extension integrated into the YOLOv8 model (Xia, 2024). This system speeds up the harvesting process by simultaneously determining ripeness and identifying where to cut the stem. The improved YOLOv8-Pose model in this study achieved a very high average accuracy value of 97.85% in the ripeness and stem detection task, and it was reported that the model improvements provided a 5.5% performance increase over the base version.

2.3 Depth Perception and Positioning

Simply detecting a strawberry fruit in an image is not sufficient for the robot to pick it up. The robot arm must be able to reach the fruit, which requires calculating the fruit's real-world coordinates (x, y, z). For this purpose, stereo cameras, structured light sensors, or depth cameras (RGB-D) are commonly used. For example, when using a dual-lens stereo camera, the distance of the fruit from the camera plane can be found by calculating the pixel parallax between the two images for each strawberry. Yu et al. (2024) detected the 3D position of strawberries by combining YOLOv7-based detection with RGB-D camera data; their model achieved the accuracy required for harvesting with millimeter-level positional error. Similarly, in a system integrating the YOLOv8-Pose model with depth data, the “stem cutting point” of each detected strawberry was mapped onto the depth map to derive its real-world coordinates, with an average position error reported to be as low as 0.63 cm (Xia, 2024). Reliable depth perception is critical for creating a collision-free arm motion plan, especially in dense foliage environments. Some advanced systems aim to minimize blind spots by viewing fruits from different angles using multiple cameras or a moving camera setup rather than a single camera (Ge et al., 2019). There are also studies where LiDAR scanners are used to extract point clouds of fruits and surrounding obstacles, and the robot plans its path according to this 3D environment (Shalal et al., 2015). However, since systems like LiDAR are costly, stereo/RGB-D cameras are more practical in agricultural robots as a trade-off.

2.4 Robotic Arm and End Effector Design

The physical implementation layer of harvesting robots is typically an adaptation of 4-6 degrees of freedom (DOF) industrial robotic arms for agricultural use. The end effector (gripper or cutting mechanism) of the arm is particularly important for strawberry harvesting, as strawberries are delicate fruits with easily damaged outer surfaces. Therefore, most designs in the literature focus on grasping the strawberry by its stem and cutting it rather than grasping the fruit directly (Han et al., 2024; Zhang et al., 2020). For example, in a robotic arm system developed by Chang and Huang (2024), the end effector operates in two stages: a scissor mechanism cuts the fruit's stem while a simultaneous gripper grasps the cut fruit from below, supporting it. Thus, after being detached from its stem, the strawberry can be held without pressure being applied to its surface and dropped into the target container. Another approach involves severing the fruit's stem by burning it with a laser; although this “contactless” method has been proposed in research, it is not widely used in practical applications (Kondo et al., 1996). The mechanical design of the robotic arm is also adapted to the agricultural environment. Since space is often limited in greenhouses, it is desirable for the joint mechanisms to be compact and able to move quickly. Some researchers have developed arms that can work in narrow spaces using snake-like flexible limbs or ball joints arranged in series. For example, in an arm design with multi-jointed ball joints, the bending angles of the joints are adjusted using two-stage fuzzy logic control, enabling precise movement even in complex environments (Kamegawa et al., 2004; Zribi and Cgioua, 1997).

2.5 System Integration and Control

An autonomous harvesting robot typically consists of an image acquisition system mounted on a wheeled or rail-based platform and a robotic arm. Moving along predefined rows in the greenhouse, the platform processes camera images at each stop to determine the location of strawberries; the robotic arm then attempts to pick the relevant fruit. For this sequential process cycle to be efficient, the vision detection module and the robotic arm control module must work in sync. In a typical control cycle, the coordinates of n strawberries detected from the camera data are stored in a buffer, and these targets are harvested sequentially by the robotic arm. During harvesting, new image acquisition can be temporarily paused, or the next targets can be determined through parallel processing. If the strawberry stem bends or changes position while the robotic arm is in motion (e.g., due to wind or the arm's movement shaking the plant), feedback mechanisms can be activated. For this purpose, some systems utilize force/torque sensors or touch sensors. For example, a force sensor placed on the end effector of the robotic arm measures the pressure applied during strawberry grasping and provides data to a fuzzy logic controller to adjust the grasping force as needed. Such a system, proposed by Zribi and Cgioua (1997), combines fuzzy logic with neural networks to achieve a homogeneous grasping pressure even on irregularly shaped fruits. This ensures that the stem is not crushed and the fruit is not damaged when the robot picks it. Control architectures are generally ROS (Robot Operating System)-based and regulate data transfer between the image processing node, motion planning node, and hardware drivers. The real-time performance of the entire system depends on factors such as image processing time, arm movement speed, and sensitivity. Therefore, optimizing each component in the harvesting robot design (e.g., a lighter and faster arm, more efficient algorithms, clearer images with powerful lighting, etc.) contributes to overall efficiency.

