A REVIEW OF END-EFFECTOR TECHNOLOGIES FOR DELICATE FRUIT HARVESTING

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Abstract
This article describes and reviews the current solutions in the field of robotic grippers and gripping methods for their applications in the agriculture and food industry. Demand for automation is driven primarily by labor shortages, which are becoming critical due to the seasonal nature of harvesting requiring impact labor. This paper focuses on the specific challenges associated with handling agricultural crops, which are irregular and usually more difficult to handle, unlike industrial products. This fact requires the development of grippers that are flexible, gentle and reliable. The conclusion of this paper identifies key challenges and outlines future trends in the development of grippers for agricultural robots.

Key words: *end-effector; gripper; Agricultural robot; harvesting robot.*

INTRODUCTION

The shortage of labour in agriculture is resulting in the development of automated solutions such as crop-specific harvesters. However, the commonly used method of harvesting by shaking the fruits often causes mechanical damage to the fruits, which reduces the quality and durability of the production (Pu et al., 2023). Consequently, manual harvesting continues to be the prevailing standard of quality, with modern robotic systems striving to emulate this level of friendliness. A significant challenge in the field of robotic harvesting pertains to the gripping mechanism for fruit. This requires not only stable contact, but more importantly the prevention of slipping and damage to the object throughout the handling operation (Brown et al., 2010).

In order to address the wide variation in requirements, a number of grippers with different strategies and mechanisms have been developed. A comprehensive overview of these strategies is offered, for example, by Patel et al. (2017) who classify grippers according to several criteria. As shown in Fig. 1, these criteria include the number of fingers, actuation type, gripping mode, mechanism type, and physical gripping principle.

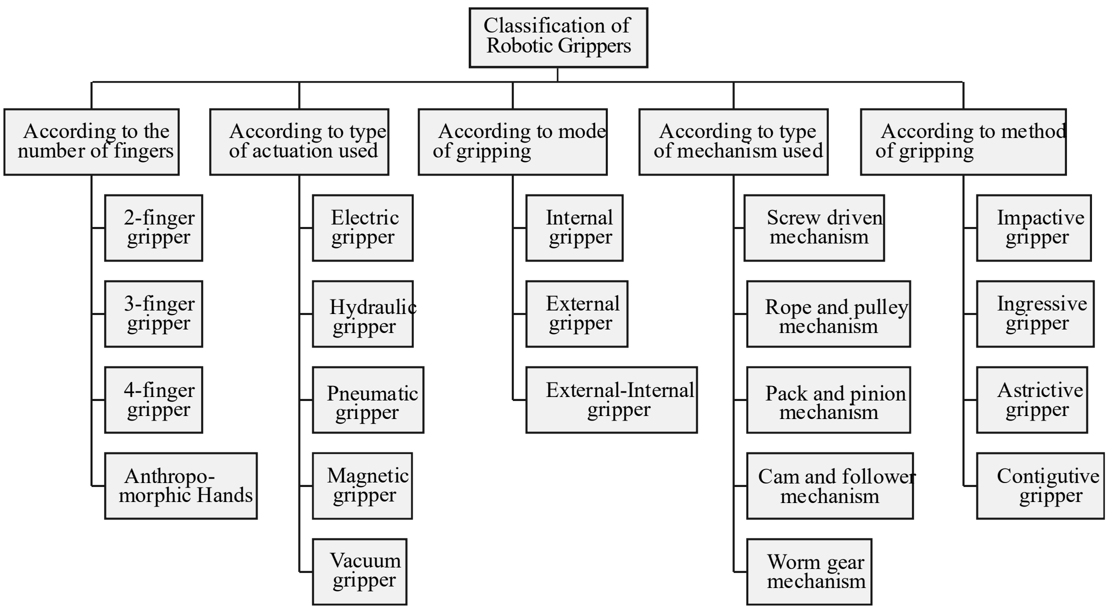

Fig. 1 Gripper classification according to different classification strategies based on Patel et al. (2017)

In the context of mechanical structures, the ability to ensure precise control and gentle handling is contingent on adequate sensory feedback The end-effector sensors related to grasping operations can be divided into four categories: switching, tactile, visual and measuring (Droukas et al., 2023).
The application of these sensor-equipped grippers in agricultural practice strongly dependent on the characteristics of the target crop. For instance, vacuum or soft grippers are frequently employed for the harvesting of fragile berries, such as strawberries and blueberries. Meanwhile, multi-finger mechanisms are the preferred choice for the harvesting of firmer fruits, including apples and citrus fruits (Zhang et al., 2023). To objectively assess and compare the performance of different solutions, several parameters are monitored in the literature. In the context of fruit harvesting, two key metrics are the harvesting success rate and cycle time. The harvesting success rate is defined as the percentage of fruit that is successfully harvested out of the total number of attempts. Cycle time, on the other hand, is defined as the time taken to perform one complete harvesting operation, from the initial identification of the fruit to its placement in the tray (Bac et al., 2014). Although the degree of crop damage is also a relevant quality factor, its standardized ranking poses a methodological challenge. Individual studies often use different, subjective scales for visual inspection or lack a uniform definition of what is considered unacceptable damage. This inconsistency complicates direct statistical comparisons of the effectiveness of different projects (Vrochidou et al., 2022).

This paper aims to review and compare state-of-the-art end-effector solutions in terms of their mechanical principles, sensory equipment and performance metrics, with a focus on robotic manipulation.

MATERIALS AND METHODS

This study uses a scoping review methodology, structured in three sequential phases, to map end-effector technologies and identify key trends.
For the literature search and selection in the first phase, the Google Scholar database was chosen as the primary source, as it covers sources from both Web of Science and Scopus, offering a broader scope through its citation data (Martín-Martín et al., 2018). Keyword combinations such as "end-effector", "gripper" and "robotic harvesting" were used to conduct searches between 2020 and 2025. A two-stage screening process was then employed. Review articles, patents, and simulations were excluded. All remaining papers were then reviewed for relevance, and those that did not provide information regarding in-field end-effectors were excluded. This ensured that only original experimental studies with physical prototypes and field data were selected.
In the second stage of the research, the data were systematically extracted from the final set of selected studies according to five key parameters. These parameters were: the type of effector (categorical), the number of degrees of freedom (DOF) of the effector, the target crop (categorical), the percentage of harvest success, and cycle time (s).
In the third stage, the extracted data was analyzed. Descriptive statistics and thematic analysis were used to compare the performance of different technologies and identify dominant design approaches. The aim was to create a clear map of the current technology landscape and its main trends.

RESULTS AND DISCUSSION

A systematic literature search identified 24 relevant studies published between 2020 and 2025. Fig. 2 provides a more detailed overview of the temporal trend of publications and the distribution of research by crop. Following a detailed review of the full texts, nine studies were included in the final synthesis. Studies were primarily excluded because they either did not test concepts under real-world conditions or did not evaluate the harvesting process.

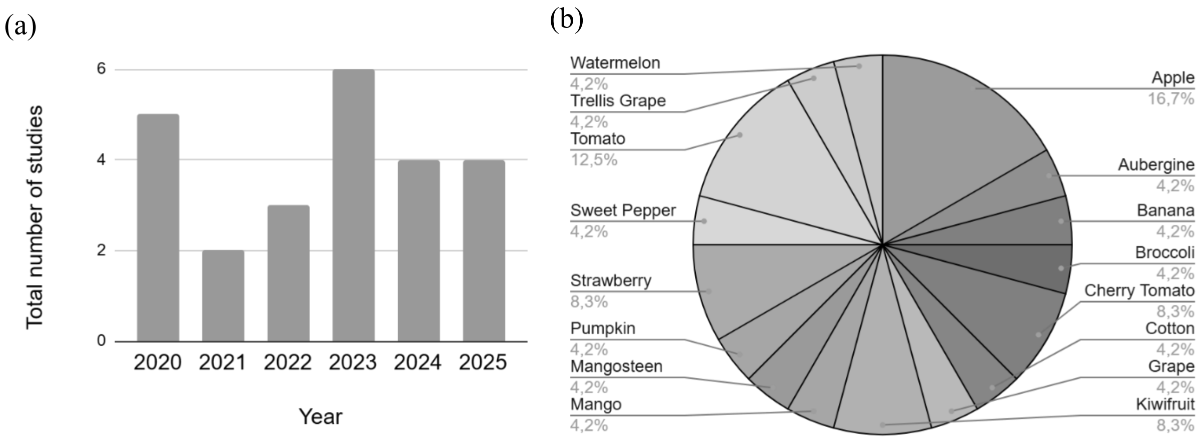

Fig. 2 Trends in the total number of studies over the years (a) and distribution of targeted crops (b)

The performance parameters of the systems studied, including the end-effector principle, the sensory equipment used, the harvest success rate achieved, and the harvest cycle time, are summarized in Tab. 1. The data, which were extracted from published studies, allow for direct comparisons to be made between different technological approaches across a range of crops.