3 Results

Autonomous strawberry harvesting systems featured in the literature have achieved significant success in recent years. In terms of image processing performance, deep learning-based methods have far surpassed classical approaches. For example, an early system using color thresholding could only correctly identify 76% of ripe strawberries and failed to detect strawberries hidden under leaves or green strawberries (Hayashi et al., 2010). In contrast, a current YOLOv8-based model can detect strawberries with an average accuracy of over 95% even against a complex greenhouse background (Chen et al., 2024; He et al., 2025). The CES-YOLOv8 algorithm developed by Chen et al. (2024) achieved a 2.05% increase in mAP compared to the original YOLOv8, reaching a mAP level of 92.1%. Similarly, the improved RLK-YOLOv8 model achieved 95.4% mAP and 95.4% precision in strawberry detection throughout the entire growth cycle (from flowering to ripe fruit) (He et al., 2025). These improvements enhance detection sensitivity, particularly in scenarios where strawberries are partially visible among leaves and vary in size.

Significant metrics have also been obtained regarding ripeness detection. A multi-purpose model using the YOLOv8-Pose infrastructure achieved 97-98% accuracy by simultaneously determining the ripeness class of the strawberry and the cutting point of its stem. In this model, the average stem point location error was reported to be only 0.63 cm (Xia, 2024). In the Mask R-CNN-based approach by Ge et al. (2019), the F1 score reached 0.94 in the detection of ripe red strawberries. These high accuracy rates show that deep learning techniques are beginning to perform at a level close to that of humans in fruit detection. Indeed, many studies emphasize that detection accuracy has exceeded 90% and that the main limiting factor is now the physical harvesting stage.

In terms of robotic harvesting achievements, the literature contains results obtained from field trials of different prototypes. The "fruit collection success rate" and "average collection time per fruit" are used as general performance metrics. One of the early robots could harvest 60% of the fruit under laboratory conditions, but its success rate remained below 50% in open field conditions (Kondo et al., 1996). These rates have improved significantly in modern systems. For example, a wheeled strawberry robot developed for open fields by Tıtuaña et al. (2024) achieved an average success rate of

71.7% in five different scenarios (close to 95% in the best case, 37.5% in the most challenging conditions). A dual-arm harvesting robot developed by Yu et al. (2024) operating in a controlled greenhouse environment successfully harvested 49.3% of strawberries in a greenhouse where flowers and small fruits had been thinned (pruned), but the rate remained at 30.2% in the unpruned natural state. This result demonstrates that plant maintenance operations (flower/vegetable thinning) can significantly impact automation success. The same study reported that a single arm could harvest an average fruit in 7 seconds, while two arms working in sync reduced the time to 4 seconds. This indicates that multi-arm systems can increase efficiency by working in parallel.

As an example of cutting-edge technology, Parsa and colleagues' (2023) system, named "Robofruit," has been tested in a commercial greenhouse and research farm. This system uses a new vision algorithm to detect dense clusters of strawberries and a specialized 2.5 DOF harvesting head to expose clogged fruits. Robofruit was able to detect ripe strawberries with 95% accuracy and distinguish their ripeness; it successfully harvested 87% of all detected strawberries. When considering fruits in a harvestable position (defined as "pluckable"), the harvesting success rate was recorded at 83%. This is one of the highest rates in the literature, demonstrating the robot's effectiveness in separating and harvesting fruits from complex clusters. It is also noted that no surface bruising occurred on any of the fruits harvested by Robofruit thanks to its specialized end effector.

Another key metric highlighted in this section is the real-time performance of sensing and harvesting integration. For a system to be practically usable, the total time between processing the image from the camera and the arm picking the fruit must be reasonable. Many studies have reported that the time required to pick a single strawberry is around 10-15 seconds (Hayashi et al., 2010). The time reduced to ~4 seconds with the dual-arm system mentioned above is a significant improvement for research prototypes (Yu et al., 2024). However, it should be noted that it is still slower than human workers. For example, an experienced human worker can place multiple strawberries into a basket within seconds under suitable conditions, while robots typically process fruits one at a time. In this context, researchers are focusing on methods that optimize the movement of robots (e.g., routing algorithms that allow them to start with the nearest fruit) or special gripper designs that can grasp multiple fruits at the same time to increase the number of fruits picked per unit of time (Han et al., 2024; Zhang et al., 2020).