Tab. 1 Comparison of robotic harvesting systems

Study	Crop	End-Effector Principle	Sensors Used	Testing Location	Harvest Success Rate (%)	Harvest Speed (s)
Arad et al. (2020)	Sweet Pepper	Vibrating knife for cutting, catching device	RGB-D camera (Fotonic F80), LED	Commercial greenhouse	18–61	24
Chen et al. (2024)	Banana	Clamping jaws and a small chainsaw (hydraulic drive)	Intel RealSense D435i	Banana plantations	91.69	33.28
Gao et al. (2024)	Cherry Tomato	Vacuum EE / Rotary EE	RGB-D camera	Commercial greenhouse	66.3–70.1	5.3–6.4
Lehnert et al. (2020)	Sweet Pepper	Suction cup and oscillating blade	RGB-D camera, pressure sensor	Greenhouse facility	47–76.5	36.9
Ochoa & Mo (2025)	Strawberry	Single-finger cutting "hook" (pneumatic)	System with camera (not on EE)	Simulation and field tests	94.7 (sim)/100 (field)	2.8/3.8
Tao Li et al. (2023)	Apple	3-fingered gripper (rotational/graspin)	4x RGB-D camera	Commercial orchards	71.3–80.5	5.8–6.7
Wang et al. (2025)	Kiwi	Soft 3-fingered effector (pneumatic silicone)	RealSense D435i	Experimental station	86.4	6.7
Xu et al. (2023)	Grapes	Disc cutting knife	RealSense D455	Commercial vineyard	92.8	6.18
Yin et al. (2025)	Mango	Integrated shearing and grasping effector	RealSense D435i	Mango orchard	73.9	9.2

A comparison of the effectors used for pepper harvesting in the studies by Arad et al. (2020) and Lehnert et al.(2020) reveals significant differences in approach. The SWEEPER effector system, as described by Arad et al. (2020)**,** utilizes a vibrating knife, the efficacy of which is contingent on the precision of data captured by an RGB-D camera (Fotonic F80). While this approach is mechanically robust, its success rate in a real-world environment decreased to 18%. This suggests that the visual sensor alone was unable to provide sufficiently accurate data to guide the cutting tool in environments with a high degree of occlusion, where leaves and stems obscure the target stem and distort depth data. In contrast, Lehnert et al. (2020) used a multimodal effector combining a suction cup and an oscillating blade. This effector was not only supplemented with an RGB-D camera, but also with a vacuum pressure sensor that provided feedback on the successful grasping of the fruit before the cut was initiated. This sensory fusion, combining 'sight' and 'touch', contributed to higher success rates (76.5% under modified conditions) as it enabled the system to verify contact with the fruit and adjust its action accordingly. However, a failure rate of 47% in an unmodified environment shows that even this combination of sensors does not fully eliminate the problem of occlusion. This highlights the need for more advanced scene interpretation algorithms.

Mechanical damage is a central theme in the work of Gao et al. (2024) and Wang et al. (2025), where the design of the effector is subordinated to gentle manipulation. Gao et al. (2024) study on cherry tomatoes found that both tested effectors relied on data from an RGB-D camera. They directly quantified the trade-off between different designs: the vacuum effector achieved zero damage, but with lower success (66.3%) due to frequent failure to adhere to the fruit's uneven, natural surface. In contrast, the rotary effector was more successful (70.1%), albeit with a damage rate of 5.2 A significant development in this field is the soft robotic effector described by Wang et al. (2025) for kiwi fruit. Guided by a RealSense D435i camera system, their pneumatic silicone fingers achieved a damage rate of 0% during gripping, with an overall success rate of 86.4%. This effector's success lies in its ability to adapt passively to the fruit's shape and apply consistent pressure, thereby minimizing the concentrated contact stress typical of rigid grippers. This biomimetic approach mimics the gentleness of the human hand, representing a fundamental departure from traditional mechanical engineering.