In terms of error rates and obstacles encountered, the most common problem is when fruits are completely hidden by leaves or branches. No matter how successful image processing is, it is impossible to detect a fruit that the camera cannot see. In the work of Yu and colleagues (2024), the fact that only one-third success was achieved in an unpruned environment was largely attributed to visual obstacles. Some fruits, even if detected and their location determined, cannot be accessed at a suitable angle by the robotic arm. For example, strawberries growing very close to the ground or very close to the roof may be outside the robot's working space. In such cases, even if the harvesting robot detects the fruit, it cannot pick it, increasing the number of failed cases. When examining the reasons for failure, another factor is detection errors: Errors such as overlapping fruits being detected as a single fruit (merged detection) or leaves/background

being mistaken for fruit (false positives) can misdirect the robot and reduce yield. However, recent studies have shown that YOLO-based models minimize such errors; for example, improved algorithms are more successful at recognizing overlapping fruits separately compared to previous YOLO versions (Chen et al., 2024; He et al., 2025).
In summary, the findings show that the visual perception component with deep learning can identify and locate ripe strawberries with high accuracy. In the physical harvesting component, although success rates are gradually increasing, there is still room for improvement. Even the most successful systems are unable to harvest some of the fruit (e.g., 10-20%) or may fall behind human harvesting speed. However, considering the rising labor costs and the downward trend in technology costs, these systems are expected to become economically competitive in the near future.

4 Discussion

The findings from the compiled literature reveal that integrated image processing and robotic systems for autonomous strawberry harvesting have made significant progress. Algorithms, such as YOLOv8 and derivative deep learning models, have provided high accuracy, enabling reliable detection even in complex backgrounds like strawberry fields. Models developed by integrating large convolutions, multi-scale feature pooling (such as FPN, BiFPN), and attention mechanisms show meaningful improvements in detecting overlapping and partially hidden fruits compared to previous generation algorithms (He et al., 2025). This has undoubtedly brought the "vision" capabilities of harvesting robots closer to human performance. However, there are still issues to be resolved on the image processing side. The biggest challenge is the problem of leaves and branches obscuring the fruits. Some approaches have attempted to ensure that fruits are seen from different angles by using multiple cameras or moving camera systems instead of a single camera. For example, Ge and colleagues (2019) used cameras moving on a two-track mechanism called "Cartesian dual-track" in a robot they developed in Norway to detect strawberries from different perspectives. Thus, fruits that were not visible from one angle could be detected from another angle. In the future, as the cost of multi-camera vision systems decreases and algorithms become faster, this approach is expected to improve in performance.
Another point of discussion is the temporal synchronization between detection and segmentation. Even a highly accurate model must be capable of real-time operation to be successful in practice. It has been demonstrated that the YOLOv8 model can run in real time on embedded devices (e.g., Jetson series GPUs) (Chen et al., 2024). However, since model improvements generally increase the number of parameters and computational load, a balance is needed in practical applications. Some researchers have sacrificed some accuracy in order to gain speed by using lightweight versions of YOLOv8 (nano or tiny versions). For example, Wang et al. (2023) optimized the YOLOv5n (nano) model for cherry tomato ripeness detection, achieving an average accuracy of 95.2% and running it on a real-time embedded system. Similarly, model size-speed optimization specific to strawberry harvesting will be an important area of research in

the future. Since additional tasks integrated into the model, such as ripeness classification (multi-task learning), can affect the algorithm's speed, hardware acceleration (GPU/TPU) and model compression techniques (quantization, pruning) may need to be applied.

In the field of robotic arms and end effectors, an important aspect of the discussion is the system's ability to harvest fruit without causing physical damage and with minimal damage to plant tissue. Various gripper and cutting designs have been proposed in the literature, and comparative analyses of these are available. For example, Zhang et al. (2020) comprehensively reviewed the types of grippers used for agricultural robots, control strategies, and application areas. The general trend is toward soft grippers that directly contact the fruit (such as silicone-based pneumatic fingers) or cutting-gripping mechanisms that do not contact the fruit at all. The most successful solution found for strawberries is to cut the stem and support the fruit from underneath. This prevents scratching or bruising the fruit's surface. However, even with this approach, there are sometimes risks such as the strawberry stem not being cut at the right point or the fruit falling to the ground after being cut. New-generation systems visually identify the stem cutting point for each fruit and guide the scissor mechanism with millimeter precision. The difficulty lies in situations where branches and leaves may be similar in color to the stem or where the stem may be partially hidden by the fruit. Therefore, He and colleagues (2022) developed a special algorithm to detect the center of strawberry stems in the field and directed the robot to the relevant point. Still, in practice, tactile feedback beyond visual perception may also be important to cut the stem from the correct place under all conditions.