The work of Tao Li et al. (2023) presents a three-fingered gripper for apple harvesting, which is a useful innovation. This system is unique in that it has a visual system comprising four RGB-D cameras that provide a comprehensive 3D model of the scene. This rich dataset is essential for guiding the gripper through dense, three-dimensional tree canopies and for calculating collision-free trajectories. Similarly, Yin et al. (2025) developed an integrated cutting and gripping effector for mangoes whose actions are controlled using data from a single, strategically placed RGB-D camera. This success is further enhanced by advanced motion planning methods, such as RRT-Connect, and "depth-first" collection strategies for multi-arm systems that minimize collisions.

Success rates exceeding 90% have been achieved with effectors for crops with clearly defined and accessible targets. The banana robot developed by Chen et al. (2024) uses a combination of robust clamping jaws and a small chainsaw powered by a hydraulic system. Its operation depends entirely on the precise localization of the stem using an Intel RealSense D435i camera, with an average positioning error of a few millimeters. Similarly, the grape robot developed by Xu et al. (2023) uses a simple circular knife guided by a Realsense D455 camera. The grapes are grown on a transparent trellis, which greatly simplifies the detection and localization problem. While these effectors are highly successful, their design and sensor support are highly specialized and difficult to transfer to other crops grown in less structured conditions.

Ochoa & Mo (2025) presented an inexpensive approach involving an effector for harvesting strawberries. A simple 3D-printed cutting 'hook' achieved 100% success in separating the fruit during manual field testing, with an extremely short mechanical action time of 2.8–3.8 seconds. However, this result must be viewed in context: only the mechanical function was tested, not the autonomous system. Paradoxically, the success of the minimalist design highlights the critical role of sensors — the limiting factor for fully autonomous deployment is the speed and accuracy of the visual system that must guide this simple tool to the correct location. This indicates a shift in focus from complex mechanics to fast and reliable software and data processing.

CONCLUSIONS

The studies presented demonstrate that progress has been made in the development of end effectors for robotic harvesting, moving the field from theoretical concepts to functional prototypes that have been tested in field conditions (Zhang et al., 2020). A summary analysis of the results confirms that a successful perception system is essential. The use of deep learning algorithms such as DCNN and YOLO variants in combination with RGB-D sensors has been shown to be essential for reliably detecting fruit in complex environments with a high degree of occlusion (Lehnert et al., 2020). Further increasing the reliability of the grip is sensor fusion, such as supplementing visual data with tactile feedback via a pressure sensor (Z. Wang et al., 2022). At the same time, it has been confirmed that there is no universal end effector and that specialization is necessary. Soft pneumatic effectors have proven to be the most successful for fragile fruits, achieving zero damage during gripping (X. Wang et al., 2025), while integrated cutting and gripping mechanisms are effective for more robust crops (Chen et al., 2024). Furthermore, deploying multi-arm systems controlled by advanced task planning algorithms, such as MARL (Tao Li et al., 2023), has been demonstrated to achieve the most significant reduction in cycle time, reducing it by up to 33% compared to heuristic methods.

Despite these advances, challenges remain that define future research directions. There is a need to focus on increasing robustness in unstructured environments, as system performance still declines dramatically in real-world field conditions (Arad et al., 2020). Future research must focus on developing algorithms that are resistant to extreme lighting conditions and dynamic occlusions. Furthermore, the flexibility and adaptability of effectors must be increased so that they can better adapt to irregular fruit shapes, which includes both more advanced soft robotic systems and intelligent control of rigid grippers. Most studies focus on specific aspects of harvesting, so the next step is to fully integrate perception, planning, manipulation, and mobile platforms into truly autonomous systems. Last but not least, the data clearly show that modifying the growing environment significantly increases the success of harvesting. Future efforts should therefore focus on a multidisciplinary approach and synergy between robotics and agronomy, where "robot-friendly" varieties and cultivation systems will be developed in parallel, which may be more economically viable than developing overly complex robots.

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