Another topic discussed to increase the success rate of harvesting robots is adapting plant cultivation techniques and agricultural practices to suit the robot. As mentioned in the findings section above, robot performance increases significantly in plants where flowers and fruits have been thinned. This highlights the need to revise traditional farming methods with robotic harvesting in mind. For example, some farms may consider selecting strawberry varieties that grow more vertically or have leaves that cover the fruit less, to facilitate robot use. Similarly, suspension systems or A-frame greenhouse structures that allow fruits to grow at the same height plane can make the robots' job easier. In summary, optimization may be necessary not only on the engineering side but also on the agricultural application side.

Looking ahead, the economic feasibility and reliability of autonomous harvesting systems are also being discussed. Current prototypes are mostly for research purposes and contain high-cost sensors and mechanical parts. However, as technology costs decrease (e.g., depth cameras and robotic arm kits becoming cheaper), the commercialization potential of these systems is increasing. In countries with high labor costs, it is predicted that investment in harvesting robots could pay for itself within a few years (Bechar and Vigneault, 2016). Regarding reliability, it is critical that the robot can operate for long periods without requiring constant maintenance. Greenhouse conditions such as high humidity, dust, and temperature variations can strain the electronic and mechanical components. Within the scope of the discussion, some studies have focused on upgrading the IP protection classes of agricultural robots (water resistance, dust protection, etc.) and designing moving parts to require less maintenance. Chang and Huang (2024) aimed to adapt to high-humidity greenhouse conditions by designing the critical parts of the robotic arm from stainless steel and within a closed body.

Ultimately, the discussion largely demonstrates the technical feasibility of autonomous strawberry harvesting systems while highlighting the ongoing need for optimization and adaptation. As faster and more agile algorithms emerge in image processing and smarter control strategies (e.g., AI-supported path planning, coordination with unmanned vehicles) are implemented in robotics, the effectiveness of these systems will increase. Furthermore, similar principles are being adapted to other fruit/vegetable products (e.g., YOLO-based harvesting studies exist for products such as apples, tomatoes, and peppers), and experience gained with one product can be transferred to others (Tian et al., 2019). In the future, the wider adoption of these systems will accelerate the digital transformation in agriculture, creating positive impacts on productivity, sustainability, and workplace safety.

5 Conclusion

The literature findings discussed in this study indicate that systems for autonomous strawberry harvesting have made significant advances in both visual perception and mechanical application. Deep learning-based algorithms such as YOLOv8 enable the high-accuracy, real-time detection of ripe fruits in greenhouse conditions, delivering reliable results even in complex backgrounds or partial overlap situations. Thanks to the integration of image processing and depth sensors, it has become possible to determine the three-dimensional position of fruits with millimeter precision, enabling robotic arms to reach the fruit from the correct point and perform the harvesting process. Innovations in the design of robotic end effectors have also contributed to the damage-free harvesting of delicate products such as strawberries, with solutions combining stem cutting and support mechanisms increasing harvestability while maintaining product quality.

Performance data obtained from trials show that some robots achieve success rates of over 80% under controlled greenhouse conditions. In particular, the reduction in picking time to an average of four seconds per fruit through the use of dual-arm systems represents a significant improvement in operational efficiency. However, structural obstacles in field conditions and difficulties arising from plant layout can reduce success rates, highlighting the need for technology and agricultural applications to be developed in a compatible manner. Plant row arrangement, leaf thinning practices, and infrastructure solutions such as rail systems directly impact automation success.

One of the most significant future impacts of autonomous harvesting systems is in the economic and social spheres. In conditions where labor costs are steadily increasing and finding workers in rural areas is becoming difficult, the increased efficiency and reduced heavy workload provided by these systems are significant advantages. Thanks to their continuous operation capacity, it will be possible to effectively utilize the harvest window. Although the initial investment costs are high, it is anticipated that economic returns can be achieved in the long term.

In general, the integration of YOLOv8-based visual perception techniques and robotic arm systems presents a promising solution for automating strawberry harvesting, particularly in soil-less farming applications. As current prototypes approach operational readiness, the combination of more advanced artificial intelligence algorithms, multi-sensor integration, and suitable greenhouse/field infrastructure will enable these technologies to find commercial applications. This will accelerate the digitalization process in agricultural production, providing significant contributions in terms of sustainability and labor efficiency.

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